World Sustainability Series

Walter Leal Filho · Tony Wall · Hendrik Müller · Peter Yang · Andrzej Klimczuk *Editors*

Artificial Intelligence in Sustainability Teaching and Research

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Due to its scope and nature, sustainable development is a matter which is very interdisciplinary, and draws from knowledge and inputs from the social sciences and environmental sciences on the one hand, but also from physical sciences and arts on the other. As such, there is a perceived need to foster integrative approaches, whereby the combination of inputs from various fields may contribute to a better understanding of what sustainability is, and means to people. But despite the need for and the relevance of integrative approaches towards sustainable development, there is a paucity of literature which address matters related to sustainability in an integrated way.

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have, over many years, been officially accepted for tenure and promotion purposes.

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Artificial Intelligence in Sustainability Teaching and Research



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Preface

Artificial intelligence and sustainability are merging into one of our most consequential crossings on the road ahead. Educators and researchers are currently facing great environmental challenges alongside the revolutionary advances in intelligent systems. How can we leverage the AI tools to push sustainability—without dragging ourselves down with its own ecological footprint? What is the way forward to not only teaching learners to use AI tools but also think critically about their place in constructing a more sustainable world?

This book, *Artificial Intelligence in Sustainability Teaching and Research*, stems from the conviction that these questions require prompt, close attention. The book is intended to gather the opinions and perspectives of a community of academics, educators and practitioners across various geographical regions, who are currently making significant strides in shaping new ways of thinking at the intersection of AI literacy and sustainability education. Their collectively oriented work reveals the revolutionary possibilities and deep-seated responsibilities of integrating AI into sustainability fields. We organised the book into four interlocking parts, each tackling a key aspect of this emerging field.

Foundations of AI Literacy and Pedagogical Design

Provides the conceptual background. The opening chapters examine what it means to engender AI literacy in sustainability students, charting the journey from ecological to algorithmic literacy and offering models for purposeful pedagogical usage. Contributors contemplate the ethical dilemmas of AI in sustainability education and adopt balanced views which account for risks and opportunities. Core issues across values, skills, and educational objectives are explored using an array of cultural and organisational perspectives.

Applied AI in Disciplinary Teaching and Skill Development

Brings to our fore the transition from a theoretical approach to practical application with the integration of AI concepts in real life which may include practices that range from business education, environmental science, agricultural training, and “new mediums for teaching” or innovative methods in pedagogical formats (like the Kankyo Café). These chapters illustrate an astonishing depth of AI applications.

AI-Driven Solutions for Environmental Resilience

Discusses new research, highlighting cutting-edge solutions of AI using it as a means to solve a number of pressing environmental issues. It is about how to advance circular economy principles, to guarantee smart sustainable cities, to optimise energy use of academic buildings, and on the role of AI to provide actionable suggestions for sustainability.

Institutional Governance, Policy, and Ethical Frontiers

Opens a more nuanced, systemic and forward thinking lens. What are some methods for higher education institutions to harness the capabilities of AI to further the attainment of the Sustainable Development Goals, with ethical management responsibilities for its application? What policies, economic models and analyses can guide sustainable AI adoption?

Over the course of the book, readers will find not technical information on descriptions of technological progress, but considered, layered discussions of ways that AI can be used in the service and occasionally in opposition to sustainability goals. The contributors are from different geographical regions, disciplinary traditions, and institutional environments, to add richness to the volume by incorporating ideas that refuse simplistic one-size-fits-all solutions.

We are sincerely indebted to the authors, whose efforts and dedication give this book life and the reviewers who have provided

quality checks. To those educators and researchers worldwide who on a daily basis engage in preparing students to better understand an unpredictable world, we hope this volume may become a source of inspiration and a resource in trying to use AI to create an education that is not only sustainable, but sustainable practice.

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Foundations of AI Literacy and Pedagogical Design

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AI Literacy and New Learning Strategies

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Abstract
AI chat bots have recently become commonplace in many daily activities. For students, they have also become a study aid—albeit in an unstructured way that varies greatly across subjects and often shows inconsistent levels of accuracy and reliability. Currently, the involvement of professors in addressing AI use in academia is often uncoordinated, due to both the diversity of educational needs and the rapid pace of technological change. This evolution demands swift adaptation during this phase of AI expansion. Following a brief review of the literature, this study presents a teaching strategy to enhance basic AI literacy, grounded in active learning techniques.

Keywords AI literacy – Team Based Learning – Statistics – Active learning

Marina Bertolini is an Assistant Professor in the Department of Statistical Science at the University of Padova. Her research primarily focuses on investment evaluation and innovation policies, with

particular attention to the intersection between economic decision-making, energy, sustainability, and technological change. She has contributed to studies on the assessment of public and private investment projects, the design and evaluation of policies supporting innovation and sustainable development, and the integration of new technologies into higher education. Her recent work also explores the role of artificial intelligence in shaping learning strategies and fostering AI literacy among university students.

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1 Introduction

AI chatbots have recently become commonplace in many daily activities, fundamentally reshaping how people interact with technology. For students, these tools have increasingly served as study aids—albeit in an often unstructured manner that varies widely across different subjects and academic disciplines. The quality of support AI chatbots provide is somehow inconsistent, with accuracy and reliability fluctuating depending on the task and context. This variability presents challenges in effectively integrating AI into formal education and it is also the reason why students have controversial attitudes towards the instrument: they often use it less than expected, or they tend to adapt their attitude depending on instructors' attitude.

Currently, the involvement of professors in addressing the use of AI in academia is frequently uncoordinated. This is due in part to the diverse educational needs across courses and departments, as well as the rapid and continual evolution of AI technology itself. As AI capabilities expand at a swift pace, academic institutions and educators face the urgent need to adapt teaching methods and curricula to incorporate these tools responsibly and effectively. If we do not address this aspect, we risk going through many years of transition during which teaching, learning objectives, and the assessment of outcomes will be misaligned with what students are actually experiencing.

There is a widespread assumption that today's students—often called digital natives—require less guidance when it comes to using new digital tools, including AI. However, this belief risks underestimating the complexities involved in harnessing AI as an effective learning partner. Without proper support and structured frameworks, AI can shift from being a powerful facilitator of knowledge acquisition to a potential hindrance, encouraging superficial engagement rather than deep mastery of academic subjects.

The pilot presented in this paper is grounded in this assumption, i.e. although students may be considered digital natives, they nevertheless require specialized guidance to harness AI effectively as a tool for their academic learning.

Following a brief review of existing literature on AI in education, this study presents preliminary findings from small-scale pilots conducted among international students of economics in Italy. These findings highlight the attitude that students have towards AI use in their learning processes, looking specifically to the support that AI can give in writing essays and answering applicative questions in the subject of Statistics. Building on these insights, the chapter highlight what is relevant to reach the basis for a foundational AI literacy. This approach leverages active learning techniques, encouraging students to critically engage with AI tools and develop the skills necessary to use them thoughtfully and effectively within their academic work.

By fostering both technical competence and critical awareness, this strategy aims to empower students to integrate AI into their studies in a way that complements traditional educational goals rather than undermines them. In doing so, it addresses the need for a balanced and reflective approach to AI adoption in higher education during this pivotal phase of technological transformation.

Efforts to integrate AI into teaching methods and support students in learning how to use it productively are the foundation for the long-term sustainability of this new tool, helping to preserve the quality of the university education system as well.

2 Background Literature

AI is widely used in teaching and it has been a strong stimulus for pedagogical research. Almasri (2024) reviewed empirical studies on the use of AI in teaching between 2014 and 2023 and found that 74 records were suitable to answer to the questions of the inquire, that varied between the impact on learning outcomes and the perception of students and teachers during the experience. The balance provided by the review is almost positive (i.e. the use of AI seems to increase students' performances), but many topics are still uncovered in terms of adaptability to different subjects, and different performances depending on the LLM adopted. Furthermore, the review detected several works studying teachers and their perspective in higher education, with no reference to academic applications and students' perspective. Given the rapid, ongoing improvement of large language models, and the widespread adoption of chatbots as a common tool among students, the nature of the data available for analysis is evolving continuously. As a result, data collected from month to month reflects significant variation and differs substantially from that gathered prior to 2023.

Looking at studies on academic activity, Wu (2024) discussed the use of ChatGPT with a pedagogic perspective and considered the potential risk of reducing critical thinking, representing—among others—one of the major concern regarding the use of LLM in the learning process. Nevertheless, most of academic research approaches the theme considering ethical aspects (Usher and Barak 2024; Pulari and Jacob 2025), and not only with a pessimistic attitude (Zeb et al. 2025). The Imperial College London is currently working on several institutional projects on the generative artificial intelligence, for example to provide feedback to students on their lab reports and to detect at-risk students (Fussel et al. 2025).

Studying how to effectively include AI tools in academic teaching and learning techniques is relevant as research indicates that optimal class sizes for effective learning in higher education range from 25 to

30 students, with smaller seminar groups (15–20) achieving the highest levels of engagement. Once class sizes exceed 50 students, the quality of interaction and individual support significantly declines (Abrahamsen et al. 2024; Bondebjerg et al. 2023). This effect varies by discipline: practical and laboratory-based fields typically require smaller groups, while theoretical disciplines may function with moderately larger cohorts. Given the growing emphasis on active learning methodologies, identifying effective means of supporting teaching practices becomes a critical priority.

The growing integration of AI tutors might help mitigate the limitations of large class sizes by offering personalized guidance, immediate feedback, and accessible support when instructors are not available (Hu et al. 2025; Yuan and Hu 2024). Moreover, this structure seems to enhance personalization, provides real-time analytics for early interventions, and improves inclusivity—particularly for shy or underrepresented students who may otherwise avoid seeking help (Mollick and Mollick 2023; Haugsbakken and Hagelia 2024). In Physics,[1] for example, the possibility to customize commercial chatbots with relatively limited resources—thus enhancing the accuracy of AI-generated responses and aligning them to the specific educational goals—is paving the way for experimentations (Lademann et al. 2025; Kortemeyer 2024; Polverini and Gregorcic 2024).

The application presented in this article is included in a Team Based Learning (TBL) approach (Michaelsen et al. 2014; Lotti 2019).

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3 Teaching Techniques: Description of Pilot Application of AI in TBL

The pilot experience for the integration of artificial intelligence into teaching practices was initially implemented at the University of Padova (Italy) during the 2023–2024 academic year and was subsequently repeated in the 2024–2025 academic year in the course of “Statistics for decision making” of the master course in Management of Sustainable Firms (MASFI).

The project was launched in response to the need to align the rapid spread of AI with the university's active learning methodologies, and in particular with TBL.

Team-Based Learning is a teaching practice in which students, divided into groups, independently study materials provided by the instructor. Groups are not spontaneous: the instructor decides how to form the groups starting from the list of students that explicitly decide to join the TBL approach.[2] Students involved in the two waves of the pilot were highly heterogeneous in terms of knowledge—despite the master level, many of them lacked basic knowledge in the topic—home university, nationality, background. Group formation needed to take into account this diversity, in order to replicate it as far as possible in the single group. In addition, gender balance was kept as a target within the groups. Groups were made up by 6 people, on average. In AY 2023–2024, groups were 18, while in AY 2024–2025 groups were 20.

Following the TBL approach, after the individual study phase at home, students come in class and complete an individual assessment to verify their understanding (I-RAT), followed by the repetition of the same test in a group format (T-RAT), using peer discussion and collaboration to resolve doubts and reinforce what they have learned.

These phases are followed by a practical application (T-APP), where students work in groups to produce, in the case described in this chapter, a project that responds to one or more questions posed by the instructor.

TBL also includes a mini-lesson from the instructor to clarify the most challenging concepts, an "appeal" phase in which students can contest answers they disagree with, and an evaluation phase involving both instructor and peer assessment.

The in class TBL session was organized in three days, the first one dedicated to I-RAT and T-RAT, the second one entirely dedicated to the T-APP and the third one for feedback and evaluation. During the time between the second and third day, the teacher and the groups work at home on the assessments that will be discussed on the third day. Each daily lesson lasts about two hours. TBL session was repeated twice

during the course, and students were awarded with a certain amount of points (to be added to their final grade) on the basis of their performance during the TBL.[3]

The use of AI was explicitly encouraged during the course as a learning support, both in an unstructured way (to autonomously generate quiz related to the topic, or to compare solutions to exercises) and structured way during the T-APP of the TBL session. Regarding the TBL, it was forbidden to use AI during the I-RAT and T-RAT phase, as the goal of the two phases was to test the level of knowledge reached through study at home (individually and with the team); the peer evaluation phase had no explicit instructions regarding the use of AI, and as it was carried out at home it was not possible to check groups behavior in this sense; during the T-APP phase, conversely, groups were asked to use an AI chatbot "as a peer", meaning that the chatbot was supposed to be part of the team.

As previously mentioned, the T-APP in this pilot consisted of the writing of a brief essay, applying the theory studied at home. The titles given to the groups were the following (adapted for sake of synthesis):

- AY 2023–24: 1st session, "Build an index to monitor environmental impact of your firm"; 2nd session, "Time series analysis";
- AY 2024–25: 1st session, "Prove that climate change does not exist[4]"; 2nd "Build an index to measure climate risk exposure of your firm".

To guide the work and be sure to verify learning objectives of the session, each topic was broken down into 5–7 points, to provide a resolution path that was also useful to later evaluate the essays.

During the two hours of the T-APP, each group needed to understand the task, organize the work, decide how to use the AI tool and organize the answers in a document to be uploaded in the system (Moodle). Time constraint is very binding.

Neither during the first experience nor during the second were any suggestions given regarding the type of chatbot to use. However, a significant difference can be observed between the two experiences, stemming both from the intent to build upon the insights gained during

the previous year and from the increased familiarity with, and advancement of, the AI tool: during the second wave, the instructor provided an introductory lesson on the AI, focusing on potential bias in the responses. Still, this lecture was not aimed at telling the students *how* to use it during the T-APP. Students were also asked to compile a *ex ante* and *ex post* questionnaire about their knowledge and use of the AI, and we can reasonably suppose that the *ex ante* questionnaire activated the attention of students towards the tool.

4 Discussion and Results

To evaluate the results of the learning experience it is necessary to look deeper in the context of the application.

The first difference concerns the varying technological maturity of AI and its diffusion. Free-of-charge AI tools have evolved significantly between the spring of 2024 (when the technique was implemented in the first wave) and the spring of 2025 (when the second experience was carried out). Table 1 shows the timeline of the spread of various tools in Italy from 2023 to the present. The source is ChatGPT itself.

Table 1 Chatbot availability in Italy. *Source* ChatGPT (July 31st, 2025. Prompt: "ChatGPT, when did you become available in Italy? And what about the other chatbots?")

The students in the second wave were therefore equipped with more and better tools to carry out the task.

The second difference, as anticipated in the previous paragraph, was related to the preparatory activity provided by the teacher. During the first week of lectures, two hours were dedicated to introducing the topic of AI, beginning with an initial phase in which students completed an individual questionnaire regarding their knowledge of how AI works and how they used it in their studies. This was followed by a basic lecture on the functioning of large language models and potential issues, with a particular focus on statistical relevance, including various examples of bias. This change was introduced to improve

communication and to give context for the task being proposed to the students, while also aiming to prevent some of the difficulties that had emerged during the previous year's educational experience. During the first wave, many students, in fact, had struggled to understand the rationale behind the introduction of AI in study and learning techniques.

For both waves, the first session of TBL was performed early during the course, approximately during the second week: this fact had a great impact for two reasons. First of all, even if the topic to be studied alone was introductory, students who were less used to the subject needed some effort to go back to the contents—and the same partially applied also to students with a stronger statistical background, as the first semester of the master has no exams dedicated to statistical analysis. It is also worth noting that, in this context, statistics is a compulsory exam for obtaining the degree; however, it is not a subject that, on average, receives particular appreciation from students applying for this specific master. This can be a limiting factor in teaching, but it can be overcome by adopting instructional approaches that emphasize practical applications over purely theoretical lessons.

Another relevant aspect for students as "users" of this experience was the need to work in group: this approach, particularly during the first wave, was considered stressful by some students as none of them experienced TBL before, even if they were exposed to other active learning techniques and group works.

These contextual elements and preliminary considerations are intended to support both the interpretation of the students' work—by aligning expectations with the level of effort required—and the potential adaptations of the approach in other courses or with students at different stages of learning. Based on observations from the experience, such an approach can be implemented—with varying degrees of difficulty—at the master's level, whereas it would likely be too demanding for students at the bachelor's level, as it is perceived as challenging and stressful.

Considering the essays written in response to the T-APP questions as the main output of the activity, the following results were observed:

- During the first session of the first wave (Spring 2024), students made extensive use of AI. This approach led to the production of texts that were often far from the "scientific" framework required by the subject. The prompts generated highly emphatic texts, rich in details that were not relevant to the questions posed. In several cases, groups neglected to answer the sub-questions included in the assignment. At the end of the session, students reflected on their use of AI and acknowledged that they had relied on it excessively.
- During the second session of the first wave, the quality of the results improved significantly. However, this was accompanied by a marked reduction in the use of AI by many groups, and in some cases, its use was entirely abandoned. This outcome was commented by groups highlighting the lack of control they had on the output during the first session, that made them loose time[5] and focus. This outcome may also be attributed to the fact that the tool used (primarily ChatGPT) did not deliver consistently reliable performance.

As remarked, the second wave benefitted from a preparatory lecture on AI to improve awareness regarding the tool and try to improve the performances. The results however, were not completely satisfactory:

- During the first session of the second wave (Spring 2025), mistakes made by the students were almost the same as those made by the first wave. Several groups skipped some sub-questions required to complete the task; they improved the language (often thanks to the prompt "humanize"), but they were not able to include coherent references or to keep a critical approach to the answers given by the tool. It is necessary also to consider that the task ("Prove that climate change does not exist") was design to force them to be critical towards the output provided by the AI: conversely, at least one group was convinced by the AI that there is not a climate change issue ongoing. At least 25% of the students were not able to adopt a critical approach towards the sources they used.

- During the second session of the second wave, students adopted the same techniques of the first wave, thus reducing the use of the AI. During this session, they were also given an indicative time-table that suggested how to divide time among different sub-questions, and this guided them also in the use of the AI. Most of them delayed the use of the tool, and tried to keep the control of the process.

One of the key takeaways from the pilot experience—beyond the fact that the experimentation took place within the context of Team-Based Learning—is that practical experience is what truly enables the development of AI literacy and the adoption of best practices in using AI as a support for studying and document production.

Although the second wave of students was exposed to a theoretical lecture, along with a partial activation phase through a questionnaire, this did not prevent them from making the same mistakes as their peers from the previous year, namely excessive reliance on AI and delegation of reasoning.

Moreover, learning through practical experience occurs only if the experience is repeated, allowing students to correct previous mistakes and to implement new strategies aimed at making the integration of AI more productive.

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5 Conclusion

The presence of generative artificial intelligence in students' lives will become increasingly widespread: although its use may not yet be pervasive among current cohorts, it is reasonable to assume that students in the coming academic years will integrate this tool more naturally into their study approaches. The role of the university should not be to anachronistically hinder the use of artificial intelligence, but rather to integrate it, providing all students with a basic literacy in its use and adapting learning objectives where necessary.

In this chapter, the practical experience conducted in the classroom during the academic years 2023–24 and 2024–25 for teaching statistics with TBL sessions was presented. Students were asked to integrate

artificial intelligence in their activity and use it as a “mate” of the TBL group.

The experience was carried out in a less structured way in 2023–24, partly because the most widespread chatbots (e.g., OpenAI’s ChatGPT) became available and gained popularity mainly in 2023: learning from the first experience, and thanks to the evolution of technology, the teaching approach was refined and applied in the 2024–2025 edition of the same course.

What emerged is that practical experience is the most effective way to achieve useful levels of literacy and awareness in AI usage for students. Only (or mainly) through applications they are able to reflect on their use of the AI and to refine it accordingly with feedback from the instructor and peers. Frontal lectures about general literacy and warnings about common mistakes were far less effective than the T-APP experience.

It also emerged that the repetition of the T-APP session was crucial to correct and integrate student’s approach: in order to gain this achievement, it is necessary to dedicate time to feedback and metacognition.

The main limitation of the pilot lies in the restricted transferability of some results, as the technique was applied to a specific subject and to students who self-selected based on their interests and aptitudes. Nevertheless, the pilot provides an opportunity to begin identifying certain emerging trends, which may later be tested in dedicated studies using statistical methods capable of ensuring the transferability of the results, such as randomized controlled trials.

It is worth noting that the use of AI is synergistic with active learning practices. AI is often claimed as a substitute for several techniques, but active learning is still crucial to make students remember and deeply understand the concepts. Future research shall focus on the effects of this kind of integration, as for TBL and active learning techniques it has been claimed that there is higher persistence of students’ knowledge—the effect of AI on all techniques might improve their relevance.

It will also become increasingly important to propose activities in which AI is integrated, while at the same time creating space for activities where AI is not used, in order to avoid skill loss, technological alienation, and excessive dependence on the tool. Unmediated use of AI can lead to a general flattening of the level of courses and exams, whereas its thoughtful integration encourages new strategies.

The major drawback of the learning technique presented in this chapter is the great investment in terms of time, from both the teacher and the students: this is also something in common with “simple” TBL approach. Another relevant issue is to take care of students’ perspective and their perception of the work load which, in these pilot experiences, seemed to be heavy: in this sense, any future application shall consider how to balance different learning components to keep the work sustainable.

What is certain, however, is that we are in a delicate transitional phase, which will require a demanding effort from everyone, and some frictions between traditional and future approaches will require much more time to be solved within the teaching community.

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Footnotes

1 Physics provides interesting examples, as it is a STEM discipline that has long been concerned with the study of its own teaching.

2 Students not joining the program can follow the lectures, but they will not take part to the active learning sessions.

3 The activity requires a lot of commitment and participation from the students, and it is necessary to have an incentive for participation.

4 One of the sub-questions was related to the reliability of the sources used to prove this statement.

5 Time constraint in the T-APP session is one of the most relevant issues, following students’ opinions.

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From Ecological Literacy to Algorithmic Literacy: Reimagining Sustainability Education in an Era of Intelligent Systems

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Abstract
It is with the advent of AI that a new era in sustainability education is beginning to take shape. Students must have a firm grasp of both ecological systems and our role within them, as well as algorithmic literacy, or the ability to understand how AI works and its effects on humans and the planet. That is the only way to guarantee they are well-equipped to deal with the problems of today. In today's world, being "sustainability-literate" basically means being well-versed in both algorithms and environmental issues. This paper reevaluates sustainable education by combining these two viewpoints. This research will examine sustainability education practices in India and

Europe as of late about incorporating a knowledge of AI, and it will analyse literature and theoretical frameworks that establish a connection between environmental education and digital literacy. Opportunities and problems are both shown by the examination. Intelligent systems provide robust resources for sustainability-related worldwide cooperation, individualised education, and environmental monitoring. Nevertheless, there are environmental and ethical problems associated with AI's growth, such as societal biases in algorithms and the impact of large-scale computers on the environment. The study proposes that to equip the next generation of citizens, it is necessary to take a holistic strategy that teaches students to think critically about algorithms while also raising their awareness of environmental issues. Finally, the study provides some suggestions on how legislation, teacher education programs, and curriculum can work together to produce students who are proficient in both ecological and algorithmic jargon, and who will be able to apply this knowledge to create a more equitable and sustainable future.

Keywords Ecological literacy – Algorithmic literacy – Sustainability education – Intelligent systems

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1 Introduction

Teaching students to be critically aware of how digital technologies impact society and to develop a profound sense of environmental awareness are two of the most pressing challenges facing education in

the twenty-first century. Despite appearances, the environmental catastrophe and the meteoric ascent of AI are not unrelated. This study's major goal is to establish that sustainability education must evolve, so as to teach students proficiency in both environmental science and algorithmic thinking.

Ecological literacy involves knowledge of how the natural world works and how human activities affect it. Ecological literacy, popularized by scholars such as Fritjof Capra and David Orr during the 1990s, prepares students to think critically about complicated systems, to appreciate biodiversity, and to act as environmentally responsible citizens. According to Orr (1992), ecological problems are symptoms of a broader cultural problem: a culture that has forgotten it is part of ecology.

At the same time, algorithms and AI are increasingly ruling our environment. Understanding how algorithms operate and how they impact data, decisions, and daily life is a prerequisite for becoming literate in them. An algorithmically literate person may assess the benefits and drawbacks of technology such as social media feeds and smart energy meters since they are aware that these systems adhere to preset data patterns and rules.

Artificial intelligence (AI) and data-driven solutions are being used to solve environmental issues in a variety of fields. Algorithms that optimise smart grid energy use and machine learning models that improve climate projections are two examples. However, the rapid development of AI has consequences for society and the environment. Two major concerns are the substantial amount of labour needed to train AI models on a wide scale and the possibility that uncontrolled algorithmic systems would worsen social inequality. Innovations in technology may either help or hurt efforts to promote sustainable development. Therefore, teaching people about sustainability is now a part of teaching them about technology. Students must be able to use AI to address environmental problems, but they also need to know how to evaluate and lessen the unintended consequences of technology.

By fusing computer literacy with environmental literacy, the authors of this essay examine the possibility of altering the way sustainable education operates. The study examines the theories and literature that have examined the connection between environmental education and digital literacy. The study then delves into Europe and India to see how identical concepts are being taught in schools there. In contrast to how green and digital education coexist in Europe, India is an excellent example of a developing nation that strikes a balance between the demand for digital literacy and the need to address urgent environmental challenges. Next, it will analyse and talk about the results by zeroing in on the questions, solutions, and best practices that crop up often when we attempt to create a unified model of education. In the end, the study hopes to back a paradigm change in education by proposing new laws, new approaches to teacher education, and new methods to incorporate ecological and algorithmic consciousness into existing curriculum.

1.1 Research Questions, Hypothesis, and Objectives

This study examines how the emphasis of sustainability education has shifted from ecological literacy to algorithmic literacy using four primary research questions as a framework:

1. How are ecological and algorithmic literacies currently defined and positioned within the broader discourse of sustainability education?
2. In what ways have educational institutions and policy frameworks in Europe and India attempted to integrate these literacies into curricular and infrastructural models?
3. What challenges and opportunities emerge when attempting to align these dual literacies with global sustainability goals?
4. What pedagogical, institutional, and normative strategies are required to harmonise these literacies into a coherent, future-ready educational model?

These issues serve as the basis for the study's testing of the following hypothesis: Students' ability to comprehend and operate within complex systems, interact critically with intelligent technologies, and take action in accordance with the Sustainable Development Goals particularly those related to education (SDG 4) and climate action (SDG 13) is improved when ecological literacy and algorithmic literacy are integrated into sustainability education (United Nations 2015).

Instead of using empirical or data-driven methodologies, this research compares and develops conceptual inferences from existing literature, policy papers, and documented educational practices. The aim is not to validate the hypothesis statistically, but to examine its theoretical coherence, practical relevance, and applicability across various geopolitical and institutional contexts.

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2 Literature Review

2.1 Ecological Literacy and Sustainability Education

Ecological literacy, or Eco literacy, is one of the most important parts of teaching people about sustainability. Ecological literacy is knowing how human activities affect the environment and how to live in harmony with it. Orr (1992) and Capra (2005) were among the first to say that a society needs people who care about the environment and know a lot about ecology to be sustainable. Ecological literacy requires a strong environmental ethic, the ability to think long-term (considering the needs of future generations), and the ability to understand systems (recognising how all parts of an ecosystem depend on each other).

Ecological literacy encompasses more than simply facts and figures; it also involves attitudes and behaviours, say teachers. Developing a sense of "ecological identity," a sense of unity with the natural world, through personal actions, is the focus of this lesson, which will also cover the significance of environmental stewardship. Through the use of pedagogies like school gardening, outdoor education, and place-

based learning, ecological education has become increasingly immersive and experiential.

By the 2010s, sustainability-related courses had already made their way into the curriculum of several schools throughout the world. Education for sustainable development seeks to equip learners with the knowledge, values, and competencies required to contribute to sustainable development goals (UNESCO 2017). Skills like strategic action and anticipatory thinking have been included in sustainable education frameworks (like the one by Wiek et al. 2011, on key sustainability competencies) to augment ecological knowledge. To gauge how well pupils grasp sustainability concepts, instruments such as the Sustainability Literacy Test (Sulitest) came into being. In order to assist pupils, make connections between their own experiences and larger ecological systems, educators have been drawing more connections between local environmental issues and global difficulties such as climate change.

To sum up, sustainability education is built upon ecological literacy. An environmentally literate student knows how ecosystems work and how important it is to change our ways so that these systems may continue to exist. Ecology knowledge is important, yet it is insufficient in the modern world. The need to expand sustainability education into the digital sphere, namely algorithmic literacy, arises from the fact that technology is increasingly involved in both the creation and the mitigation of environmental problems.

2.2 Algorithmic Literacy and AI in Education

Acquiring a critical grasp of the algorithms and AI systems that mediate society is becoming just as important as being literate about the environment. A person who is well-versed in algorithms (which are essentially sets of instructions for processing data) can recognise their use in everyday situations and understand how they impact the data and decisions we face. It entails being cognisant of the fact that recommender systems filter content on online platforms, that AI models may be biased due to the data used to train them (Noble 2018),

and that automated judgements in domains such as finance or law enforcement can have physical effects on people's lives.

Due to this demand, environmental education has gained significant momentum within schools worldwide over the last couple of decades. A fundamental grasp of AI algorithmic operation is required, as is the ability to identify how algorithms influence online material and social media feeds, as well as the capacity to assess the accuracy and fairness of algorithmic results. While it's true that not all students will need to take sophisticated programming classes, they must understand data, models, and the moral and legal considerations around artificial intelligence. UNESCO has similarly emphasised the need for education systems to adopt human-centred, ethical, and inclusive approaches to artificial intelligence (UNESCO 2021).

This demand is starting to be addressed by schools and educators. To help people understand how algorithms are formed, some of them use coding and elementary computer science. Societal views on the issue exist; for instance, case studies of computer bias could be used in a social studies or civics lesson. Also, there are new state programs. For example, AI-related topics are now part of K-12 schooling in several countries, and tech companies and NGOs are starting AI clubs and online classes for students, too.

For long-term success, mastery of formulae is essential. Some of the potential pathways that AI might contribute to sustainable development include increases in agricultural yields, enhancements in energy system efficiencies, and monitoring pollution via satellite data, among others (Vinuesa et al. 2020). However, AI has the potential to harm humans and the environment. First and foremost, training and running large AI models require huge amounts of energy. Other concerns include jobs and equity as AI-driven technologies proliferate (Strubell et al. 2019). Anyone who cares about the future of the world should be able to train AI in furthering human well-being and environmental care, and also be responsible for any damages caused by it. Utilising AI to make decisions on climate change laws raises ethical

questions, as do “Green AI” projects that try to lower the amount of energy that machine learning uses.

Finally, being able to understand algorithms opens up the internet as a medium for sustainability teaching. Students learn to analyse and evaluate technological developments with an eye towards how they could influence sustainable development outcomes. The literature is increasingly in favour of bringing AI awareness into classroom education, continuing the trend of earlier attempts to increase environmental consciousness (Oeldorf-Hirsch and Neubaum 2023), even if research in this area is still in its early phases.

Within the realm of active inquiry, the intersection of ecological literacy and computational literacy is becoming more important. One thing that is consistent is the need for systems thinking: ecological systems and algorithmic systems are both complex, with pieces that are dependent on one another; thus, it is essential to know feedback loops and unintended effects. One alternative is to see issues of power and ethics through a critical lens. Taking cues from critical theory, sustainability education questions conventional wisdom. In the same way that data and algorithms impact our daily lives, understanding how algorithms function encourages us to challenge power dynamics and identify technological shortcomings. It is common to use the term “socio-technical-ecological viewpoint” to characterise students’ understanding of the interconnected nature of society, the environment, and technology. Therefore, these skills are essential for a cohesive system, and children need to master them. All of these areas also demonstrate a sense of duty and caring. Like the UNESCO Recommendation on the Ethics of Artificial Intelligence from 2021, this line of thought is in harmony with what the world needs. This proposal emphasises the need to employ AI in accordance with ethical standards, continuing the trend of incorporating environmental ethics into technology.

Incorporating data analysis into climate change education, for example, does double duty: it deepens students’ understanding of the subject and prepares them to utilise technology to solve environmental

problems. Those who hold this approach argue that the two literacies can be better developed via their simultaneous instruction.

2.3 Recent Developments in Algorithmic Literacy Research

Over the last several years, algorithmic literacy has changed significantly in both scope and concept. Although early study by Noble (2018) and others highlighted the structural biases and unseen data labour in search algorithms, more recent studies have broadened the focus to include civic, ethical, and critical dimensions. Archambault (2023) suggests a model that places algorithmic literacy at the nexus of democratic involvement and systems thinking in his appeal for educators to teach pupils about algorithms. He exhorts educators to demonstrate to students how algorithms function and how they affect epistemologies and power.

Additionally, "responsible generative AI literacy" (Cox 2024) is described as a field of algorithmic knowledge that requires ethical judgement, discernment, and contextual awareness in situations where students are moderating their own content production. At the same time, Boots et al. (2024) stress the need for immediate curricular changes in K-12 and higher education to address concerns about the ecological footprint of ML systems, the lack of transparency around AI decision-making, and the fluidity of who is responsible for what. All of these new viewpoints add credence to the idea that teaching students to be proficient with algorithms will help them be more conscientious and responsible users of technology in the classroom.

To synthesise the preceding conceptual review, two comparative tables have been added in this study. Both ecological literacy and algorithmic literacy involve multifaceted competencies, but their focus differs across cognitive, ethical, and systems dimensions. Table 1 highlights key competencies in each domain.

Table 1 Competencies in ecological versus algorithmic literacy across cognitive (knowledge), ethical (values), and systems (holistic) dimensions

International and national education policies increasingly recognise the need to integrate sustainability and digital (AI) competencies. Table 2 maps several key policy documents to their support for ecological and algorithmic literacy objectives.

Table 2 How selected policy frameworks advance dual literacy goals in sustainability (ecological literacy) and digital technology (algorithmic literacy)

In summary, policy trends show a convergence toward integrating environmental and digital literacies.

3 Methodology

The methodology of this study is based on a qualitative technique that incorporates case studies and literature reviews. The first comprehensive literature evaluation focused on ecological literacy, algorithmic literacy, and the educational setting where these concepts intersect. Academic databases, books, and peer-reviewed journals, as early as 2025, were thoroughly reviewed for this study. International agencies that provided the basis of the policy reports pursued for this study include the European Commission and UNESCO.

The study also looks into two situations side by side, this time comparing India with Europe. The study delved into Europe, a developed area with many rules in place, and India, a massive developing nation with many sustainability initiatives and artificial intelligence education programs in the pipeline, to illustrate the similarities and contrasts between the two areas' approaches to digital education and sustainability. Every scenario was researched and examined by collecting and analysing relevant policy documents, curriculum frameworks, and educational initiative examples:

A. **Europe**: The authors examined policy documents on Education for Sustainable Development and the European Commission's Digital Education Action Plan 2021–2027, together with other EU-level strategic papers. They also looked at European pilot programs and

national curricula that teach both sustainability and artificial intelligence.

B. **India**: The authors looked at several national policy documents on India, including the National Education Policy 2020, which talks about objectives for digital and environmental education, and the "AI for All" initiative from the NITI Aayog. They also gathered information on programs that teach sustainability and how AI has been included in Indian school curricula, such as the CBSE's AI elective and related programs.

As part of the exploratory research of this study, the authors analysed these items for commonalities and differences. The authors looked at many different settings to see how ecological literacy and algorithmic literacy are handled, integrated, and prioritised. Education culture, policy objectives, and resource availability are a few of the factors that they considered as they may impact its implementation. There were many learning outcomes that came as a result of taking up the comparative study between Europe and India. It can be said that the authors are taking an experimental approach to this study. Case studies do not use classroom-based primary data but instead depend on document analysis and instances that have been documented. Still, this method provides a clear picture of where things are headed and what people are working on. Instead of offering a conclusive assessment of any one program, the results are meant to show possible routes forward and contribute to a conceptual conversation about combining sustainability and AI literacy in the academy.

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4 International Case Comparisons

4.1 Europe: Integrating Sustainability and AI Literacy in Education

In addition to being an aggressive area in regulating and directing the digital transition, Europe has been at the forefront of sustainability efforts in education. Education policymakers in Europe have come to

acknowledge the need to prepare students for the digital and environmental transitions; in fact, these are two of the EU's 2020s strategic goals. Efforts to attain the objectives of the European Green Deal may be facilitated by the use of digital tools and literacy, as stated in documents such as the Digital Education Action Plan 2021–27 of the European Commission (European Commission 2020). On the flip side, digitalisation is being mentioned more and more in policies that aim to protect the environment, such as the Guidelines on Education for Sustainable Development put out by the Council of the EU.

Introduced by the European Union in 2022, the European Sustainability Competence Framework (GreenComp) stands out among European frameworks. GreenComp lists systems thinking, futures planning, and values-driven action as some of the skills that are important for sustainability. Even though GreenComp doesn't explicitly deal with digital competence, there have been efforts to connect it to DigComp, which is a well-known framework for citizens' digital competence. Digital citizen science initiatives and online research on environmental concerns provide opportunities for students to use DigComp's abilities in areas like information literacy and digital content production to real-world sustainability challenges.

Pilot programs that integrate data analysis and digital storytelling into sustainability education have received funding from the European Commission. More and more classrooms throughout Europe are including technology-focused courses, with lessons that draw connections to students' everyday lives and the problems they face. As an example, a highly recognised program that combines computer science with more conventional high school curriculums is available in Finland. Students will learn about the relationship between technology and global challenges such as climate change via these programs. Similarly, high school students in France are studying the effects of technological advancements, including the advantages and disadvantages that these developments provide. The class also discusses ethical dilemmas, some of which may include protecting the planet.

The German program “KI@School” (AI at School) helps get AI projects going at some schools. A few of these projects are based on sustainability. For instance, AI-based devices can be used by students to keep an eye on the air quality in their neighbourhood. Schools from around the world have worked together on “digital for climate” projects thanks to Erasmus+ and other European Union (EU) programs. Students from various countries work together online to share their new energy-saving ideas.

Europe also encounters challenges, even in these instances. The conventional division of topics is one obstacle. Teaching across disciplines is easier said than done; for example, many schools include sustainability lessons in science or geography curricula, but computer science in information and communication technology courses. Not many educators have the luxury of time to devote to cross-curricular initiatives since they are so focused on covering the material in their respective subjects. In countries like Finland and Scotland, where the curriculum is built on skills, it is easier to include thematic learning.

Teacher training is another important development that is gaining popularity as well. New professional development programs are popping up all throughout Europe to help teachers use new lesson ideas. The European Union (EU) supports online workshops and massive open online courses (MOOCs) that teach teachers how to use data sensors and educational AI apps in lessons on climate change and biodiversity. In the same way, some programs provide teachers with the tools they need to talk to their pupils about the ethical issues surrounding AI or the technology’s harmful impacts on the environment by helping them become more critical digital readers and thinkers in the context of larger societal issues.

European policy also stresses governance and ethics, which indirectly support algorithmic literacy and ecological standards. While the 2019 Ethics Guidelines for Trustworthy AI in Europe promote research that benefits both people and the environment, the impending EU AI Act is expected to mandate transparency in AI systems used in schools. Teachers and students must have an open dialogue about the

big questions brought up by AI in light of these concepts. One possible angle from which to approach climate change education is to enquire about the impact of AI on the spread of misinformation and the promotion of correct climate knowledge on social media. This would explore environmental issues while also integrating critical thinking skills in the realm of technology.

Incorporating technology into the classroom requires great caution and a value-based approach, according to the European viewpoint. The incorporation of technological advancements with ecological objectives is gaining traction in educational institutions worldwide, however with different approaches in different nations. More and more students in Europe are putting their technical degrees to use by researching and learning about methods to make technology more sustainable. The principal similarities and differences between European and Indian approaches to sustainability and AI education are summarised in Table 3.

Table 3 The table outlines how Europe and India approach sustainability and AI education within distinct policy and developmental contexts

4.2 India: Navigating Sustainability and AI Education in a Developing Context

The landscape of India is both familiar and foreign. Water and air pollution, susceptibility to climate change, and fair distribution of limited resources are just a few of the pressing environmental concerns confronting this rapidly rising country at a time of unparalleled technological progress. Memorisation and STEM (science, technology, engineering, and mathematics) programs have long been at the forefront of India's extensive educational system. But recently, there has been more scrutiny of critical thinking, multidisciplinary research, and successful pedagogical approaches.

A new strategy for education is emerging in India as a result of NEP 2020. The curriculum includes up-to-date subjects like computer

programming and artificial intelligence, with an emphasis on green initiatives.

Additionally, diverse and inclusive curriculum will be mandatory by 2020 according to the Ministry of Education. Under NEP 2020, students should learn not just the required topics and "twenty-first-century skills," but also "ethical, human, and constitutional values." Understanding the importance of technology, AI, SD, and EP in today's world is a critical component of youth education.

To begin achieving the objectives of NEP 2020, the Central Board of Secondary Education (CBSE) has integrated AI into high school curricula. The National Council of Educational Research and Training (NCERT), the highest educational body in India, has reported that AI has been part of the curriculum for pupils in grades nine through twelve since 2019.

The course covers the fundamentals of artificial intelligence (AI), its applications, the benefits of project-based learning, and the ethical and societal considerations that arise from AI. Several Indian schools started providing this option with funding and cooperation from non-governmental organisations (NGOs) and information technology (IT) companies. The "AI For Youth" initiative, for instance, was a collaboration between Intel and CBSE.

While sustainability shared certain examples and duties with other programs, its primary purpose was to help students become more digitally aware and future-ready. Students have tackled real-world problems, including reducing water waste, enhancing energy efficiency, and sorting trash, by applying the fundamentals of machine learning. Although these classes cover environmental issues using computational methods, they are not officially "sustainability education."

Science and social studies curricula in the Indian education system often include topics such as sustainable practices, climate change, and conservation. Eco-Clubs, which get funding from the government, are one example of a program that promotes extracurricular activities like cleaning up schools, planting trees, and recycling. But they have always functioned independently of tech education. The new trend is to

address that need. As an example, in certain progressive schools and state-level initiatives, kids are encouraged to use digital tools to supplement their environmental education. For instance, they may learn about solar energy via virtual simulations or do biodiversity surveys using a mobile app.

Indian aspirations to use technology for development are a major impetus for incorporating these literacies. In 2018, the "National Strategy for Artificial Intelligence" was published by the government's think tank NITI Aayog. The report positioned AI as a tool for "social good" and sustainable economic growth (NITI Aayog 2018). Priorities were set in many sectors, including education and agriculture. After this, initiatives such as "Responsible AI for Youth" came into existence, when students from different states participated in innovation challenges centred on artificial intelligence. These challenges included topics such as health, agriculture, and the environment. In addition, prominent programs in India like Digital India and Atal Tinkering Labs in schools (which provide innovation workspaces and kits to schools) indirectly help with this integration by giving kids the tools and support they need to try out technology on real-world issues. There have been a number of hackathons and challenges held by Atal Tinkering Labs with an emphasis on environmental issues, such as waste management and biodiversity.

Implementation remains an issue for India, even with backing from high-level officials. Opportunities to develop artificial intelligence or apply digital technologies in sustainability initiatives are unequal due to the wide range of school types, from affluent metropolitan schools with modern facilities to rural schools without access to power. If investments in the infrastructure of under-resourced communities and teacher training are not made concurrently, the introduction of algorithmic literacy runs the risk of widening the equity gap. Considering this, both public and commercial organisations have begun capacity-building initiatives, such as online AI teacher training programs and low-cost technological solutions, such as science

laboratories built into students' smartphones, for schools in remote areas. But these initiatives still need a larger scale.

The culture that is focused on exams presents another obstacle. Schools often overlook a subject until it appears on the board exams. Integrating environmental education, which is required for certain courses, with artificial intelligence, which is available as an option, requires innovative school administration and educators. The good news is that the emphasis on projects and hands-on learning in NEP 2020 could help alleviate some of the test pressure while also making room for more interdisciplinary study.

Environmental stewardship and moral technology use are congruent with the concept of responsible citizenship, which is highly prized. Some sustainability programs depend on ideas from Indian tradition, such as the need to maintain a harmonious relationship with the natural world (as espoused by Gandhi and other thinkers). The concept that we should use AI inclusively and ethically is now starting to be brought up in discussions, along with the idea that harmony should also extend to our digital ecosystems. For instance, in an effort to include sustainability and digital literacy into their curriculum, the Mahatma Gandhi Institute of Education for Peace and Sustainable Development (MGIEP) in New Delhi, which is part of UNESCO, has been testing out a new approach that integrates digital pedagogy with social-emotional learning and global citizenship.

To summarise, India is only starting to integrate ecological and algorithmic literacy. Recognising both, the policy environment is favourable. Several factors are driving the gradual yet steady incorporation of technology into classrooms, including new electives such as artificial intelligence (AI) and initiatives that encourage students to utilise their skills for the greater benefit of society and the environment. Due to systemic limitations, the rate of change may be slow, but the course is determined. India is proof that even a developing country can prioritise basic education for its people and train the next generation to thrive in a global economy that values both rapid economic development and environmentally friendly technologies. One

thing we can take up from India's experience is the need to consider cultural context, equity, and flexibility when launching integrated literacy programs.

4.3 Integrating AI into Sustainability Education: Two Case Studies

This study examines two initiatives in the field of education that integrate sustainability-related courses with AI: one in India and one in the United Kingdom. Algorithmic literacy is becoming an increasingly important part of sustainability education, and we want to demonstrate this.

A.

Kotak School of Sustainability at IIT Kanpur (India)

Intelligent Intelligence for Sustainability is a brand-new Master of Technology program at IIT Kanpur's Kotak School of Sustainability. This interdisciplinary programme integrates state-of-the-art AI training with fundamental concepts in environmental and social sciences and is hailed as the first postgraduate degree in India to utilise AI to address climate change and sustainable development. Learners acquire practical experience in data analytics and machine learning with theoretical knowledge in politics, climate change, and urban planning. Our goal in preparing students for leadership roles in industry, academia, and government is to empower them to tackle critical social and environmental issues, such as pollution and energy inefficiency, via the use of artificial intelligence (AI).

B.

UKRI Centre for Doctoral Training in AI for Sustainability at the University of Southampton (UK)

Applying artificial intelligence (AI) to pressing environmental issues is the goal of the four-year Ph.D. program known as UKRI Centre for Doctoral Training in AI for Sustainability (SustAI) at the University of Southampton in the United Kingdom (southampton.ac.uk). The Research and Innovation fund in the UK is supporting an

interdisciplinary project that will bring together experts in computer science, engineering, business, and environmental science to tackle issues like decarbonisation, sustainable transportation, and biodiversity loss. A Ph.D. student's research could include a wide range of topics, including artificial intelligence (AI) for green buildings and energy, AI for the environment, and ways to make AI more ethical and energy efficient. The goal of the SustAI program is to educate future researchers in cutting-edge AI techniques and sustainability principles via partnerships with businesses and a wide range of academic disciplines.

These examples show how universities are starting to include environmental and social literacy alongside algorithmic literacy, so that the leaders of tomorrow may use AI to make the world a better, more sustainable place.

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5 Discussion

There are some parallels and some contrasts between sustainability education in Europe and India with regard to the goal of integrating ecological and computational literacy. In this article, we review the cases and the literature, rethinking educational practice in light of climate change and artificial intelligence by using their key themes.

5.1 Converging Rationales, Diverging Contexts

Both Europe and India have seen the need to update their educational systems to address the challenges of the contemporary world. No one disputes the fact that the next generation must take it upon themselves to prepare for the technological and environmental crises of the future. This provides support for our theory that in order for people to be sustainability literate, they must possess both ecological literacy and algorithmic literacy. But there are other settings. In Europe, there is a heavy focus on ethics and prudence due to the policy-driven, top-down approach. Rapid digital adaptation and addressing critical social and environmental issues are developmental priorities for India. The

strategies and rates of integration are affected by each of these contextual factors. As compared to Europe's general standards and sluggish progress, India may initiate pilot initiatives in certain areas but proceed more slowly in others. Still, we can agree on one thing: there needs to be an educational system that teaches children to be tech-savvy and ecologically aware.

5.2 Interdisciplinary Learning as Key

Optimal integration of literacy practices is a topic that keeps coming up in conversations about the need to break down subject silos. Concepts of computational sustainability are not exclusive to the academic world. In both instances, we can see the current trend towards competency-based and project-based learning, which encourages students to explore ideas outside their majors. For example, many schools in Europe let students work together on projects like "smart irrigation systems" that naturally combine computing, science, and environmental studies. Hackathons, which are like surprise lab projects in India, bring together specialists from different professions to work on problems in their own communities.

These linked literacies are best taught using pedagogical techniques such as design thinking, problem-based learning, and project-based learning. They emphasise the importance of pupils solving problems by combining information from various fields. To implement such strategies on a large scale, it will be necessary to prepare educators and adjust evaluation methodologies.

5.3 Teacher Capacity and Professional Development

Teachers have a crucial role in both areas. Many of the teachers who are now on the job did not have any formal training in artificial intelligence or in advanced sustainability ideas while they were in school. Because of this, there is a chasm in the implementation process; even with an excellent curriculum, integration will be slow if instructors do not feel ready to teach. When compared to India, Europe has fewer student–teacher ratios and greater funding for training, while India struggles

with issues of size and resource inequality. However, programs in both locations are bringing attention to solutions: seminars for teachers on the fundamentals of artificial intelligence, online teacher communities for the exchange of best practices, and pre-service teacher education programs that include sustainability and digital subjects. Among the most crucial takeaways is the realisation that instructors want concrete examples of how to integrate ecological and algorithmic concepts into their lessons. While teaching about climate change, a training module may demonstrate how to utilise data from an AI-based climate model. Similarly, while teaching about cloud computing, a training module could demonstrate how to address computer energy use.

5.4 Ethical and Critical Thinking Dimensions

When coupled, the already-present ethical concerns raised by both literacies take front stage. European frameworks have an emphasis on environmental ethics (e.g., climate justice) and technological critical thinking (e.g., challenging AI biases). Even in India, this is brought to light by the values, education heritage and the recent focus on ethics in AI courses. The cultivation of a mentality that questions and reflects on human values is just as important as subject knowledge when it comes to merging ecological and computational literacy. “Should we really do something with AI just because we can?” is a good question for students to ask. In what ways will this play out in the future? In other words, it is analogous to the worries that environmental teachers have about growth and sustainability in similar situations. This might be because of classroom talks, scenario evaluations, and the combination of conservation and digital privacy issues. For example, one may look at the pros and cons of using surveillance technologies to stop poaching and protect privacy, which might lead to complicated moral problems.

5.5 Infrastructure and Resource Needs

Infrastructure is important, especially in India, since it is useful. To teach algorithmic literacy, you usually need to know how to utilise devices, the internet, and energy. This isn’t always the case in the world.

In the same way, classrooms or outdoor spaces may be needed for environmental education to work. In Europe, where schools are better supported, students may test out advanced programs like robotics kits for environmental monitoring. On the other hand, Indian students sometimes have to be creative, like using the power of a single student's smartphone to measure the whole class. This emphasises the requirement of individualised treatment plans. As a hopeful beginning towards eliminating affordability discrepancies, inexpensive technologies are on the increase. For example, microcomputer boards that cost $35, solar-powered chargers, and offline digital stuff. Collaboration between the public and private sectors, as shown by the donation of AI laboratories to certain Indian schools, may also provide positive results. Legislators should consider methods to fund schools that are implementing these new literacies if they wish to prevent the income gap between the best and worst schools from widening.

5.6 Policy Coherence and Long-Term Vision

An instructive example is the way in which digital and environmental initiatives in Europe have been coordinated. A parallel trend is developing in India with digital projects mentioning environmental results and vice versa; nevertheless, for uniform execution, the country's education, environment, and information technology ministries would need to work together. Both examples show how long it takes for changes to take effect, particularly in the realm of education. A ten- to fifteen-year plan with incremental goals is required. As an example, by year X, all educators should have received basic AI literacy training; by year Y, all students should have completed a sustainability-tech project; etc. Since both artificial intelligence and sustainability are experiencing fast changes, it is crucial to continuously evaluate these areas and be flexible to modify policy accordingly.

5.7 Community and Global Collaboration

By incorporating these literacies, schools may also connect with the community at large and international organisations. Students from

different parts of the world working together was one example we saw, as was a group of Indian students using technology to solve problems in their own communities. By looking outside their own communities, students are able to better understand the global nature of sustainability and technology issues and how they affect them on a local level. Initiatives such as sister-school initiatives have the potential to greatly improve motivation and cross-cultural understanding. For example, a school in Europe and one in India may collaborate on an SDG project by sharing ideas on how to use artificial intelligence. One way to make studying more relevant and inspiring for students is to invite local community professionals, such as tech entrepreneurs or environmental activists, to speak in the classroom. Integrating AI literacy into sustainable development education might require reaching out to the tech community, similar to how software engineers can mentor student projects focusing on green tech solutions.

5.8 The Need for New Metrics of Success

Systems thinking and algorithmic moral reasoning are not readily captured by traditional tests. Through PISA and other international tests, Europe is actively looking into new ways to assess students. For example, PISA will now include an evaluation of "learning in the digital world" and has begun to quantify creative problem-solving. The National Evaluation Plan (NEP) for India suggests abandoning memorisation in favour of competency-based evaluation. In order to make effective use of new literacies, this change is crucial. Knowing that their exams would only cover topics like computer languages or biological ideas could discourage pupils from studying hard. In contrast, these abilities will be more evident in judgments when asked to examine pollution statistics or assess the fairness of an AI algorithm. That is why modifying quizzes and examinations may lead to improvements.

Lastly, sustainable education often aims to integrate computational literacy with ecological literacy; nevertheless, this is not an easy task and must be customised for each location. Perhaps we may learn from

India's example how to be innovative within constraints, how to embrace youth and enthusiasm, and how to stay focused on the end objective. The lessons learned from Europe's blunders may inform our own rule-making, resource allocation, and moral reasoning. For the most part, they provide a picture of what a global "Education for Sustainable and Digital Futures" initiative may include. When taught properly, these literacies improve students' chances of gaining the technical know-how, ecological consciousness, empathy, and analytical reasoning abilities they will need to succeed in this age of unprecedented technological and environmental transformation.

5.9 Limitations and Scope of the Study

This chapter is more of a conceptual inquiry than a research chapter. It relies on secondary data, legislative documents, and educational systems in addition to current academic work that pulls from European and Indian contexts. To assess the assumption, this research depends on interpretative and comparative reasoning rather than fieldwork, experimental design, or primary data collection.

This method is not without its flaws. To make definitive findings on the effectiveness of dual-literacy strategies in the classroom, researchers must observe both students and teachers. Another thing it does not do is attempt to find out how various methods of teaching influence the conduct and knowledge of pupils. However, in the design, these strategies do not exist. This study aims to provide the basis for a unified theory, document new methods, and propose areas for further research. Building models of anticipatory teaching requires this sort of foresight and integration of ideas due to the increasing interconnectedness of algorithmic technologies, sustainability initiatives, and climate policy.

5.10 Critical Evaluation: Justice, Power, and Technological Displacement

While algorithmic systems do provide new opportunities for sustainability teaching, they also need deep philosophical and ethical

reflection. Aside from the obvious technical aspects, two viewpoints that shed light on critical concerns emerge, one grounded in Amartya Sen's capacity approach and the other in Vandana Shiva's ecological justice framework.

The core focus of Sen's capacity theory is the extension of people's real liberty. Having access to relevant knowledge, meaningful opportunities, and meaningful lifestyles are a few examples (Sen 1999). When applying this approach to sustainable learning with the aid of AI, questions of equity and inclusion arise. With the use of algorithms, we may be able to comprehend complicated environmental data and tailor our learning experiences. Having said that, not everyone reaps the rewards. Due to differences in infrastructure, language availability, and institutional resources, some children may have access to more sophisticated technologies in schools that are better financially. The competence gap typically becomes wider, therefore. Recent worldwide policy assessments have shown that online learning platforms lacking inclusive protections may exacerbate inequality.

Equally, Sen's paradigm stresses the need to examine the agency. Automated grading systems that use data to make assumptions might limit students' agency in the classroom. For learning to take place, pupils need to be able to challenge, change, and even reject the system's suggestions at times. As a result, AI systems need to be open and honest. It is important for students to be cognisant of the fact that some data points may be missing, as well as the assumptions and methods utilised to form conclusions. This kind of critical thinking activity encourages students to take an active role in the learning process rather than just witness it. From a capacities perspective, the aesthetics of smart classrooms are less important than whether or how these technologies assist students from varied backgrounds in acquiring community-relevant information, skills, and attitudes.

Environmental justice is an extra essential dimension that Vandana Shiva brings to the table. Cooperation between humans and the planet's ecosystems is central to her vision of a democratic Earth. In many cases, technological interventions cause biodiversity loss, power

concentration, and the marginalisation of indigenous knowledge systems (Shiva 2016). For instance, local traditions may clash with the demand for uniformity by digital platforms in the fields of conservation and agriculture. Institutional entities, such as companies, pose a threat to local communities' ability to manage their environment by handling data on soil, water, and weather.

If our educational system is too focused on AI-driven solutions, students may not learn how to apply what they learn in the classroom to actual environmental problems. If students rely too heavily on data from sensors and satellite photos, they risk losing touch with seasonal rhythms, community narratives, and ground-based observations. Shiva cautions against a mechanical decision-making process that excludes democratic involvement. Her worldview is based on three main points: pluralism, embodiment, and ecological links (Shiva 2013).

Based on these views, a curriculum would combine algorithmic resources with existing bodies of local knowledge. As a result, students would learn to think critically about environmental trends, including who creates data, who stands to gain or lose from projections, and how technological advancements may disrupt delicate ecological and social equilibrium. For instance, to create an accurate map of urban heat stress, it is necessary to use both statistical models of heat stress and first-hand accounts from residents in such areas. In the absence of this, algorithmic systems run the risk of hiding rather than revealing the societal causes of environmental degradation and reinforcing technological remedies.

A common interest in fairness unites the frameworks put out by Sen and Shiva. In contrast to Shiva's emphasis on environmental sovereignty and purity, Sen's emphasis is on human liberties. They unite in their demand for educational opportunities that teach students to critically analyse technology systems and to work towards creating more equitable and environmentally friendly ones.

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6 Conclusion and Recommendations

The course of education is about to take a dramatic turn. Addressing the challenges posed by climate change and rapid technological advancement will need the future generation to possess imaginative literacy abilities. According to this theory, the first step in modernising education is to include ecological and algorithmic literacy. The many forms this integration has taken and the difficulties it presents have been better understood via an examination of Indian and European thought and practice.

6.1 Reimagining Curriculum and Pedagogy

Rethinking our curriculum to make digital skills and sustainability required rather than electives is necessary if we want to see meaningful change. One option is to create a curriculum that connects green economy technology with society, while another is to integrate data science into scientific teachings with the aim of resolving environmental challenges. One possible format for students' capstone projects is to investigate an issue with local sustainability and propose a data-or AI-driven solution.

By doing so, they would be able to practise both types of literacy. The complexity of the actual world necessitates that teaching revolve around inquiry, problem-solving, and collaboration. Children in Berlin have used sensors to examine urban heat islands, while teenagers in Delhi have used artificial intelligence models for water management. These projects show that children can grasp complex concepts given the right circumstances.

6.2 Teacher Empowerment

The quality of the instructors who put educational innovations into action is what makes them work. One important idea is to sponsor programs that help teachers grow in all areas. One approach to make sure that future teachers know a lot about AI and sustainability and how to get students to think critically about these topics, is to change the way they are trained. Ongoing professional development for educators needs to be approachable, useful, and motivational.

Incentives (such as certifications or career advancement credit) may be created by organisations and governments to encourage teachers to enhance their skills in these areas. In addition, the dissemination of effective practices may be accelerated by the establishment of networks, such as professional learning groups, where instructors exchange lesson ideas and success stories.

Others may learn from teachers who have experience implementing integrated projects. The importance of encouraging such collaborative networks, especially on a global scale, cannot be overstated, since many educators find that they learn the most from their colleagues.

6.3 Policy and Support Systems

Education standards and curricula should provide clear support for the integration of literacies as a matter of policy. It is possible that the education ministry would update the present curriculum to include additional abilities, such as "understands the ethical implications of technology on society and environment," alongside the existing competencies for scientific comprehension and computer literacy. Assessing progress towards these goals of integrated learning should be a continuous process. Availability of resources is also important. All of this includes subsidies for schools to establish sustainability-tech innovation laboratories, financing for resources (such affordable science kits or renewable energy-powered computer labs), and collaborations with tech companies or environmental organisations to provide data and supplies. For the sake of all students, lawmakers should consider passing equity-based legislation to ensure that schools in rural areas and those serving low-income communities have access to training and technology.

6.4 Global and Cross-Sector Collaboration

The scope of the issues and the remedies are both global. The environmental crisis and the information technology revolution are two worldwide problems that need concerted action. By taking part in UNESCO's programs, exchanging educational frameworks, or organising

exchange trips for educators, we may assist educators worldwide in communicating and cooperating more efficiently. Organisations like corporations may give advice and hands-on experience, non-governmental organisations can advocate for regional issues, and schools can strive to enhance their curriculum. These interactions have the potential to greatly improve education. Students may be better able to apply what they learn in the classroom to real-world issues if the ecosystem approach is successful in demonstrating that education is not an isolated event but rather an interconnected component of larger sociotechnical systems.

6.5 Cultivating Mindset and Agency

Ecological literacy and algorithmic literacy are two areas that might greatly enhance classroom instruction. They do double duty by equipping students with new information and abilities while also fostering a sense of competence and autonomy. The objective is to produce a new generation that is confident in its ability to address global issues by combining a deep respect for nature with a mastery of modern technology resources.

To get a whole picture of an issue like urban floods, you need to add things that people cannot see, including data from sensors and larger climatic trends. As a subsequent stage, they may think about developing a remedy, such an app prototype or an awareness campaign. They would be very careful to avoid unforeseen consequences while prioritising equality and sustainability.

Algorithmic literacy should be a part of sustainability education, last but not least. This step recognises the growing importance of technology in reducing environmental problems and the need of creating new technologies with sustainability in mind. Recent events in Europe and India are among the causes of this shift.

We can gain a deeper understanding of ourselves, others, and the universe as a whole through these experiences. Impending tasks include revamping the curriculum, educating teachers, stocking classrooms with necessary materials, and contributing to the

formulation of policies. Large advantages, however, do exist. Instead of focusing solely on a single job route, a well-rounded education that encompasses multiple literacies prepares students to be active, engaged global citizens. Students learn to think critically and creatively, which equips them to combat climate change using AI and to improve the world's usage of AI by developing their ethical reasoning and problem-solving abilities.

According to the results of this research, sustainability education programs that teach students to be ecologically sensitive and proficient with algorithms would better equip them to deal with the effects of climate change and the proliferation of automated systems. This two-pronged strategy works better together than separately. Students may work together to analyse the technical and environmental systems that determine the limits and possibilities of human happiness. The next logical step in translating these theoretical concepts into workable frameworks would be to conduct evaluation studies that measure the impact of such integrated curricula on students' capacity for critical thinking, ethical reasoning, and systemic awareness.



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Pedagogical Practices and Reflections on AI-Enhanced Innovation in Sustainability Education: Guiding AI Integration Through the IDEA Framework

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Abstract
Artificial intelligence is increasingly influencing sustainability education by providing dynamic tools that foster systems thinking, data literacy, ethical reasoning, and creative problem solving. Yet despite growing experimentation with AI in teaching and learning, there remains a notable gap in practice-based frameworks that guide educators in integrating AI into ESD in ethically grounded and pedagogically purposeful ways. Addressing this need, this chapter

explores how AI can be thoughtfully integrated into Education for Sustainable Development (ESD) through innovative pedagogical approaches. Drawing on teaching cases and reflective analysis, it introduces the IDEA (Innovation, Design, Evaluation, and Anchoring) framework as a structured yet flexible guide for integrating AI into practice. The framework is illustrated through practice-informed vignettes, including the use of generative AI for futures thinking, machine learning for environmental data analysis, AI-powered feedback in ethics debates, and co-designed projects with pre-service teachers. These examples highlight both the affordances and tensions of using AI in higher education and teacher preparation programs. The IDEA framework encourages educators to critically examine how AI tools align with sustainability goals, support meaningful learning outcomes, and surface issues of ethics, equity, and digital competence. Situating AI not as a disruptive novelty but as a pedagogical mediator, the chapter contributes to the discourse on ESD and the responsible integration of emerging technologies. Drawing on interdisciplinary scholarship, it reflects on implications for curriculum design, faculty development, and education policy, offering actionable recommendations for creating ethical, inclusive, and future-facing learning environments.

Keywords AI-enhanced innovation – Sustainability education – Education for sustainable development – Pedagogical practices – Reflective inquiry

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emerging technologies such as artificial intelligence. His current research explores how AI can be integrated into science and sustainability education to foster creativity, systems thinking, and ethical reasoning among learners. This interest underpins his contribution to the present chapter, where he examines reflective teaching cases that apply AI tools in advancing sustainability competencies. His ongoing projects also investigate scientific creativity and innovative problem-solving in STEM contexts, reflecting his broader commitment to preparing educators and students for a technology-empowered, sustainability-oriented future.

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1 Introduction

Amid rising seas, warming skies, and shifting social landscapes, artificial intelligence (AI) has emerged as a transformative force across sectors. It introduces new capacities for interpreting complexity and navigating rapidly changing global conditions (Toderas 2025). Its expanding influence is reshaping how knowledge is created, accessed, and applied in contemporary society. Within education, AI provides powerful tools that can enhance pedagogy, personalize learning pathways, and deepen engagement with real-world challenges such as those posed by sustainability transitions (Leal Filho et al. 2025; Strielkowski et al. 2024). As climate change, biodiversity loss, social inequities, and other manifestations of unsustainable development intensify, the need for education systems to cultivate adaptive, future-oriented, and critically aware learners has become increasingly urgent (Asian Development Bank 2024). The complexity and interconnected nature of sustainability issues require pedagogical approaches that help learners work with uncertainty, analyze large datasets, and consider multiple future scenarios. AI-supported methods offer capacities that can contribute to these aims in practical and meaningful ways. Integrating AI into sustainability education holds considerable potential to support this work by strengthening data-driven inquiry, systems-level thinking, and ethically grounded decision-making processes (Torres-Rivera et al. 2025). These possibilities create a foundation for examining how AI can contribute to sustainability learning in higher education and how educators can engage with these tools in responsible and reflective ways.

Framing these pedagogical possibilities within the broader agenda of Education for Sustainable Development (ESD) positions AI as a tool that can support transformative learning. ESD promotes a holistic, interdisciplinary, and action-oriented approach that prepares learners not only to understand sustainability issues but also to respond to them in informed and responsible ways. The United Nations Educational, Scientific and Cultural Organization (UNESCO) Roadmap for ESD (2020) highlights the need for pedagogical innovation that encourages learners to examine dominant systems, imagine alternative futures, and

participate meaningfully in sustainability transitions. This vision requires a shift away from transmissive forms of instruction and toward participatory, reflexive, and experiential approaches that strengthen learner agency and dialogue (Acut et al. 2025a). AI technologies can contribute to these goals when they are used with intentionality. They provide tools that can enhance collaboration, model complex systems, and support interdisciplinary exploration (Tian and Zheng 2025). These capacities align closely with the aims of sustainability learning, which seeks to build competencies that prepare learners to engage with uncertainty and change.

Integrating AI into educational environments introduces a range of risks that require careful consideration. Adaptive systems, intelligent tutoring platforms, and natural language models can expand opportunities for personalized learning and offer access to real-time feedback (Sharma et al. 2025). These opportunities must be balanced with a critical awareness of ethical and epistemological concerns that continue to surface in the field (Garcia et al. 2025). Algorithmic bias, inadequate data privacy protections, techno-solutionist tendencies, and the potential erosion of human judgment represent key critiques that educators and institutions need to address (Alvarez et al. 2024). For AI to serve the goals of sustainability education, its integration needs to maintain equilibrium between innovation and caution (Chigbu and Makapela 2025). This balance ensures that educational technologies support values of justice, equity, and human dignity rather than compromise them. A critical and reflective approach is essential for navigating these tensions.

Responding to this complex landscape, the present chapter explores innovative pedagogical practices in sustainability education that utilize AI tools and technologies in higher education settings. It draws from the experiences of educators engaged in designing and delivering courses where AI supports lesson development, classroom engagement, assessment strategies, and student inquiry. The aim is to provide examples that are locally situated yet globally relevant. These teaching cases offer insights into how AI integration can enrich

transformative sustainability learning while also foregrounding the ethical, practical, and pedagogical considerations that accompany its use. Through a practice-informed lens, the chapter engages with both the tensions and affordances of AI-enhanced pedagogy and contributes to ongoing dialogue about responsible innovation in education.

To support this reflection, the chapter introduces the IDEA (Innovation, Design, Evaluation, and Anchoring) framework as a structured approach that guides educators in analyzing and improving their use of AI in sustainability teaching. The framework consists of four interconnected dimensions. *Innovation* highlights emerging pedagogical strategies and practices that become possible through AI use. *Design* focuses on how instructional planning, contextual alignment, and tool selection shape the implementation of AI within learning environments. *Evaluation* centers on critical reflection related to impact, challenges, and unintended consequences. *Anchoring* situates teaching practice within broader research, theoretical perspectives, and the core values of sustainability education. Together, these dimensions form a scaffold for documenting and interpreting practice in ways that are both reflective and generative. They support educators, researchers, and policymakers in examining the pedagogical opportunities and limitations associated with AI as they work to advance sustainability competencies. The remainder of the chapter outlines the methodological approach used to collect and synthesize the reflective teaching cases, presents a series of practice-based vignettes analyzed through the IDEA framework, and concludes with insights, limitations, and implications for integrating AI into ESD.

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2 Methodology

This chapter is guided by a practitioner-informed reflective inquiry approach, grounded in our lived pedagogical experiences as higher education educators engaged in sustainability teaching (Schön 1992; Zeichner and Liston 2013). Reflective inquiry, as used here, positions our instructional practices as both the subject and source of analysis,

enabling a deeper understanding of how AI-enhanced innovations unfold in real classroom contexts (Cochran-Smith and Lytle 2009). Through systematic reflection on our planning decisions, classroom interactions, and student outcomes, we aim to surface pedagogical insights that are context-sensitive and critically informed (Brookfield 2017). This approach acknowledges the iterative, situated, and value-laden nature of educational innovation, particularly when integrating emerging technologies like AI into curriculum and instruction in support of transformative sustainability education.

To guide this inquiry, we draw on three interrelated conceptual frameworks that inform both the design and interpretation of AI integration in our teaching practice. The Technological Pedagogical Content Knowledge (TPACK) model (Mishra and Koehler 2006) offers a lens to examine how disciplinary knowledge, pedagogical strategies, and digital tools intersect to shape instructional decision-making. The SAMR (Substitution, Augmentation, Modification, Redefinition) model (Puentedura 2014) provides a continuum for evaluating the depth of technology integration, ranging from surface-level enhancement to the transformation of learning experiences in ways previously unattainable. Complementing these, Kolb's Experiential Learning Theory (1984) frames our ongoing professional learning as a cyclical process of concrete experience, reflective observation, abstract conceptualization, and active experimentation. Together, these frameworks support a dynamic, practice-sensitive understanding of educational change, enabling us to critically examine how AI mediates both teaching and learning within sustainability-focused contexts.

2.1 Study Context and Participants

The reflections and data presented in this chapter were drawn from three education-related courses offered at a public university in Central Visayas, Philippines, during the academic years 2024 and 2025. These courses spanned undergraduate science teacher education, graduate-level technical and vocational education, and development education, which collectively provided complementary contexts for exploring how

AI can be meaningfully integrated into sustainability-focused learning across disciplines.

Each course incorporated AI-enhanced activities aligned with its specific outcomes. In science education, students used ChatGPT and AI-assisted visualization tools to generate climate models and interpret sustainability scenarios. In the technical and vocational program, generative AI and automation simulators supported discussions on Industry 4.0 and sustainable workforce development. Meanwhile, in the development education course, learners engaged in AI-mediated storytelling and ethical decision-making on global sustainability challenges.

Three educators participated in this reflective inquiry, including the first author. The other two educators, specializing in development education and technology management, consented to the inclusion of their anonymized reflections and instructional materials but opted not to take part in authorship. This arrangement ensures transparency and alignment with COPE authorship and ethical standards.

At the time of the study, the university did not yet have formal institutional guidelines on AI use in teaching and learning. This absence created both flexibility and uncertainty, allowing instructors to experiment with innovative pedagogical applications while engaging in ethical self-regulation. The inquiry thus served as an informal testbed for examining the pedagogical, ethical, and institutional implications of AI in higher education.

All three educators shared a commitment to transformative pedagogy grounded in the principles of ESD, using AI not merely as a tool but as a catalyst for ethical reflection, systems thinking, and creative problem-solving. The study adhered to institutional and national ethical standards, with voluntary participation and informed consent obtained from all educators. Reflective records and instructional materials were anonymized to ensure confidentiality. Compliance with Republic Act No. 10173, or the Philippine Data Privacy Act of 2012, was maintained throughout to ensure responsible data handling.

2.2 Data Collection and Synthesis

Data for this chapter were generated through multiple sources that captured both planned and emergent aspects of AI integration in teaching. We documented reflective teaching journals, prepared weekly during and immediately after class sessions, which detailed instructional decisions, student interactions, and observed challenges. We also compiled classroom vignettes describing notable moments of AI use, such as student engagement with generative tools for project work. In addition, learning artifacts, in particular student outputs, lesson materials, and assessment rubrics, were collected to provide evidence of how AI applications shaped both teaching practice and learner outcomes. Course syllabi and instructional resources further contextualized the pedagogical approaches under review.

The synthesis of these materials followed an iterative process informed by the IDEA Framework (Fig. 1). Episodes of AI integration were coded and organized into four dimensions:

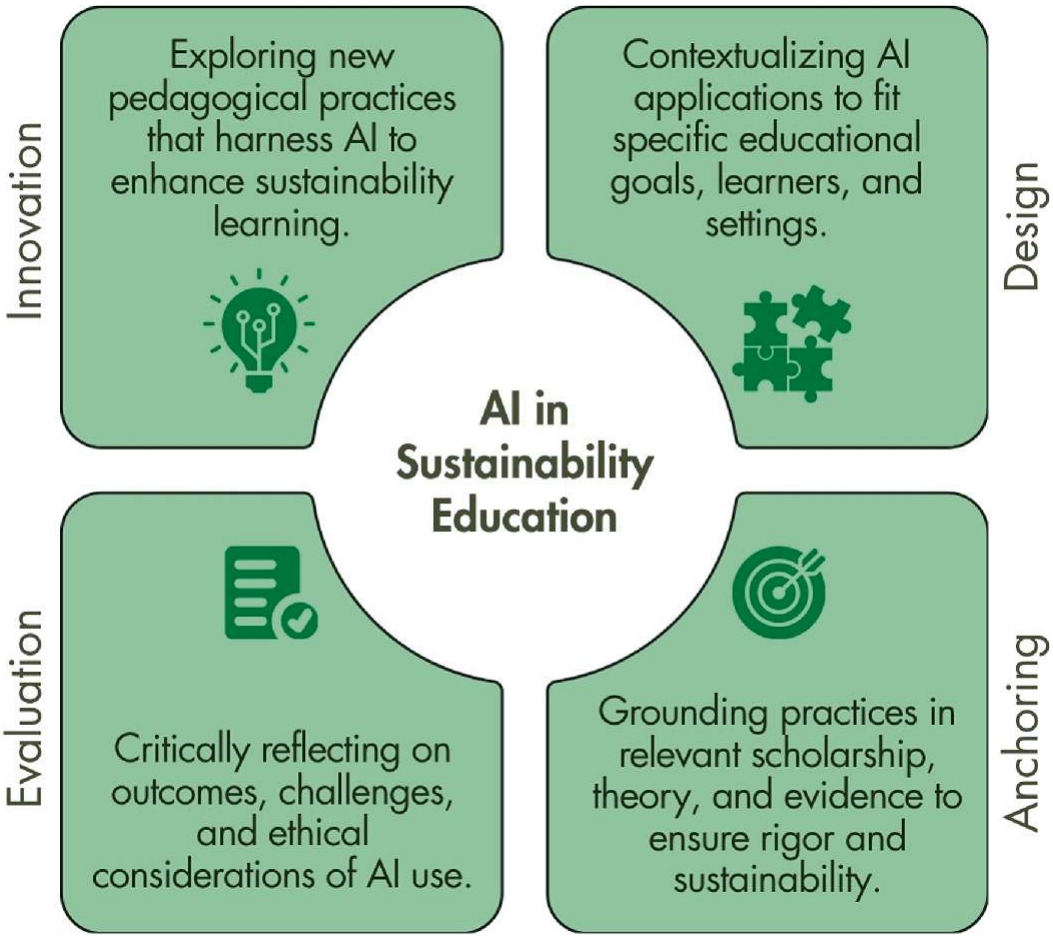


Fig. 1 The IDEA framework for analyzing teaching cases on AI in sustainability education. *Source* Author

- **Innovation**: identifying what was introduced or altered in practice, such as novel uses of generative AI or redesigned student tasks.
- **Design**: documenting the curricular and classroom contexts where innovations occurred, including the rationale for tool selection and pedagogical alignment.
- **Evaluation**: capturing critical reflections on outcomes, highlighting both opportunities and challenges in teaching and learning.
- **Anchoring**: linking the practices and reflections to relevant research and theoretical constructs, ensuring that insights were both experiential and scholarly.

To enhance the robustness of the analysis, we engaged in collaborative sense-making, reviewing journals, vignettes, and artifacts

across the three courses to identify recurring themes and divergences. Pattern coding (Saldaña 2016) was applied to surface broader insights, such as the affordances of AI for fostering creativity, the risks of over-reliance on automated systems, and the pedagogical shifts required for meaningful integration. The synthesis thus represents a blend of personal reflection, participant experience, and conceptual grounding, providing a practice-informed contribution to the discourse on AI in sustainability education.

2.3 Trustworthiness and Rigor

Given the reflective and practice-based nature of this inquiry, we employed several qualitative research strategies to ensure trustworthiness and rigor, guided by the Standards for Reporting Qualitative Research (SRQR) (O'Brien et al. 2014) and recent guidelines for conducting qualitative research (Lim 2024). Reflexivity was maintained throughout the process, as we explicitly examined our dual roles as educators and researchers, recognizing how our positionalities and commitments to sustainability education shaped the interpretations we drew from classroom experiences. We documented reflexive memos alongside our journals to surface assumptions, biases, and value orientations, thereby aligning with methodological standards that emphasize transparency, researcher characteristics, and contextual sensitivity.

To strengthen credibility, we drew on triangulation across multiple data sources, including journals, classroom vignettes, student outputs, and instructional materials, which allowed us to compare and corroborate insights from different perspectives. This multi-source approach reduced the risk of overreliance on a single type of evidence.

Collaborative review further enhanced the dependability of findings. The three educators involved in the courses revisited one another's reflections and artifacts, which enabled a cross-checking of interpretations and opened space for dialogue about points of convergence and divergence. While students were not formal co-researchers, informal member-checking was achieved by revisiting

interpretations against student feedback and observed classroom responses, ensuring that the insights resonated with actual learner experiences.

Finally, thick description of the instructional context—public higher education in Central Visayas, Philippines, within science teacher education, technical education, and development education programs—supports transferability by enabling readers to assess the applicability of our findings to other teaching and learning environments. Collectively, these practices provide a foundation for rigor while honoring the situated, experiential, and value-laden character of reflective inquiry.

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3 Reflective Vignettes: AI-Enhanced Practices in ESD Contexts

The following vignettes illustrate concrete examples of how AI tools were integrated into sustainability-focused teaching and learning across undergraduate and graduate courses. Each vignette highlights a distinct pedagogical innovation, the design and implementation of AI-enhanced activities, and the corresponding outcomes observed in learners. These cases are organized according to the IDEA framework and aligned with the key domains of AI application in ESD, including systems thinking, data literacy, ethical reasoning, and creative problem solving, as shown in Fig. 2. Together, the vignettes provide practice-informed insights into the affordances, challenges, and ethical considerations of AI integration, serving as illustrative touchpoints for educators seeking to implement AI responsibly in sustainability education contexts.

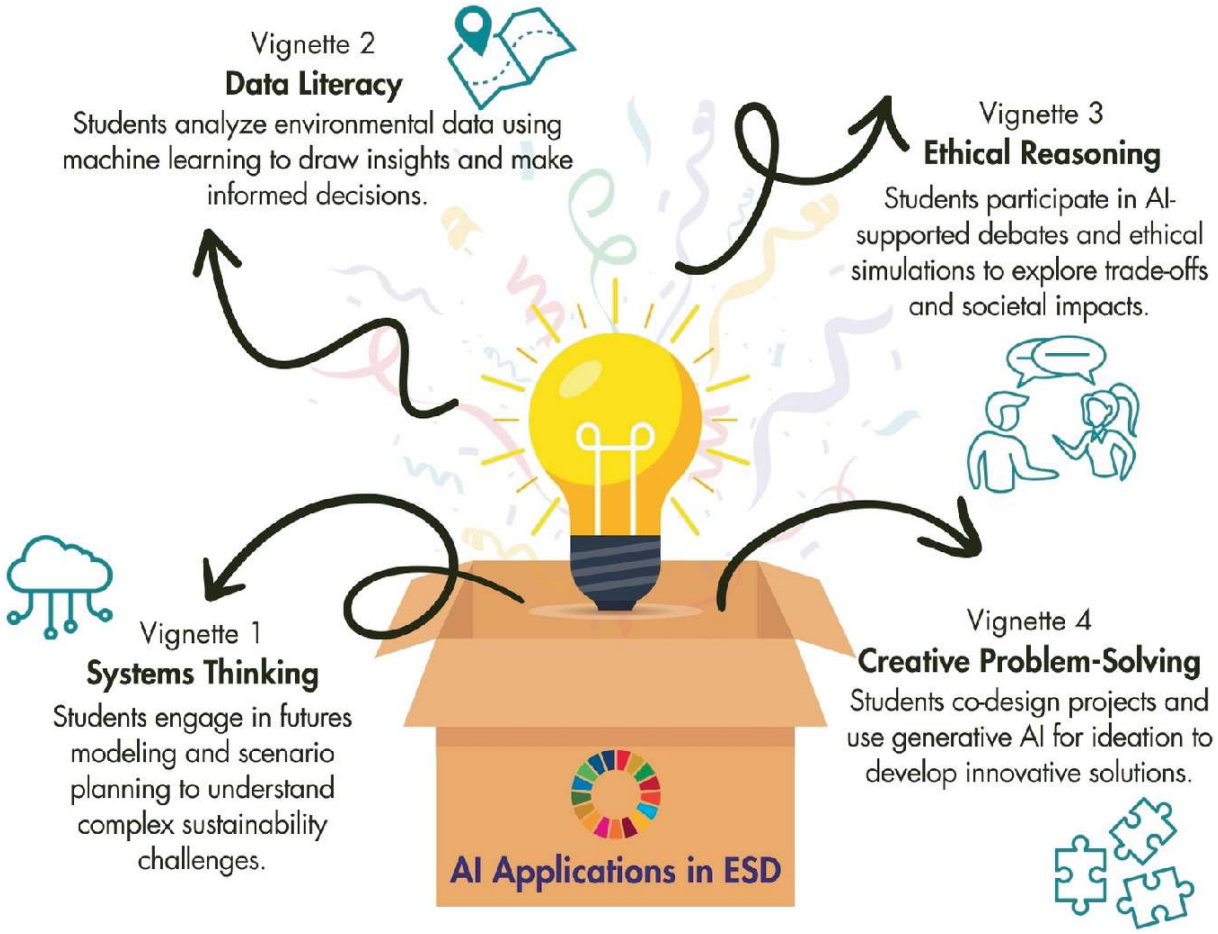


Fig. 2 AI applications in ESD with key domains and sample use cases.
Source Author

Vignette 1: Generative AI for Climate Futures Thinking

Innovation. In an undergraduate module on environmental justice, we experimented with the use of generative AI to support climate futures thinking. The innovation centered on AI-assisted storytelling, where students used ChatGPT to co-develop narrative prompts and Google Gemini to generate visualizations of possible climate futures. Gemini's multimodal capabilities allowed learners to move beyond text-based scenarios by producing illustrative images and infographics that reflected their climate narratives. These outputs provided students with creative pathways to imagine and communicate complex environmental transformations.

Design. The activity was structured around climate scenario exploration. Students began by analyzing scientific datasets and policy

reports on climate impacts across biomes, then crafted speculative narratives that explored both sustainable and unsustainable futures. Using ChatGPT, they generated storylines, which were then paired with Gemini-produced images of future landscapes, cities, or ecosystems under varying conditions. The combination of textual and visual artifacts encouraged multimodal engagement and stimulated discussion about the plausibility, ethics, and consequences of each scenario.

Evaluation. The integration of generative AI fostered greater creativity and expanded the imaginative range of student projects. Learners reported that visual outputs from Gemini helped them think more concretely about abstract climate data, while narratives from ChatGPT provided structure and depth. However, critical issues emerged: some Gemini images tended to exaggerate dystopian themes or simplify complex systems, prompting reflection on AI's limitations. The exercise reinforced the importance of human judgment in interpreting AI outputs and situating them within ethical and scientific frames.

Anchoring. This vignette draws on principles of futures thinking (Miller 2018), where learners anticipate and evaluate multiple possibilities for environmental change. It also resonates with speculative design (Dunne and Raby 2013), in which creative provocations are used to question assumptions and inspire alternative imaginaries. Finally, the activity promotes AI literacy (Leal Filho et al. 2023), encouraging students to critically engage with generative AI outputs while developing agency in shaping sustainable futures.

Vignette 2: Machine Learning for Environmental Data Exploration

Innovation. In an undergraduate sustainability education module, we adapted Microsoft's (2025) Hacking STEM lesson plan, "Analyze astronauts' photos of Earth to predict climate change", to introduce students to machine learning as a tool for environmental inquiry. The innovation lay in combining authentic satellite and astronaut imagery with computational techniques to detect seasonal changes in biomes

and explore long-term climate impacts. Bridging hands-on classroom learning with AI-enabled analysis allowed students to engage with real-world data in ways that made abstract concepts of climate systems and machine learning more tangible.

Design. The lesson was structured as a progressive inquiry cycle. Students began with an introduction to Earth's seven major biomes and their seasonal characteristics, using temperature and precipitation data. They then examined attributes of their local biome before exploring how computers represent color through the hexadecimal system. Next, students worked with astronaut and satellite photographs to model seasonal color changes within biomes. This activity transitioned into using machine learning modules to detect seasonal patterns in the images and compare the interpretive processes of humans versus AI systems. The sequence concluded with students projecting how biomes might change under climate stressors and articulating actions (social, political, environmental, or economic) that individuals and communities could take to protect the planet.

Evaluation. This activity enhanced students' data interpretation skills and their ability to connect computational reasoning with sustainability challenges. Learners valued the opportunity to compare human and machine perspectives, recognizing both the potential and limitations of AI in environmental monitoring. At the same time, the lesson revealed the need for scaffolding, as students often required support in understanding technical aspects of hexadecimal color codes and ML outputs. Without adequate guidance, some learners struggled to critically interpret AI-generated classifications, underscoring the importance of framing these tools as complements to, rather than replacements for, human judgment.

Anchoring. The vignette reflects principles of inquiry-based learning (Pedaste et al. 2015), encouraging students to investigate real-world phenomena through cycles of questioning, exploration, and reflection. It also aligns with the integration of data science in education (Weintrop et al. 2016), providing learners with computational experiences that extend disciplinary knowledge in

environmental science. Embedding AI and ML within a structured pedagogical design demonstrated how digital innovation can cultivate not only technical literacy but also sustainability-oriented civic engagement.

Vignette 3: AI-Powered Feedback in Sustainability Ethics

Innovation. In a graduate course on sustainability leadership, we introduced the use of ChatGPT as a feedback partner in structured debates and policy writing exercises centered on the Sustainable Development Goals (SDGs). The innovation involved positioning generative AI as a "critical interlocutor" that could provide real-time counterarguments, highlight overlooked dimensions, or suggest refinements to students' reasoning. Students engaged with AI both during debate preparation and in the drafting of short policy briefs, using the feedback to strengthen their arguments and critically examine trade-offs in sustainability decision-making.

Design. The activity was implemented over two sessions. In the first, students were divided into debate teams representing different SDG priorities (e.g., economic growth vs. climate action, industrial development vs. biodiversity preservation). Prior to the debates, teams used ChatGPT to generate potential counterarguments and identify weaknesses in their own positions. During the debate, AI outputs were consulted in real time as provocations for rebuttals or evidence-building. In the second session, students drafted short policy briefs on their assigned SDG trade-offs, again employing ChatGPT to receive suggestions for structure, clarity, and rhetorical persuasiveness. AI-generated feedback was treated as a draft scaffold, with students required to critically review, edit, and annotate AI contributions.

Evaluation. The use of ChatGPT enriched argumentation by exposing students to perspectives they might not have initially considered, fostering more nuanced engagement with sustainability dilemmas. Learners reported that AI feedback encouraged them to anticipate counterarguments and clarify their ethical reasoning. However, the activity also surfaced concerns. AI-generated arguments

occasionally revealed bias or oversimplification, and some students worried about overreliance on AI for rhetorical support. This underscored the importance of positioning AI as a dialogic tool rather than an authoritative source, with human critical judgment remaining central.

Anchoring. This vignette draws from traditions of argumentation in science education (Jiménez-Aleixandre and Erduran 2007), which emphasize the development of critical reasoning, evidence evaluation, and dialogue in grappling with socio-scientific issues. It also engages with scholarship on ethical AI use (Floridi and Cowls 2019), particularly the imperative to frame AI as augmenting rather than displacing human deliberation. Situating AI within structured debate and policy writing demonstrated its potential to cultivate both argumentative competence and ethical reflexivity in sustainability education.

Vignette 4: Collaborative Sustainability Project Design with AI

Innovation. In a graduate course on technical and vocational education focused on civil construction, ChatGPT was introduced as a collaborative partner in the design of sustainability-focused construction projects. The innovation centered on using AI to scaffold creativity in project ideation, planning, and documentation. This support helped students generate proposals that addressed sustainability concerns such as green building practices, waste reduction, and energy efficiency in construction.

Design. The activity was structured in three stages. First, student groups identified pressing sustainability challenges in construction, such as materials sourcing, carbon footprint, or water management in building design. Next, they engaged with ChatGPT to brainstorm possible project solutions, refine their objectives, and outline implementation steps. AI support was used to suggest sustainable construction methods, stakeholder involvement strategies, and measurable environmental impacts. Finally, students integrated AI contributions with professional standards and local regulations to draft

comprehensive project proposals. Instructors facilitated discussions where learners critically evaluated AI outputs, comparing them with technical best practices and feasibility within the Philippine context.

Evaluation. Students reported that AI helped expand their thinking about sustainable construction, particularly by introducing practices and technologies they had not previously considered. The tool was especially valuable in structuring proposals and exploring alternative approaches. However, concerns about overreliance were noted, with some groups initially adopting AI recommendations without sufficient technical scrutiny. This underscored the importance of positioning AI as a creative aid rather than a substitute for technical expertise and critical judgment.

Anchoring. This vignette builds on the principles of project-based learning in technical and vocational education, where learners tackle authentic, applied challenges (Thomas 2000; Guo et al. 2020). It resonates with research on creativity support in professional practice, highlighting how AI can extend idea generation in highly technical fields (Shneiderman 2007; Lubart 2017). Finally, it draws from the literature on human–AI collaboration in engineering education, emphasizing the need for critical engagement with AI-generated content to ensure both technical accuracy and ethical responsibility in sustainability-oriented construction projects (Elmousalami et al. 2025).

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4 Discussion

Across the four vignettes, innovation surfaced as a central characteristic of AI integration, with digital tools enabling forms of teaching and learning that extended beyond traditional pedagogical constraints. Whether through generative storytelling, machine learning–driven data exploration, AI-supported ethical debates, or collaborative design of sustainability-oriented construction projects, AI functioned as a catalyst that opened pathways for experimentation, multimodal engagement, and new forms of inquiry. These innovations suggest that the pedagogical value of AI lies not in technological novelty

but in its capacity to reorganize how learners interact with content, collaborate with peers, and construct meaning around complex sustainability challenges. This aligns with recent scholarship, such as Henriksen et al. (2024), who highlight AI's potential to personalize learning and foster creative problem solving while cautioning against approaches that lack interdisciplinary grounding or real-world applicability. Likewise, Leal Filho et al. (2025) emphasize how the thoughtful deployment of AI in education can enrich learning experiences, strengthen exploratory thinking, and support the development of sustainable solutions through more adaptive instructional designs. Taken together, these perspectives and our classroom observations illustrate that AI-driven innovation becomes pedagogically meaningful when it amplifies human creativity, deepens engagement with sustainability concepts, and enables learners to explore ideas and practices that would be difficult to realize through conventional methods.

AI as a Partner in Creativity Enhancement

Creativity emerged as a recurring theme across the vignettes, with AI expanding the imaginative range of learners by supporting speculative futures thinking, offering alternative design pathways, and providing multiple perspectives in ethical decision-making. In these contexts, AI acted as a collaborator that helped students reframe problems and consider ideas they might not have otherwise explored, aligning with research suggesting that AI can enhance creative problem-solving when learners maintain agency and guide the direction of exploration. Urmeneta and Romero (2025) emphasize that AI's value in creative tasks depends on its role as a co-participant that broadens rather than constrains human ideation, while Zhang et al. (2025) argue that emerging technologies are reshaping creativity itself by fostering a dynamic interplay between human and machine inputs. This process is described by Garcia (2024) as artificial creativity, where algorithmic contributions augment human imagination. This reconceptualization has practical implications for sustaining innovation in educational

settings, particularly when creativity intersects with sustainability challenges that require flexible thinking and interdisciplinary synthesis. As Mangubat et al. (2025a) note, the expansion of creative possibilities through AI must be supported by equitable policy frameworks and safeguards that ensure intellectual contributions (whether human-generated, machine-assisted, or hybrid) remain ethically and professionally recognized. Across the vignettes, AI enabled learners to generate diverse options, iterate complex ideas, and approach sustainability problems with greater originality than traditional methods alone often permit, illustrating the transformative potential of human–AI creative partnerships in ESD.

AI as a Cognitive Amplifier for Complexity

Another common thread across the vignettes is the capacity of AI to support learners in engaging with complexity, particularly in domains such as climate change, sustainability ethics, and civil construction where systemic interdependencies and uncertainty shape both understanding and decision-making. In our cases, AI helped students visualize multifaceted climate patterns, frame ethical trade-offs in SDG debates, and explore interlinked design considerations in technical projects, illustrating how digital tools can act as cognitive amplifiers that help synthesize diverse information sources and reveal patterns that may be difficult to discern through manual analysis alone. However, this amplifying role must be approached with caution. As Jose et al. (2025) warn, the convenience of AI-generated synthesis can inadvertently suppress higher-order thinking skills by encouraging students to rely on automated responses rather than developing their own judgment, analytical reasoning, or reflective critique. Scholes (2025) similarly emphasizes that while AI can strengthen adaptability and responsiveness in learning, such benefits depend on sustained human oversight to ensure that students interpret outputs with nuance rather than deferring to them as authoritative. The risk of inaccuracy further complicates this dynamic. As Acut et al. (2025b) demonstrate, generative AI can produce speculative, misleading, or fabricated

information that compromises academic rigor when used uncritically, particularly in domains where decisions have ethical and ecological consequences. Together, these insights reveal that AI's role as a cognitive amplifier is contingent on pedagogical design that foregrounds critical engagement, scaffolds interpretive judgment, and cultivates learners' ability to interrogate automated outputs, ensuring that AI enhances rather than erodes the intellectual rigor essential to ESD.

Persistent Challenges in AI Integration

Despite the promising outcomes illustrated across the vignettes, persistent challenges complicate the meaningful integration of AI in sustainability education. Digital literacy gaps emerged as a significant barrier, with some students struggling to interpret AI-generated content or lacking the foundational knowledge necessary to critically evaluate automated outputs, which in turn heightened the risk of uncritical adoption. Ethical dilemmas also surfaced, especially in activities that relied on generative AI for debates, policy analysis, or project design, where issues of algorithmic bias, authenticity, and overreliance became evident and exposed the need for deliberate pedagogical framing. These challenges were compounded by structural inequities, since not all learners or institutions had access to stable internet connectivity, advanced AI platforms, or appropriate technical support. As Mangubat et al. (2025b) emphasize, strengthening technological self-efficacy is essential in teacher education because confidence with digital tools shapes both instructional choices and learner engagement, yet such capacity is unevenly distributed. Similarly, Hammerschmidt et al. (2025) argue that the "AI divide" operates across interdependent sociotechnical layers where systemic inequalities can cascade. These structural constraints are further echoed in the findings of Gantalao et al. (2025), who highlight how infrastructure limitations, uneven access to hardware and software, and persistent algorithmic biases complicate attempts at equitable AI integration. Taken together, these challenges reveal that without

intentional strategies that address literacy, ethics, and structural inequity, efforts to embed AI in sustainability education risk deepening disparities rather than fostering the just learning environments envisioned in ESD.

Implications for Teacher Training and Professional Development

The findings from the vignettes underscore important implications for teacher training and professional development, particularly as educators navigate the pedagogical, ethical, and epistemic shifts introduced by AI in sustainability learning. Preparing teachers to use AI meaningfully requires training that moves beyond functional tool familiarity and cultivates reflective, critical, and sustainability-oriented perspectives that help educators frame AI as a support for inquiry rather than an automated shortcut. This includes developing AI literacy tailored to developmental contexts, strengthening educators' capacity to interrogate bias and algorithmic limitations, and fostering the dispositions necessary to guide students toward ethical and critical engagement with generative and data-driven technologies (Funa and Gabay 2024). Continuous professional development must also emphasize the evolving nature of AI systems, helping teachers adapt to rapid technological change through collaborative learning communities, iterative experimentation, and shared pedagogical reflection. As Acut et al. (2026) highlight, sustained reskilling and upskilling efforts require cross-sector collaboration among educational institutions, industries, and government agencies to cultivate a future-ready teaching workforce equipped to integrate AI responsibly. Embedding these competencies within teacher preparation programs can ensure that educators are well positioned to support learners in navigating complex sustainability challenges in ways that maintain human judgment, ethical awareness, and pedagogical integrity.

Institutional and Policy Imperatives for Responsible AI Integration

At the institutional and policy levels, the strategic integration of AI in sustainability education requires alignment with broader digital

transformation agendas so that adoption moves beyond surface-level technological add-ons and instead supports coherent pedagogical and developmental goals. Institutions must invest in infrastructure, technical support, and curriculum redesign to ensure that AI meaningfully enhances learning processes and does not reinforce existing inequities in access or participation. Policy frameworks likewise need to balance innovation with safeguards for ethical use, data privacy, transparency, and inclusivity by establishing mechanisms that monitor AI deployment, support accountable decision-making, and ensure that learning environments remain responsive to diverse student needs (Funa and Gabay 2024; Xiao et al. 2025). National and international models such as Germany's Industry 4.0 initiative demonstrate the importance of scalable workforce development strategies, yet also reveal the structural constraints (e.g., limited budgets, uneven access to digital tools, and gaps in technical expertise) that institutions must address to create equitable and context-sensitive AI ecosystems (Acut et al. 2026). Coordinated efforts across educational institutions, government agencies, and industry partners will be essential to sustain ethical AI integration that genuinely advances the goals of sustainability, equity, and social justice, ensuring that technology serves as an enabler of transformative learning rather than a driver of further educational stratification.

Positioning AI as a Pedagogical Mediator in ESD

This practitioner inquiry contributes to the broader discourse on ESD by illustrating how AI can function as a pedagogical mediator that supports transformative learning aligned with sustainability principles. When AI is embedded in futures thinking activities, inquiry-based approaches, ethical argumentation, and project-based tasks, it extends pedagogical practices that resonate with UNESCO's ESD framework, which emphasizes critical reflection, anticipatory competence, and collaborative problem-solving (UNESCO 2020). The vignettes show how AI can help learners visualize complex scenarios, interrogate socio-environmental trade-offs, and iterate solutions in ways that

deepen engagement with SDGs. These findings align with prior studies highlighting the importance of student-centered integration of sustainability themes, the role of institutional leadership in fostering ESD adoption, and the value of interdisciplinary approaches in sustaining curricular reform (Acut et al. 2025a; Leal Filho et al. 2019, 2020). Foregrounding the interplay between human agency and AI-mediated support illustrate how technology can enable educators to design learning environments that are context-sensitive, reflective, and action-oriented. In this sense, AI reinforces the notion that responsible innovation depends on educators' ability to situate technological tools within ethical, ecological, and societal commitments at the heart of sustainable development.

Future Directions for AI–Human Collaboration in Sustainability Education

Looking ahead, the integration of AI into sustainability education invites a deeper shift in how educators balance human judgment with machine intelligence. It also opens pathways for practices that are more inclusive and responsive to global challenges. Future work can explore how AI supports long-term scenario building in ways that cultivate foresight rather than simple prediction and how learners can co-create sustainability solutions with AI through iterative design environments that mirror real-world complexity. More research is also needed on AI tools that adapt to local ecological and cultural contexts so that sustainability learning remains grounded and relevant across diverse communities. Teacher education will benefit from models that integrate AI literacy with ethical reasoning and systems thinking so educators can guide students in using AI for critical reflection rather than automated shortcuts. Institutions can experiment with collaborative labs where students, industry partners, and community groups work with AI to address urgent sustainability problems, which can build civic capacity and strengthen interdisciplinary problem-solving. As these directions evolve, the field must pay close attention to issues of equity, transparency, and accountability to ensure that AI amplifies human

agency rather than narrowing it. Approaching AI as a partner in inquiry and innovation can help shape learners who are equipped to navigate uncertainty, act with ethical purpose, and imagine futures that honor both human and ecological well-being.

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5 Conclusion

This chapter has demonstrated how the IDEA Framework offers a structured yet flexible approach for reflecting on the integration of AI into sustainability teaching. Through four vignettes, we explored diverse pedagogical practices that illustrate both the promise and the challenges of bringing AI into higher education contexts. Across cases, AI tools supported innovation, enhanced creativity, and helped learners grapple with the complexity of sustainability issues, while also raising critical questions of access, ethics, and responsible use. The reflections underscore the importance of fostering reflective, ethical, and creative engagements with AI in teaching and learning. Rather than treating AI as a neutral instrument, educators must guide students in critically examining how algorithms shape knowledge, whose perspectives are amplified, and what risks arise from automation and bias. In this way, AI becomes not only a pedagogical tool but also an object of inquiry, enabling students to understand its implications for sustainability, equity, and justice.

While the vignettes offer rich, practice-informed insights, several limitations should be acknowledged. The cases presented were drawn from a limited number of contexts and disciplines, which may not represent the full spectrum of AI integration efforts in ESD. Because the study focused on qualitative synthesis, it privileges depth of reflection over breadth of coverage, and thus cannot claim statistical generalizability. Moreover, the interpretations relied on researcher and practitioner perspectives, which may introduce subjective bias despite efforts toward triangulation and reflexivity. The framework itself, while useful as a conceptual scaffold, remains open to refinement through empirical validation and cross-cultural application. Future work could

benefit from longitudinal, mixed-method, and comparative studies that test the IDEA framework's transferability across diverse educational systems and sustainability domains.

Moving forward, the integration of AI in ESD requires interdisciplinary collaboration that brings together educators, technologists, policymakers, and students. Faculty upskilling will be crucial, as many educators need both technical literacy and pedagogical strategies to meaningfully embed AI in their courses. Equally important are research–practice partnerships that can document, test, and refine emerging approaches, ensuring that innovations are not only creative but also scalable, equitable, and context-sensitive. Hence, we envision AI as a co-pilot in shaping education for sustainable futures. When thoughtfully and responsibly integrated, AI can expand the capacity of educators to design transformative learning environments that cultivate critical thinking, creativity, and ethical responsibility, which are competencies at the heart of ESD. The challenge and opportunity ahead lie in harnessing AI not as a replacement for human judgment, but as a collaborator in the urgent task of preparing learners to address the intertwined social, environmental, and technological challenges of the twenty-first century.



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Design of AI-Supported Scenario-Based Learning Activities for Teacher Education in the Context of Sustainable Development

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Abstract
This chapter examines how artificial intelligence (AI)-supported scenario-based learning approaches can be utilised in teacher education to develop sustainable development-oriented thinking, ethical reasoning, and systems thinking competences for decision-making. Within the framework of Education for Sustainable Development (ESD), it is critically important for pre-service teachers to understand the interrelationships among environmental, social, and economic dimensions and to develop holistic solutions tof complex problems. In this context, the chapter discusses how AI tools (specifically ChatGPT) can serve as a "learning partner" in data analysis, scenario generation, simulation, and reflective thinking. Two exemplary learning activities aligned with the SDGs are presented, modelling pre-service teachers' decision-making processes concerning

multidimensional problems such as sustainable school design, community-based environmental issues, and social justice. It is anticipated that the developed activities will enhance pre-service teachers' data-driven thinking skills, enable them to compare the impacts of different scenarios, and support ethical evaluations. The study advocates that AI should be positioned not as an independent decision-maker but as a decision-support tool that encourages critical thinking, enhances pedagogical creativity, and strengthens sustainability awareness. In conclusion, AI-supported scenario-based teacher education offers an innovative pedagogical model that prepares future educators to be equipped both technologically and ethically, capable of guiding sustainable development.

Keywords Artificial intelligence – Education for sustainable development (ESD) – Scenario-based learning – Teacher education – Learning activities

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1 Introduction

Global issues such as climate change, resource depletion, environmental justice, inequalities, and digital transformation are

compelling education systems to adopt approaches that centre transformative learning rather than merely transmitting knowledge. In this context, the Education for Sustainable Development (ESD) approach aims to develop individuals' capacities to think and act within the framework of sustainability principles at both local and global levels (UNESCO 2023a, b, 2017). Sustainable development education aims to help students understand the interdependencies among environmental, social, and economic systems. In line with SDG 4.7, teachers cease to be mere transmitters of knowledge and become agents of transformation, guiding the construction of a sustainable future. Therefore, teacher education programmes must be redesigned to enable candidates to develop systems thinking, ethical reasoning, and decision-making skills (Kulkov et al. 2023).

Addressing global problems requires coordinated actions towards urgent issues such as climate change, extreme weather events, hunger, and inequality (Kulkov et al. 2023). In this context, the United Nations Sustainable Development Goals aim to promote equality and sustainable growth in environmental, health, education, and economic domains. In achieving these goals, artificial intelligence (AI) technologies emerge as a promising tool for supporting sustainable development by enabling the analysis of complex, interconnected systems, the development of alternative scenarios, and the anticipation of ethical consequences (Jarrahi 2018). AI enables personalised and adaptive learning in teacher education, offering experiences tailored to students' diverse learning needs (Strielkowski et al. 2024). This technology paves the way for innovative approaches in sustainable education and transforms traditional teaching methods into dynamic, student-centred experiences.

The use of AI in education is transforming the nature of instructional processes and strengthening teachers' pedagogical decisions with data-driven approaches (Holmes et al. 2019). AI literacy encompasses not only pre-service teachers' ability to use AI tools but also their understanding of the logic of algorithmic systems,

development of data-driven thinking skills, and critical evaluation of recommendations (Long and Magerko 2020).

Sustainability literacy comprises systems thinking, anticipatory, normative, and strategic competences. The integration of AI into teacher education transforms the teacher's role from knowledge transmitter to learning facilitator and ethical mediator. In this context, pre-service teachers become not only users of technology but also conscious individuals who question its ethical boundaries (Şahin 2025). Within this transformation, adaptive learning and AI-based tools enable pre-service teachers to take an active role in community-based sustainability projects, analyse local environmental problems using data-driven approaches, and develop solution proposals. Thus, students acquire the ability to develop decisions based not only on knowledge but also on ethical and systemic foundations (Strielkowski et al. 2025). Another pedagogical approach that deepens these decision-making processes is scenario-based learning (SBL). SBL is a pedagogical approach that enables students to engage in complex decision-making processes through real-life problems (Jonassen 2011). In this method, students are placed in problem situations, develop alternative solutions, and evaluate action plans. AI integration makes the SBL process more interactive and dynamic; for instance, through ChatGPT or data analysis tools, they can generate possible future scenarios and discuss their environmental and social impacts. Here, AI functions not as a “decision-maker” but as a “decision-support” partner that supports pre-service teachers’ data-based analysis, scenario comparison, and ethically-based decision development processes (Bammer 2005; Bender et al. 2021; Bäckstrand 2003; van Kerkhoff and Lebel 2006; Blackstock and Carter 2007; Talwar et al. 2011).

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2 Artificial Intelligence and Sustainability in Education: A Teacher Education Perspective

Artificial intelligence (AI) has the potential to support pedagogical innovations in teacher education by personalising learning, developing

professional skills, and optimising classroom management. Antonio and Sison's meta-analysis demonstrates that AI-supported interventions create significant positive effects on pre-service teachers' cognitive, affective, and psychomotor learning outcomes (Antoni and Sison 2025). In light of these findings, it is notable that most applications are used merely to improve existing processes, and the transformative potential of AI in teaching is not sufficiently realised. AI can strengthen pedagogical processes as a thinking partner, feedback provider, and simulation environment creator for pre-service teachers. Generative AI-supported scenario-based learning designs have enhanced pre-service teachers' pedagogical problem-solving, anticipatory development, and classroom situation analysis skills (Meegan and Young 2024). This approach demonstrates that AI not only produces content but also plays a transformative role, triggering learning processes.

However, for this potential to be realised, ethical considerations and data security issues are critically important in AI-supported teacher education. Personal data privacy, algorithmic biases, and non-transparent decision-making processes threaten the fair and reliable use of AI in education (Costa et al. 2025; Pedreschi et al. 2019). Therefore, pre-service teachers need to be equipped with the skills to use AI tools effectively, critically, and ethically (Meegan and Young 2024).

AI-supported Education for Sustainable Development (ESD) practices enhance student collaboration, problem-solving, and communication skills whilst strengthening the guiding role of teaching staff (Abulibdeh et al. 2024; Kar et al. 2022; Leal Filho et al. 2021). However, risks such as the digital divide and rapid technological change may threaten sustainability and inclusivity in AI integration (Ahmad et al. 2023; Lambrechts et al. 2013). It is critically important for higher education institutions to create a sustainable and innovative education ecosystem by integrating pedagogical innovation, ethical responsibility, and societal stakeholder engagement. In conclusion, AI-supported teacher education is a transformative tool that integrates pedagogical innovation with sustainability principles. When ethics, data security,

and pedagogical competences are considered, it is thought that AI can enrich pre-service teachers' learning experiences, strengthen classroom management, and support long-term sustainability in education.

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3 AI-Supported Teacher Education and Sustainable Development: Pedagogical Opportunities and Ethical Approaches

Higher education institutions emerge as critical actors within the scope of Sustainable Development Goals (SDGs) due to their pedagogical and research capacities (Hamdan 2020; Khan 2023; Rodés-Paragarino et al. 2024). In the context of SDGs, intersectional issues such as poverty position universities at an essential juncture for disseminating knowledge, transforming it into public policies, and changing management strategies to support economic sustainability. This situation emphasises the importance of universities in promoting community engagement and a culture of sustainable development through their academic and research frameworks. The heterogeneous nature of challenges related to poverty and sustainability necessitates a comprehensive approach encompassing economic and social strategies; dimensions such as innovation, gender equality, and social justice are integral parts of this approach (Hirsch et al. 2021; Kusi-Mensah et al. 2022). These complex sustainability requirements make the use of AI in education faculties more critical.

AI is increasingly significant in achieving the SDGs (Leal Filho et al. 2024). AI, which can create short- and long-term effects in areas such as global production, environmental consequences, equality, and inclusivity, possesses transformative potential, especially for teacher education within educational processes. The integration of AI in higher education provides benefits such as reduced learning anxiety, greater access to knowledge, and the provision of learning materials customised to student profiles (Hu et al. 2023; King et al. 2021; Laine et al. 2022). The use of AI in environment and sustainability-focused

education can enhance students' sustainability knowledge through machine learning, data analytics, personalised and adaptive learning systems, and virtual learning environments. Application areas include the simulation of environmental scenarios (climate, ecosystems, resource management), the development of data analytics-based sustainability projects, and AI-supported reflection and decision-making activities (Leal Filho et al. 2025).

However, teaching staff's limited perceptions of AI and robotic technologies, and their lack of conscious development of community welfare, are significant challenges to AI integration (Leoste et al. 2021; Shenkoya and Kim 2023). In this context, generative AI-based platforms enable pre-service teachers to develop their pedagogical skills by interacting with different student and mentor agents in virtual classroom environments. This constitutes an essential pedagogical foundation that supports the management of complex classroom dynamics, the development of strategies, and the making of pedagogical decisions grounded in ESD values (Aperstein et al. 2025). Pre-service teachers' gaining experience on AI-based interactive platforms is also related to their readiness for AI integration. Understanding teachers' readiness for and levels of expertise in AI integration is critically important for developing effective and fair educational practices. The systematic integration of generative AI tools into STEM education enhances problem-solving skills and supports personalised, inquiry-based learning. AI has the potential to improve students' decision-making processes through e-books, simulations, and virtual applications (Şahin 2025). In their research, Bircan et al. (2025) had pre-service teachers write stories with AI-supported tools around STEM-themed topics. According to the research results, this process developed pre-service teachers' digital competences and 21st-century skills (such as critical thinking, creativity, problem-solving, and digital literacy). Such a scenario-based writing activity has shown potential to develop pre-service teachers' pedagogical, sustainability, and systems-based thinking skills, and technological competencies concurrently. Recent studies propose multi-stage modelling methods for integrating

generative AI tools into STEM education and demonstrate that this systematic approach not only enhances problem-solving skills but also supports personalised and inquiry-based learning, which is of great importance for the development of sustainable education. In this context, the current literature also emphasises the importance of AI-supported STEM education in developing 21st-century skills and contributing to the Sustainable Development Goals (Bas and Kiraz 2025; Štuikys et al. 2025).

Sustainable development-oriented teacher education necessitates a holistic transformation that goes beyond traditional approaches prioritising knowledge transmission and encompasses normative and structural dimensions such as pedagogical innovation, gender equality, social justice, and inclusivity. This multi-layered perspective provides a fundamental conceptual framework, particularly for the effective design and implementation of Artificial Intelligence (AI)-supported teaching practices (UNESCO 2023a, b, 2019). Pre-service teachers' self-regulation skills, social-emotional competencies, and knowledge and skills for using AI-based teaching technologies for pedagogical purposes emerge as critical determinants in constructing a sustainable education ecosystem (OECD 2021; Zimmerman 2002). The literature demonstrates that in learning environments where these components are strengthened, pre-service teachers' autonomy towards technology integration increases, their ethical awareness develops, and they become more competent in decision-making processes based on sustainability principles (Selwyn 2022; Mishra and Koehler 2006).

In this context, higher education institutions have the potential to contribute to the Sustainable Development Goals (SDGs) at a strategic level, not only through their teaching, research, and societal outreach functions, but also through the integration of sustainable practices into institutional culture (Tilbury 2011). Therefore, aligning AI-supported teacher education with the SDGs requires both the development of teacher competences at the individual level and the creation of ethical, inclusive, and sustainable education policies that support these competences at the institutional level.

4 Scenario-Based Learning Approach and Artificial Intelligence (AI) Integration

Scenario-based learning offers interactive experiences in authentic classroom settings to enhance pre-service teachers' confidence and classroom preparation (Klassen et al. 2021). Due to the high risk of direct transition to field experience, simulated classroom environments enable candidates to prepare for face-to-face teaching whilst reducing potential emotional and professional costs (Errington, 2011). This approach supports learning through interactive social practices in school and classroom contexts rather than direct transmission of pedagogical knowledge. Research shows that field experiences offer more dynamic opportunities than formal instruction for candidates to reconceptualise their values and beliefs (Korthagen 2010). Scenario-based learning enables students to develop skills such as problem-solving, critical thinking, creativity, collaboration, and communication by engaging them in complex and realistic situations (Volpe 2024; Zitouniatis et al., 2023). This approach provides a safe environment where pre-service teachers can experience strategies to increase motivation, resolve conflicts, and adapt to different learning styles (Karimovna 2024).

Digital tools and simulation technologies provide critical support to enhance the pedagogical advantages of scenario-based learning. The success of SBL depends mainly on how educators design and implement scenarios (Rodés-Paragarino et al. 2024; Bardach et al. 2021). Educators shape student-centred SBL frameworks with their pedagogical perspectives; these frameworks aim to develop problem-solving, decision-making, and classroom management skills (Daniels et al. 2022; Lin et al. 2020). Furthermore, augmented reality (AR) and virtual reality (VR) technologies enhance the effectiveness of SBL by increasing realism and engagement (Álvarez-Nieto et al. 2023; Wu and Wen 2020). Digital tools play a critical role in preparing and implementing scenarios (Yilmaz et al. 2020).

Combining this pedagogical foundation with AI-supported scenarios can more effectively develop pre-service teachers' problem-solving and AI literacy skills. AI integration plays a transformative role in scenario-based teacher education. Scenarios generated with generative AI tools (e.g., ChatGPT) support pre-service teachers' professional judgement, problem-solving, and AI literacy development. AI can be used in scenario generation and as a "learning partner" that triggers students' thinking processes; however, for effective use, teachers need to develop appropriate prompting and critical AI literacy skills (Meegan and Young 2023). AI can enhance teachers' decision-making skills, improve instructional planning, and support data-driven, collaborative decision-making processes (Celik et al. 2022; Li 2022; Ghamrawi et al. 2023; Imran et al. 2025). Additionally, AI-based simulations strengthen teachers' ethical awareness, adaptive teaching strategies, and classroom management skills (Karakuş et al. 2025; Yaşar 2025; Viruel et al. 2025). AI-supported activities, such as STEM-themed story writing, offer potential for developing pre-service teachers' digital competences, 21st-century skills, and systems-based thinking abilities (Bircan et al. 2025). AI-supported scenarios enable students to develop both pedagogical and sustainability-based thinking skills (Zitouniatis et al. 2023; Asbell-Clarke et al. 2021). AI-supported activities strengthen not only pedagogical competences but also sustainability-based thinking and systems thinking skills.

AI-supported learning also contributes to sustainability education. Students can directly observe the effects of climate change, deforestation, and pollution on ecosystems by simulating environmental scenarios; they can share different perspectives through collaborative projects and conduct big data analytics in sustainable research projects (Leal Filho et al. 2025). This process empowers students and communities to contribute to a more sustainable future.

SBL and AI integration offer a comprehensive approach that simultaneously develops pre-service teachers' pedagogical, digital, and sustainability-focused skills. This integration strengthens candidates' classroom management, problem-solving, and ethical decision-making

abilities whilst making education design aligned with the SDGs possible. The literature demonstrates that AI-supported SBL activities equip candidates with not only knowledge-based but also systems thinking and ethically-based decision-making competences (Celik et al. 2022; Karakuş et al. 2025; Leal Filho et al. 2025).

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5 Research Questions

Drawing upon the evidence and scholarly discussions presented in the literature, the present study aims to address the following research questions:

1. How can AI tools be integrated into scenario-based learning activities as a learning partner within teacher education in the framework of Education for Sustainable Development?
2. Within the context of the Sustainable Development Goals (SDGs), how can AI-supported scenario-based learning activities be conceptually designed to foster pre-service teachers' systems thinking, ethical reasoning, and data-driven thinking competences for decision-making.

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6 Methods

This study is grounded in a design-oriented conceptual research approach and does not aim to generate empirical data. Instead, it proposes and elaborates conceptual activity designs for AI-supported scenario-based learning in teacher education. Situated within the framework of Education for Sustainable Development (ESD), the study systematically outlines exemplary learning activities and offers a critical discussion of their pedagogical rationale.

In this chapter, ChatGPT is used as the sole AI tool to illustrate the proposed scenario-based learning activities. No comparison across different AI models is intended, and references to AI are illustrative rather than evaluative. The findings presented in this chapter are

conceptual in nature and are derived from the proposed activity designs. No empirical data were collected, and no comparative analysis of different AI models is included.

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7 Scenario-Based, AI-Supported Activities Aligned with Education for Sustainable Development Goals

In this context, two different activity implementations using a scenario-based learning approach and AI integration are shared to contribute to teacher education. In the prepared activities, artificial intelligence is positioned not as a "decision-maker" but as an "intelligent learning partner" that supports learning. Artificial intelligence tools such as ChatGPT were used in the planning process for the activities in this section (OpenAI 2025).

Activity 1: Community-Based AI Projects

Aim: In this activity, it is intended that pre-service teachers develop an AI-supported solution project to produce sustainable solutions to an environmental problem experienced by local communities.

Related Sustainable Development Goals: SDG 4, SDG 11, SDG 12, SDG 13

Expected Learning Outcomes

- Analyse local environmental problems with a data-driven approach
- Develop solution proposals using artificial intelligence tools
- Plan community participation within the framework of sustainability principles
- Create a "Community-Based AI Action Plan" draft

Duration

3 lesson hours (135 min)

Required Tools and Materials

- Computer or tablet
- AI tools such as ChatGPT, Google Gemini, or Copilot
- Local environmental data (e.g., municipal statistics, waste collection data, electricity energy consumption invoice information)
- Internet connection
- Canva/PowerPoint (for presentation preparation)

Implementation Process Steps

Step 1: Introduction and Awareness (10 min)
At this stage, the instructor poses the following questions to pre-service teachers about social sustainability (social justice, inclusivity, cultural diversity, welfare, equal opportunities, etc.). Students' prior knowledge on this subject is explored.

- Think of a problem you encounter in daily life (discrimination, security, social equality, cultural differences, etc.). In your opinion, how can the solution to this problem be related to social sustainability?
- In your opinion, which challenges that students face in their daily lives should be considered for a school to be socially sustainable?
- In the city where you live, which services provided by the municipality (for example: public transport, social assistance, culture-arts activities, neighbourhood councils, disability services, youth centres, etc.) do you think contribute to social sustainability and how?

Step 2: Identification of the Local Problem (20 min)
SCENARIO: *According to your city's municipal waste management reports, only 30% of recyclable waste is correctly sorted. This situation leads to both environmental and economic losses. Municipal waste collection statistics, energy consumption data, and water usage reports indicate that local resources are not being used efficiently. Environmental awareness levels vary amongst different segments of society. Whilst recycling awareness is high in some neighbourhoods, it is observed that*

students and teachers in schools are not proficient in practical applications. It is noted that there is insufficient cooperation amongst the municipality, NGOs, and schools. Nevertheless, it is noteworthy that the increase in online education and social media use following the pandemic offers new opportunities to enhance community engagement.

After reading the scenario, students are divided into heterogeneous groups of 3–5 people. Groups are asked to identify a local environmental problem (e.g., waste management, energy efficiency, water resource usage). In determining the problem, they are requested to develop solution proposals for the problem they have selected using municipal data, open data sources, and AI-supported analysis tools. At the end of the activity, they are expected to create a "community participation plan". As progression steps of this process, groups are enabled to utilise AI tools to define and analyse the local environmental problem in detail. In the first stage, AI is asked to create a "Problem Definition Framework".

Preliminary Information Gathering

The following questions are posed to the AI tool:

- Analyse the waste collection and recycling data of the neighbourhoods in our city. (Existing recycling centres, waste collection points, online data sources.)
- In which regions has the increase or decrease in waste amounts been concentrated over the past 5 years? (Which neighbourhoods or schools, which communities are most affected?)
- What are the sorting rates by waste type? (What are the sorting rates for plastic, organic, glass, metal, etc.?)
- Are recycling education and awareness programmes available at schools or community centres? (What is the participation level?)

Groups can request AI to present data sources in the form of tables, graphs, or summary reports by scanning them. Based on these data, pre-service teachers can visualise the geographical and demographic distribution of the environmental problem they examine.

Prioritisation of the Problem

AI is enabled to answer questions such as:

- Which problem area requires an urgent solution?
- Which neighbourhood or school should receive more support?
- What are the social, economic, and environmental impacts of the problem?
- What is the likelihood of community participation and potential impact?
- How do current legal regulations affect the problem?

The obtained data is shared and discussed within the group as an AI-supported report or presentation. This expanded framework facilitates pre-service teachers' analysis of the problem not merely superficially but in a data-driven, comprehensive manner associated with sustainability goals. The AI-supported "Problem Definition Framework" report is transformed into a community-based action plan.

Step 3: Data Visualisation and Preparation of Proposal Report (20 min)

At this stage, each group is requested to visualize the data they have obtained with AI assistance. To guide them at this stage, they can be asked to prepare information cards regarding total waste production and sorting rates. The visualization of plastic, organic, and glass sorting rates by neighbourhood can be presented using bar graphs. Schools with/without curricula on social sustainability, recycling, and environmental education, and students' participation percentages in the conducted activities can be visualized in a bar chart. School locations can be identified on a map, and this information can be presented visually on the map. Subsequently, groups prepare a brief analysis report by AI explaining "the root causes of the problem (e.g., 'Low sorting rate in Neighbourhood X is related to low container numbers and insufficient awareness-raising')".

Step 4: AI-Supported Solution Development (45 min)

Following the prepared report, groups develop sustainable solution strategies to resolve the environmental problem they have selected by evaluating AI recommendations. Groups plan how they will involve the local population or students in the project. A "participatory action plan model" is created by obtaining recommendations from AI. The created action plan is evaluated on the participation level and stakeholder diversity dimensions.

Step 5: Community-Based AI Action Plan (15 min)

AI is requested to create a "participatory action plan format". Groups transform their learning into a community-based action plan aligned with the headings listed below. Final products are evaluated and reported. As the activity progresses, to enrich the process, groups can implement the solution they propose on a small scale (e.g., a waste-sorting system at school). They can share solution proposals by establishing local collaborations with municipalities and NGOs.

When preparing the community-based action plan, the following headings must be completed by each group.

Community-Based Participatory Action Plan Model

1. Problem Definition
   - Local problem:
   - Affected neighbourhoods/school/community:
   - Current status of the problem (data-driven):
2. Targeted Behavioural Change
   - Who will do what?
   - What behavioural change is expected?
   - What are the success indicators?
3. Stakeholder Mapping
   - Students
   - Families
   - Teachers

- Municipality
- NGOs
- Volunteers

Each stakeholder's role ↴

- …

4. Community Participation Strategies
   - Participation level:

     Information
     Consultation
     Co-production
     Empowerment
   - Resources and tools to be used:

     Workshop
     Mobile application
     Local media
     Artificial intelligence tools
     Gamification…
5. Implementation Steps
   - Step 1—Preparation
   - Step 2—Introduction
   - Step 3—Implementing sustainable action proposals
   - Step 4—Monitoring and evaluation
6. Impact Assessment
   - Short-medium and long-term impact

Step 5: Project Presentation and Feedback (20 min)

AI is requested to create a “presentation evaluation rubric” (Table 1). Each group presents its community-based action plans and receives feedback from peers.

Table 1 Sample presentation evaluation rubric

Reflective Evaluation Questions

1. Following the completion of the activity, pre-service teachers are asked the following reflective thinking questions, and their opinions are obtained.
2. Why is community participation important in AI projects?
3. How can data-driven decisions be balanced with local realities?
4. Are AI solutions always sustainable?
5. How can a bridge be built between community needs and technological possibilities?

Activity 2: Sustainable Schools Simulation

1. Purpose of the Activity

This activity aims to develop pre-service teachers’ systems thinking, ethical reasoning, data-driven decision-making, and AI-supported solution generation skills in the sustainable school design process.

Related Sustainable Development Goals: SDG 3, SDG 4, SDG 7, SDG 11, SDG 12, SDG 13.

Expected Learning Outcomes

At the end of the activity, pre-service teachers will:

- Analyse a school's environmental and economic sustainability problems.

- Produce alternative and applicable solution proposals using artificial intelligence tools.
- Evaluate the solution options they produce along with ethical, social, and technological sustainability dimensions.
- Create an applicable action plan for a sustainable school model based on systems thinking.

Duration

2 class hours (100 min)

Required Tools and Materials

- Computer/tablet
- ChatGPT or similar AI tools
- School energy, water, waste management datasets (ready-made/fictional)
- Excel or Google Sheets
- Canva/PowerPoint
- Simulation scenario (to be provided by the instructor)

Application Process Steps

Step 1-Introduction and Scenario Presentation (10 min)

The instructor begins the lesson with a brief brainstorming session on the concept of "Sustainable School". The following questions are posed to participants:

- What are the fundamental features that make a school sustainable?
- How can technology-supported sustainability solutions be used in schools?
- How should the sustainable design of school buildings be?
- What kinds of practices can be implemented in schools for students to acquire behaviours appropriate to sustainable living?
- How can we include families in sustainable school projects?

Participants are enabled to share their views with classmates. Subsequently, the following command is given to ChatGPT:

Give examples of sustainable school practices from around the world. Explain models that include energy savings, water management, waste reduction, and community participation.

These examples are shared with the class to expand students' mental models. If desired, the instructor can also limit this command to the country level.

Presentation of the Scenario

The instructor distributes the following scenario to pre-service teachers:

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8 SCENARIO: "Transformation of Green Roof Secondary School"

Green Roof Secondary School is a state school with 600 students, located 20 km from the city centre. The school's annual electricity energy consumption has increased by 18% over the past three years, and water consumption has risen above normal due to faults in taps and toilets. Waste management is only at the "general rubbish" level; there is no recycling system. The school management wishes to initiate a transformation project within the scope of sustainability studies. However, this transformation needs to be carefully planned in terms of budget, technology use, compliance with ethical principles, and long-term impact.

The Ministry of National Education has provided schools with an AI advisory tool to support this process. In this simulation, pre-service teachers will:

- *Examine school data,*
- *Obtain recommendations from artificial intelligence,*
- *Discuss the advantages, risks, and ethical dimensions of the recommendations received,*
- *Create an applicable sustainable school model.*
- *Work with a stakeholder group comprising school management, parents, and students.*

The project is evaluated in three dimensions. Below are example evaluations belonging to the components of sustainable development and decision points that can be taken regarding these dimensions:

1. **Environmental Dimension**

- The school's current energy consumption is high; electricity bills are increasing by 15% annually.
- Old lighting systems in classrooms and inefficient landscaping practices in the school garden exist.
- Water usage is uncontrolled; there is no rainwater harvesting.
- Waste management is insufficient; recycling bins are underused.

Decision Points:

- Energy-efficiency investments (LED conversions, solar panels, sensor-based systems).
- Redesigning the school garden (local plants, water-efficient landscaping).
- Installation of a waste segregation system.

2. **Economic Dimension**

This dimension allows teacher candidates to understand the financial impacts of sustainability investments. This dimension enables pre-service teachers to understand the financial impacts of sustainability investments.

- The school's budget is limited; only **150,000 TL** has been allocated for annual investment.
- Quotation for solar energy system installation: **300,000 TL**, but will reduce electricity costs by 40% annually in the long term.
- Quotation for LED conversion: **80,000 TL**, saves **25,000 TL** annually.
- Water-saving system cost: **40,000 TL**; saves **8,000 TL** annually.
- The waste sorting programme costs low (10,000 TL) but lacks a revenue model.

- Municipality's small-scale sustainability grant: **50,000 TL** (can only be spent on educational materials).

Decision Points:

- Which investments should be chosen as short-term and which as long-term?
- Is funding support from the community, sponsor collaborations, or circular economy practices possible?
- How should payback periods based on savings be calculated?
- How can maximum impact be achieved with a limited budget?

3. **Social Dimension**

This dimension includes key components that will strengthen perceptions of sustainability in the educational environment.

- The region where the school is located has high socioeconomic diversity, and income inequality is high.
- Whilst some parents support sustainability efforts, some have concerns that costs will increase.
- The level of environmental awareness amongst students is heterogeneous.
- There are accessibility problems for disabled students at the school; sustainability efforts require an inclusive approach.
- The school's connection to the local community is weak, and family participation is low.

Decision Points:

- How do you involve the community in the process? (parents, local NGOs, municipality)
- How can the sustainability education programme be made inclusive?
- How are social justice and equality principles integrated into the project?
- What activities can be undertaken to strengthen student leadership?

Integration of the Scenario into the Activity

In Activity 2, pre-service teachers are directed to perform the following tasks:

Task 1—Creating a System Flow Chart
Pre-service teachers produce a system flow diagram that includes all three dimensions of sustainable development.

- *They establish cycles such as: Energy → cost → social acceptance → student awareness → environmental impact*

Pre-service teachers are expected to create system flow diagrams similar to the example "When energy consumption increases → School heating and electricity bills rise. → School parent association, management and families begin to complain. → Resistance to energy-saving campaigns forms at school. → Sufficient awareness cannot be instilled in students → Energy-saving behaviours do not develop → Energy consumption increases again."

Task 2—Simulation Decision Points
In this stage, pre-service teachers explore the potential consequences of their scenario-based decisions by using system-based simulation and visualisation platforms (e.g., C-ROADS, the En-ROADS climate solutions simulator, Minecraft Education: Sustainability Mods, and Kumu.io). These tools are employed to model alternative decision pathways and to support the analysis of systems-level impacts, thereby complementing the AI-supported reflective dialogue facilitated throughout the activity.

Task 3—Ethical and Social Justice Analysis
Pre-service teachers analyse the ethical and social justice implications of alternative investment decisions by identifying their potential positive and negative impacts.

Task 4—AI-Supported Solution Report
Pre-service teachers prepare a solution report supported by AI-assisted reflection, justifying the selected investment decision based on

sustainability and ethical criteria.

Step 2—Goal Setting (10 min)

A. Group Formation
Pre-service teachers work in heterogeneous groups of 3–5 people.

B. AI-Supported Goal Development
Each group gives ChatGPT the following command:

Each group gives the following command to ChatGPT:

"Create sustainability goals in accordance with SMART (Specific, Measurable, Achievable, Relevant, Time-bound) principles to improve a secondary school's electricity, water, and waste management."

Example: Water Management Sustainability Goal
Goal: *To meet 50% of the school garden's irrigation needs by installing a rainwater harvesting system (S: Installation of the system; M: 50% utilisation; A: Simple tank structures; R: Water conservation; T: Within 4 months).*

Each group selects the ChatGPT-generated goals that best align with their institutional context.

C. Creation of the Goal Table
Groups create a table in Excel or Google Sheets. This table will be revised in later stages of the simulation.

Step 3—Data Analysis and Simulation (20 min)

A. Data Review
Groups are provided with three school-level data sets:

1. Monthly energy consumption (kWh/month)
2. Monthly water consumption (m^3/month)
3. Monthly waste generation (kg/month)

B. AI-Supported Data Analysis

Groups provide ChatGPT with the following prompt:

"Analyse the energy–water–waste data below. Identify trends, peak points, potential causes, and areas for improvement. Generate alternative scenarios and tabulate the results."

The AI also provides low-carbon strategies and energy-saving models.

C. Excel/Sheets Simulation Exercise

Groups construct an Excel file that includes the following simulations:

- Annual impact of achieving a 10% reduction in energy use
- A scenario for reduced water consumption
- Change in waste volume if recycling practices are implemented
- Cost-impact analysis

D. Emphasis on Local Collaboration

The instructor offers the following guidance: "Assume that support may be obtained from the municipality's environmental department to verify these data. Also consider consulting a local technical expert to enhance the realism of the simulation."This emphasis reinforces the community-based learning dimension.

Step 4—Discussion of Ethical and Social Dimensions (15 min)

A. Ethical Discussion Guideline

Groups receive the following questions and are asked to develop responses:

- Do smart sensors designed for energy saving compromise students' privacy?
- In the case of limited budgets, whose needs should be prioritised?

- Should the needs of students from low-income families take precedence over general energy-efficiency investments? How is social justice ensured?
- Does mandatory recycling in water and waste management create accessibility challenges for disabled or low-income students? How can inclusivity be guaranteed?
- Do algorithmic recommendations provide equitable service to all school stakeholders?

B. Obtaining Ethical Feedback from AI

Groups ask ChatGPT:

"Explain the ethical risks, their impact on stakeholders, and mitigation strategies that might arise in a sustainable school project involving energy and data management." Groups follow the steps below, considering the ethical dimension and the risk management process.

Step 5—Decision Making and Planning (20 min)

A. Solution Selection

Groups select the most viable solution or solutions based on the simulation results.

B. Obtaining Risk Analysis from AI

Groups instruct ChatGPT: "Prepare a table detailing the risk analysis, potential obstacles, cost, and stakeholder impact of the sustainability plan we selected." They generate the risk analysis reports.

C. Action Plan Draft

Groups prepare for the PowerPoint/Canva presentation:

- Objective
- Data analysis
- AI recommendations
- Ethical evaluation
- Action plan
- Success indicators

Prepare the draft action plan for their work using these headings.

Step 6—Presentation and Feedback (15 min)
Groups present their findings. Groups evaluate each other's work. If necessary, groups may request alternative suggestions from ChatGPT.

Step 7—Reflective Evaluation (10 min)
The instructor asks pre-service teachers to respond to the following questions:

1. How did artificial intelligence support your work?
2. Which values did you prioritise when making sustainability-related decisions?
3. How did you balance human judgment and algorithmic recommendations?
4. Can this type of simulation be implemented in schools? If so, how?

Pre-service teachers are then asked to document their responses in their reflective journals.

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9 Conclusions

This chapter has demonstrated the transformative potential of integrating artificial intelligence into the development of pre-service teachers' skills in sustainability-oriented decision-making, ethical reasoning, and systems thinking. The combination of scenario-based learning and generative AI enables pre-service teachers to undertake a holistic analysis of complex environmental, social, and economic variables, supporting them in comparing the potential outcomes of different scenarios and in formulating data-driven solutions. In this process, AI acts not as an autonomous decision-maker but as a "learning partner" that enriches pre-service teachers' thinking, fosters critical inquiry, and enhances pedagogical creativity. However, the

findings also indicate that AI-supported sustainability education can generate meaningful impact only when anchored in the principles of inclusivity, social justice, and ethical awareness. Factors such as socioeconomic diversity, levels of community engagement, variations in environmental awareness, and accessibility play a decisive role in the design of learning activities and simulations. Within this context, AI-assisted analyses, ethical evaluations, and community-based project work help pre-service teachers develop more sensitive, holistic, and contextually grounded solutions by enabling them to navigate complex educational environments more effectively.

This chapter is conceptual in nature and does not draw on empirical data obtained through classroom implementation. The proposed AI-supported scenario-based learning activities are presented as illustrative pedagogical designs intended for use by both in-service teachers and pre-service teachers, rather than as empirically tested instructional interventions. Accordingly, the educational outcomes discussed in the chapter should be interpreted as anticipated rather than measured effects.

In addition, the study is based on the use of a single artificial intelligence tool (specifically ChatGPT). This limited technological scope may restrict the transferability and generalisability of the proposed activity designs to other AI tools or digital platforms. Furthermore, the applicability and effectiveness of the suggested activities may vary according to contextual factors such as institutional conditions, technological infrastructure, and learner characteristics. Future empirical research conducted across diverse educational contexts and employing multiple AI tools is therefore required to examine the implementation and impact of these activity designs.

Ethical Use of AI Tools

During the preparation of this chapter, the author used AI tools, including ChatGPT, Claude.ai, and Grammarly, solely as supportive tools for language translation, linguistic refinement, and the enhancement of author-developed educational activities. All content, including the

educational activities, was originally created by the author and subsequently reviewed and edited by the author. The author takes full responsibility for the publication's content.



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Ethical Considerations and Challenges of Integrating AI in Sustainability: Teaching Students a Balanced Risks Narrative Approach

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Abstract
This chapter considers the role a balanced risks narrative can play in enhancing a students' understanding of the challenges of integrating AI in sustainability.

Keywords Balanced risks narrative – Higher education – AI-driven sustainability – Green AI

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1 Introduction

In management research, AI is described as a new generation of technologies that can interact with their environment by: (a) collecting information from external sources (including natural language) or other computer systems; (b) interpreting this information through pattern recognition, rule induction, or event prediction; (c) producing outputs such as results, answers, or instructions for other systems; and (d) assessing the outcomes of their actions and refining decision processes to achieve specific objectives (Ferràs-Hernández 2018). Sustainability refers to the responsible management and preservation of Earth's finite resources, ensuring their balance and availability to safeguard the planet for future generations (Kola-Olusanya 2008, 2012). The irony in this definition, when considered alongside artificial intelligence (AI), lies in the fact that although AI is increasingly

employed to advance sustainability across sectors by improving efficiency, reducing waste, and enabling smarter decisions, with the potential to address complex sustainability challenges (Leal et al. 2024:726), it simultaneously raises concerns about its own environmental impact. It is therefore considered a transformative technology with broad applications to many sectors (Rashid and Kausik 2024). In recent years we have seen the emergence of the concept of Green AI (Akinsemolu 2025) demonstrating a dual focus on performance alongside sustainability, however the measurement of this is often demonstrated as energy efficiency (Verdecchia et al. 2023) rather than the lesser definitions of carbon footprint or ecological footprint. This limitation obscures the wider environmental and social costs of AI deployment. To explore these tensions, this chapter adopts an integrative literature review and conceptual synthesis as its methodological approach (Torraco 2016). This method allows for the critical examination of scholarship on AI, sustainability, and pedagogy, and supports the development of a new conceptual framework. Sources were included if they addressed the intersection of AI with sustainability, pedagogy, or ethics, and excluded if they focused solely on technical AI development without relevance to education. By synthesising insights across these literatures, the study seeks to generate a framework that is both evidence-based and pedagogically grounded.

In light of these challenges, there is a pressing need to prepare future managers and students to critically evaluate AI's paradoxical role in sustainability and therefore the following aim and objectives were developed:

Research Aim: To design and evaluate a pedagogical framework that enables students to critically engage with the risks and opportunities of AI in sustainability.

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2 Research Objectives:

1. To develop a pedagogical framework that supports students in

adopting a balanced approach to the risks and benefits of AI for sustainability.

2. To identify educational strategies and interventions that can strengthen students' capacity to ensure AI contributes positively to sustainability rather than undermines it.

Several sectors face ethical tensions arising from the integration of AI into sustainability practices. For instance, applications in the circular economy (Bashynska 2025), healthcare (Mohammed 2021), finance (Cao 2022), farming (Mallinger and Baeza-Yates 2024) and education (Holmes and Tuomi 2022) reveal both the promise and the pitfalls of AI. These tensions include issues of data privacy, algorithmic bias, and unequal access, underscoring the need for robust regulations and governance structures. As Ibitoye et al. (2025) emphasize, responsible AI requires attention to socio-technical contexts as well as ethical principles. This then needs to be reflected in the sustainability teaching that occurs in Higher Education institutions, as there are pedagogical ethical concerns that need attending to when integrating AI driven sustainability into the curriculum as many students still consider sustainability to be predominantly environmentally focused (Zeegers and Clark 2014). The ethical challenges reflect the need for students to be more aware of the risks involved in AI-driven sustainability and the approaches needed for AI to support rather than undermine sustainable goals. This chapter addresses some of the key challenges facing educators in AI sustainability before exploring the role of a balanced risks narrative as a pedagogical approach. There is then a critique of two pedagogical frameworks that support interdisciplinary and ethical education and inform the creation of a seven stage AI Sustainability Pedagogical Framework to support student learning with balanced risks narratives. A discussion around teaching beyond the curriculum and a conclusion then follow.

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3 Teaching AI in Sustainability

There is much literature around the role of SDGs in HE, the positive integration of sustainability in the curriculum and the growth of universities becoming PRME signatories. Alongside this shift to a sustainability lens, is the focus on the use of AI in the classroom. Leal et al. (2025) emphasise AI's role as a positive pedagogic tool, highlighting it's capacity to provide students with interactive and immersive learning experiences. However, their work tends to privilege the opportunities of AI use, while neglecting the inherent tensions when AI is applied to sustainability. Students are taught how to use AI in their studies and the benefits of AI in sustainable practices, but less emphasis is placed on the negative combination of AI and sustainability. HE institutions have been criticised for not teaching students how to understand interconnected global issues (Henriksen et al. 2024). Our position aligns with this critique, as we contend that without pedagogical approaches that foreground both risks and benefits, AI's paradoxical role in sustainability remains insufficiently interrogated in higher education. Wali et al. (2017) position sustainable education as grounded in values-based principles; however, this orientation alone is insufficient when confronted with the tensions of AI-driven sustainability. Zonnchen et al. (2024) extend this argument by insisting on the need for higher education to equip students with analytical skills to understand and critique complex AI systems. Building on their perspectives, this research contends that sustainable education must move beyond normative values and towards frameworks that actively engage students in evaluating AI's dual role as both a driver and underminer of sustainability.

One of the key ethical considerations is the hidden cost of AI and the paradox of (un) sustainability. The very technology designed to foster sustainability carries significant environmental and social costs. Potential concerns around energy consumption, carbon emissions, water for cooling, non-renewable energy resources, habitat destruction, water pollution, and geopolitical tensions highlight the underlying pressures that come with the use of AI. It is crucial that the lifecycle of AI systems, from design to use and disposal, embodies the principles it

aims to promote. Ibitoye et al. (2025) explicitly question the fragility of responsible AI by foregrounding the hidden environmental and social costs embedded across the AI lifecycle, from design to disposal. Their analysis reinforces the paradox noted earlier: that AI simultaneously advances and undermines sustainability. Positioning this paradox within higher education, we argue that these contradictions should not be abstract concepts, but central elements of teaching through a balanced risks narrative.

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4 Methodology

This chapter is guided by the research aim of designing a pedagogical framework that enables students to critically engage with the risks and opportunities of AI in sustainability. To address this aim, two objectives were set: first, to develop a pedagogical framework that supports students in adopting a balanced approach to the risks and benefits of AI for sustainability; and second, to identify educational strategies and interventions that can strengthen students' capacity to ensure AI contributes positively to sustainability rather than undermines it.

To meet these objectives, the chapter employs a structured literature review and conceptual synthesis. This approach does not test hypotheses but is appropriate for developing theoretical and pedagogical models. Following Torraco's (2016) notion of the integrative literature review, the intention was not only to summarise existing studies but also to critique and combine them in order to propose new conceptual directions.

The review considered material published between 2008 and 2025, reflecting both foundational debates on sustainability education and more recent discussions of artificial intelligence, Green AI, and ethical governance. Sources were drawn from Scopus, Web of Science, and Google Scholar, with search terms including "AI and sustainability," "Green AI," "AI ethics in higher education," "interdisciplinary pedagogy," and "experiential learning." The review incorporated peer-reviewed journal articles, policy documents, and conference papers. Additional

sources were identified using snowballing techniques from reference lists. Inclusion criteria were set to capture studies addressing AI applications with sustainability implications, higher education pedagogy, or ethical challenges in technology adoption. Studies focusing exclusively on technical AI development without relevance to sustainability or education were excluded.

The analysis progressed in three stages. First, the literature was mapped to identify how AI's role in sustainability has been discussed across management, education, environmental studies, and ethics. Second, pedagogical frameworks were evaluated, with particular attention given to Kolb's (1984) *Experiential Learning Cycle* and Utrecht University's *Four-Stage Model for Interdisciplinary Learning*. These were situated within wider debates on interdisciplinarity and pedagogy (Klein 2010; Szostak 2016) to understand their relevance and limitations in addressing the paradoxes of AI-driven sustainability. Third, the insights from this review were synthesised into the AI Sustainability Pedagogical Framework, developed iteratively to ensure consistency with both established educational theory and the ethical challenges identified in the literature.

To ensure transparency and reproducibility, the timeframe, databases, keywords, and inclusion/exclusion criteria have been specified, providing a clear pathway for replication by other scholars. The methods employed are sufficient to address the research objectives, as they enable a rigorous synthesis of theory and evidence into a new pedagogical framework. Consistent with Torraco (2016), this integrative approach draws on past and present scholarship to propose a novel conceptual model that can inform both future research and practical teaching strategies. The resulting framework explicitly embeds a balanced risks narrative, preparing students to navigate the dual role of AI in sustainability as both a source of promise and a site of ethical and environmental tension.

The subsequent sections of this chapter—examining the balanced risks narrative, reviewing pedagogical frameworks, and applying these to AI-sustainability contexts, are each structured to directly address the

research objectives. In particular, the development of the AI Sustainability Pedagogical Framework responds to Objective 1, while the analysis of educational strategies and teaching beyond the curriculum responds to Objective 2.

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5 Balanced Risks Narrative

This section addresses objective 1, which is to develop a pedagogical framework that supports students in adopting a balanced approach to the risks and benefits of AI for sustainability. By outlining the concept of a balanced risks narrative, it establishes the conceptual foundation for embedding both opportunities and challenges of AI into higher education teaching. A balanced risks narrative advocates for an approach to AI risk governance that acknowledges both the positives and immediate societal risks posed by AI. It encourages finding meaningful connections between the two, and suggests that addressing them in tandem can lead to more comprehensive and effective risk mitigation strategies and policies. This approach is not one that should be developed in isolation. Collective sense-making (Ibitoye et al. 2025) would ensure that not only the immediate and more long term benefits can be identified, it also allows for current and emerging risks to be highlighted, identifying uncertainty whilst supporting responsible regulation and transparency. Thus identifying strategies for AI-driven sustainability that are nuanced and evidence-based.

There are many ethical challenges that are derived from the use of AI-driven sustainability. A key driver for this is inclusive innovation, ensuring diverse voices are represented in AI development, especially those of vulnerable communities. This prevents algorithmic bias which would otherwise reinforce discrimination in health, education, and public services. Using a balanced risks narrative would support checking for bias and making AI design more inclusive. Using sustainability-aligned metrics would also provide a balanced view of the impact of AI. A balanced risk narrative would consider the economic impact alongside the social, ecological and environmental,

therefore addressing the likely events alongside the unprecedented outcomes, providing a clearer forecasting model for future strategy.

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6 Pedagogical Frameworks for Interdisciplinary and Ethical Education

This section further develops objective 1 by critically evaluating existing pedagogical models—namely Kolb's Experiential Learning Cycle and Utrecht University's Four-Stage Interdisciplinary Model, that inform the creation of the AI Sustainability Pedagogical Framework. In doing so, it links theory to the design of a framework that can respond to the paradoxes of AI-driven sustainability.

To effectively teach higher education students about the complex interplay of AI and sustainability, particularly in balancing risks and benefits, it is crucial to leverage robust pedagogical frameworks. Interdisciplinary teaching has long been recognised as a way of integrating knowledge and methods from multiple academic disciplines to address complex problems (Szostak 2015). However, as Borrego and Newswander (2010) caution, interdisciplinary approaches often falter without clear scaffolding for students to make sense of diverse perspectives. Against this backdrop, two models were selected to inform the development of our framework. The framework was inductively derived from the synthesis of two pedagogical models (Kolb 1984; Utrecht University Four-Stage Model), insights from interdisciplinary education literature (Szostak 2016; Klein 2010), and empirical studies of AI in sustainability (Leal Filho et al. 2025; Ibitoye et al. 2025). Each stage reflects recurring themes identified in the literature review, ensuring that the model is both evidence-based and pedagogically grounded."

The Four Stage Model for Interdisciplinary Learning (Utrecht University) proposes that educators adopt a structure that allows students to process the complexities of a topic with a critical, multi-dimensional approach. The first stage is disciplinary grounding, which refers to having a foundational understanding of a discipline, including

how knowledge within it is developed, validated, and communicated, developing a critical approach, rather than simply acquiring information. Perspective taking is the second stage which involves examining a problem through the lens of each relevant discipline and recognizing both their shared and differing viewpoints and limitations. In the third stage students need to learn to discover common ground, identifying shared concepts, methodologies, or problems across disciplines before embarking on the fourth stage of integrating perspectives. This four-stage schema gives a clear path for curriculum design but it assumes a fairly linear progression, which is not always the case with student learning. There also needs to be an acknowledgement of the challenges involved when integrating disciplines and the potential that each subject could be explored in less depth.

Kolbs Experiential Learning Cycle (1984) was also considered to inform our framework as it aligns well with approaches of problem-based learning and interdisciplinary project work and includes reflection and application as much as knowledge acquisition. The cycle determines that people learn best through continuous action and reflection, rather than by passively receiving information. The stages begin with concrete experience which is learning by doing, followed by reflective observation, reflecting on what happened and considering different perspectives. The next stage in the cycle is abstract conceptualization when learners can develop theories or concepts from their reflections, then active experimentation which allows learners to apply what they have learned to new situations. Each stage is repeated through iterative cycles and helps educators design activities that balance experience, reflection, theory, and application. Informed by the 2 models above, we have developed a 7 stage AI Sustainability Pedagogical Framework to support student learning with balanced risks narratives.

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7 Application to AI-Sustainability Context

This section advances objective 1 by presenting the AI Sustainability Pedagogical Framework and illustrating its application to the paradox of AI in sustainability. By demonstrating how students can critically engage with both the benefits and risks of AI, it provides a practical outcome of the framework-building process. Combining insights from the interdisciplinary and ethical pedagogical frameworks, we propose a model as per Fig. 1 for teaching that adopts a balanced-risks approach to the paradox of AI in sustainability. This responds directly to Klein's (2010) call for pedagogical designs that help students grapple with the contested and uncertain nature of interdisciplinary knowledge. Unlike conventional models that privilege disciplinary silos, our framework is explicitly designed to expose students to the dual role of AI as both a driver of sustainable solutions and a source of environmental and ethical challenges. It begins with problem-based learning, where students explore real-world sustainability issues that AI might address, while also being encouraged to interrogate the inherent risks, for example, the optimisation of energy grids weighed against the energy consumption of AI itself. Interdisciplinary collaboration is central to this model, as it brings together students from different areas to foster holistic and multi-perspective learning. Ethical decision-making is embedded throughout the curriculum, prompting students to analyse trade-offs between AI's contributions to sustainability and its potential harms. Case studies and simulations further reinforce this process by illustrating AI's dichotomies in practice, allowing students to conduct risk–benefit analyses and propose balanced, responsible solutions. The model also promotes systems thinking, encouraging students to view AI and sustainability as interconnected domains where interventions in one area generate ripple effects elsewhere. Reflective practice provides opportunities for students to recognise their own assumptions and biases, while situating AI within broader ethical and societal debates. Finally, students are taught to consider the entire AI lifecycle, from data collection and model training to deployment and maintenance, with attention to environmental and ethical consequences at each stage. By integrating these strategies, the proposed model equips students with

the knowledge, skills, and ethical compass to navigate the complexities of AI in sustainability, enabling them to engage with both its promise and its perils in a more informed and balanced manner.

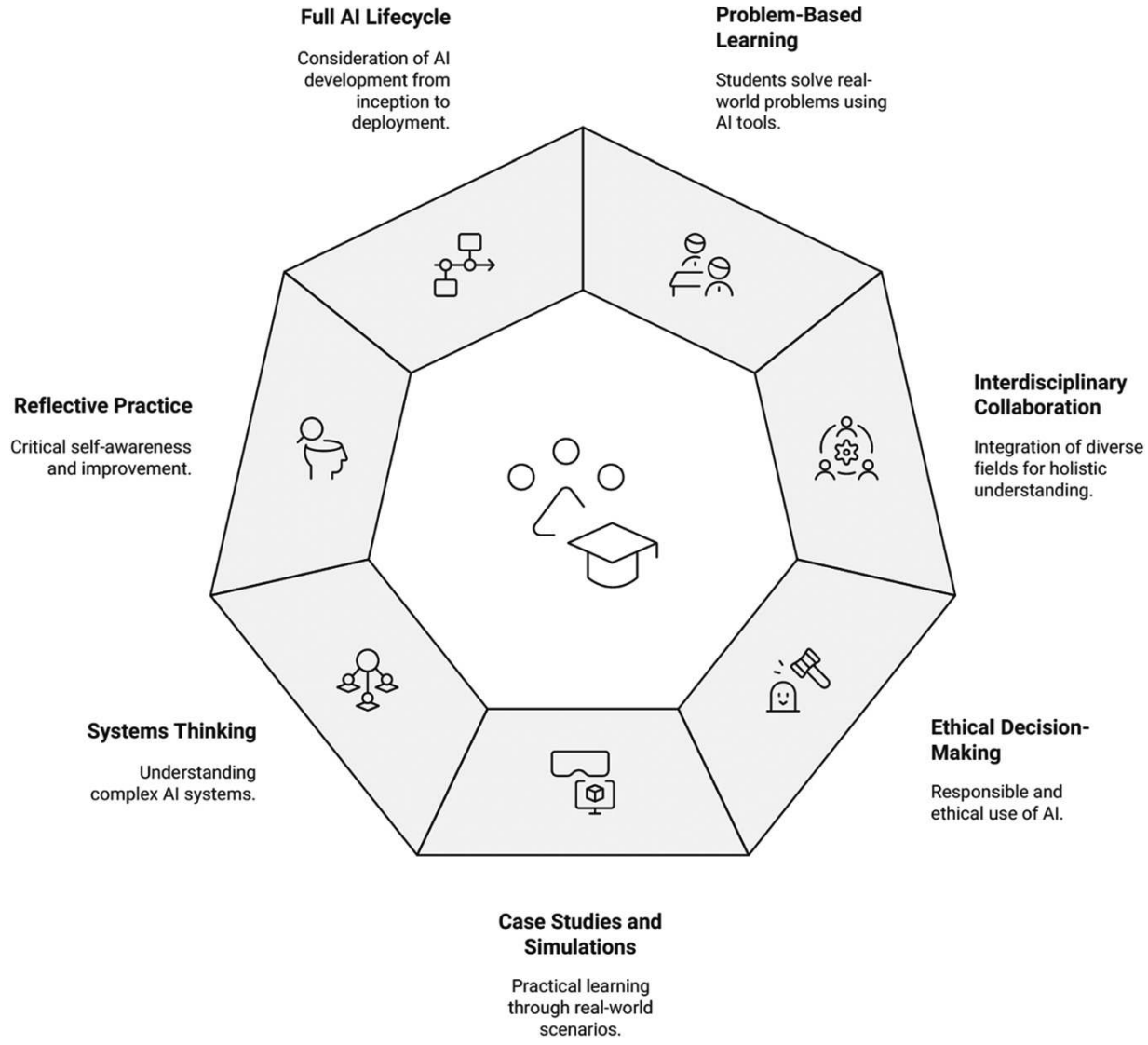


Fig. 1 AI-Sustainability pedagogical framework

8 Teaching Beyond the Curriculum for a Balanced Risks Approach

This section responds to objective 2, which is to identify educational strategies and interventions that can strengthen students' capacity to ensure AI contributes positively to sustainability rather than

undermines it. By considering approaches that extend beyond formal curriculum design, it highlights strategies for fostering critical curiosity, forecasting, and robust decision-making in students. Students are often given case studies to work from, and are tasked with identifying the problems that are highlighted within the paper. What, as educators, we do less of, is to ask students to forecast, to think about information they haven't been given, to read between the lines and identify potential future implications for organisations and markets. Encouraging curiosity in students is a crucial factor in teaching, instilling a thirst for the whole picture, rather than accepting what they have to hand. This is what is needed for a balanced risks approach, seeking out information that may contradict what has been decided, but in doing so, it provides a clearer and therefore more robust and informed strategy for future development and growth.

Every sustainability intervention carries associated costs, limitations, or unintended consequences. It is important that students are taught to identify and analyse these inevitable trade-offs in sustainability decisions. Preparing students for the underlying tensions that are inevitable in an AI driven environment is an essential facet of teaching sustainability in HE. Students need to be encouraged to restructure their current perspectives on AI (Henriksen et al., 2024) to consider the possibilities of AI-driven sustainability being part of the problem as well as part of the solution. The holistic nature of this approach, encourages a view that departs from more traditional pedagogical perspectives on sustainability and AI, taking students through a process of analysis and creative thinking, forecasting potential problems that go beyond the outcomes of efficiency through AI use. Encouraging students to consider the negative impact of AI-driven sustainability, provides them with the tools to engage in a balanced risks narrative, recognising there may be unwanted outcomes, but allowing these to sit alongside the benefits, to assess the strategic value in proceeding with an initiative.

Within higher education, it is essential that students are equipped to critically interrogate both the benefits and risks of deploying AI for

sustainability, with transparency forming a central principle of this process. By fostering the ability to assess not only the potential efficiencies and innovations AI can deliver but also the ethical, social, and environmental challenges it introduces, educators can prepare graduates to make informed, evidence-based, and ethically responsible decisions (Henriksen et al., 2024). Transparency is widely recognized as a fundamental prerequisite for building trust, ensuring accountability, and promoting fairness in AI systems (The Future of Life Institute 2017).

Getting AI governance right represents one of the most consequential challenges of our time. It requires a commitment to mutual learning and dialogue, drawing on lessons and good practices emerging from diverse jurisdictions worldwide. By sharing experiences and approaches across cultural, political, and regulatory contexts, policymakers and educators can co-develop governance frameworks that are inclusive, adaptable, and responsive to the rapidly evolving landscape of AI (UNESCO 2023). UNESCO's *Recommendation on the Ethics of Artificial Intelligence* (2021) positions human rights as the foundation for ethical AI governance, foregrounding principles such as dignity, fairness, non-discrimination, and equality. These principles provide a valuable scaffold for teaching AI ethics in higher education, where students must be encouraged to critically evaluate the societal implications of emerging technologies. By adopting a human rights lens, educators can guide students to interrogate real-world AI applications, such as recruitment algorithms, predictive policing tools, or healthcare diagnostics, by asking whose rights are protected, who benefits, and who may be disadvantaged. Pedagogical strategies might include scenario-based learning and role-play exercises (Schrier 2014) in which students take on the perspectives of policymakers, developers, and civil society actors to negotiate governance dilemmas that balance innovation with rights protection (Henriksen et al. 2024).

In addition, UNESCO's emphasis on mutual learning across jurisdictions offers opportunities for comparative analysis of global practices, enabling students to recognize the diverse cultural and

political contexts in which AI governance unfolds (United Nations 2023). Reflective assessments can further support this approach by encouraging students to evaluate whether specific AI systems uphold human rights and to grapple with the tensions between innovation and protection (Holmes and Tuomi 2022).

In line with these considerations, the learning outcomes for higher education students extend across multiple levels of Bloom's taxonomy. At a foundational level, students should be able to identify and explain UNESCO's human-rights-based approach and its core principles of dignity, fairness, equality, and non-discrimination (UNESCO 2021). Building on this understanding, they should be able to apply these principles to analyse practical cases and innovation of AI use in domains such as employment, law enforcement, and healthcare (George and Wooden 2025). More advanced learning outcomes include the ability to compare how different jurisdictions implement human-rights principles in AI governance (UK Government 2023) and to evaluate critically the extent to which specific AI systems uphold or undermine these principles (Leal Filho et al. 2025). At the highest level, students should be able to design their own recommendations, policy proposals, or project plans that integrate a human-rights perspective into the development and governance of AI for sustainability (Ibitoye et al. 2025). Together, these outcomes ensure that graduates are not only conceptually informed about AI ethics but also capable of applying, critiquing, and creating human-rights-based solutions in practice.

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9 Conclusion

The conclusion brings together the insights developed across the chapter in direct response to the two research objectives: the design of a pedagogical framework that embeds a balanced risks approach (Objective 1), and the identification of educational strategies that equip students to navigate AI's paradoxical role in sustainability (Objective 2).The ethical challenges across the three pillars of sustainability, social, economic and environment (van Wynsberghe 2021) are

becoming more apparent as the potential for AI in sustainability grows. This chapter has demonstrated the ethical considerations and challenges that are surfaced when integrating AI in sustainability education and highlights the role that a balanced risks narrative can have in a student's understanding of such challenges and policies, that ensure a safe and ethical approach for AI-driven sustainability initiatives. The AI Sustainability Pedagogical Framework provides a system of actions that can support student learning. By students understanding a balanced risks narrative approach, they can recognise the dual nature of AI, its transformative potential and its inherent risks, and how those risks and ethical implications associated with new approaches to sustainability can be explored and communicated to government agencies to ensure a transparent and cohesive framework for policy implementation. In line with our framework, AI can be understood as a new generation of technologies that actively interact with their environment: collecting and interpreting information, recognising patterns and predicting events, generating results or instructions, and continuously refining decision processes to achieve defined objectives (Ferràs-Hernández 2018). When embedded within pedagogy that emphasises problem-solving, interdisciplinary collaboration, ethical reflection, and the full AI lifecycle, such capabilities position AI not merely as a technical tool, but as a transformative enabler for responsible and sustainable learning and practice.

This chapter is limited by its reliance on a conceptual literature review rather than empirical testing, meaning the proposed framework has not yet been validated in classroom practice. The scope of the review was bounded by specific databases, timeframes, and search terms, which may have excluded some relevant studies. In addition, the analysis focused primarily on two pedagogical models, leaving out other approaches that might also inform sustainability education. Finally, given the rapidly evolving nature of AI and sustainability, some issues discussed here may shift over time, and the framework should therefore be seen as adaptive and open to refinement.

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Balancing Skills and Values: Harmonizing AI in International Higher Education for Training and Upbringing

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Abstract

This chapter explores the dual role of artificial intelligence (AI) in international higher education, highlighting its potential to integrate skill-based training with value-oriented development across various cultural contexts. By utilizing continuous surveys and interviews

conducted with both local and international students and faculty members from Belarus, Uzbekistan, and China, this study explores the perceptions, adoption, and integration of AI tools within sustainability-focused curricula. The findings, presented as recommendations, aim to balance technological efficiency with a human-centered approach to education, by offering a framework for culturally sensitive AI integration which aligns with the United Nations Sustainable Development Goals (SDGs). Furthermore, the recommendations emphasize curriculum development, faculty training, and institutional policies to ensure that AI supports the dual mission of higher education. The chapter was prepared within the research project "Develop a concept for using artificial intelligence to ensure the quality of the educational process in a higher education institution."

Keywords Artificial Intelligence in higher education – Cross-cultural education – Skills and values in education – Sustainable Development Goals – International student perspectives – Ethical AI integration – Competency-based training – Sustainability pedagogy

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1 Introduction

Over the past decade, artificial intelligence (AI) has significantly transformed the higher education landscape, presenting numerous opportunities for personalized learning, administrative optimization, and data-informed curriculum design. From adaptive learning platforms to automated grading systems and predictive analytics, AI

technologies are becoming increasingly integrated into the everyday functions of universities globally. This widespread integration reflects a broader shift towards digitalization and innovation in education, driven by the imperative to prepare students with skills relevant for the future in a time of rapid technological advancement.

In contemporary higher education, AI has become excessively integrated into educational and administrative frameworks. However, this integration has promoted key discussions regarding the fundamental purpose and guiding principles of higher education. While AI is highly effective in enhancing skill acquisition in disciplines (for example programming, language education, and STEM), its usability often aligns with models that prioritize efficiency, standardization, and quantifiable results.

When educators focus on technical skills, they sometimes overshadow the equally important mission of higher education, including ethical reasoning, intercultural awareness, and personal development. Additionally, the conflict among skill-based training and value-oriented education is particularly evident in international contexts, where various cultural traditions influence expectations regarding educational outcomes.

This study focuses on higher education institutions in emerging non-western contexts, specifically Belarus, China, and Uzbekistan. Education in these states serves a dual purpose, because it prepares individuals for professional life while also nurturing ethical awareness, civic engagement, and the preservation of cultural identity. Thus, a main concern for educators and policymakers in this context is how to integrate artificial intelligence into academic systems without compromising the human-centered values of local educational traditions.

Despite the increasing integration of AI into global academic systems, its application frequently embodies a uniform approach influenced by Western educational standards. Such models often emphasize quantifiable results and operational efficiency, thereby restricting the inclusion of cultural and ethical aspects that shape

educational values in various regions. In Belarus, China, and Uzbekistan, where higher education is intertwined with traditions of moral development and collective accountability, this disparity becomes particularly evident. In the result, there remains a notable gap in understanding how AI can be adapted to support these culturally embedded educational missions. Educational frameworks may not account for the nuanced expectations of students and educators. Stakeholders view universities as sites of technical training and as spaces for personal growth and societal contribution. To address this, the present study investigates how AI is perceived and experienced by both local and international (primarily from China) students studying in universities across the three countries. This allows for rich comparative insights as Chinese students bring firsthand exposure to advanced AI applications, contrasting with traditional educational values in host countries, including Belarus, which is home to over 12,000 China students in 2024, and Uzbekistan, where Belt and Road initiatives are boosting enrollment of China students.

The primary goal of this research is to explore how AI can be harmonized within international higher education systems in Belarus, China, and Uzbekistan to balance skills training with upbringing components, including ethical reasoning, intercultural awareness, and cultural identity preservation, and based on quantitative and qualitative assessments of local and international (primarily Chinese) students' attitudes toward AI integration in education.

To reach this goal, we aim to settle the following research tasks:

- Conduct a quantitative survey among local and international students in the selected countries to measure their perceptions of AI's impact on skills acquisition versus its influence on upbringing elements, identifying patterns in gains and potential value erosions.
- Perform interviews with learners and educators, examining nuanced experiences of AI tools in cross-cultural contexts.
- Compare findings to develop recommendations for adapting AI frameworks to support both technical training and value-oriented

upbringing, addressing gaps in culturally sensitive educational missions aligned with SDG-oriented higher education.

The study's framework includes a brief overview of approaches to integrating AI into educational systems and an analysis of current trends. Based on this, a qualitative and quantitative study of student and academic opinions was developed and conducted. A survey and interviews across six knowledge areas identified in the review allowed for the consideration of diverse student and faculty perspectives. A discussion allowed for a synthesis of the findings and a series of recommendations for integrating AI into educational processes in non-western contexts.

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2 Literature Review

The integration of artificial intelligence into education began in the 1960s (Doroudi 2023). A pivotal early development came from a device designed for game-based learning, which introduced adaptive elements to educational simulations, laying the groundwork for more personalized teaching methods. These early steps were inspired by concepts from the 1956 Dartmouth conference, where Herbert Simon and Allen Newell first explored connections among machine reasoning and humans learning (Hook and Norman 2002).

By the 1970s, intelligent tutoring systems gained momentum, emerging in fields such as geography, linguistics, and electronics. The aim was to offer customized feedback and track how students behaved, but they were held back by the era's tech constraints, like rigid rule-driven setups and rather limited computing power.

In the decades that followed, AI in education evolved towards constructivist methods, with AI tools mirroring wider debates in educational theory—think the push-and-pull between cognitive and situational approaches to learning. Commercial pressures started influencing how these were developed, too.

From the early 2000s and onward, the emphasis moved to machine learning, analytics fueled by data, and flexible learning platforms (Guan

et al. 2020). This brought fresh hurdles, from safeguarding data and ensuring algorithms were fair, to the ongoing tug-of-war between automated tools and the vital input of human teachers—problems that have only sharpened with the advent of generative AI.

The rapid development of generative AI in recent years has only exacerbated a number of issues, prompting educators to rethink how technology can contribute not only to the development of skills in these areas but also to the development of moral, cultural, and personal qualities that shape a well-rounded individual. The history of AI in education, varying from simple tools to advanced systems, lays the foundation for advanced research in recent times. There is a clear need to harmonize the capabilities of AI in skill teaching with the development of educational elements. Table 1 attempts to summarize the key research directions linking AI with educational skill teaching and upbringing. Education is a key function of education and covers ethical, moral, cultural, and personal elements of development, promoting holistic growth along with technical competence.

Table 1 Research directions linking AI with educational skill teaching and upbringing

These trends reflect a multifaceted evolution toward balancing technical proficiency with ethical, moral, and cultural dimensions. They also reflect skills training and upbringing as two integral parts of education. These approaches signal a departure from early AI's focus on rigid rule-based tutoring toward more integrative, value-oriented systems that address cognitivism-situativism debates and commercial scalability. Looking to the future, as of 2025, trends are accelerating with generative AI and EdTech innovations (Lee et al. 2024). Examples of them are AI-powered platforms for personalized pathways and predictive analytics. These innovations promise to redefine teaching by reevaluating curricula relevance amid rapid tech advancements (Walczak and Cellary 2023). However, they also introduce disruptions like post-plagiarism challenges and ethical dilemmas, necessitating robust guidelines for equitable implementation.

Recent advancements in educational technology demonstrate a robust synergy with the SDGs (Leal Filho et al. 2024). Notably SDG 4, which prioritizes inclusive and equitable quality education for all. When implemented with care, artificial intelligence holds considerable promise for transforming pedagogical approaches and broadening avenues for lifelong learning across diverse contexts. In non-Western environments, prioritizing ethical considerations in AI system design can effectively address cultural and societal biases, thereby advancing SDG 10 through enhanced equity and the mitigation of disparities (AlSagri and Sohail 2024). Hybrid learning frameworks, integrating AI-enhanced tools bolster SDG 9 by empowering individuals with essential competencies that promote economic resilience and innovative capacities. Examples from UNESCO's policy guidelines highlight how AI can be harmonized with local cultural norms to facilitate international collaboration and collective educational aspirations (Miao and Holmes 2021). Platforms that adapt to cultural nuances—such as bespoke learning trajectories tailored for overseas students—facilitate greater mobility and cultivate mutual understanding among diverse groups.

Based on the reviewed research trends, we designed a 6-domains survey for quantitative analysis. The survey was complimented with interviews, based on the same domain structure. The survey and interviews results were obtained from international and local students from Belarus, China, and Uzbekistan. Attitudes toward the integration of traditional values into AI-enabled education were also explored, as were views on the viability of the gig economy and the contradictions of NEETs, which challenge these norms.

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3 Research Methods

In this research, we used a mixed-methods approach. This approach enables the examination of AI integration within university curricula, aiming to strike a balance between skill enhancement and personal development, aiming to provide a comprehensive understanding of the views held by students and educators in non-Western contexts.

Additionally, it supported the triangulation of findings, enhancing validity by combining numerical trends from surveys with insights from interviews.

The questions were grouped into 6 domains. These domains were influenced by the literature review's focus on the integration of AI with skills development and a value-centered upbringing, while also considering perspectives on contemporary ideologies such as gig work and NEET, which may challenge traditional values like diligence, familial responsibility, and community cohesion (Table 2).

Table 2 Knowledge domains of survey and interviews

The qualitative phase of this study focused on employing semi-structured interviews that aligned with the survey domains, facilitating a more profound investigation into the impact of AI across various cultural contexts and the possible dilution of values.

The quantitative part involved both local and international students from Belarus, China, and Uzbekistan. The survey targeted of 700 students: Belarus (N = 300, comprising 160 international and 140 local students); China (N = 300, consisting of 54 international and 246 local students); and Uzbekistan (N = 100, which included 34 international and 66 local students). The rate of responses ranged from 75 to 85%. Students were selected through a convenience sampling method. For the qualitative component, 30 educators (10 from each country) were interviewed, recruited via university networks due to their proficiency with AI tools in educational settings. Ethical considerations encompassed informed consent, anonymity, and the maintenance of cultural sensitivity throughout the recruitment and data management processes. To facilitate comprehension, the survey was translated into local languages and validated by native speakers.

4 Results

In line with the established framework, this section presents the findings across each of the six domains. These domains, shaped by the literature review's focus on achieving a balance between technical skills and ethical, moral, and cultural development, cover a range of perspectives including the integration of traditional values with AI functionalities and the conflicts arising from contemporary ideological changes such as gig economies and NEET attitudes. The responses, based on sample sizes, corrected with response rates (Belarus: 120 international, 119 local; China: 49 international, 210 local; Uzbekistan: 26 internationals, 56 local), illustrate perceptual patterns among local and international students, supplemented by educator insights from interviews.

Domain 1. Traditional Values in AI-Integrated Cultures

This domain begins by exploring how students perceive the integration of lasting cultural values. This encompasses familial ties, reverence for authority, and a commitment to diligence. The primary objective of the study is to harmonize the role of AI in skill development via tailored adaptive platforms with its impact on upbringing factors such as moral reasoning and the safeguarding of cultural heritage. To illustrate these viewpoints, we have determined three critical questions. The results are compiled alongside qualitative interview findings to reveal patterns in the responses of both domestic and international students, highlighting the capacity of AI to either reinforce or contest traditional norms within cross-cultural higher education settings.

Regarding the question about the degree to which AI tools in education can integrate traditional values such as family and community solidarity to improve both skills training and ethical development, international students expressed agreement levels of 68% in Belarus, 85% in China, and 75% in Uzbekistan. In contrast, local students demonstrated slightly higher agreement rates of 72% in Belarus, 90% in China, and 80% in Uzbekistan, indicating a general sense of optimism tempered by cultural nuances.

In relation to the effectiveness of AI-driven educational systems in fostering respect for authority and diligence within local cultures, while balancing technical skill enhancement with cultural preservation, international respondents showed support levels of 65% in Belarus, 88% in China, and 78% in Uzbekistan. This is compared to local respondents who perceived an even stronger alignment, with figures of 70% in Belarus, 92% in China, and 85% in Uzbekistan, underscoring the locals' deeper sense of compatibility amidst cross-cultural adaptations.

The results of answers on the questions "In what ways can AI in higher education harmonize traditional values such as patriotism/national pride and hospitality with modern skills training and personal growth?" are available in Table 3.

Table 3 The results of answers on the questions "In what ways can AI in higher education harmonize traditional values such as patriotism/national pride and hospitality with modern skills training and personal growth?"

Linking these results with the other side of educational process, we gathered the opinions of academia (Table 4). Educators generally expressed optimism about AI's potential to integrate traditional values like family and diligence into education, but highlighted challenges in non-Western contexts where AI's Western bias might erode cultural preservation. Belarusian educators stressed patriotism in AI tools for collective skills, Chinese focused on harmony for ethical upbringing, and Uzbekistan on hospitality for communal growth. Common themes included AI's adaptability for skills training while needing customization to avoid value erosion.

Table 4 Educators' perspectives on AI Integration

Domain 2. Cultural Attitudes Towards AI in Education

Traditional cultural values, such as respect for authority and the pursuit of harmony, play a significant role in shaping preferences for AI-

influenced learning styles across different regions. Among international students, 70% in Belarus, 82% in China, and 76% in Uzbekistan show a tendency toward personalized technical training. Local students, however, demonstrate slightly higher alignment with these values, with 75% in Belarus, 88% in China, and 82% in Uzbekistan favoring AI-driven approaches that reflect their cultural frameworks.

When examining the impact of cultural perspectives on the use of AI tools in education, it becomes clear that there is a need to balance skill development with moral growth. In Belarus, 68% of international students and 72% of local students endorse the use of AI for educational purposes. In China, these numbers increase to 85% and 90%, respectively, while in Uzbekistan, 74% of international students and 80% of local students show similar support.

International students focus on enhancing their technical skills through AI. However, local students prioritize the incorporation of ethical considerations and intercultural communication. This trend is especially evident in China, where the principle of harmony is highly valued, and in Uzbekistan, where community-oriented values influence educational choices. These results highlight the complex relationship between cultural background and the adoption of technology in educational settings. These facts are confirmed with the next selected question (see Table 5).

Table 5 In what ways do traditional values shape your overall attitude toward AI's role in fostering both technical skills and moral/intercultural upbringing in higher education?

Interviews with educators revealed varied cultural attitudes, with educators viewing AI as a double-edged sword: effective for skills training but potentially disruptive to upbringing if not culturally attuned. Belarusian responses emphasized resilience in AI adoption, Chinese on authority-respecting systems, and Uzbekistan on inclusive communal learning. Overall, attitudes leaned positive toward AI's role in technical proficiency, but concerns arose over moral development gaps (Table 6).

Table 6 Cultural reflections on AI in education

Domain 3. Participation in AI-Facilitated Intercultural Dialogue and Collaboration

In this domain, we have collected insights pertaining to AI-enhanced dialogue and collaboration. Students are actively engaging with collaborative tools.

Among international students, the rates of participation in intercultural discussions are remarkably high, which are 72% in Belarus, 84% in China, and 78% in Uzbekistan, and demonstrating AI's role in fostering team-oriented skills and promoting values such as mutual respect. Local students also show involvement, with 68% in Belarus, 88% in China, and 82% in Uzbekistan, indicating that AI-supported platforms are widely accepted for improving collaborative learning. When assessing the influence of AI on cross-cultural collaborations, the data indicates a similar pattern. Additionally, International students express positive educational experiences, with 70% in Belarus, 86% in China, and 75% in Uzbekistan recognizing the role of AI in harmonizing technical innovation with cultural comprehension. These results are supported with the results of answers to another key question (Table 7).

Table 7 In what ways has AI-facilitated intercultural dialogue influenced your personal growth and collaborative abilities in a multicultural higher education environment?

Educators reported moderate to high participation in AI-supported intercultural activities, praising platforms for bridging skills (for example, innovation) and upbringing (for example, respect). Belarusian educators noted structured tools for collective dialogue, Chinese for harmonious collaborations, and Uzbek for hospitality-driven exchanges. Tensions included AI's potential to overlook local norms in diverse settings (Table 8).

Table 8 Educators' insights on AI-facilitated intercultural collaboration

Domain 4: Significance of SDGs in AI-Enhanced Academic Disciplines

This section examined how global development goals are perceived within digitally supported academic settings. Students highlighted the role of emerging technologies in strengthening professional competencies. In Belarus, there was a strong focus on advancements in infrastructure and management, with a significant majority acknowledging its importance in structured education. Chinese participants highlighted the significance of collaboration and technical partnerships, which align with broader objectives of cooperation. Learners in Uzbekistan concentrated on inclusive education, particularly in economic fields, recognizing its role in fostering social unity. When examining the intersection of personal and cultural values with these objectives, voices from Belarus advocated for the incorporation of national identity into digital education to tackle social inequalities.

Educators linked AI to SDG relevance, viewing it as amplifying skills in fields like economics (SDG 8) while supporting upbringing for equity (SDG 10). Belarusian focus was on infrastructure (SDG 9), Chinese on partnerships (SDG 17), and Uzbekistan on inclusive education (SDG 4). Interviews stressed AI's need for cultural alignment to enhance SDG impacts (Table 9).

Table 9 Educators' perspectives on AI and SDGs

Domain 5: Perceptions of Gig Economies and NEET Awareness in AI Contexts

In examining the impact of contemporary economic transformations on education, students from Belarus, China, and Uzbekistan exhibited differing levels of awareness regarding flexible work models. International participants observed that the digital platforms utilized in educational settings facilitated their preparation for evolving career trajectories that necessitate adaptability and self-

direction. Local students also interacted with these concepts, though to a somewhat lesser degree, recognizing that technology in education facilitates the development of practical skills while reinforcing values such as persistence and responsibility (Tables 10 and 11).

Table 10 To what extent are you familiar with gig economics, and how does AI in education prepare you for it through skills training (e.g., flexible digital tools) while aligning with upbringing values like diligence?

Table 11 How do NEET attitudes among peers influence your views on AI's role in mitigating youth disengagement, balancing career preparation (skills training) with cultural values (upbringing)?

The connection between personal growth and professional readiness surfaced as a recurring theme. In considering the effects of disengaged youth—those not involved in formal education or employment (NEET)—students reflected on how digital tools could offer a way forward. International participants underscored the potential of personalized learning to re-engage their peers with significant goals, combining technical training with cultural context. Local students mentioned the importance of integrating ethical development with career preparedness (Table 12).

Table 12 In what ways can AI in higher education address conflicts between gig/NEET paradigms and traditional upbringing values to foster innovative, value-aligned training?

Educators perceived gig economies as viable via AI skills training but conflicting with upbringing values like diligence, with NEET seen as a disengagement risk. Belarusian educators worried about stability, Chinese saw opportunities in harmonious flexibility, and Uzbekistan emphasized communal prevention. AI was viewed as a mitigator through value-aligned preparation (Table 13).

Table 13 Educators' views on AI, gig economies, and NEET mitigation

Domain 6: Perceived Conflicts Between AI, Traditional Values and NEET/Gig Concepts

In Domain 6, we examined the conflicts between traditional values and the gig economy. The results illustrate student perspectives on how artificial intelligence in education could resolve these tensions through flexible skills training and the reinforcement of cultural values.

In terms of evaluating perceived conflicts and the possible role of AI in their resolution, international students reported strong or moderate levels of conflict at 68% in Belarus, 75% in China, and 72% in Uzbekistan. In contrast, local students indicated slightly higher percentages, with 75% in Belarus, 82% in China, and 80% in Uzbekistan, suggesting a mutual acknowledgment of ideological disagreements, with local students expressing greater concerns regarding cultural norms.

Concerning the conflicts stemming from the shift to gig economies and NEET attitudes in relation to values instilled by cultural upbringing, and whether AI-enhanced education alleviates or intensifies these issues, international respondents noted strong or moderate conflicts at 65% in Belarus, 78% in China, and 70% in Uzbekistan. Local students observed even greater tensions, with reports indicating 72% in Belarus, 85% in China, and 78% in Uzbekistan. This highlights the opportunity for thoughtfully designed digital tools to close gaps by harmonizing innovative career preparation with ethical and community-oriented upbringing. These results are also supported with Table 14. Both international and local students identified specific strategies through which educational technologies could support personal and professional growth while remaining culturally grounded. Their responses reflect a desire for systems that not only deliver flexible career training but also reinforce values such as patriotism, harmony, diligence, and hospitality—ensuring that innovation in education remains aligned with societal expectations and identity.

Table 14 In what specific ways could AI in higher education bridge gaps between traditional values and modern gig/NEET paradigms to promote value-aligned personal and career development?

Educators' interviews highlighted strong perceived conflicts, with AI positioned as a resolver for balancing gig viability (skills) and cultural norms (upbringing). Belarusian educators focused on patriotism vs. instability, Chinese on harmony vs. flexibility, and Uzbekistan on solidarity vs. disengagement. Recommendations centered on culturally sensitive AI designs (Table 15).

Table 15 Educators' reflections on AI as a mediator between gig/NEET paradigms and cultural values

The findings from both quantitative and qualitative research across the six domains reveal consistent patterns of optimism that are influenced by culture-specific concerns among students and educators in Belarus, China, and Uzbekistan.

International students often exhibit a higher degree of adaptability to the skills-training opportunities presented by AI, such as through flexible gig preparation, while local individuals emphasize stronger ties to upbringing factors like diligence and harmony. This uncovers the differences, highlighting the need for localized adaptations.

Opinions of educators further enhance these viewpoints. They are advocating ethical AI frameworks that promote community cohesion and address NEET challenges. Their views are in alignment with SDGs objectives, including quality education (SDG 4) and decent work (SDG 8).

These findings establish a basis for the subsequent discussion, where we analyze their implications for cross-cultural higher education, investigating barriers to integration and strategies for culturally sensitive AI implementation. This leads to the conclusion that presents consolidated recommendations for wider audience, including policymakers and institutions to advance equitable, SDG-aligned

reforms, positioning AI as a catalyst for sustained, value preserving, innovation within global systems.

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5 Discussion and Conclusions

This study aimed to analyze the relationship between the incorporation of AI in higher education and the dual demands of skills development and value-centered education. The study focused on non-Western contexts in Belarus, China, and Uzbekistan. The application of artificial intelligence offers possibilities for improved efficiency and student-centered experiences across different educational fields. Universities frequently operate within frameworks shaped by demands that prioritize quantifiable outcomes, often overlooking cultural and ethical dimensions. The findings reflect regional perspectives and value-driven educational approaches, yet it is crucial to emphasize the constraints. A significant constraint is the dependence on personal narratives from both students and educators. While these narratives offer valuable insights, they may be influenced by idealized perceptions or limited familiarity with the technologies. Furthermore, the cultural emphasis on Belarus, China, and Uzbekistan, does not represent the complete global spectrum of educational environments. The research captures impressions and thematic trends rather than long-term developmental pathways. It may remain challenging to ascertain how these educational practices affect personal development, career preparedness, or civic involvement over prolonged periods. Furthermore, the study presumes a relatively stable understanding of cultural values; however, such values are fluid and can differ markedly across regions and generations, complicating the pursuit of universal insights.

Future studies should adopt comparative and longitudinal approaches across continents, including Africa, Latin America, Asia, to offer a thorough insight into how learning environments adopt to local values while engaging with global frameworks. Additionally, an important avenue for further research may involve exploring how

educational systems can be transformed to better reflect cultural values and philosophies. This encompasses examining the integration of traditional knowledge and local teaching methods into digital platforms to ensure relevance and inclusivity. Institutions need to consider how educators are trained to merge technical instruction with cultural sensitivity, thereby guaranteeing that teaching practices are both effective and ethically sound.

Aligning educational practices with global development objectives, including equitable access to education, meaningful employment opportunities, and the reduction of social inequalities, can contribute to creating a more cohesive framework for evaluating progress. This strategy supports the broader mission of nurturing individuals who are not only skilled and adaptable but also socially conscious and culturally aware, prepared to contribute to diverse and interconnected communities.

The evaluation of perspectives from learners and educators in Belarus, China, and Uzbekistan underscores both the possible advantages and the obstacles linked to the integration of AI into educational systems that emphasize not only technical competencies but also ethical development and cultural conservation. These results form the basis for the recommendations, which explore the broader implications of integrating AI into education and propose following strategies for aligning technological innovation with human-centered values.

1. Establishing culturally inclusive educational environments requires educators' efforts to incorporate traditional values into AI-supported learning materials. This duty predominantly lies with educators, who are instrumental in developing curricula that embody both global competencies and local traditions. By collaborating with cultural experts and community stakeholders, universities can incorporate essential principles such as family cohesion, hard work, and social accountability into flexible learning systems.

   Equally important is the progression of culturally responsive

2. Equally important is the progression of culturally responsive teaching methods that address diverse learning preferences. Educators must be prepared to modify digital platforms in ways that resonate with local values whether through frameworks that highlight harmony, hospitality, or collective responsibility. By incorporating intercultural feedback mechanisms, educational institutions can ensure that technological advancements in education are aligned with the ethical and social dimensions of learning, thus reducing inequalities and fostering a more just academic environment for every student.
3. The strategic implementation of digital tools also enhances intercultural collaboration. Universities have the opportunity to invest in platforms that promote teamwork across cultural boundaries, blending innovation with mutual respect. These tools can integrate the regional values and customs, offering students the chance to engage in significant discussions and collaborative endeavors. Such initiatives not only improve global competencies but also highlight the importance of cultural awareness in both academic and professional settings.
4. To align educational technologies with global development objectives, institutions should consider harmonizing digital learning strategies with disciplines relevant to the SDGs. This necessitates the incorporation of artificial intelligence into areas such as economics, infrastructure, and management, while concurrently fostering values that advocate for equity and inclusion. By creating interdisciplinary modules that monitor progress towards SDG targets, universities can ensure that both the technical and ethical aspects of education are addressed with cultural sensitivity. Such initiatives not only improve global competencies but also highlight the importance of cultural awareness in both academic and professional settings.
5. To align educational technologies with global development objectives, institutions should consider harmonizing digital

learning strategies with disciplines relevant to the SDGs. This necessitates the incorporation of artificial intelligence into areas such as economics, infrastructure, and management, while concurrently fostering values that advocate for equity and inclusion. By creating interdisciplinary modules that monitor progress towards SDG targets, universities can ensure that both the technical and ethical aspects of education are addressed with cultural sensitivity.

6. Equipping students for the changing job market, including positions within the gig economy, requires a comprehensive approach that merges flexible skills training with value-oriented guidance. Universities can develop simulations and career planning resources that reflect local customs and ethical standards, assisting students in navigating new economic environments while underscoring community and personal responsibility. This strategy also strengthens initiatives aimed at decreasing youth disengagement, offering pathways that are both adaptable and culturally affirming. Addressing ideological tensions between traditional values and modern economic shifts calls for the development of educational frameworks that are both innovative and culturally aligned.

The integration of AI into higher education represents more than a technological enhancement, which presents a chance to redefine the essence of learning in the twenty-first century. Rather than focusing on efficiency and quantifiable skills, this research shows that AI is thoughtfully designed and used with clear educational purpose, which can connect global skills with local cultural and ethical values. This requires a deliberate shift from a technology-driven approach to a human-centered framework, using digital tools to strengthen, rather than diminish, the essential values such as community solidarity, diligence, and intercultural respect.


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AI-Driven Sustainability Education in Business Schools: Expectations of Educators

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Abstract
Accelerated progress in digital technologies has influenced all industries. Interest in embracing Artificial Intelligence (AI) in education and research is flourishing among scholars, practitioners, educators, students, and the general public. Educational institutions now need to transform their traditional approach towards teaching and research by implementing innovative technologies. However, controversies surrounding the use of AI in education or research require deeper examination. Moreover, integration sustainability in business education has become an obligation for universities around the world. The significance of universities in empowering generations to tackle complex sustainability issues calls for ground-breaking solutions. In

this regard, AI with its immense capabilities can offer a unique approach. This chapter aims to explore AI trends and tendencies in teaching and research and to shed light on the role of AI in sustainability education. The main research question is: How can AI be incorporated into teaching to enhance sustainability education? To achieve research aims, the qualitative research method was used and expert interview approach was applied. This research contributes to the discussion of introducing AI in sustainability education and research agenda by delving into the multifaceted intersection of AI, sustainability and education. Based on the results, a theoretical framework is proposed to adopt AI into sustainable development teaching. The findings benefit academics, educators, researchers, policymakers and industry representatives to grasp future trends in sustainability education through AI-powered initiatives.

Keywords Artificial Intelligence – AI – Sustainability – Business education – Teaching – Learning – Sustainable development – SDGs

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1 Introduction

Today, educational institutions strive to transform their traditional approach towards teaching and research by implementing innovative technologies. Accelerated trends in digitalization and sustainability are paving the way for advanced technologies to solve global challenges (Martínez et al. 2022), and shaping almost every aspect of modern society (Gigauri 2024). In light of this, universities have a crucial role in the twin—digital and sustainability transition. They can transform education by utilizing innovative methods to teach sustainability. In this context, administrative support and organizational culture are of great importance.

At present, Artificial Intelligence (AI) is used in different fields. Over time, its cost is expected to decrease and its performance to increase. Consequently, educators can now integrate AI technology into their teaching and encourage students to conscious use (Lin and Chen 2024). Since AI has the ability to mimic the human brain and self-improve through machine learning, educators can bring AI systems into play in their activities.

Moreover, the integration of sustainability issues into curricula in business education has become a necessity globally to empower future leaders to find multifaceted solutions. Sustainability issues are integrated into curricula to enlighten future leaders on the Sustainable Development Goals (SDGs) and to raise awareness of Corporate Social Responsibility (CSR) among students. Studies indicate that sustainability must be incorporated into university programs while ensuring problem-based and experiential learning to nurture responsible citizens (Leal Filho et al. 2025). In this regard, Artificial Intelligence (AI) is regarded as a unique approach to sustainability education. The recent development of novel AI applications is revolutionizing teaching and learning. Machine learning algorithms, generative AI, and AI chatbots offer new education experiences through personalized and adaptive learning (Yu et al. 2024; Sundaresan and Zhang 2022). Multidisciplinary pedagogical approaches and integrated education programs ensure the creation of awareness of sustainability issues among students (Leal Filho et al. 2025). Previous survey results suggest that students improve their performance using the ChatGPT application as it responds quickly and can explain concepts while providing relevant sources and feedback at any time (Ngo 2023).

However, controversies surrounding the use of AI require profound examination. Although AI has a transformative capability, its use in education causes ethical and technical challenges. Besides privacy and data protection issues, the long-term impact of AI on the creativity and analytical skills of users is yet to be determined. Giordano et al. (2024) found that ChatGPT influences 185 different skills. In order to improve its performance, users should know prompt language, i.e., how to formulate effectively their queries and understand the concepts and models behind generative AI (Giordano et al. 2024). Essentially, AI should help and serve, not replace the efforts of people in teaching and learning.

On the one hand, AI in education offers a personalized experience, tutoring, automated grading and content development, collaborative learning and research (Kim et al. 2022). On the other hand, bias,

hallucination, excessive dependence and trust in AI present significant limitations (Umme et al. 2024). Nevertheless, AI systems are changing the role and function of educators. They are no longer expected to know everything as students can find answers quickly by asking GenAI (Yu et al. 2024). Therefore, some educators consider AI tools a danger to the education sector due to their negative impact on learning and teaching, as well as on integrity and ethics (Selwyn 2022). While others are enthusiastic and believe that teachers and students should learn new skills to use AI effectively (Ng et al. 2023). Thus, discussions and controversies on this topic continue.

Therefore, this chapter aims to examine AI trends and tendencies in teaching and research. It addresses the main research question of how AI enhances sustainable development teaching. This chapter, using a qualitative interview method, sheds light on the role of AI in sustainability education, with a special emphasis on business schools. The research sample consists of education experts with working experience in academia. The semi-structured interview guide included questions about the transformational abilities of AI in education and research, and the applicability of AI in sustainability education, specifically in business schools.

In addition, interview participants discussed the responsibility of universities and ethical concerns while adopting AI in education. Moreover, potential trajectories in teaching methods and changes in tasks of professors were examined.

The chapter suggests a theoretical framework—Triadic Model of Technology-Organization-Environment (TOE), Transformative Learning Theory (TLT), and Responsible Research and Innovation (RRI), to integrate AI into sustainability education.

2 Sustainability, AI, and Education

Growing environmental and social challenges require joint actions from various partners (Gigauri et al. 2021). Organizations of all sizes and types are expected to contribute to the UN's Sustainable Development

Goals (SDGs). Education and research play a significant role in achieving SDGs by sparking students' interest through innovative approaches (Leal Filho et al. 2021). Moreover, abrupt changes happen, and future leaders should be prepared to handle uncertainties. As a result, sustainability education stems from the demand of the business and government sectors for leaders who are aware of the current pressing problems and who know how to solve them (Gabelaia 2025). Indeed, previous studies confirmed the significance of teaching sustainability, social responsibility, and ethics to business students (Gigauri 2021). Recent research has found that most teachers apply case studies, research, and project-based methods to teach sustainability (Leal Filho et al. 2025).

In addition, the exponential growth of AI-powered tools leads to their acceptance and adoption in different fields, including education. Since teaching through normative theory no longer responds to modern educational requirements (Gigauri et al. 2021), innovative approaches should be used (Pelet et al. 2025) to equip graduates with the skills and knowledge needed for the real world. In this regard, the importance of AI in education increases.

AI apps induce innovative teaching and learning that makes them attractive to the education sector. In particular, Generative Artificial Intelligence (GenAI) systems become widely used due to their practicality in generating texts and images and engaging in a dialogue with the user. However, since GenAI utilizes machine learning methods, it reproduces contents from the existing data they have learned. These apps can analyse a large dataset and study patterns based on which they build similar structures (Morgan 2023). This, in turn, causes bias and inconsistencies, of which the user must be aware.

In education, tutoring and dialogue-based AI technologies are applied, using various databases to enhance performance in a specific area while providing individualized learning experiences. Dialogue-based applications offer instant feedback, enriching students' educational adventures (Zhai and Wibowo 2023). AI systems assist teachers in creating innovative approaches and technology-driven

activities in the classroom. AI apps can help teachers evaluate students' assignments and performance (González-Calatayud et al. 2021). Moreover, AI-created writing instruction improves students' writing ability. Studies show that AI supports feedback that positively affects the quality of writing (Guo et al. 2024).

For business education, scenario planning is an important tool to explore a concept or business strategy from different angles. However, this activity requires resources and time, which may cause educators to avoid it. With AI technology, scenario activities have become effective and efficient in demonstrating issues to students, engaging them in discussion, and encouraging them to find solutions.

Morrell (2004) highlighted the Socratic approach to instructing business ethics. Similarly, critical thinking and creativity are emphasized to teach corporate social responsibility and sustainability (Gigauri et al. 2022). These methods help students to understand complex problems and inspire them to find real solutions. In this sense, AI tools extend these approaches by posing questions, presenting dilemmas, illustrating actual problems, visualizing the future, and engaging in dialogue with students.

Researchers emphasize that Liberal Learning (LL) philosophy and Social Constructivist Pedagogy (SCP) can transform business education as they fuel critical thinking and creativity (Chandler and Teckchandani 2015). Moreover, teaching approaches enable students to become active learners, improve problem-solving skills, encourage critical thinking, and lead to desirable educational results (Gigauri et al. 2022). These skills are essential for future business leaders to deal with sustainability issues.

Previous research found that different digital tools demonstrated effectiveness in teaching and learning about sustainability. For example, Alonso-Martínez et al. (2019) confirmed that mobile and other apps, videos and technological aids augmented business students' outcomes in learning sustainability. Sholihin et al. (2020) found that virtual reality (VR) shows the relationship between theories and real-world relevance while stimulating interest and strengthening motivation.

Recent studies reveal that AI presents valuable teaching support while main concerns about privacy, trust, and addiction to technologies remain unsolved (Kwiatkowska et al. 2025). Survey results illustrate that although teachers do not promote AI tools, Polish students use them in the learning process to access educational materials and are content with the positive influence of AI on the quality of their education (Kwiatkowska et al. 2025). The authors suggest that university professors adopt AI in teaching while being aware of its limitations. Moreover, universities should implement transparency policies for the ethical use of AI and inform students about the drawbacks of AI tools (Kwiatkowska et al. 2025). These measures will increase the benefits of AI in education and decrease risks.

Thus, the role of business schools is not to provide "knowledge for knowledge's sake" but to adapt to the changing environment, respond to the demand of the labour market, and, hence, offer education that will correspond to a digital and sustainable future (Gigauri et al. 2022; Ma et al. 2024).

Some cases and practical examples illustrate teaching sustainability with AI-powered tools. For instance, students can be introduced to real-world sustainability challenges such as deforestation or clean water scarcity, inclusion or hunger, and use AI tools to visualize data from research (Tripathi et al. 2024). In this context, machine learning models can predict the effects of climate change on crop yields (Sidhu et al. 2023). In addition, AI-driven simulations demonstrate the outcomes of different environmental policies or practices. Real-time data and trends allow students to understand the scale of the challenge and its long-term effects. Thus, students, through AI technology, understand the tangible impact of global collaboration in solving sustainability problems.

Another example is Google Earth Engine, which helps guide environmental monitoring by analysing satellite images with AI (Yang et al. 2022).

In the same way, IE Business School in Madrid has embedded sustainability and AI into its business curriculum to prepare future

leaders for responsible decision-making. Its Tech Lab merges AI tools with a sustainability strategy. For this reason, students can use AI-powered scenario simulators to test sustainability strategies, such as supply chain decarbonization and ESG (Environmental, Social, Governance) investment. These tools leverage machine learning to model consequences based on decisions, such as changes to energy sourcing or waste management.

Similarly, students use Natural Language Processing (NLP)-based AI tools—MonkeyLearn or ChatGPT to analyse large volumes of ESG disclosures. AI tools help them to identify greenwashing, benchmark sustainability claims, or summarize material issues across industries. Students can also use predictive analytics platforms for sustainable finance, such as Tableau with AI extensions or Power BI with Azure Machine Learning. Accordingly, students can develop predictive models for forecasting emissions, modelling long-term financial impacts of climate risks, and evaluating the ROI of sustainability initiatives.

In addition, IE University launched ChatGPT Edu in 2023 for students and staff to foster learning and respond to the job market demand for AI-native graduates. Consequently, students can not only learn sustainability but also gain proficiency in AI tools to apply for sustainability strategy, ESG metrics, and stakeholder engagement.

Thus, the presented examples show that AI can be adopted to teach sustainability by enabling personalized learning, automating educational tasks, and integrating real-world environmental challenges into the curriculum. Teachers should bridge technical AI skills with ethical business leadership.

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3 AI for Sustainability Education in Business Schools: Research and Results

3.1 Methods

This research is based on a qualitative interview method to gather data from education experts. Educators were asked to reflect on the transformational abilities of AI in education and research and the

applicability of AI to teach sustainability in business programs. Data was analysed through content analysis.

Qualitative research methods enable researchers to understand opinions and experiences regarding the research questions. An expert interview approach was employed due to its convenience in obtaining specific information about an unknown field (Von Soest 2023; Döringer 2021).

The sample size included 14 respondents selected with purposive sampling (Douglas 2022; Robinson 2023), where data saturation occurred (Bouncken et al. 2025). The main selection criteria (Czernek-Marszałek and McCabe 2024) were determined by their experience in teaching at a business program or business school and working in academia, notably, at a university. The semi-structured interview guide contained three questions reflecting their opinions on the use of AI in education and research, what ethical concerns they might have in this regard; how they view the applicability of AI in sustainability education; and how AI can enhance sustainable development teaching in business programs.

The content analysis allowed us to find themes and categories, uncover meanings, and finally, generate a theory (Serafini and Reid 2023). We propose a theoretical framework to be integrated into sustainable development teaching using AI. Particularly, the Triadic Model of Technology-Organization-Environment, Transformative Learning Theory, and Responsible Research and Innovation has been found to have the potential of successfully integrating AI into sustainable development teaching.

3.2 Results

The interview participants believed that AI could be used to summarize existing literature and publications on sustainability issues. This technology will enable students to learn about any specific issue effectively and interactively. They can pose a question to AI tools to find some previous studies, for example, about climate change. After receiving a prompt response, they can critically analyse and think

deeply about the problem. However, educators must teach students about the biases of AI and encourage them to check sources provided by AI. Furthermore, students can explore solutions to the same sustainability problem and assess generated responses through their creative thinking skills. This still means that AI helps students in getting knowledge without replacing that knowledge.

In addition, for students to conduct research on sustainability issues using AI tools, they need to break out the research process into certain stages and identify, which stages AI can be useful for. Small, specific tasks can be delegated to AI tools. However, knowing which AI tool can be helpful for which task is vital. In this manner, AI can be used consciously and effectively while adding insights, thinking critically, and analysing the generated content.

Besides, professors can also use AI to create examples for their teaching materials, build discussion questions that will lead to classroom engagement, and urges students to think deeper. Further, sustainability professors, through AI, can clarify the concepts, theories, or models to adapt to different students' needs. Analogously, AI can provide examples and case studies to illustrate a particular sustainability issue, which assists students in clearly seeing the problem in the real world. It can offer models and solutions as well. Nevertheless, there is still a lack of guidelines and training to effectively adopt and incorporate AI in the teaching, research, and education process.

Two main categories emerged from the data: AI challenges and AI benefits (Table 1). Within these categories, the following key themes emerged: (i) Education process, (ii) Using AI, (iii) Human learning, (iv) Adapting to changing technologies, (v) Relying on GenAI (Fig. 1).

Table 1 Two main categories when discussing AI in sustainability education

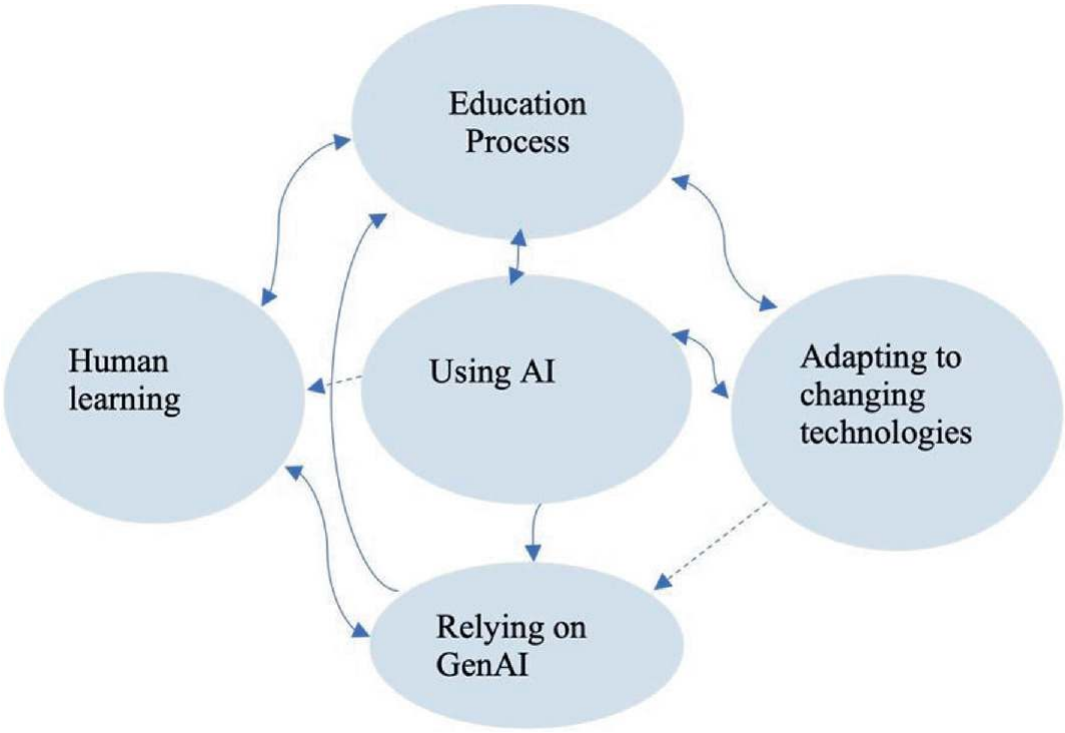


Fig. 1 Key themes.
Source Authors

(i) Education process. Professors of business schools recognize that AI is changing the education process. Current trends in advanced technologies dictate that universities to incorporate AI in their teaching and research. Since the labour market grows in demand for graduates with AI tools, higher education institutions, particularly business schools, need to teach emerging skills to students. This leads to alterations in curricula. Business schools regard education as preparation for a future job; accordingly, education "on its own sake" or "as an end in itself" has lost its value. Modern education means for graduates to be competitive in the job market. Hence, it should offer them the corresponding skills.

Furthermore, students increasingly use AI tools for home assignments, writing or searching. However, they still need the basic knowledge to assess what generative AI tools offer them. Although it is easy to prompt, generated texts must be examined using creative and analytical skills. Without such skills, AI is

fruitless. Therefore, educators should teach students that AI may help them understand concepts, but it cannot substitute thinking. Besides, it is dangerous to entrust their intelligence completely to artificial agents. On the other hand, repetitive tasks can be successfully delegated to AI. It also assists in analysing big data and excessive information. Thus, AI can augment sustainability education rather than replace it.

(ii) Using AI. Educators recognize the need to understand how to use AI in business schools for sustainability education and what its purpose should be. They believe AI is effective for coding, programming, or time-consuming tasks. Likewise, it is helpful for the research process, literature search and review. In addition, AI helps in brainstorming, generating and filtering ideas, summarizing, analyzing and explaining data or concepts, while improving writing style and correcting mistakes. However, incomplete references and bias must be taken into account. For this reason, AI should be regarded as a catalyst for critical thinking and generated content must be challenged with analytical skills.

Additionally, AI can enhance sustainability research and analyze data about sustainable development goals. AI tools assist in conducting experiments, modelling and simulations to broaden knowledge about problems and find solutions effectively. Thus, it can facilitate thinking and cognitive tasks. Nonetheless, AI tools are, in many cases, less reliable, inaccurate, and expensive. Although generated responses are similar to human writing, AI still hallucinates and is associated with privacy problems. Consequently, recognizing its boundaries, AI must be used carefully, specifically, for complex problems that require robustness.

(iii) Human learning. Educators are of the opinion that AI may harm learning. Their concerns are related to the widespread use of AI among students without questioning the generated content and even considering it as the “absolute truth”. Specifically, GenAI

tools make an impression that the response to all questions is easily accessible. Using these applications, students can produce responses effortlessly. But these technologies cannot imitate human learning, which implies efforts being the basis of education and development. Therefore, professors should raise awareness among students that there is no learning without effort.

The next generation of business leaders needs knowledge in both sustainability and AI. Simultaneously, they must possess analytical skills to make responsible decisions in favor of society. Accordingly, business schools should teach actual knowledge and skills without relying immensely on AI. However, it can be used as an assistant, not as a replacement for learning. Students should be aware how to learn without its help as well, as fundamental knowledge cannot be replaced by "prompting".

(iv) Adapting to changing technologies. Despite its limitations, AI should be integrated into sustainability education. Since the technologies are there to stay forever, the new generation needs to gather experience in its proper and responsible use. Moreover, further development of AI technologies will improve their performance. Therefore, educators and students can explore the challenges and opportunities these technologies offer. In addition, using AI depends on the purpose and objectives of business schools and their respective programs. For sustainability education, AI can serve as an assistant tool while people contribute to the solution or comprehensively analyze the problem. Concurrently, emerging technologies should be monitored from various lenses, considering legal, ethical, or scientific consequences.

(v) Relying on GenAI. Generative AI is the most used tool by students. However, its well-known drawbacks are hallucination, inconsistencies, and limited understanding of context. Additionally, they can describe only general concepts and have

limited access to new literature and article databases. These

deficiencies can be overcome by testing different AI apps to determine which is useful for a certain task. Their capabilities can be compared. In order to decrease bias, more than one AI app can be applied. Thus, users might spend lots of time to test and choose one.

In general, AI technologies assist teachers, researchers, and students, but they must not completely rely on technologies. Instead, AI can be helpful in understanding, expanding knowledge, creating, or improving. The younger generation counting on GenAI will not remember anything nor develop their actual skills and knowledge, as they have the temptation to quickly address GenAI. In contrast, thinking and finding solutions are the basis for development and growth. Accordingly, educators should explain the shortcomings of overly reckoning on GenAI by engaging students in discussion and reflection.

Thus, most educators took a middle position, weighing pros and cons of using AI in education. Therefore, business schools should decide how intensively they will use it and in which area.

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4 Discussion

4.1 Theoretical Frameworks for AI in Education

Adopting Artificial Intelligence (AI) into sustainability education, especially within business schools, demands a multilevel analytical procedure that includes technological adoption, pedagogical transformation, digital literacy, and ethical foresight. To address these adoptions, the authors used three theoretical frameworks: Technology-Organization-Environment (TOE), Transformative Learning Theory (TLT), and Responsible Research and Innovation (RRI). Each framework has a distinctive philosophy for exploring AI's complexity and growing role in higher education.

Technology-Organization-Environment (TOE) Framework

The TOE framework (Tornatzky and Fleischer 1990) offers a structural standard for understanding the institutional conditions that encourage the adoption of technological innovations like AI. Within the research context, this framework provides the following trustworthiness. First, the technological context involves AI's technical complexity, ease of use, compatibility with existing Learning Management Systems (LMS), and the perceived usefulness of AI instruments such as AI tutors, predictive analytics, learning analytics, and digital literacy (Gabelaia et al. 2024) and natural language processing for student feedback examination. Moreover, the technological affordances of AI promote personalized learning routes, simulation-based sustainability modeling, and ESG-focused data storytelling, necessary for successful adoption.

The organizational context incorporates institutional culture, leadership and administrative support, faculty competencies, resource allocation, and strategic vision. Today, the AI-readiness of faculty, particularly in sustainability-focused curricula, has become a fundamental topic of discussion. Besides, HEIs with agile governance and a proactive innovation culture are set to implement AI mechanisms that enrich sustainability learning. On the contrary, issues like resistance within organizational culture and training and development for AI adoption are visible in many HEIs. Furthermore, environmental context discourses variables such as accreditation demands, national sustainability policies, global SDG alignment, and growing expectations of graduates' ESG competencies.

TOE determines the systemic enablers and constraints that must be explored to implement AI into sustainability-focused educational ecosystems.

Transformative Learning Theory (TLT)

Mezirow's Transformative Learning Theory (1991) explores reflection and perspective transformation as paramount to adult learning. When applied to AI-enabled sustainability education, it provides critical insights for researchers and practitioners in HEI. First, AI can activate disorienting dilemmas, such as ethical questions around environmental

trade-offs, encouraging students to reconsider or rethink assumptions and engage in critical discussions. Moreover, AI-enhanced instruments, for instance, sustainability dashboards, suggest inquiry-driven learning. Besides, these instruments represent a constructivist foundation of TLT, inspiring students to co-create rather than passively accept sustainability.

Furthermore, TLT offers students affective and moral development. This makes TLP even more appropriate for sustainability education, as it develops and promotes cognitive mastery and value-oriented change. Besides, AI offers real-time ethical scenarios, allowing students to make reflective and principled decisions. Consequently, TLT connects the cognitive, emotional, and behavioral characteristics necessary to produce sustainability-oriented graduates.

Responsible Research and Innovation (RRI)

The RRI framework (Owen et al. 2012) states that technological innovation is aligned with societal values, predicts future consequences, and incorporates various stakeholder voices in decision-making. This supports the research direction in AI in sustainability education. First, anticipation highlights and addresses AI's societal and ethical implications. For instance, student data exploitation, algorithmic bias, and reliance on automation in student assessments are massive concerns for HEIs as they could offer unnecessary automated surveillance and bias. Moreover, reflexivity requires HEIs to assess personal motivations and values when applying AI in curricula, requiring them to be bias-free. Questions to be addressed are: Are AI instruments being used to genuinely improve student learning, or do efficiency metrics and surveillance logic lead them?

Furthermore, inclusion endorses participatory curriculum design involving faculty and administrators, students, AI developers, and sustainability practitioners. This co-creation secures the ethical grounding and contextual sensitivity. Finally, the RRI concept in this research is fundamental to manage unintended consequences and strengthen AI ethical use of applications in education.

Integrative Value of the Framework

The authors based on the convergence of TOE, TLT, and RRI produce a triadic model that discourses:

- The structural and procedural dynamics of AI implementation (TOE) in Higher Education Institutions (HEIs)
- The cognitive and moral development of learners (TLT) in Higher Education Insitutions (HEIs)
- The ethical and social governance of technological innovation (RRI) in Higher Educations Institutions (HEIs).

This triadic mode, or framework proposes a holistic roadmap for educational institutions guiding the AI-sustainability nexus. It acknowledges that adopting AI in HEI, especially in business schools is not just a technological alternative but a pedagogical and ethical commitment that demands alignment across organizational systems, instructional philosophies, and societal responsibilities highlighting AI in Education (Fig. 2).

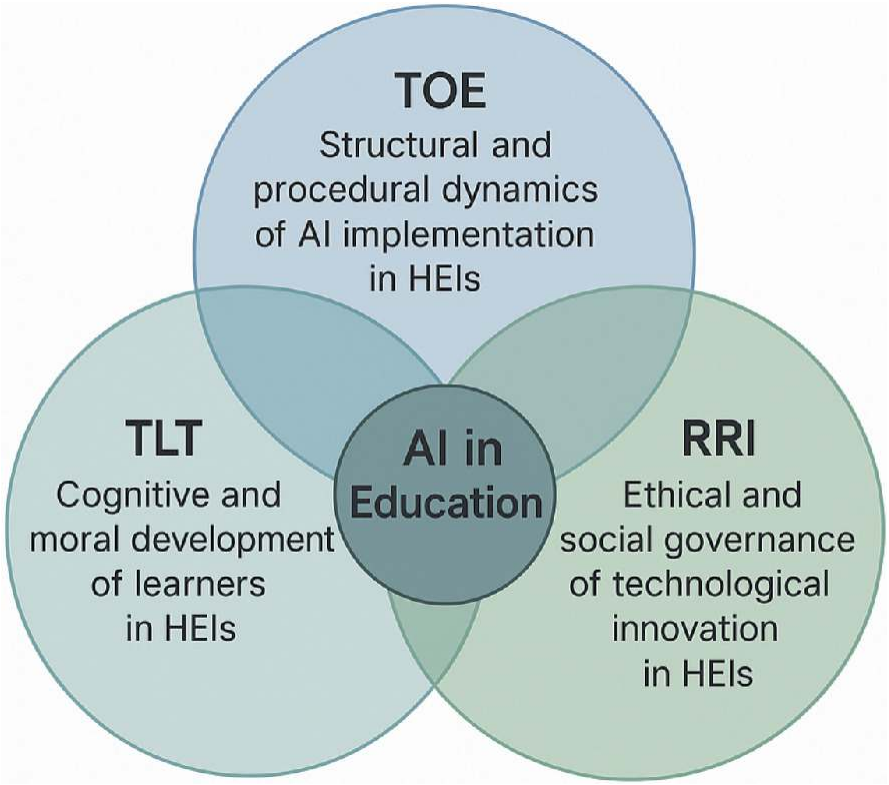


Fig. 2 Triadic model—integrative value of the framework.

Source Authors (developed by the Authors using Drawio)

5 Conclusions

Exponential improvement in technology has shaped our society and transformed education. Artificial Intelligence (AI) has dramatically reshaped human activities and the education process.

In this chapter, the AI-driven sustainable development teaching framework was outlined, with a particular emphasis on business education. Incorporating AI into curriculum can enhance sustainability teaching. Based on the research results, we suggested the Triadic Model of Technology-Organization-Environment (TOE), Transformative Learning Theory (TLT), and Responsible Research and Innovation (RRI), to successfully integrate AI into sustainability education.

Moreover, the importance of teaching sustainability was discussed. The purpose of business has been broadened, embracing sustainable development goals. This evolution is further expanding, incorporating AI technologies in business education. Respectively, a new generation of business graduates is expected to be equipped with modern skills involving both sustainability and AI knowledge. Thus, adopting innovative approaches will help to bridge traditional education and advanced technologies (Chan 2023).

The tendency of business education programs to integrate SDGs and sustainability-related subjects into various courses is growing. Furthermore, universities increasingly offer sustainability programs to prepare future business leaders with adequate abilities to deal with crucial sustainability issues (Ma et al. 2024). Additionally, non-formal education also enables students to acquire sustainability and AI competencies. Similarly, case studies and experiential learning improve students' strategic thinking and problem-solving abilities. In this context, AI can provide cases and examples, empowering innovative teaching and learning approaches. In the case of the right prompts, AI can help instructors generate case studies illustrating sustainability problems that need to be solved, generating appropriate questions, and even keeping the tone and writing style engaging for students.

Universities, as change agents, can transform political, economic, and social systems in favour of more sustainable behaviour driven by technological progress. Transformation of business education towards sustainability and AI will bring considerable benefits to the education system, society and future generations. AI-powered projects aiming at teaching sustainability shape modern education systems (Pasca and Arcese 2025).

However, compared to AI, humans possess a nuanced understanding of context and can interpret it accordingly. Currently, all language models show limitations and naturally cannot reproduce similar creativity or thinking. In this regard, the concept of "technological somnambulism" can be relevant. Despite the enthusiasm towards AI, its limitations should be considered. Although AI can perform quickly and effectively with extensive data overcoming time constraints, unreflective use or blind adoption of AI tools may harm long-term societal welfare. The tendency to focus only on the advantages of AI should not lead to ignoring its adverse impact on humans. Especially the young generation is vulnerable. For this reason, it is important to determine when and how AI should be used to benefit global society while simultaneously taking into account ethical considerations and business perspectives (Holmes and Tuomi 2022). Therefore, AI can be used under human supervision to achieve balanced performance.

The limitation of this research is derived from its qualitative nature, including data collection and interpretation bias, as well as sample size limiting the generalizability. Nevertheless, this research contributes to the knowledge of sustainability education in business programs reinforced by AI technologies. This chapter emphasizes the importance of integrating AI-driven approaches to teach sustainability and proposes a theoretical framework for AI in sustainability education.

Still, the question remains: How to design the education process, teaching, and learning to make AI a benefit, overcoming its disadvantages and limitations; how to foster education to develop critical and analytical skills for business students while implementing

AI in sustainability education. Furthermore, it is essential to consider how to adapt to a world, changing under the influence of technologies. Thus, further research should be conducted to grasp the nuances in the controversial and critical topic of using AI in teaching and research. Specifically, future qualitative and quantitative studies can focus on obstacles and opportunities to integrating AI into sustainability business education. Finally, future research should delve deeper into the sustainable development teaching methods that use AI.



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AI-Augmented Business Training and Development for Organizational Sustainability

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Abstract
This chapter examines how artificial intelligence (AI) can be integrated into business training and development (T&D) to strengthen organizational capacity for long-term viability. Drawing on action learning, experiential learning, and enterprise education, it outlines how AI-enabled tools, such as intelligent coaching systems, adaptive feedback mechanisms, and decision-support platforms, can support the development of transversal capabilities, including systemic thinking, problem-solving, and decision-making. The analysis adopts a design perspective, advancing an architecture for AI-augmented training that connects educational and workplace contexts. Strategic considerations are proposed for creating individualized and scalable learning environments that address the dual imperative of workforce development and organizational adaptability under complex, evolving conditions. The chapter integrates pedagogical models and systems

design principles to offer a coherent framework for embedding AI in organizational T&D.

Keywords Artificial intelligence – Organizational sustainability – Business training and development – Experiential learning – Systemic thinking – Capability development

Dr. Rickard Enstroem is Associate Professor of Decision Sciences at MacEwan University, Canada, and past Chair of the Department of Decision Sciences. He is a Chartered Fellow (CMgr FCMI) of the Chartered Management Institute (CMI), UK. At MacEwan, he initiated and led the development of the Business Intelligence minor in the BCom program. He teaches Supply Chain Management, Analytics, and Computational Thinking. He is the Co-Editor-in-Chief of *Leadership & Organization Development Journal*, Associate Editor for the *Journal of Management Development* and the *Journal of Academic Ethics*, and Editorial Board Member of the *Journal of Work-Applied Management*. He also serves as Board Chair of the national Canadian Initiative for Nordic Studies (CINS), housed at the University of Alberta, which promotes multidisciplinary academic and cultural links between Canada and the Nordic countries through scholarships and grants. His research examines how digital transformation changes the nature of work, the role of managers, and the design of organizations.

1 Introduction

Contemporary organizations operate under complex and interrelated global conditions that require adaptive responses to societal, economic, and technological dynamics (Aguilera et al. 2024; Omidvar et al. 2023). These dynamics are mirrored in operational domains, where coordination and competitive structures govern system-level performance (Son and Enstroem 2021). In response, business professionals need to combine technical proficiency with systemic

reasoning and the capacity to function in digitally mediated environments (Enstroem and Schmaltz 2023; Enstroem and Schmaltz 2024). As digital transformation progresses, captured in concepts such as Industry 5.0 (Rožanec et al. 2023) and human-machine collaboration (Ameen et al. 2025), resilience, flexibility, and innovative capabilities are vital. Addressing these demands requires Training and Development (T&D) models that integrate domain-specific and transversal competencies for organizational viability.

Artificial intelligence (AI) is already impacting business operations (Enstroem et al. 2025b; Zebec and Indihar Štemberger 2024), but its role in strengthening forward-looking capabilities in T&D is still in its infancy (Bhatt and Muduli 2023; Dixit and Jatav 2024). This chapter discusses how AI can assist in designing experiential and personalized learning environments that contribute to organizational sustainability. Drawing on established learning models (see e.g. Enstroem 2026a; Kolb 1984), AI-assisted implementations can provide scalable delivery, individualized learning routes, and adaptive feedback that align professional development with organizational needs. Attention is given to leadership and managerial training, where AI can help strengthen the development of moral reasoning, strategic decision-making, and metacognition.

Traditionally, T&D has focused on performance improvement through technical expertise and interpersonal skill development (Akdere et al. 2023; Spiteri Axiak 2025). Emerging operational realities, however, highlight the need for models that further character-based judgment in complex environments (Crossan et al. 2017; Shotter and Tsoukas 2014). Leadership development, a central element of T&D, exemplifies this shift. AI can enable coaching systems, adaptive feedback mechanisms, and decision-support environments that emulate business scenarios (Akdere et al. 2023). These scenarios allow participants to work through trade-offs in dynamic conditions resembling actual work. Such environments can incorporate opportunities for introspective reflection while engaging with

progressively more challenging tasks, a structure to support mastery learning.

AI-assisted learning environments offer several advantages, but their integration into T&D requires a deliberate design. For instance, shifts in labour expectations, regulatory frameworks, and stakeholder values place pressure on learning to move beyond episodic interventions toward continuous professional recalibration (Noe et al. 2014; Ostmeier and Strobel 2022). AI can support this shift by facilitating ongoing, context-aware development that links individual growth with organizational priorities. This chapter contributes to this discussion by exploring how AI may be embedded in business T&D for organizational sustainability and outlining design principles for AI in training infrastructures.

The remainder of this chapter is structured as follows: Sect. 2 examines organizational sustainability and its underlying capabilities and behaviours; Sect. 3 reviews foundational training and development models; Sect. 4 outlines a design perspective for AI-augmented training systems; Sect. 5 discusses the integration of learning into the flow of work; Sect. 6 presents an integrated view of AI-augmented T&D; and Sect. 7 concludes the chapter by synthesizing the arguments and implications.

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2 Organizational Sustainability: Perspectives, Capabilities, and Behaviours

2.1 Perspectives on Sustainability

The different uses of the term sustainability influence how organizations construe their mission and development. In management and policy discourses, three central perspectives are environmental, social, and economic (Elkington 1997; Scott 2014). They overlap in practice but differ in capability requirements and evaluative standards (Tipu 2022). Environmental sustainability is the most visible framework. In this view, organizations are assessed on their ecological footprint and compliance with environmental standards (Tipu 2022).

Technical expertise in areas such as regulatory frameworks, carbon accounting, or emission reduction is critical (Suraj et al. 2025). However, to achieve these goals, transversal competencies and behaviours—including systemic thinking (understood as a cognitive orientation toward recognizing interdependencies rather than systems thinking in the narrower analytical sense; Wang and Enstroem 2024), collaboration, project management, and adaptive problem-solving—are instrumental (Birdman et al. 2022; Brundiers et al. 2021). This perspective is indispensable in sectors with material ecological impact, but its scope is bounded, as it prioritizes environmental outcomes over the complete set of dynamics that determine organizational survival.

The social dimension of sustainability extends beyond ecological concerns to fairness, equity, and legitimacy (Grybauskas et al. 2022; Schönborn et al. 2019). In this view, sustainability is linked with organizational responsibility and responsiveness to societal expectations. Capabilities such as judgment, cultural sensitivity, and the ability to respond to contested values become increasingly important. This orientation has gained importance as organizations face intensified scrutiny from stakeholders, regulators, and society (Kelling et al. 2021). However, it is often treated as peripheral to the organization's core strategy, a form of decoupling (Meyer and Rowan 1977). However, decoupling can also reflect strategies through which organizations manage institutional complexity and build integration over time (Bromley and Powell 2012). The challenge is to embed social sustainability into organizational practice without reducing it to reputational management.

From this chapter's standpoint, organizational sustainability offers the most generative interpretation: how can organizations sustain viability across technological, economic, and institutional conditions (Oliver 1997; Teece et al. 1997). It depends on developing capabilities and behaviours that enable adaptation and renewal, such as business model innovation, strategic agility, stakeholder integration (Hart and Dowell 2011; Teece 2018), and exercising character-based judgment (Crossan et al. 2013). This interpretation clarifies that sustainability is

an ongoing process of balancing stability with change. It therefore treats institutional complexity, in the neo-institutional tradition, as a natural condition across time (Greenwood et al. 2011). This perspective provides a natural entry point for integrating AI into T&D. Accordingly, AI operates as a mediating technology: it senses competence levels, adapts learning scenarios, evaluates performance, and provides feedback (Enstroem and Schmaltz 2024; Zebec and Indihar Štemberger 2024). These functions support the development of generic capabilities and behaviours that form the foundation for organizations to pursue their missions sustainably. This view resonates with the Resource-Based View (RBV) of the firm, which suggests that sustained advantage rests on resources that are valuable, rare, and difficult to imitate (Barney et al. 2001).

2.2 Capabilities as Microfoundations

Classic management perspectives highlight the complementary facets of organizational sustainability. The resource-based view underscores the role of tangible and intangible assets and human resources such as knowledge, competencies, and organizational routines (Barney et al. 2001). Sustainability can be achieved when these resources are configured in ways that are valuable, rare, and difficult to imitate. Building on this foundation, the dynamic capabilities framework introduces a temporal dimension by examining how organizations reconfigure in response to changing business environments (Teece et al. 1997). The neo-institutional tradition then draws attention to the legitimacy and responsiveness across institutional logics (Greenwood et al. 2011). Together, these perspectives demonstrate that organizational sustainability depends on developing human capabilities and behaviours for continuous recalibration under evolving conditions.

Capabilities are structured competencies that allow individuals to address complex challenges and align their contributions with organizational objectives (Enstroem et al. 2025a; Teece 2007). They include systemic thinking, which facilitates recognition of interdependencies (Atwater et al. 2008; Wang and Enstroem 2024);

problem-solving and analytical judgment, which guide responses to uncertainty (Dane and Pratt 2007; Hodgkinson and Healey 2011); and decision-making, which integrates information streams into actionable choices (Elbanna and Child 2007; Shollo and Galliers 2016). These capabilities are dynamic and transferable across contexts. Strategy research often describes them as microfoundations of dynamic capabilities, since individuals' competencies form the basis for organizational adaptation and innovation (Felin and Foss 2005; Salvato and Rerup 2011; Teece 2007). Embedding learning outcomes that strengthen these capabilities allows organizations to improve performance and build proactive capacity to anticipate emerging conditions.

2.3 Behaviours in Practice

Behaviours are the observable manifestations of capabilities. They include collaboration, which integrates expertise (Benson and Enstroem 2017; Edmondson 1999); moral reasoning, which anchors decisions in legitimacy (Enstroem 2025); and adaptability, which enables constructive adjustment to change (Enstroem and Schmaltz 2023; Pulakos et al. 2000). These behaviours underpin resilience, innovation, and trust—attributes repeatedly linked to organizational sustainability (Lengnick-Hall et al. 2011; Westley et al. 2011). Whereas capabilities represent the potential for effective action, behaviours constitute their everyday enactment. Sustaining organizational resilience therefore requires the development of technical skills and behavioural repertoires that support shared responsibility and continuous improvement. Figure 1 illustrates this relationship: capabilities such as systemic thinking and problem-solving influence behaviours, including collaboration and adaptability, which affect the organization's viability in dynamic environments.

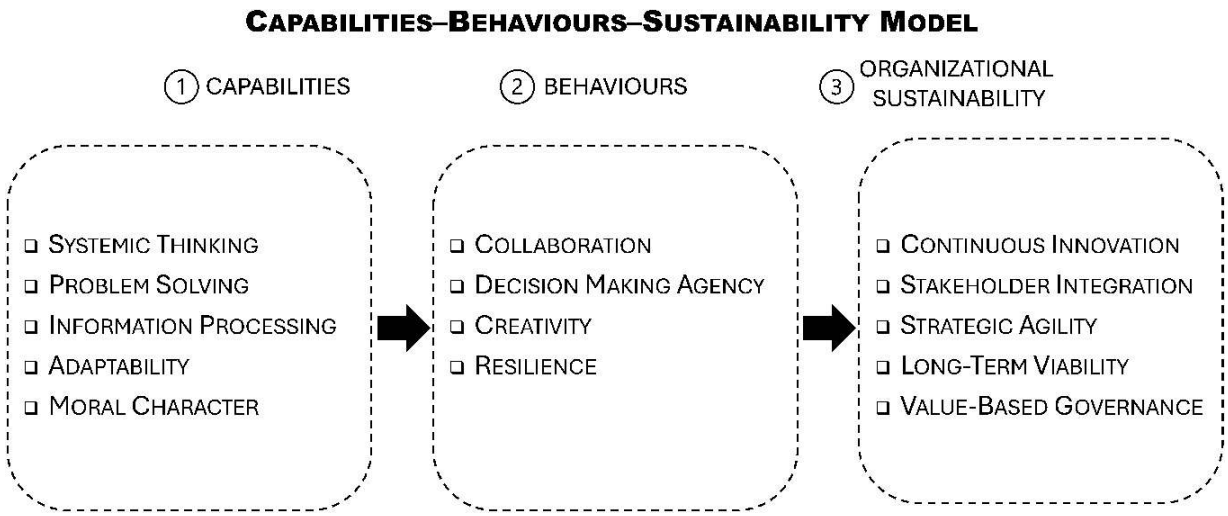


Fig. 1 Linking individual capabilities and behaviours to organizational sustainability. *Source* Author

The link between individual behaviours and organizational sustainability is supported across several theoretical traditions. Human capital theory stresses that individual capabilities, including technical skills and cognitive abilities, contribute directly to organizational performance (Ployhart and Moliterno 2011; Winterton and Cafferkey 2019). Behavioural research on organizational citizenship behaviours (OCBs) shows that actions such as cooperation and initiative improve collective effectiveness (Ocampo et al. 2018). Research on organizational resilience further underscores the importance of individual and collective capacity to absorb disruptions and recover from setbacks (Andersson et al. 2019). These views imply that organizational sustainability is reinforced when individual capabilities and behaviours are developed.

The systematic development of capabilities and behaviours provides a basis for considering how AI can contribute to T&D. As a mediating technology, AI can tailor learning pathways, provide adaptive feedback, and emulate complex decision environments (Enstroem and Bhawna 2025; Enstroem and Schmaltz 2024). Through intelligent coaching systems and decision-support platforms, AI can assist in strengthening the capabilities and behaviours needed for problem-

solving, judgment, and resilience in information-rich environments (Enstroem and Bhawna 2025).

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3 Training and Development Models for Organizational Sustainability

Training and development (T&D) are integral to equipping individuals with the necessary capabilities and behaviours for the organization's long-term viability. This section explores three influential learning models: Action Learning, Experiential Learning, and Enterprise Education. The section then introduces Experiential Mastery Learning, an integrative model where participants progress through cycles of increasing difficulty with interlaced reflections (Benson and Enstroem 2025), supported by AI.

3.1 Action Learning

Action Learning links organizational problem-solving with individual growth. Small groups work on real problems, take action, and reflect on their decisions (Revans 2011). This dual goal develops transferable capabilities while generating organizational solutions (Perusso et al. 2021). Reflection is an essential part of the learning process in Action Learning. Individuals and teams reflect on their actions and decisions to improve future problem-solving. In the context of organizational sustainability, Action Learning can cultivate behaviours that are not easily developed through formal instruction. For instance, working with multilayered problems requires adaptability and stakeholder awareness, while the group process itself develops participants' ability to work in teams, listen, and communicate.

Artificial intelligence can extend the reach and depth of Action Learning by functioning as a digital facilitator that strengthens the reflective process (Enstroem and Bhawna 2025; Enstroem and Schmaltz 2024). For instance, AI tools can monitor real-time group dynamics, analyze participation patterns, and surface underrepresented perspectives to ensure a more balanced dialogue.

Natural language processing can generate reflective prompts tailored to themes emerging in discussion to support collective learning. In practice, a multinational company might employ AI-enabled dashboards during Action Learning sessions on supply chain resilience. The system could highlight when the conversation is dominated by operational perspectives while neglecting environmental or stakeholder concerns. This would prompt the group to reconsider the problem from a more holistic sustainability lens. AI can help groups move beyond narrow framings without replacing human facilitation by nudging participants to incorporate several logics into their deliberations. Instead, it augments the strengths of Action Learning—problem focus, reflection, and collaboration—while making the process more inclusive, resilient to group biases, and scalable across organizational contexts.

3.2 Experiential Learning

Experiential Learning, most prominently associated with the work of David Kolb, is based on the premise that effective learning arises through cycles of doing, reflecting, conceptualizing, and experimenting (Kolb 1984). This four-stage model—Concrete Experience, Reflective Observation, Abstract Conceptualization, and Active Experimentation—has influenced management and professional education for decades. Its strength lies in its versatility: the model can be applied in classrooms, field settings, or directly in organizational practice. Experiential Learning cultivates higher-order capabilities beyond technical proficiency (Enstroem and Benson 2024; Kayes 2002; Kolb and Kolb 2005). By cycling between experience and reflection, individuals develop the ability to make sense of complex contexts, identify interdependencies, and apply insights to novel situations. Behaviours such as adaptability, creativity, and character-based reasoning are reinforced when learners confront ambiguity, reflect critically, and test alternative courses of action. For organizations, these outcomes support resilience by embedding reflective and adaptive habits that are difficult to achieve through conventional training.

Artificial intelligence can augment Experiential Learning by enhancing each phase of Kolb's cycle. In the Concrete Experience stage, AI-driven simulations can generate realistic and adaptive scenarios that mirror the pressures of business environments, such as competing stakeholder demands or crisis conditions. During Reflective Observation, natural language processing can analyze learners' reflective journals or discussion transcripts and provide prompts to stimulate further analysis. In the Abstract Conceptualization phase, AI can synthesize patterns across multiple learners and suggest counterpoints that expand the range of conceptual resources available. Finally, in Active Experimentation, AI can track performance across trials to highlight incremental progress and signal readiness for greater complexity. For instance, AI could dynamically adjust stakeholder positions during negotiations in leadership development programs to generate dilemmas that force adaptation. Post-exercise, the system can provide feedback that highlights bias or creativity to accelerate the feedback cycle. Experiential Learning then evolves from a cyclical process into a data-enriched environment where learners are continuously challenged at the limits of their competence.

3.3 Enterprise Education

The focus of Enterprise Education is to develop behaviours and dispositions that prepare individuals to take initiative and act resourcefully, creatively, and responsibly (Gibb 2002; Enstroem 2018). It includes identifying opportunities, reframing problems, mobilizing available resources, and pursuing solutions. The method encourages initiative, experimentation, and reflective judgment. In doing so, it develops professionals who can translate ideas into actionable improvements (Enstroem and Benson 2024; Pittaway and Edwards 2012). Unlike training that stresses technical proficiency, the goal of Enterprise Education is to instill a mindset of curiosity, persistence, and calculated risk-taking that can be applied across organizational settings. Participants develop the capacity to scan environments for emerging signals, experiment in low-risk ways, and align initiatives

with stakeholder expectations. This opportunity recognition and responsibility blend makes Enterprise Education a sound pedagogy for organizational sustainability.

Artificial intelligence can augment Enterprise Education by creating environments where experimentation and calculated risk-taking are safe and scalable. AI-enabled simulators allow learners to test strategies in low-risk conditions while observing financial, operational, and stakeholder implications. Predictive analytics can be embedded in training to model changing market dynamics or regulatory changes and help participants anticipate otherwise overlooked scenarios. Generative AI tools can support creative recombination by suggesting novel configurations of resources. At the same time, adaptive AI mentors can surface blind spots in reasoning and provide real-time feedback tailored to the learner's stage. Practical applications exist in accelerators, where AI evaluates proposals and gives feedback. In established firms, similar systems encourage intrapreneurship by permitting employees to trial new ideas before committing significant resources (Roberts and Candi 2024). In each case, AI augments Enterprise Education's reflective and experimental orientation.

3.4 Experiential Mastery Learning

Experiential Mastery Learning integrates and extends established experiential approaches by structuring development around calibrated progression through cycles of increasing difficulty (Benson and Enstroem 2025). It draws on the reflective cycle of Experiential Learning, the problem-centred collaboration of Action Learning, and the opportunity orientation of Enterprise Education, while adding mastery learning so that competence is consolidated before advancement. Unlike conventional models that assume linear acquisition, Experiential Mastery Learning requires evidence of proficiency before proceeding to the next level. This approach responds to the organizational need for transferable capabilities, which cannot be reliably developed through brief interventions or generic modules. Figure 2 illustrates this integration by showing how the three

foundational models align under the augmentation of artificial intelligence and converge into Experiential Mastery Learning.

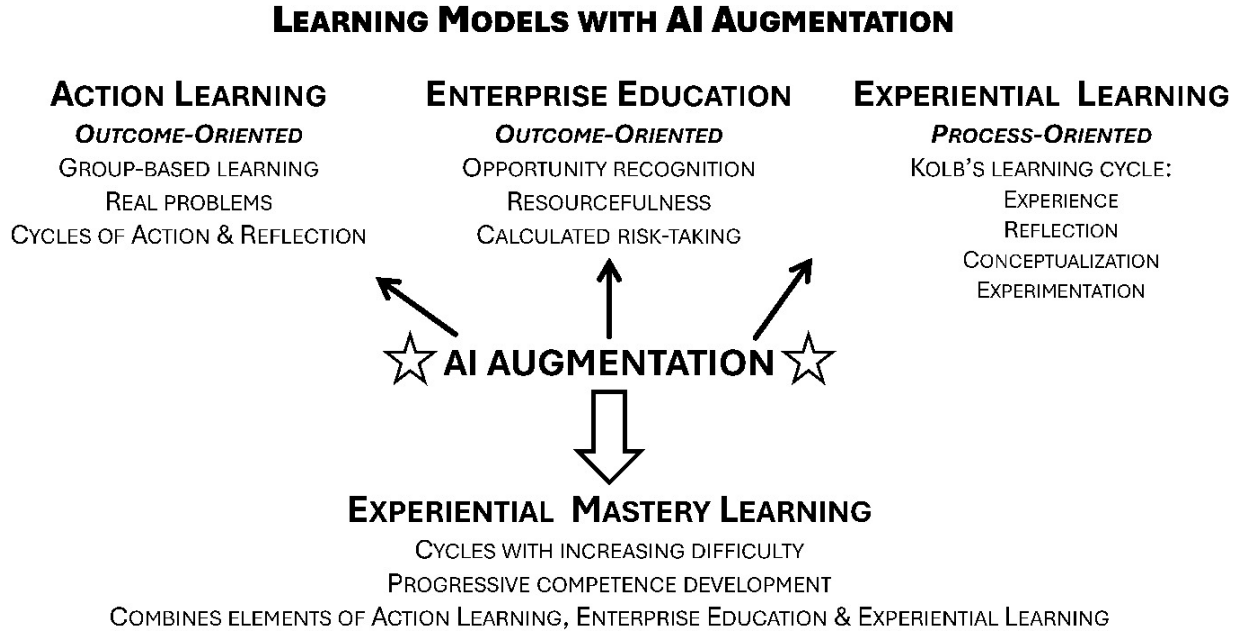


Fig. 2 Learning models with AI augmentation. Source: author

Artificial intelligence makes Experiential Mastery Learning feasible and scalable by monitoring performance, analyzing process indicators, and providing adaptive feedback that signals when a learner or team is ready for greater complexity. At the individual level, AI can personalize learning trajectories and calibrate challenges to developmental needs. At the collective level, it identifies when groups have built collaborative capacity to progress. Figure 3 depicts this progression logic, representing mastery as nested cycles in which learners advance from simple to increasingly complex challenges. Because learners must demonstrate proficiency at each stage before progressing, coping strategies are consolidated and strengthened to make them enduring capabilities.

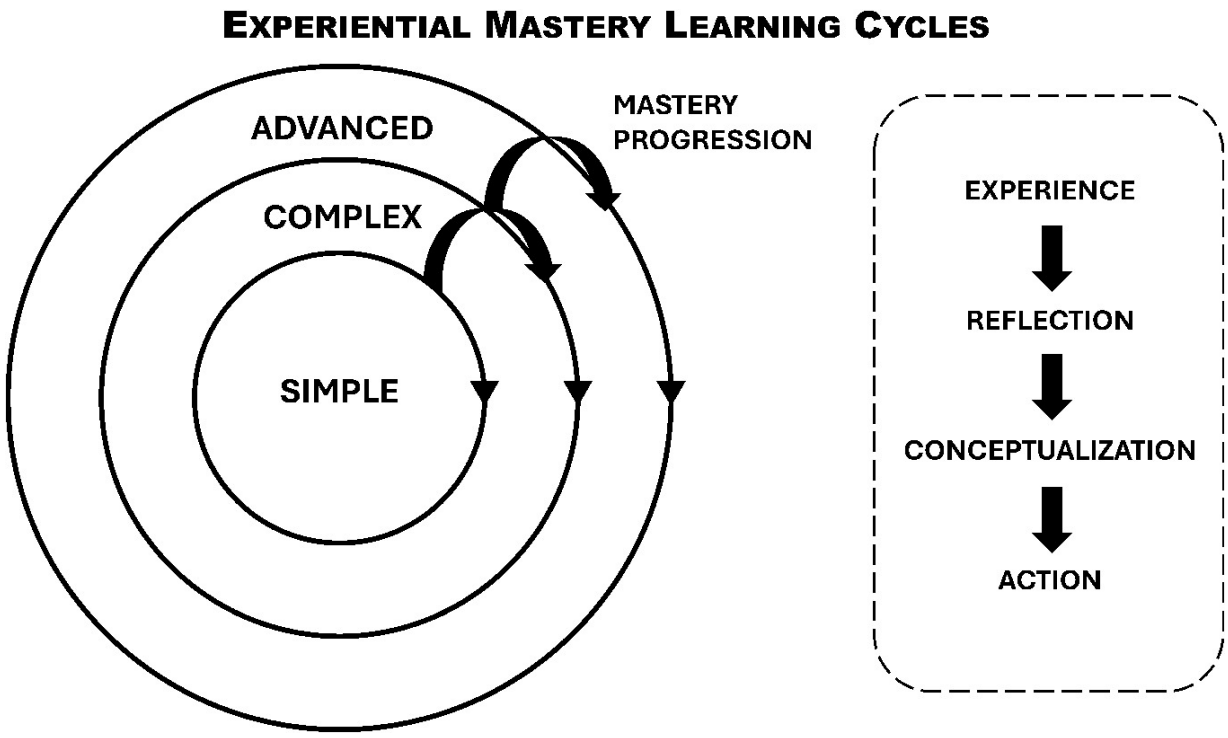


Fig. 3 Experiential mastery learning cycles. *Source* Author

3.5 AI Augmentation of Traditional Learning Models

The learning models discussed in this section illustrate pathways for developing capabilities and behaviours that underpin organizational sustainability. Despite their differences, they converge on learning through experience, reflection, and application. Each model brings distinct strengths: Action Learning cultivates collaboration and problem-solving, Experiential Learning reinforces adaptability and reflection, Enterprise Education stresses innovation and opportunity orientation, and Experiential Mastery Learning ensures calibrated progression. Together, they form a portfolio of approaches that can develop the transversal capabilities that sustain organizational viability.

These models also face shared limitations. They are resource-intensive, requiring time, commitment, and skilled facilitation. Scaling them across large or geographically dispersed organizations is challenging, and feedback can lack reliability and reflect the quality of observation and reflection instead of evidence of competence. Progression can also default to time spent instead of true capability

demonstrated. These constraints matter because they limit the extent to which experiential learning can be relied on to build capabilities across an entire workforce. Without augmentation, the strengths of these models may be confined to smaller groups rather than embedded in organizational practice.

AI addresses many of these limitations by providing precision, scalability, and integration. AI can monitor learning processes in real time, generate adaptive feedback, and ensure progression based on demonstrated mastery. It enables personalization at scale while consolidating group insights into shared knowledge systems. In this way, AI allows extending experiential models from discrete programs to system-level architectures for T&D.

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4 Designing AI-Augmented T&D for Organizational Sustainability

4.1 From Learning Models to System Architecture

Action Learning, Experiential Learning, Enterprise Education, and Experiential Mastery Learning show how capabilities and behaviours develop through cycles of practice, reflection, and calibrated progression. To advance organizational sustainability, these approaches should be situated in architectures that link individual development to collective outcomes. An effective design aligns several components: At the top are organizational outcomes such as innovation, stakeholder integration, strategic agility, and value-based governance, which define training objectives. Competency frameworks translate these outcomes into observable indicators of mastery. Learning scenarios then provide the environments where capabilities are exercised and tested. The AI augmentation monitors progress, adapts the sequencing, and generates feedback. Governance arrangements establish rules for data use, evaluation, and accountability. The strength of such systems lies in the feedback loops that connect these layers. Evidence of competence gathered during training feeds into program refinement and

organizational choices about resource allocation, leadership development, and capability priorities.

The architecture of AI-augmented training should be determined by a set of principles that reflect practical tensions. Alignment is central; learning activities must connect back to the outcomes an organization defines as critical for sustainability, such as innovation capacity or stakeholder responsiveness. Without this anchoring, training risks producing engaging activity that is disconnected from strategic objectives. A second principle concerns progression through demonstrated mastery. Advancement should depend on evidence of competence rather than time spent or material covered, which ensures that learning outcomes accumulate durably. This principle draws on the logic of Experiential Mastery Learning (Benson and Enstroem 2025) but extends it to systems design.

Continuous feedback is a central design principle. While AI systems can generate timely data on learner performance and group dynamics, these outputs require interpretation to be meaningful. Facilitators and coaches play a crucial role in this process by contextualizing feedback and guiding reflection. Human oversight protects the credibility of the process while AI enhances the precision. System integrity, in turn, depends on the transparency, fairness, interoperability, and proportional data use. These elements are vital, as unclear assessment criteria, biased content, or excessive monitoring could undermine trust and reduce engagement.

4.2 Evidence, Evaluation, and Implementation

Evidence is central to determining whether AI-augmented training contributes to organizational sustainability. Conventional metrics, including attendance, completion rates, or learner satisfaction, provide little insight into developing meaningful capabilities. A more valid approach should focus on indicators aligned with the organization's sustainability outcomes: innovation capacity, stakeholder integration, strategic agility, and value-based governance. These outcomes can be translated into observable behaviours and levels of mastery through

competency frameworks. AI can support this process by generating continuous records of learner decisions, reflection patterns, and responses to complex scenarios. However, human judgment needs to validate this data to distinguish between superficial performance and genuine competence.

Evaluation also needs to connect individual progress with collective outcomes. At the team level, indicators could include participation distribution, collaboration quality, and the ability to integrate diverse perspectives. At the organizational level, evaluation may consider leading resilience measures, such as responsiveness to stakeholders or the capacity to reconfigure strategy under uncertainty. Linking these levels creates a line of sight from micro-level development to macro-level outcomes. Credible designs include pre–post comparisons, pilot-to-scale transitions, and implementation strategies that build evidence without overstating causal claims. Attention to unintended consequences is equally important, since AI systems may privilege easily quantifiable outcomes or reduce opportunities for human judgment. Monitoring for such effects ensures that the evaluation functions as a safeguard and measure of progress.

Implementation benefits from being treated as a learning process itself. A sequenced pathway could begin with a discovery phase in which organizations clarify which capabilities and behaviours matter most for sustainability and translate these into rubrics. This stage also addresses governance by setting rules for privacy, proportionality, and oversight. The pilot phase should then evaluate the feasibility in a contained setting to provide early insight into how learners and facilitators respond to AI augmentation. Once the pilot testing has established reliability and acceptance, scaling can proceed gradually to expand the range of scenarios and build facilitator capacity to interpret AI outputs. By approaching evidence, evaluation, and implementation as interdependent elements, organizations can construct training systems that are cumulative, transparent, and responsive to learner needs and strategic priorities.

Figure 4 illustrates the architecture of AI-augmented training and development. Through experiential learning cycles, it links the learner and organizational context to individual capability and behaviour. Competence sensing, adaptive feedback, and scenario escalation connect learner profiles and organizational priorities with the progression of learning tasks. The outcomes include systemic thinking and moral character, expressed in behaviours that support agility, learning capacity, and value-based governance. The figure also reinforces that effective design rests on three forms of alignment: coherence with established experiential models, infrastructural capacity for real-time data and modular content, and clarity about how individual development contributes to organizational outcomes.

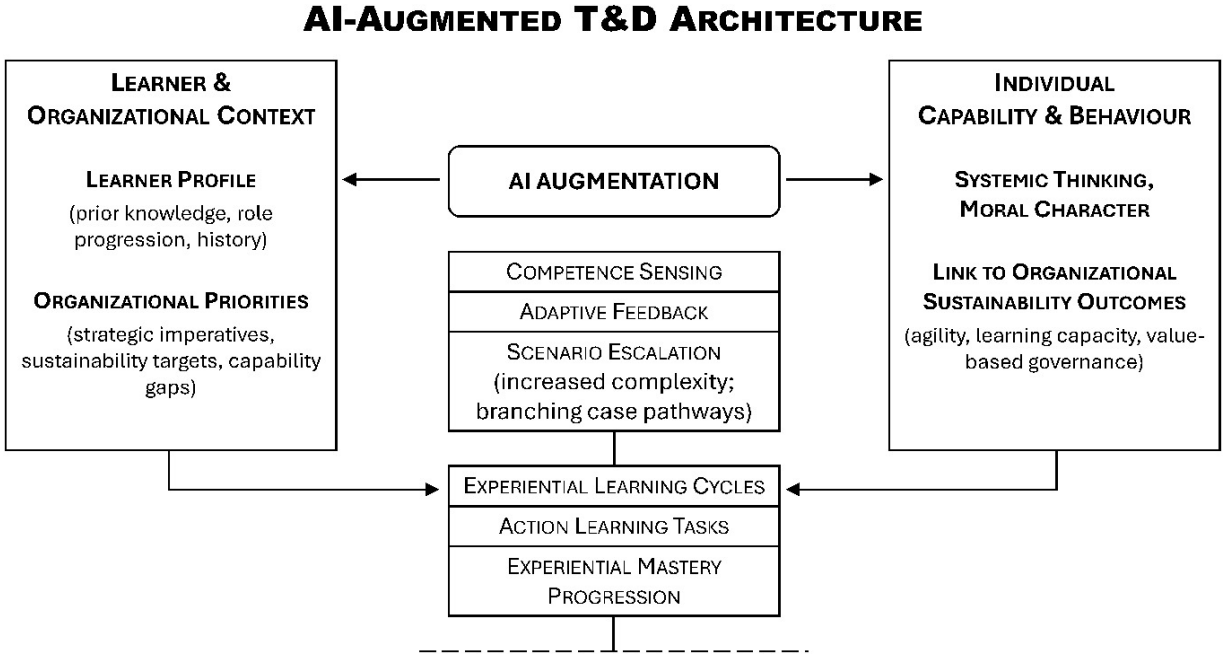


Fig. 4 Architecture of an AI-augmented T&D system for capability and behaviour development. *Source* Author

5 Learning in the Flow of Work

Training interventions are often designed as bounded experiences in classrooms, workshops, or digital simulations (Marsick and Fassler 2015). These settings are valuable because they create structure, safety,

and the possibility of deliberate practice without immediate organizational consequences. For instance, simulation is useful for escalating complexity in controlled conditions and allowing learners to develop judgment under uncertainty. Such interventions are indispensable for building new capabilities (Salas et al. 2009). However, it is in the routines of everyday work that organizational resilience is required. Research on organizational learning, from Argyris and Schön's studies of double-loop learning (Argyris and Schön 1978) to Lave and Wenger's analyses of situated practice (Lave and Wenger 2009), consistently stresses that reflection, adaptation, and knowledge-sharing are properties of organizational life. This perspective highlights that the line between working and learning is often porous, as daily activities create opportunities for performance and development.

Artificial intelligence can embed learning support directly into the flow of work. Digital coaching systems can provide real-time prompts, highlight blind spots, or suggest alternative perspectives as individuals and teams complete their tasks. Meeting analytics can identify imbalances in participation, decision-support tools can draw attention to underrepresented stakeholder concerns, and reflective companions can encourage review after project milestones. These interventions create conditions that make learning more continuous and embedded in daily work. They also make more feasible the aspiration, long present in organizational learning theory, of integrating reflection and adjustment into daily practice at scale.

The complementarity between simulation and embedded learning is important. Simulations provide opportunities for experimentation and deliberate practice, while embedded systems sustain developmental momentum once learners return to their roles. Together, they can create a continuum in which learning does not conclude with the end of a course but continues in the cadence of daily work. This continuum also extends leadership development to questions of character. Research on virtue in business suggests that sustainable organizations depend on the development of integrity, humility, and moral presence (López González et al. 2024). AI can play a

supporting role by surfacing considerations in decision-making and by helping learners connect actions to aggregate purposes. Although such augmentation cannot replace the social and relational processes through which character is formed, it can create conditions where moral reflection and flourishing become visible elements of organizational practice.

Figure 5 presents the continuum between simulated environments and embedded practice. Simulations provide structured, safe-to-fail conditions where complexity can be escalated and skills consolidated through deliberate practice. Embedded practice situates learning in daily routines, supported by real-time prompts, reflective aids, and AI coaching that strengthen awareness and adaptation. The figure highlights their complementarity; developmental progress is reinforced when structured practice and everyday reflection are linked through transitional practices.

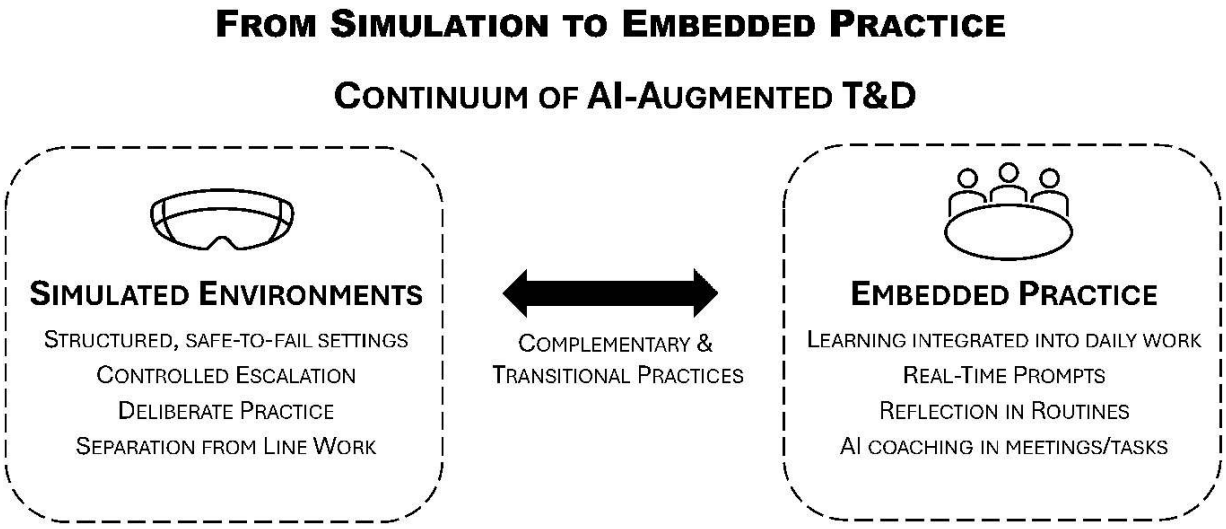


Fig. 5 Continuum of AI-augmented training and development. *Source* Author

6 An Integrated View of AI-Augmented T&D

The preceding discussion outlined practices that can inform the design and application of AI-augmented training. Pedagogically, using established experiential and action-oriented models is critical. Their integrity must be preserved, since their value lies in embedding

learning through cycles of experience, reflection, and calibrated progression. AI extends these models by providing more precise feedback, adaptive progression, and scalability. In doing so, it addresses long-standing challenges of resource intensity, uneven feedback, and limited reach. The essential task is to ensure that the use of AI strengthens rather than dilutes experiential learning principles.

Infrastructural considerations determine whether AI-augmented training works in practice. Effectiveness depends on modular content, interoperable systems, and reliable data flows that allow learning scenarios to escalate in complexity while being anchored in competency frameworks. AI services can then adapt, assess, and feed results back into the cycle. The emphasis should be on system reliability and integration with existing infrastructures. Effective AI-augmented training depends less on deploying cutting-edge features than on embedding technologies in stable, interoperable systems that can support continuous learning cycles. Respect for privacy and proportionality is part of this reliability to ensure that data is used in ways to protect trust while supporting continuous improvement.

The strategic level connects individual learning to organizational outcomes. Calibrated mastery only matters when it aggregates into improved innovation, stakeholder integration, agility, and value-based governance. Achieving these requires explicit mapping from outcomes to capabilities, and from capabilities to training scenarios and metrics. This explicit line of sight between training activities, capability development, and organizational outcomes ensures that learning data is strategically meaningful. Taken together, pedagogical coherence, infrastructural reliability, and strategic clarity position AI-augmented training as a system of alignment.

Finally, evaluation should be organized within an explicit measurement architecture. Classic models, i.e. Kirkpatrick's four levels and ROI-oriented extensions (see e.g. Enstroem 2026b), can structure evidence, but AI-augmented contexts call for behaviourally anchored, competency-linked indicators and, where feasible, validated psychometric scales to capture capability development (Enstroem

2026b). Triangulating continuous process data with pre–post assessments and periodic follow-ups preserves a linkage from individual learning to organizational outcomes, while meeting standards of reliability and validity.

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7 Conclusion

This chapter examined how artificial intelligence can augment business training and development with the objective of strengthening organizational sustainability. It defined sustainability in organizational terms to address how firms maintain viability under technological, economic, and institutional pressures. Capabilities such as systemic thinking, problem-solving, and decision-making, together with behaviours including collaboration, adaptability, and moral reasoning, were identified as microfoundations of resilience and long-term performance. The analysis was anchored in the Resource-Based View, a perspective that stresses the importance of durable and inimitable resources. It further incorporated insights from the neo-institutional tradition, where complexity is treated as the normal condition across time.

On this basis, the chapter reviewed Action Learning, Experiential Learning, Enterprise Education, and Experiential Mastery Learning as pedagogical approaches for developing capabilities and behaviours. It showed how AI can extend these models by personalizing progression, providing adaptive feedback, and monitoring collaborative dynamics. In doing so, it addresses limitations of scale, uneven facilitation, and resource intensity.

The analysis then advanced a design perspective. An architecture for AI-augmented training was outlined, consisting of outcomes, competency frameworks, scenarios, augmentation services, and governance. Design principles were distilled around alignment with organizational outcomes, progression by demonstrated mastery, continuous feedback with human interpretation, and safeguards of transparency and proportionality. Evidence, evaluation, and

implementation were presented as interdependent processes, supported by phased implementation and deployment and continuous refinement.

A further strand of development connected training with everyday practice. The discussion underscored the complementarity between simulation and embedded learning. It further illustrated how AI tools can sustain development in the flow of work through real-time prompts, reflective support, and digital coaching. This continuum extends the reach of traditional interventions and makes the aspiration of continuous learning more feasible. It also broadens the remit of leadership development to include character and moral presence.

These elements show that the value of AI in training and development lies less in automation than in alignment. When pedagogical coherence, infrastructural reliability, and strategic clarity are established, AI can strengthen experiential learning and support systems that are cumulative and transparent. Across the chapter, five figures illustrated how these arguments can be consolidated into a visual architecture. They demonstrated the progression from conceptual framing to design, practice, and integration. The chapter has outlined how such alignment can be designed and implemented. Finally, it shows how AI can help make long-standing aspirations in organizational learning—continuous reflection, situated development, and character formation—more feasible to realize at scale.



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Case Studies on AI Applications in Sustainability Teaching Across Environmental Science

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Abstract

Artificial intelligence (AI) is increasingly shaping the future of science education, offering powerful tools to support more inclusive, scalable, and sustainable teaching practices. In the context of environmental sciences, AI-driven platforms enable the development of intelligent, interactive learning environments that simulate complex ecological systems and fieldwork scenarios. This chapter investigates how such technologies—particularly virtual reality (VR) and gamification—can support the development of practical ecological skills, improve access and inclusion, and reduce the environmental footprint of field-based education. Framed by three guiding questions, the chapter covers (i) how immersive technologies can develop employability-relevant skills, (ii) address accessibility and sustainability challenges in fieldwork, and (iii) student and educator perceptions of use as pedagogical tools. Two case studies are presented: one exploring VR-based field training, and another focused on gamification for species conservation awareness.

Together, they highlight the transformative potential of AI in environmental science education—not only as a supplement to in-person learning, but as a sustainable alternative that aligns with the growing emphasis on digital skills, inclusion, and environmental responsibility. By integrating AI into field-based teaching, institutions can broaden access, personalise learning, and promote more sustainable research practices across disciplines.

Keywords Sustainability – Conservation technology – Fieldwork – Environmental sciences

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1 Introduction

Fieldwork has long been held as a defining feature of environmental science education and research. Its value lies not only in the tangible skills students and researchers gain—such as data collection, species identification, and spatial analysis—but also in the immersion it offers in real-world ecological systems. The tactile, embodied experience of observing environmental processes firsthand fosters a deep, often transformative, understanding of complexity, variability, and interdependence within the natural world (Chitty and Hesp 2024). Defined broadly as any educational activity requiring students to leave the classroom and engage in situated learning (Haigh and Gold 1993), fieldwork is integral to the teaching of biological, geographical, and environmental sciences, and is formally embedded in UK national

subject benchmark statements (QAA 2022). Despite its revered status, fieldwork as traditionally practiced faces significant and mounting challenges. These challenges are pedagogical, ethical, environmental, economic, and increasingly political. From the environmental cost of long-distance field courses to issues of accessibility and inclusion, the fieldwork model is under pressure to evolve. At the same time, a wave of technological innovation—most notably in artificial intelligence (AI) and virtual reality (VR)—is offering new tools that could support, supplement, or, in some cases, transform the way field-based learning is delivered.

1.1 The Centrality of Fieldwork and its Contradictions

There is little dispute over the value of fieldwork in environmental science curricula. Field experiences provide authentic, inquiry-led learning opportunities that develop core disciplinary competencies, critical thinking, and collaborative working. Indeed, fieldwork has been shown to enhance student satisfaction, retention, and learning outcomes across a range of science subjects (Payne 2017). Many educators argue that being physically present in the environment —"being there"—is irreplaceable, capturing not just data but also the subtle context and emotion of place (Pole and Hillyard 2016). Yet, these benefits are not experienced equally. Fieldwork as currently designed often excludes more students than it includes. Accessibility challenges —physical, financial, cognitive, and emotional—can disproportionately affect disabled students, neurodivergent individuals, women, and those from minoritised ethnic and socioeconomic backgrounds. For example, only 1.7% of environmental science students report a physical disability, compared with 13–15% of the UK's 15–24-year-old population (DWP Family Resources Survey; AdvanceHE 2023). The barriers are systemic, reflecting not only physical access issues but also a culture of ableism and narrow expectations around participation. The intersectionality of these barriers is especially concerning. Disability reporting rates are higher among women and minoritised ethnic groups, including Bangladeshi, Pakistani, and mixed-race students

(Gov.uk, HoC Library 2023). Yet these same groups are underrepresented in environmental science. Without deliberate interventions—both pedagogical and institutional—the discipline risks reproducing patterns of exclusion that conflict with its own goals of justice, sustainability, and global stewardship. In addition to equity concerns, traditional fieldwork carries a significant carbon footprint. International fieldtrips contribute to the very environmental degradation students are being trained to prevent. The rise of what Telford et al. (2024) term the "arms race of exotic fieldtrips" has seen universities increasingly package experiential learning as a competitive advantage in student recruitment. This is especially visible in postgraduate programmes that promise career-relevant, globally oriented experiences. While such courses may boost student enrolment, they often do so at an environmental cost that remains unexamined or poorly justified.

1.2 The Changing Landscape of Higher Education and Fieldwork

Compounding these challenges are shifts in student expectations, behaviours, and constraints. The impacts of the COVID-19 pandemic have been far-reaching: today's students are less field-confident, less experienced in outdoor contexts, and more attuned to mental health and wellbeing needs (Cramman et al. 2024). While the appetite for field experiences remains high, students now expect more information and support in advance, particularly regarding risk management, cultural differences, and environmental expectations. Many students report anxiety about unfamiliar spaces, and there is an increasing demand for reasonable adjustments as standard practice rather than exceptional accommodation (Mawdsley and Bracken 2022). Financial pressures, too, are reshaping student engagement. The rising cost of living, compounded by tuition fees, has made fieldwork—especially residential or international trips—financially inaccessible for many (Education Policy Institute and Advance HE 2023; Jacques-Talbot et al. 2023). Students are increasingly working part-time jobs, leaving less

time for extracurricular learning or unpaid placements. Moreover, in a saturated and competitive employment market, students are prioritising programmes and modules that offer clear pathways to employability. In an unpublished 2024 survey of MSc Wildlife Conservation students at Liverpool John Moores University, 100% of respondents cited employability as their primary reason for programme selection. Despite this, fieldwork remains closely linked with employability in environmental and conservation careers, where practical field skills, spatial literacy, and ecological awareness are often viewed as essential. Yet, the pedagogical models we use to teach these skills have not always kept pace with the changing context of higher education. In some cases, fieldwork is still demonstrative rather than participatory, lacking imagination and failing to foster creativity or critical engagement. Staff, too, face mounting pressures. Organising fieldwork requires navigating complex bureaucracies, rising risk management protocols, and ever-tightening institutional regulations. Many educators feel that the burden of inclusion falls disproportionately on individual staff, rather than being institutionally supported. This raises the question: where should responsibility lie for ensuring that fieldwork is safe, inclusive, and pedagogically meaningful?

1.3 Rethinking the Field: Enter AI and VR

In this shifting context, AI and related digital tools are emerging not as replacements for fieldwork, but as transformative complements. VR-based fieldwork, for instance, is gaining traction as a method for immersing students in remote or otherwise inaccessible environments. Defined as a digital resource enabling users to visualise and interrogate a location through immersive imagery, maps, datasets, and scholarly materials (Hurst 1998; Stainfield et al. 2000; Klemm and Tuthill 2003), VR fieldwork offers a pedagogical bridge between classroom learning and real-world application. The “3E Framework” (Enhance, Extend, Empower) provides a useful conceptual model for understanding how technology can be meaningfully embedded into curricula. VR and AI

applications can enhance traditional learning by increasing engagement and active participation; extend learning by simulating complex environments and datasets; and empower students by developing professional-level skills relevant to contemporary environmental practice.

More importantly, these tools offer a response to the sustainability and inclusion crises facing fieldwork. A well-designed VR module can offer low-carbon alternatives to international travel while maintaining learning outcomes. For example, one study did a comparison of 10-day physical vs virtual field trips and showed that the virtual version produced < 1% of the CO_2 emissions of the physical trip, yet students reported generally comparable perceptions of learning outcomes across both modes (Kilburn and Barnett 2024). It can also expand access to students who might otherwise be excluded, whether due to disability, financial hardship, or geographic location. Neurodivergent students, for example, may benefit from pre-immersive exposure to field sites, helping to reduce anxiety and support gradual acclimatisation (e.g. Santos et al. 2023; Carlina et al. 2023; Creed et al. 2024). AI systems can further support this vision by enabling adaptive learning environments that respond to individual student needs. AI can generate personalised feedback, simulate ecological systems under various scenarios, and even use natural language processing to guide students through complex field-based tasks. These features can improve student preparedness, autonomy, and reflective capacity—addressing many of the concerns staff raised around declining student resilience and engagement post-COVID.

1.4 From Techno-Optimism to Pedagogical Transformation

Technology alone cannot fix systemic problems in education or society. Nor should VR be seen as a full substitute for the embodied, affective dimensions of in-person fieldwork. Rather, the value of AI and VR lies in their potential to diversify pedagogical strategies, enabling educators to tailor learning in ways that are environmentally responsible, socially inclusive, and intellectually rigorous (e.g. Leal Filho et al. 2025). AI can

also help bridge the gap between academia and the workforce by equipping students with the "green skills" increasingly demanded in environmental sectors. These include systems thinking, spatial analysis, digital literacy, and an understanding of ecological modelling and scenario planning (e.g. Fuchs 2024). Initiatives like Biodiversity Net Gain (BNG) and other policy-driven frameworks highlight the need for graduates who are comfortable working with both data and the environment. AI-infused field learning supports the development of such hybrid skillsets. However, this requires more than technological adoption. It calls for a pedagogical shift—from viewing technology as an optional add-on to integrating it as a core part of environmental science training. This shift must be supported at all levels: by institutions that invest in infrastructure and training; by curriculum designers who rethink learning outcomes; and by educators who are willing to experiment with new forms of field engagement. It also requires confronting the contradictions of our current system. For example, how can universities advocate for sustainability while encouraging air travel as part of standard pedagogy? How can fieldwork be made compulsory without also making it inclusive? And how can we ensure that students leave university not only with technical skills but also with a sense of justice, stewardship, and planetary responsibility?

Environmental science education stands at a crossroads. The field must retain the richness of *in-situ* learning while addressing the ecological, social, and pedagogical shortcomings of traditional fieldwork models. AI and VR technologies, used wisely, offer powerful tools for this task (Fig. 1). They can lower carbon emissions, reduce barriers to participation, and foster the professional skills students need in a rapidly changing world. These innovations also support key Sustainable Development Goals (SDGs) (Leal Filho et al. 2025). However, the goal should not be merely to digitise or replicate existing fieldwork practices. Rather, it should be to reimagine them—to envision a field pedagogy that is dynamic, inclusive, and future-focused. One that acknowledges both the value and the limitations of physical presence

and embraces the full spectrum of human and technological capacities for engaging with the natural world. AI presents a way to rethink how we teach, who we teach, and what kind of world we are preparing students to help shape.

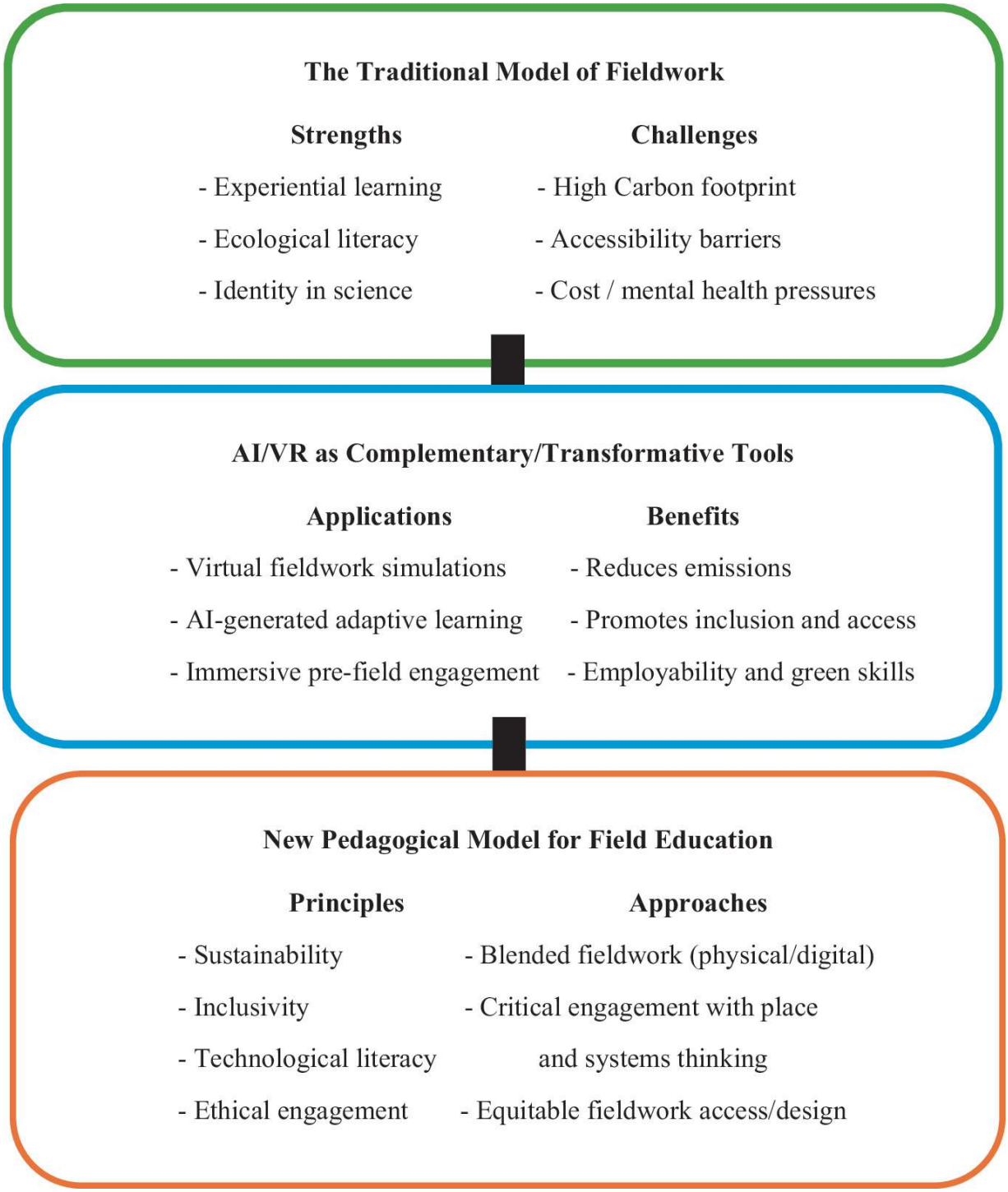


Fig. 1 Rethinking fieldwork through the integration of AI and VR technologies, addressing key challenges in sustainability, equity, and employability. The model proposes a shift from traditional, exclusive models of field education toward a blended, inclusive, and low-carbon pedagogy

1.5 Research Questions

This chapter presents two illustrative case studies that explore the use of emerging digital technologies—specifically virtual reality (VR) and gamification—as alternative or complementary approaches to traditional fieldwork. The first case study investigates the design and implementation of a VR-based fieldwork experience aimed at developing core practical ecological skills. The second case study focuses on the use of gamification to raise awareness of UK species conservation priorities. Both interventions were developed and evaluated within higher education settings and are grounded in participatory pedagogical design. Through these cases, the chapter explores how technological innovation can address long-standing issues of inclusion, access, and sustainability in environmental science education. It aims to address the following questions:

1. How can digital technologies such as VR and gamification support the development of practical ecological skills in higher education?
2. In what ways can immersive and game-based learning interventions address issues of accessibility, inclusion, and sustainability in field-based environmental science education?
3. What are students' and educators' perceptions of the effectiveness, limitations, and future potential of these technologies as complements to traditional fieldwork?

These questions aim to interrogate not only the pedagogical outcomes of each intervention, but also their broader methodological and institutional implications in a time of shifting educational, environmental, and technological landscapes. Methodologically, the chapter draws on a combination of qualitative data, including student feedback and reflective accounts, as well as design-based research

principles that foreground iterative development and contextual responsiveness. These approaches allow for a nuanced understanding of the pedagogical affordances and limitations of immersive technologies in field-based education. The implications of these case studies—for curriculum design, equity, and environmental responsibility—are critically analysed in the concluding section.

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2 First Case Study: Nature Lab

Ecological education programs traditionally emphasise hands-on skills critical for employment and research, including species identification, survey methodology, and data management. For wildlife conservation graduates, proficiency in such practical skills is a core employability criterion, reflecting their ability to contribute effectively to biodiversity monitoring and conservation projects. However, recent trends show a worrying decline in sustained field exposure due to condensed curricula and resource limitations, exacerbated by disruptions such as the COVID-19 pandemic (Crawford and Cifuentes-Faura, 2022). This scenario underlines the need for innovative pedagogical approaches that blend the strengths of in-situ learning with technological enhancements. By simulating real-world ecosystems, VR offers a controlled environment where students can repeatedly practice and refine skills without the constraints of weather, terrain, or logistics. The following case study investigates how virtual reality (VR) can support the development of core ecological competencies, principally species identification, through a simulated bird monitoring exercise. This directly addresses Research Question 1, while also contributing insights into the perceived effectiveness and accessibility of immersive fieldwork alternatives (RQs 2 and 3).

2.1 Methodological Approach and Findings

The study centred on a classic ecological task—conducting bird point count surveys—to evaluate three intended learning outcomes defined by the module leader (ILOs):

1. Apply practical survey skills: Accurately perform point count surveys with reliable species identification and abundance estimation.
2. Demonstrate observational skills: Utilise visual and auditory cues to identify bird species and document behavioural observations.
3. Practice data recording and management: Systematically log survey data according to standardised protocols.

Students enrolled in BSc Wildlife Conservation, Zoology, and Animal Behaviour programmes at Liverpool John Moores University completed the survey in two distinct environments:

- In-person fieldwork: Conducted along a 2 km transect at a local nature reserve, with five designated survey points. Students recorded all bird species heard or seen during 5-min intervals at each site, including counts and behavioural notes.
- Virtual fieldwork (Nature Lab): VR simulation recreated the same transect and survey points using 360-degree imagery and embedded real-world bird audio recordings. Students explored the virtual space, performing surveys with identical protocols.

Auditory and visual detections were categorised as: Visual-only, Sound-only, or Both combined. Student species identification performance was assessed by the number of correct species detections in each setting. Complementing quantitative analysis, a feedback survey captured student reflections on confidence, enjoyment, and perceived educational value of both field and virtual experiences.

In response to RQ1, results demonstrated no significant difference in overall species identification performance between in-person and VR surveys. Students utilised combined visual and auditory cues most frequently in the field (43%), with a slightly more balanced sensory distribution in VR (combined 36%, sound-only 35%, visual-only 29%). Statistical tests confirmed similar detection patterns across both methods, supporting VR's validity as a sensory-rich learning

environment that supports the development of ecological skills such as bird ID.

Addressing RQ2, student feedback emphasised the accessibility benefits of the VR experience. Participants highlighted the usefulness of Nature Lab for preparing in advance of field trips and unanimously endorsed VR as a complementary teaching tool. Several comments noted VR's potential to lower physical and financial barriers to participation, especially for students with limited field experience or mobility constraints. Environmental concerns were also raised, with students recognising the reduced carbon footprint of virtual fieldwork compared to traditional residential trips.

Regarding RQ3, perceptions of VR were largely positive. While more students reported greater confidence in species identification during in-person surveys, enjoyment levels remained high across both formats (mean enjoyment scores: 9.4 in-field, 8.6 in VR). Students appreciated the flexibility of VR as a training tool and highlighted the potential for tailoring environments to specific learning objectives. They viewed both modes of delivery as valuable but complementary, with in-person fieldwork offering situational realism, and VR providing repeatability, safety, and accessibility. Feedback also revealed a strong appetite for continued integration of immersive technologies into curricula, particularly in preparatory or skills-based modules (Table 1).

Table 1 Student rankings for skills and their importance for animal surveys, with 1 = most important and 10 = least important, in both field and virtual reality (VR) conditions. Colours indicate direction of change in ranking with green representing a positive change, red is a negative change, and blue is neutral

2.2 Implications for Sustainability and Pedagogy in Ecology Education

The findings align with broader calls to innovate field-based teaching to meet sustainability goals and educational equity (Dudok and Pigniczki-Kovács 2023). VR simulations like Nature Lab can effectively replicate critical ecological skills training, fulfilling key learning outcomes

without compromising educational quality. VR's potential to lower carbon emissions by reducing travel and resource use resonates with the Sustainable Development Goals (SDGs), particularly SDG 4 (Quality Education), SDG 10 (Reduced Inequalities), SDG 11 (Sustainable Cities and Communities), and SDG 13 (Climate Action). By making field experiences more accessible to students with diverse needs and backgrounds, VR supports inclusion while fostering sustainable practices in higher education. This pilot study's limited sample size warrants cautious interpretation. Furthermore, certain field skills—such as physical sampling or working under variable conditions—cannot yet be fully simulated. However, VR's capacity for repeated, safe, and feedback-rich practice offers distinct pedagogical advantages, including boosting student confidence and engagement through gamified elements (Vera-Morales et al. 2024; Aizprúa et al. 2023).

Looking forward, integrating VR alongside traditional fieldwork can create a blended model, enhancing resilience and adaptability in teaching. This hybrid approach aligns with emerging paradigms that reimagine field pedagogy as dynamic, inclusive, and future-focused—leveraging both human and technological strengths. Overall, this study supports VR fieldwork as a complementary, sustainable alternative for ecological skills training, capable of achieving core learning outcomes comparable to in-person experiences. Incorporating VR in curricula enriches student learning, expands access, and reduces environmental impacts—key components in educating future conservation professionals equipped to meet evolving global challenges.

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3 Second Case Study: Butterfly Gamified Simulations

The global biodiversity crisis has elevated the urgency for innovative conservation education strategies that can engage diverse audiences. Here is a case study on the use of AI-enhanced virtual fieldwork and gamified learning environments to teach ecological concepts and species identification, focusing on native UK butterflies. We are very

much aware of the conservation challenge of biodiversity decline (Pimm et al. 2014; IPBES 2019) and as such the demand for scalable and effective conservation education tools continues to grow. Butterflies, long recognised as ecological indicators, offer a visible and engaging entry point into broader ecosystem concepts. Yet even common species remain poorly recognised by the public. In the UK, the decline in butterfly abundance mirrors a broader disconnection from nature—a disconnect that hinders public support for conservation action. This case study explores the use of an AI-enhanced gamified learning platform designed to improve ecological understanding and species identification skills—specifically focused on native UK butterflies. Addressing RQ1, the activity touches on key competencies such as pattern recognition, habitat association, and taxonomic classification through interactive gameplay. In relation to RQ2, the gamified platform was designed for mobile and desktop use, making it accessible regardless of geographic location or physical ability. Addressing RQ3, the application of gamification aimed to promote student engagement and enjoyment.

3.1 Methodological Approach and Findings

This study explored how 360° virtual environments, populated with AI-integrated gamified elements, can promote species recognition and ecological knowledge retention. The target group included both novice learners and individuals with conservation experience, enabling us to assess the inclusivity and adaptability of the simulation. The simulation content was grounded in real field data from a UK woodland recognised for its butterfly diversity. The virtual environment allowed users to navigate through realistic digital representations of the habitat, with AI-enhanced interactivity enabling real-time engagement. Each butterfly species was represented as a clickable, movable object. When a user “caught” a butterfly by interacting with it, they received species-specific ecological information and visual cues (Fig. 2). AI algorithms tracked user behaviour in real-time, including time spent per species, selection order, and accuracy of identification tasks. A gamified scoring

system provided immediate feedback. Volunteer gamers were categorised into two groups: (i) C0 (non-conservationists)—participants with no formal or informal experience in conservation, or (ii) C1 (conservationists)—participants with academic, professional, or voluntary conservation backgrounds. Pre- and post-simulation assessments were administered online to measure changes in ecological knowledge and identification accuracy.

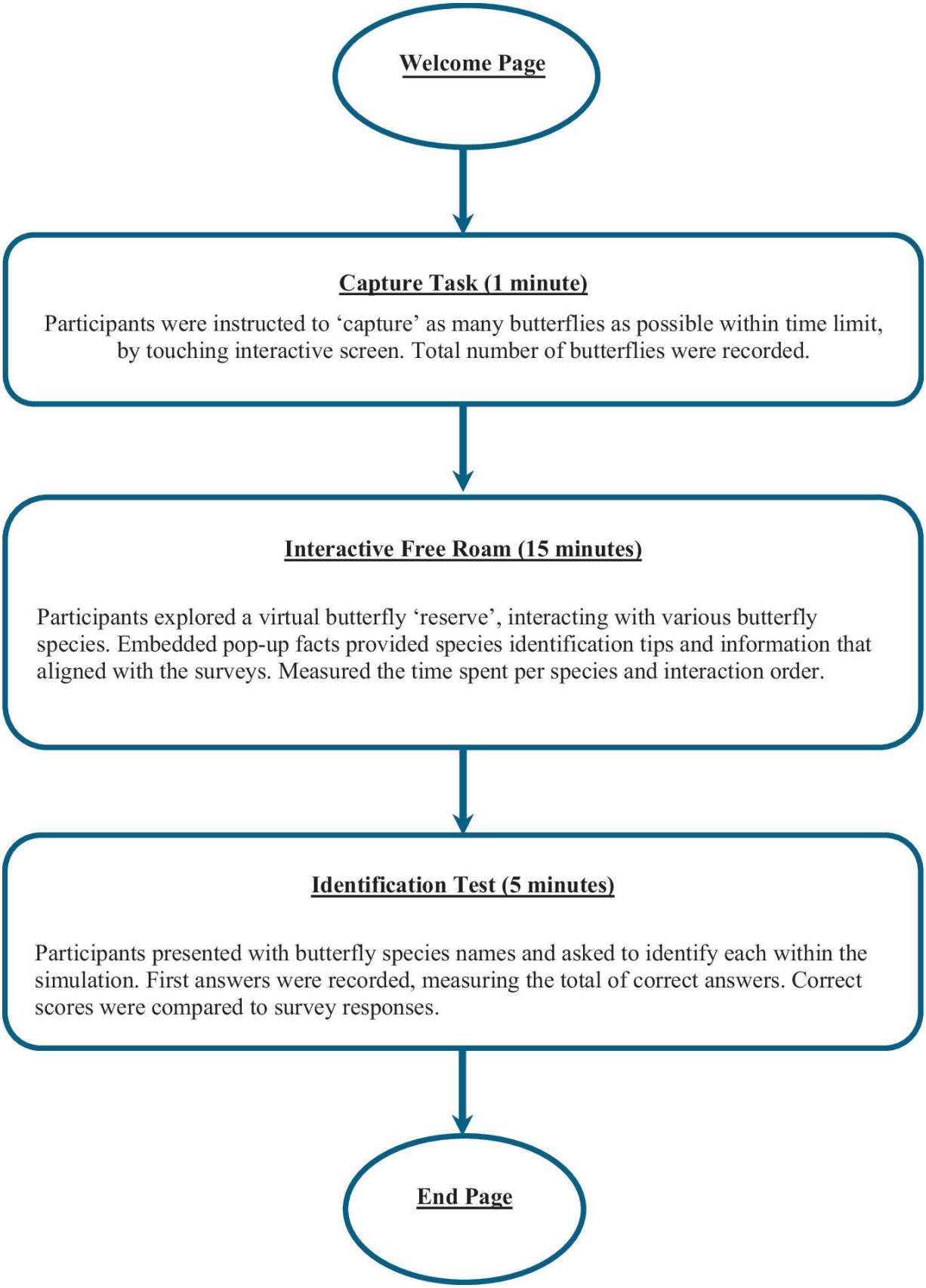

Welcome Page
Capture Task (1 minute)
Participants were instructed to 'capture' as many butterflies as possible within time limit, by touching interactive screen. Total number of butterflies were recorded.
Interactive Free Roam (15 minutes)
Participants explored a virtual butterfly 'reserve', interacting with various butterfly species. Embedded pop-up facts provided species identification tips and information that aligned with the surveys. Measured the time spent per species and interaction order.
Identification Test (5 minutes)
Participants presented with butterfly species names and asked to identify each within the simulation. First answers were recorded, measuring the total of correct answers. Correct scores were compared to survey responses.
End Page

Fig. 2 Flow diagram of the virtual butterfly experience

In the virtual simulation activity, participants in Group C0/non-conservationists outperformed those in Group C1/conservationist on the butterfly capture task, with significantly higher capture scores (C0 $\bar{x}$ = 59 vs. C1 $\bar{x}$ = 49; $p = 0.010$). Group C0 also spent more time freely exploring the virtual environment than Group C1 (C0 $\bar{x}$ = 360 s vs. C1 $\bar{x}$ = 274 s), but this difference was not statistically significant ($p = 0.077$).

In line with RQ1, the gamified simulation significantly improved participants' ecological knowledge and species identification skills, even though Group C1/conservationists scored significantly higher than Group C0/non-conservationists (C1 $\bar{x}$ = 9 vs. C0 $\bar{x}$ = 7; $p = 0.047$). Mean knowledge scores increased from 21 to 28 ($t = 7.36$, $p < 0.001$), and median species identification scores rose from 3.5 to 10, indicating strong gains in relevant field competencies. Retention was also high, with a significant learning effect observed across pre-, during-, and post-intervention phases ($\chi^2 = 28.21$, $p < 0.001$). Performance differences between groups also shed light on how different learner profiles engaged with the tool. Group C1/conservationists achieved significantly higher identification accuracy ($\bar{x}$ = 9 vs. 7, $p = 0.047$), while Group C0/non-conservationists performed better in the gamified capture task ($\bar{x}$ = 59 vs. 49, $p = 0.010$) and explored the virtual environment more extensively, though this was not statistically significant. These findings suggest that the tool supports both skill acquisition and exploratory learning across experience levels.

Addressing RQ2, the high performance and learning gains among non-conservationists indicate the potential of gamified digital tools to engage broader, less experienced audiences—supporting inclusion. Furthermore, 66.7% of Group C0 participants reported an intention to participate in future conservation activities, suggesting the simulation may serve as an entry point into conservation engagement. The platform's virtual nature also implies inherent benefits for scalability, low carbon delivery, and accessibility across diverse learner populations.

In relation to RQ3, although detailed perception data was not the focus of this analysis, participant behaviour indicates high levels of engagement, learning, and future intent. The strong performance and self-reported intent to engage in conservation signal the perceived relevance and effectiveness of the experience, particularly among novice learners.

3.2 Implications for Sustainability Education

This study demonstrates that AI-driven gamified simulations are not only feasible but highly effective for conservation education. By embedding ecological knowledge into a digital environment enhanced with real-time feedback and interactive species elements, the simulation encouraged both cognitive learning and emotional engagement (Zhang and Liu 2024). Key educational benefits include:

- Scalability: Virtual simulations remove geographic and logistical barriers, making field experiences more accessible.
- Customisation: AI can adapt difficulty levels or content based on user background or learning pace.
- Inclusivity: Novice participants engaged deeply with the material, suggesting strong potential for outreach to underrepresented audiences.
- Behavioural Intent: Gamification promoted not just knowledge, but also willingness to engage in future conservation activities.

This case study offers compelling evidence for the value of AI-augmented, gamified virtual fieldwork in conservation education. All learning outcomes were met as participants improved ecological knowledge, demonstrated species identification skills, and showed motivation to engage in future conservation activities—particularly among those with no prior experience. By merging immersive media, real-world ecological data, and AI-driven feedback, digital simulations can create powerful learning experiences that address the urgent need for public engagement with biodiversity. As conservation challenges intensify, education must evolve.

4 Discussion

Field-based teaching remains a cornerstone of environmental science education, offering immersive, place-based experiences that build ecological understanding, practical fieldcraft, and a sense of environmental stewardship. Yet the converging pressures of the climate and biodiversity crises, combined with increasing demands for inclusivity, accessibility, and educational equity, call for a radical reimagining of how fieldwork is designed and delivered in higher education. Central to this reimagining is the transformative potential of artificial intelligence (AI) and immersive digital technologies to support more sustainable, inclusive, and skills-oriented learning.

The two case studies presented in this chapter—the VR bird monitoring simulation and the AI-enhanced, gamified butterfly identification tool—demonstrate how such technologies can be effectively embedded into environmental curricula to meet evolving educational and industry demands. In the first case, the use of VR in a bird survey exercise allowed students to develop key ecological competencies, including species identification and sensory integration, within a low-carbon, accessible, and controlled virtual environment. Student performance and feedback indicated that virtual fieldwork could produce comparable learning outcomes to in-person experiences while also promoting sustainability awareness and confidence in field skills. In the second case study, a gamified virtual environment was used to teach butterfly species recognition and ecological concepts to conservation and non-conservation participants. The simulation not only improved species identification accuracy and ecological knowledge but also sparked interest in conservation among users with no prior engagement—suggesting strong potential for public-facing conservation education. These findings highlight how gamification and adaptive learning can engage diverse learners, tailor learning pathways, and build both cognitive and emotional connections with biodiversity.

Together, these case studies provide a compelling case for reimagining fieldwork through AI—not as a replacement for outdoor learning, but as a complementary mode that extends access, enhances

skill development, and aligns with the digital competencies increasingly required in environmental careers. Virtual field environments can serve as pre-trip preparation tools, risk-free rehearsal spaces, or alternatives where in-person fieldwork is not feasible due to financial, logistical, or accessibility constraints. AI-enabled platforms also allow for personalised, data-informed learning experiences that can adapt to individual needs, support Universal Design for Learning (UDL; Meyer et al. 2014), and offer meaningful alternatives to traditional, text-based assessment models. Importantly, these innovations also help institutions critically reassess long-standing assumptions about fieldwork destinations and delivery. AI and immersive tools can shift decisions away from legacy-based or resource-convenient models toward pedagogically driven, low-carbon, and locally relevant alternatives. This includes re-focusing fieldwork on regional conservation priorities, engaging students in community science, and integrating place-based challenges into virtual experiences. In doing so, digital fieldwork can foster deeper connections between students and the landscapes they are preparing to protect—while addressing the carbon footprint, cost burden, and accessibility gaps that have long plagued traditional field courses.

4.1 Limitations and Constraints

Building on the insights gained from the two case studies, several specific limitations and constraints became evident in practice. Both the VR bird monitoring and butterfly gamification interventions were conducted within controlled academic environments and involved relatively small participant cohorts, limiting their generalisability across broader contexts. While each case demonstrated clear potential for skill development, neither fully replicated the ecological complexity, unpredictability, or affective dimensions of in-person fieldwork. The sensory experience, spontaneous interactions with nature, and peer collaboration—hallmarks of traditional field learning—remain difficult to simulate digitally. Furthermore, the technological requirements for these interventions, including access to VR hardware and sufficient

digital infrastructure, may unintentionally introduce new barriers for students or institutions with limited resources. Although short-term learning outcomes were promising, the studies did not assess long-term skill retention or transferability to real-world conservation contexts. Finally, the successful adoption of such tools depends heavily on educator capacity and institutional support, so there is a broader need for structural investment in digital pedagogy within environmental science education.

Despite these limitations, digital and AI-enhanced approaches to field learning offer a powerful response to many of the constraints currently facing environmental education. AI can support risk management, streamline logistics, and provide just-in-time training resources for staff, reducing the hidden workload of fieldwork delivery. Generative tools can help educators design inclusive, skill-specific, and locally grounded field experiences, while simultaneously engaging students through adaptive, reflective, and scenario-based learning. Crucially, these technologies also help educators respond to the rise of eco-anxiety among students by equipping them with agency, employable competencies, and meaningful opportunities to engage with urgent environmental issues. Reimagining fieldwork through AI does not mean abandoning the field—it means expanding it. The future of field-based education lies in hybrid, flexible models that preserve the richness of in-situ learning while opening new pathways for access, inclusion, and innovation. By leveraging AI not just as a tool, but as a catalyst for pedagogical transformation, higher education can better prepare students to navigate and shape the complex socio-ecological systems they are entering as future professionals.

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5 Conclusion

In an age of planetary crisis and digital transformation, fieldwork must evolve. It must be reimagined not as a static tradition but as a dynamic, inclusive, and sustainability-driven pedagogical practice. Artificial intelligence and other digital tools present a unique opportunity to

redefine what counts as field experience, who can participate, and how learning is achieved. Environmental science educators are now called to embrace AI-enhanced models of teaching and field practice and prioritise local, applied, and socially relevant fieldwork. They must design environmental science curricula with universal accessibility and equity at the forefront that aligns with climate-resilient and low-carbon educational strategies; in addition to supporting student wellbeing, career aspirations, and environmental agency through meaningful, real-world engagement. The transformation of fieldwork is not just desirable—it is essential. As we confront a future of climate uncertainty, digital acceleration, and shifting student expectations, environmental science education must lead the way in modelling sustainable, ethical, and technologically empowered approaches to learning.



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Holding *Kankyo* Cafés with the Support and Participation of Generative Artificial Intelligence

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Abstract
The *Kankyo* (Environment) Café is a dialogue-based forum that fosters mutual understanding and empathy on environmental and social issues through shared learning between researchers and the public. Since 2015, over 200 Cafés have been held in Japan and abroad, including university campuses and public spaces, integrating perspectives from scientific research, the humanities, and daily life. Each Café explores the relationship between nature, society, and human life through themes such as biodiversity, symbiosis, and sustainability, often drawing on literary works like Rachel Carson's *Silent Spring* and *The Sense of Wonder*. During the COVID-19 pandemic, face-to-face meetings transitioned online, expanding accessibility and participation. Since 2022, the National Institute for Environmental Studies (NIES) has hosted regular online Cafés focusing on coexistence with nature, literature, and environmental ethics. In 2024, the Cafés introduced artificial intelligence (AI), particularly ChatGPT, as a participant and co-creator of dialogue content. Monthly online sessions were organized around three main themes: "Considering the Marine Plastics Problem," "Silent Spring and the Triple Planetary Crisis," and "Environmental

Education." AI contributed by generating discussion materials and suggesting keywords, while participants reflected on its potential role as an information provider and empathetic interlocutor. Post-session surveys indicated that AI facilitated learning and stimulated awareness of differences in perception, but also highlighted concerns about authenticity and interpretation. The study presents the Café's philosophy, methods, and outcomes as a model of participatory environmental education that bridges science, ethics, and culture. It emphasizes that dialogue—not debate—leads to "improvement of experience," enabling participants to transform knowledge into wisdom and empathy into cooperative action. The introduction of AI demonstrated new possibilities for inclusive, reflective communication on environmental issues, suggesting that human–AI collaboration can enhance environmental literacy and ethical awareness in the pursuit of sustainability.

Keywords Dialogue – Understanding – Empathy – Sustainability – *Silent spring*

Mitsuru Tada is a visiting research fellow in the Biodiversity Division at National Institute for Environmental Studies, Japan, and he is also a fellow member of UNESCO Inclusive Policy Lab. His research focuses on environmental communication by social dialogue between researchers and the public. Since 2015, he has regularly held *Kankyo* cafés concerned with environmental studies and issues in person and online.

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1 Introduction

The integration of Artificial Intelligence (AI) in teaching and research presents both opportunities and significant challenges. While AI tools can enhance productivity, creativity, and access to knowledge, they also raise concerns about academic integrity, bias, and the erosion of critical

thinking skills (Selwyn 2023). In teaching, overreliance on AI-generated materials may reduce students' engagement with authentic learning processes, while in research, questions about authorship, originality, and data ethics remain unresolved (van Dis et al. 2023). Moreover, AI systems often reproduce the biases embedded in their training data, which can perpetuate existing inequalities in education and academia (Bender et al. 2021). Addressing these issues requires not only technical solutions but also an ethical and pedagogical framework for responsible AI use in higher education and research communities (Floridi and Cowls 2022).

A *Kankyo* [environment] Café is a forum for discussion (dialogue) on environmental and social issues, where participants listen to each other's experiences (feelings, knowledge, thoughts) on an equal and fair basis. The aim of the dialogue is to deepen mutual understanding and promote empathy (taking issues personally) by enjoying the differences in what each person says and by "learning" and "thinking" together (Tada 2018a, b; Tada and Tomatsuri 2018; Tada and Tanaka 2020).

The authors have held *Kankyo* Cafés more than 200 times over the 10 years from April 2015 to March 2025—between once and three times a month. In 2015, *Kankyo* Cafés were held in public cafés, on campuses in Tokyo, Tsukuba, Yokohama, Kyoto, and at other locations. In 2016 they were held mainly on campuses (University of Tokyo, Kyoto University, Waseda University), and in 2017 they were again held mainly on campuses (University of Tokyo, Keio University, Kyushu University, Tsukuba University) (Tada 2018a, b; Tada 2019). In 2018–2019, in addition to the Cafés being held in public cafés and on campuses, we cooperated with students in holding them at universities overseas, including in the United States, the United Kingdom, and Russia.

A *Kankyo* Café incorporates knowledge from scientific research results, the humanities (literature) (Tada and Tomatsuri 2018), and lifestyle sensibilities. It is a place where people can think together about "being human" and "how to live" in terms of an understanding of the relationship (symbiosis, circulation, diversity) between nature,

society (the economy), and life (people) (Tada 2018a). Themes include symbiosis with nature, biodiversity, and sustainable development goals (SDGs). Literary discourses such as Rachel Carson's *Silent Spring* (1962) are also taken up, making the Café a "place of empathy" for thinking about environmental issues (Tada 2018a; Tada 2023).

As a result of the COVID-19 pandemic in 2020, these face-to-face events were switched to online events using a web conferencing system (Zoom) (Tada and Tanaka 2021). By using this online format, the University of Tokyo held a *Kanko* Café on the theme of environmental issues such as climate change at its 94th (Tada et al. 2022) and 95th May Festivals. In addition, the study group of the youth environmental NGO Climate Youth Japan (CYJ) held 21 student-led online *Kankyo* Cafés 9in 2021 and 22 in 2022 (Tada 2023; Tada et al. 2024a). In addition to the authors' personal efforts to date, the National Institute for Environmental Studies' Biodiversity Division (hereinafter referred to as NIES) has been hosting online *Kankyo* Cafés nine to 11 times a year since 2022, with themes of coexistence with nature, biodiversity, and literature such as Carson's *Silent Spring* and *The Sense of Wonder* (1965).

The United Nations Environment Programme (UNEP 2020) has identified climate change, biodiversity loss, and environmental pollution by hazardous chemicals—which Carson addressed in *Silent Spring*—as triple planetary crises. We have already reported on the holding of *Kankyo* Cafés on the themes of climate change (Tada et al. 2024a) and biodiversity (Tada et al. 2024b, c). Although the issue of plastics—known for their environmental pollution— was brought up by a student at the 94th May Festival (Tada et al. 2022), it has not been taken up as a theme in the NIES *Kankyo* Cafés. Marine plastics pollution, in particular, is linked to the loss of biodiversity, and marine debris and microplastics have a major impact on marine ecosystems.

In recent years, advances in artificial intelligence (AI) technology have led to the emergence of many new AI services, including ChatGPT. ChatGPT is a text-generative AI (hereafter referred to simply as AI) that generates content on the basis of text entered in a conversational

format. The authors thought that introducing AI to the *Kankyo* Café would lead to unprecedented understanding and empathy among participants. Therefore, Cafés sponsored by NIES were held online once a month from January to December 2024, with a series of themes, namely "Considering the Marine Plastics Problem" (four sessions), "R. Carson's *Silent Spring* and the Triple Planetary Crisis" (four sessions), and "Considering Environmental Education" (three sessions), each introducing AI. After each session, we conducted a survey regarding the introduction of AI and considered how it should be introduced in the future.

The *Kankyo Café* thus represents a new model of environmental communication that bridges scientific reasoning, humanistic inquiry, and technological mediation. By fostering empathy through dialogue—both human and AI-assisted—it provides a participatory platform for reexamining environmental education in the age of the *Triple Planetary Crisis*. This study reports on its philosophy, methodology, and outcomes, highlighting the transformative potential of AI-facilitated dialogue for sustainable, ethical, and empathetic engagement with environmental issues.

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2 Intervention Design and Integration of AI

Scientists must consider what kind of social role their research plays, as well as the social impact of the research. It is therefore necessary to reconsider science from a social perspective, and social dialogue is required for that purpose. The charter of NIES states that environmental research is "research based on a firm understanding of the interaction between nature, society, and life on our planet," and that an "understanding of the relationship between life (people), nature, and society (the economy)" is required in mutual interactions between researchers—with their expertise—and the public—with their knowledge of everyday life.

The practice of environmental dialogue through a *Kankyo* Café has members of the general public and researchers interacting with the

goal of fostering empathy among all participants, in addition to sharing and improving the general understanding of specialized knowledge (Tada 2018a). Generally, humans are selfish and self-centered, but they can be deeply interested in, and empathetic with, others. If a deeper relationship and sense of commonality of one person with another is gained through dialogue, it becomes easier to foster and strengthen empathy between them. This empathy then allows them to act in cooperation with other people.

The goal for participants (researchers and the public) in the Cafés is to gain "awareness" and "improvement of experience"—that is, "transformation by experience" or "enrichment through experience" (Fig. 1) by talking to each other—not only about knowledge, but also about their own experiences (feelings and thoughts) on a theme related to the environment (Tada 2018a). The purpose of the dialogues is not to discuss an issue and decide on a right or wrong (win or lose) position. Participants do not try intentionally to reach a conclusion. Rather, they go through a natural discovery process and gain awareness of each other as a topic or issue develops and their perspectives widen.

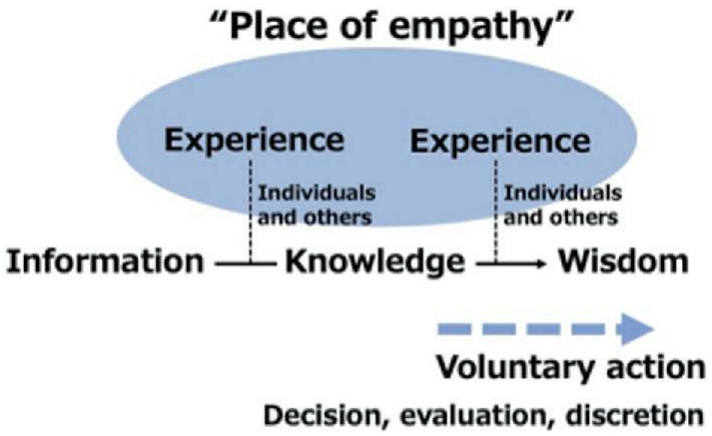


Fig. 1 Schematic diagram of improvement of experience (adapted from Tada 2018a, page:209)

In general, knowledge is gained by using vast amounts of information gathered personally through various media (e.g., newspapers, magazines, books) and websites. When a person gains additional experience by using such information and knowledge, this experience becomes wisdom. People can use not only information but

also wisdom to decide on voluntary actions to be taken with proper decision, evaluation, and discretion (Fig. 1). Through dialogue in which they can participate in the experiences of others by using their imagination, people can expand on their individual experiences by coming into contact with things that are not encountered in their normal daily lives (Tada 2018a).

The themes and keywords that have been frequently used since the first Café are presented in Table 1. In theme no. 1, we consider the basic perception of the environment and the relationship between scientific civilization and environmental issues. In theme no. 2, we deepen our understanding of environmental issues and aim to solve them from the perspective of science, technology, society or the social system, and humans, as well as to link them to ethical issues.

Table 1 Main seven main themes and keywords for *Kankyo* Cafés (adapted from Tada 2018a, page 210)

In theme no. 3, we clarify the relationship between natural symbiosis and biodiversity and ecosystem services, and in theme no. 4 our understanding of our sensitivity to nature is deepened and considered in the context of Rachel Carson's *Sense of Wonder* (Carson 1998; Tada 2011). In theme no. 5, participants examine our understanding of bioethics, human ethics, and environmental ethics on the basis of a discourse on Carson's *Silent Spring* (Carson 2000; Tada 2011).

In theme no. 6, we deepen our understanding of the relationship between the biosphere that supports society and the economy and sustainability in relation to the SDGs (Tada and Tanaka 2020). In theme no. 7, we organize the content of environmental research conducted by scientists on the basis of the relationships between life, nature, and society by using keywords such as symbiosis, circulation, and diversity, as well as the relationships between environmental science and environmental literature and environmental education.

Each participant writes words of interest in response to a “question” related to the theme on a large sticky note in person or in a chat box online and categorizes using a Venn diagram below. The words and types of each participant are aggregated as data and summarized in Table 2.

Table 2 Responses (keywords and category names) of participants in the 10th *Kankyo* Café and responses of AI. N, Nature; S, Society; L, Life. INC-5, fifth session of the intergovernmental negotiating committee under the United Nations environment programme

Cafés sponsored by NIES were held online once a month from January to December 2024, with a series of themes, namely “Considering the Marine Plastics Problem” (four sessions), “R. Carson’s Silent Spring and the Triple Planetary Crisis” (four sessions), and “Considering Environmental Education” (three sessions), each introducing AI. After each session, we conducted a survey regarding the introduction of AI and considered how it should be introduced in the future.For each Café, a date, time, place, and theme are selected. Seven main themes have been explored (Table 1), and the places selected for the Cafés are generally calm and quiet (university facilities or public cafés). Information is posted on social-networking sites such as Facebook and X to promote awareness of the *Kankyo* Café, along with the date, time, place, and theme. People who are interested in the environmental theme can then choose to participate (Tada 2018a).

The Cafés generally last for about 60–90 min in person or online. Each Café has about four to eight participants, including high school students and university students, graduate students, ordinary members of the public, or members of non-profit organizations. The process can be summarized as follows:

$$\text{Question} \rightarrow \text{Answer} \rightarrow (\text{grouping}) \rightarrow \text{Dialogue}.$$

At the beginning of the event, each participant writes words of interest in response to a “question” related to the theme on a large sticky note (about three to five notes per participant) in person or in a chat box

online. This is done to create opportunities for learning and thinking through the dialogue contributed by all participants. Depending on the theme, each word on the sticky note or in the chat box is categorized into two or three types (e.g., life, region, and Earth; nature, society, and culture; or nature, society, and life). A Venn diagram is then created visualizing the words, their types, and their relationships for grouping.

In addition, each person talks about their own experiences (feeling, knowing, thinking) in regard to the words (answers) in the dialogue. This leads to a common understanding of, and empathy for, the theme. Categorizing each person's words creates a new opportunity for dialogue; the participants' talking about their experiences can lead to new perceptions (i.e., the participants notice things differently) and thereby to "improvement of experience" (Fig. 1). In addition, topics are provided or expanded upon as necessary by using slides projected from a laptop computer and printed materials to deepen the participants' understanding.

AI contributed by generating discussion materials and suggesting keywords, while participants reflected on its potential role as an information provider and empathetic interlocutor. By fostering empathy through dialogue—both human and AI-assisted—it provides a participatory platform for reexamining environmental education in the age of the *Triple Planetary Crisis*. The introduction of AI demonstrated new possibilities for inclusive, reflective communication on environmental issues, suggesting that human–AI collaboration can enhance environmental literacy and ethical awareness in the pursuit of sustainability.

The online AI-based *Kankyo* Cafés described in this report were held by using AI (ChatGPT 3.5, 4o), which created some of the materials for the topic provision and generated "answers" (keywords and their types) to "Questions." At each meeting, a computer was prepared for the AI, and the AI participated together with one of the authors via Zoom under the name "KankyoAI."

At the end of each event, participants completed a questionnaire regarding their level of comprehension and the points that they had

understood, as well as about their “degree of empathy” and “points of empathy.” We also asked participants to fill out a Google form describing their opinions and thoughts about the introduction of AI. The results of the questionnaire were used as a reference for preparing materials for the next event.

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3 Results

Overall, participants learned together about “being human” and “how to live” from their understanding of the relationship between life (people), nature, and society (the economy) (Tada 2018a). They thought about the value of life in order to make better use of life through each theme.

3.1 Session Held Under the Theme of “Marine plastics issues— Their relationship with environmental education”

The 10th *Kankyo* Café for FY 2023 (14 April 2024) was held online by using AI with five participants. In the topic presentation, the question “What is the relationship between environmental education and the marine plastics problem?” was sent to the AI in advance, and the responses (see Appendix 1) were presented in a few slides at the event. The participating author referred to the Ministry of Education, Culture, Sports, Science and Technology’s website regarding Education for Sustainable Development (MEXT 2002) in relation to the keyword “sustainable” (3 in Appendix 1) among the AI responses. In relation to 3 in Appendix 1, “Promotion of sustainable lifestyles,” social and economic development that emphasizes “the value of life (making the best use of life)” from the perspective of consumers, rather than emphasizing economic value from the perspective of consumers, were considered by AI to lead to sustainability (Fig. 2).

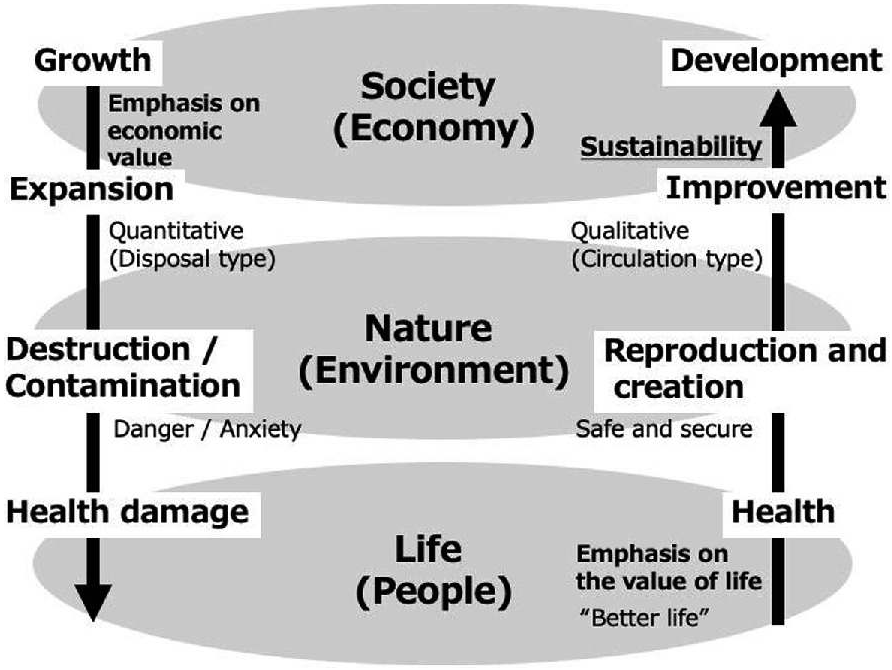


Fig. 2 Comparison of growth and development through connections between life (people) and nature (environment), and society (the economy)

Next, participants were asked, "After listening to the topic presentation, what are the keywords you are interested in?" By using a Venn diagram of their keywords and the keywords' types of "Nature (N)," "Society (S)," and "Life (L)," participants categorized (associated) their keywords and posted them in the Zoom chat (Table 2). The previously obtained responses of the AI ("AI" in Table 2) to the message, "List five keywords related to the relationship between environmental education and the marine plastics problem," were "awareness," "enlightenment," "behavioral change," "sustainability," and "next generation."

Among these keywords, we obtained AI responses (see Appendix 2) regarding "behavioral change," "sustainability," and "next generation" and their relationships with Nature, Society, and Life (Table 2). The keywords that AI selected, such as "behavioral change" and "next generation," were commonly known and representative. On the other hand, the keyword responses given by the participants were based on their personal experiences and included such responses as "words to

inform the younger generation" and "effective ways to communicate information about regulations" (Table 2).

Additionally, the percentage of participant-selected keywords that were associated with all three types (N, S, and L) was 20% for each theme (Table 2). In contrast, 100% of the keywords selected by AI were associated with all three types (Table 2). This is thought to be due to the fact that the amount of information held by the AI was vast compared with the amount of information held by individuals, even if the participants in the event were highly environmentally conscious. Finally, ChatGPT 3.5 explained that, as of October 2023, the information had been collected from the Internet up to 2021 and included the latest information on "Chemicals in plastics" (UNEP 2023).

In a survey conducted after the event, participants were asked to respond via a Google form to three questions: "What aspects of the event helped them to deepen their understanding?", "What aspects of the event were they able to empathize with?", and "What are your opinions and thoughts about the introduction of AI?" First, regarding the participants' ability to deepen their understanding at the event, the following responses were given: "There is a possibility of using AI in environmental awareness for consumers," "There are differences in the extent to which information can be scrutinized and collected depending on the person, and I felt that, as a result, there may be gaps in this area of the dialogue," and "We were able to discuss and reconsider the importance of sharing fundamental awareness regarding environmental education, as well as of our state of awareness and attitude toward the introduction of AI."

In regard to what the participants empathized with, their responses included, "Just as with generative AI, the information output differs depending on each person's possible background, and I felt that this resulted in differences in awareness of environmental problems and human rights protection today," and "I empathized with the importance of environmental education and appreciating the environment." Regarding the introduction of AI, responses included, "I felt that it was necessary for all participants to be aware of the position that AI has

been given (whether it was as an information provider or as a participant that could also provide opinions and impressions)," "I completely agree," and "I thought it would be good to introduce AI as a reference point, rather than making it the main focus."

Educators and researchers face the challenge of balancing AI's potential for personalized learning and research assistance with the risk of overreliance, misinformation, and loss of human judgment.

3.2 Session Held Under the Theme of "Thinking about Environmental Education 1. *Silent Spring* and Environmental Education"

On 13 October 2024, the 5th *Kankyo* Café for FY 2024 was held online with six participants by using the AI method. First, to have a dialogue with AI, we sent the following message to AI (ChatGPT 4o):

"Message 1: From now on, we intend to have a discussion at the dialogue event, *Kankyo* Café. The *Kankyo* Café is a dialogue event about environmental and social issues through public interaction that transcends the boundaries of specialty and occupation. The *Kankyo* Café is based not only on science (scientific knowledge and logic), but also on humanities such as humanities education (literature) and environmental ethics, so that experts (researchers) and the public can understand these issues together through the process of dialogue. The purpose is to empathize with an issue and to own it. Furthermore, participants will think together about "being human" and "how to live" from an understanding of the relationship between life (people), nature, and society (the economy)."

Next, to provide topics on the theme, we sent AI the question "Can you talk about the relationship between Carson's *Silent Spring* and environmental education?" We received the Appendix 3 response, which we showed to the participants. Furthermore, we sent AI the question "Can you talk about the relationship between *Silent Spring* and Japanese environmental education." We received the response in Appendix 4, which we showed to the participants. We then asked AI about the relationship between DDT in *Silent Spring* and environmental

education, and we provided the response (see Appendix 5) to the participants.

In a questionnaire survey conducted after the event, two participants answered, “I wonder how the topic of environmental education in the world can be summarized by using AI,” and “I found it difficult to understand the answers given by the AI just by reading them.” In addition, some people said they could relate to the book, referring to “how they could read *Silent Spring* without giving up hope” and “the power of literature.” Regarding the use of AI, responses included, “It’s an interesting read, and I’d like to think of other words supplied by humans, not AI (including me),” and “I empathize that the timeline for the AI’s answers is unclear. If the AI itself does not reveal the source, it may be best to always be aware of the possibility that it may be fake.”

3.3 Session Held Under the Theme of “Thinking about Environmental Education 2. The Triple Planetary Crisis and Environmental Education”

On 10 November 2024, the 6th *Kankyo* Café for FY 2024 was held online with four participants by using the AI method. First, we asked the AI about the relationship between the triple planetary crisis and environmental education, and we introduced each of the items listed by the AI (see Appendix 6) by using slides.

Next, following message 1, we sent a message to KankyoAI saying, “Please participate as a junior high school teacher in Japan.” In response to the question, “Is there an opportunity to teach about the Triple Planetary Crisis in junior high school? In which subjects do you teach it?”, the author used ChatGPT’s speech function to read out the contents for each subject: Science, Social Studies, Moral Education, Integrated Studies, and English. The end of the response that we received was, “Although the triple planetary crisis is not always explicitly mentioned in the curriculum, its key elements—climate change, biodiversity loss, and pollution—are covered across different subjects. Schools with a focus on SDGs or environmental education may provide more in-depth

learning opportunities (see Appendix 6).” In addition, when considering the relationship with environmental education in Japan, we thought appropriate to know the situation in junior high school, which is the last 3 years of compulsory education.

In response to the question, “What are you struggling with in your junior high school’s environmental education initiatives?”, the participating author used ChatGPT’s speech function to read out the contents for the following seven items related to the question:

1. Limited Time in the Curriculum
2. Lack of Specialized Teachers
3. Students’ Engagement and Awareness
4. Insufficient Practical Activities
5. Balancing Scientific Knowledge and Ethical Perspectives
6. Lack of Collaboration with Experts and Communities
7. Short-Term vs. Long-Term Impact.

The end of the response that we received was, “Addressing these challenges requires curriculum reform, teacher training, and stronger collaboration between schools and external organizations.”

Finally, the AI was asked, “Can you give us some advice on future initiatives in Japan?” and a response (see Appendix 7) was received. In a questionnaire survey conducted after the event, one participant said that they had gained understanding, such as, “I learned some things that I didn’t know about education in junior high schools today.” In addition, one participant said that they empathized with the fact that “there are other ways of providing environmental education besides science.”

4 Discussion

The author's topic presentations were based on limited knowledge within his area of expertise, which restricted the number of participants who continued to engage. Creating topic presentation materials with the support of generative AI could complement the expert's knowledge and encourage sustained participation. Furthermore, previous *Kankyo* Cafés held both in person (Tada 2018b, 2019; Tada and Tanaka 2020, 2021) and online (Tada et al. 2024a) were limited in scope because the same members participated each time. However, the use of generative AI may expand the range of discussions. Similarly, the online events hosted by the National Institute for Environmental Studies have also had a fixed participant base throughout the year, yet the use of non-generative AI has enabled broader dialogue.

Using AI to create materials and participate in discussions, as in this study, may broaden each participant's perspective on their previous responses and dialogue. In other words, it may lead to an "expansion of dialogue through AI." Moreover, careful consideration is required to manage the risks of AI hallucination and to address the ambiguity of AI's response process in practical settings such as school education. When AI participates as a character, as in the case of "AI Carson," issues related to AI and copyright must also be taken into account.

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5 Conclusions

By creating topics with the support of AI, we were able to summarize the topics comprehensively from a bird's-eye view without being tied to individual scientific specialties. Participants commented that the use of AI could provide comprehensive understanding of a topic and could help to make adjustments to ensure that the session stayed on topic. This also demonstrated that it was now possible for non-researchers to provide topics of conversation, thus offering the potential to promote autonomous dialogue in everyday life.

The keywords selected by the AI for the “answer” to the “question” related to the theme were broadly known and representative of societal views, whereas those chosen by the participants were based on their experiences.

At the 6th *Kankyo* Café, AI participated as a junior high school teacher, but in the future we would like to create a system whereby, when the Café is held, the AI as a certain profession or other person (for example, Carson) related to the theme will act as a co-host on Zoom to provide topics and participate in the dialogue. In addition, the participants at the Café so far have mainly been students and working adults with a strong interest in environmental issues, as well as students and working adults who are active internationally. We would like to continue to be involved in cultivating leadership among young people such as students who will tackle environmental issues from an international perspective by hosting Cafés. We hope to continue this activity by inviting not only students, but also members of the public and university professors. We hope that the sharing of various opinions from people of different cultures and educational backgrounds will contribute to a better understanding of environmental issues.

Declaration of Conflicting Interests.

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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Appendix 1

Environmental education plays a crucial role in addressing the issue of marine plastic pollution. Its contributions are as follows:

1. Raising Awareness and Understanding: Environmental education enhances public awareness and helps people understand the severity of marine plastic pollution. Through educational activities and campaigns in schools and communities, knowledge about the proper use and disposal of plastics is disseminated, encouraging individuals to recognize their responsibility toward the environment and take action.

2. Behavioral Change: Environmental education promotes behavioral change. Reducing plastic consumption, recycling, and properly managing plastic waste require awareness and education. When people make choices that consider their environmental impact, solutions to the marine plastic problem become more achievable.

3. Promotion of Sustainable Lifestyles: Environmental education contributes to the promotion of sustainable lifestyles. By encouraging the use of plastic alternatives, reuse, waste minimization, and efficient resource utilization, it fosters environmentally responsible actions that help mitigate marine plastic pollution.

4. Impact on Future Generations: Environmental education nurtures leadership and a sense of responsibility in future generations. By helping young people understand the importance of environmental issues and encouraging them to take action for a sustainable future, it supports long-term efforts to address marine plastic pollution.

Ultimately, environmental education plays a key role in transforming consumer behavior and societal structures, which are the root causes of marine plastic pollution. (Created by ChatGPT3.5 on April 9, 2024).

Appendix 2

1. Behavioral Change: Behavioral change refers to shifts in actions that reflect concern and understanding of nature and life. For example, adopting sustainable consumption habits and recycling activities while considering environmental conservation and biodiversity. Recognizing the dignity of life and the importance of ecosystems also encourages participation in environmental protection activities.
2. Sustainability: Sustainability refers to the balance between nature, social aspects, and life. Building a sustainable society requires the protection of the natural environment and respect for life. Constructing sustainable lifestyles and social systems necessitates respecting nature and life while taking environmentally conscious actions.
3. Next Generation: Efforts for the next generation impact the future of nature, society, and life. Preserving the natural environment and biodiversity and creating a sustainable society are crucial responsibilities for future generations. By teaching the importance of nature and life to the next generation, interest in environmental protection and sustainable living can be fostered. (Created by ChatGPT3.5 on April 9, 2024)

Appendix 3

Silent Spring (1962) by Rachel Carson is one of the most influential books in environmental history. It changed how people saw pesticides like DDT, revealing their harm not only to pests but also to birds, fish, and humans.

Carson made complex science understandable through storytelling, helping readers *feel* the problem rather than just learn facts. Her work asked deeper questions: how should humans live responsibly, and who decides what's safe for the environment?

Silent Spring was more than a warning—it was an early form of environmental education. It inspired people to think critically, connect

science with ethics and emotion, and take action for the planet. (Created by ChatGPT4o on October 11, 2024 and reviced by ChatGPT5 on October 21, 2025).

Appendix 4

Rachel Carson's *Silent Spring* (1962) deeply influenced global and Japanese environmental awareness. At the time, Japan was experiencing rapid economic growth but also severe pollution, such as Minamata disease and urban air pollution. Carson's work helped people see these issues as part of a global environmental crisis.

In Japan, environmental education grew to combine scientific knowledge with a cultural respect for nature rooted in traditions like Shinto and haiku. Since the 1970s, it has emphasized coexistence and sustainability—values closely aligned with Carson's message.

Silent Spring also inspired citizen activism. In the 1960s–70s, Japanese citizens protested pollution and demanded stronger laws. Today, environmental education continues that legacy by teaching not only science but also social responsibility.

Carson's call for both rational understanding and emotional connection to nature remains vital as Japan seeks balance between development and environmental stewardship. (Created by ChatGPT4o on October 11, 2024 and reviced by ChatGPT5 on October 21, 2025).

Appendix 5

One major focus of *Silent Spring* was DDT, once seen as a "miracle" pesticide for controlling mosquitoes and agricultural pests. Rachel Carson revealed its hidden dangers—it built up in the food chain, thinning bird eggshells and harming species like bald eagles and falcons.

Her work teaches a key lesson for environmental education: actions that seem helpful short-term can have harmful long-term effects. It encourages us to ask critical questions about how human activities impact ecosystems.

Carson also showed how science can engage the public. *Silent Spring* made complex issues understandable, inspiring people to take action. This reflects the goal of environmental education—to connect science and society for informed decision-making.

Finally, the DDT story shows how science can drive policy change. Once its risks were known, nations like the U.S. and Japan restricted its use. *Silent Spring* helped shape modern environmental education by promoting critical thinking, ecological awareness, and responsibility for our planet. (Created by ChatGPT4o on October 11, 2024 and reviced by ChatGPT5 on October 21, 2025).

Appendix 6

The Triple Planetary Crisis refers to three interconnected global environmental challenges: climate change, biodiversity loss, and pollution. These crises are not isolated issues but are deeply intertwined, collectively threatening the sustainability of life on Earth. Environmental education plays a crucial role in addressing these crises by raising awareness, fostering understanding, and encouraging action toward sustainable solutions.

1. Understanding the Triple Planetary Crisis

1.1 Climate Change

- The rise in global temperatures due to greenhouse gas emissions causes extreme weather events, rising sea levels, and ecosystem disruptions, directly affecting both human and natural systems.

1.2 Biodiversity Loss

- Habitat destruction, overexploitation of resources, and environmental changes lead to the rapid extinction of species, threatening ecosystem services that support human life.

1.3 Pollution

- Air, water, soil, and plastic pollution harm ecosystems, human health, and biodiversity, exacerbating the other two crises.

2. The Role of Environmental Education

Environmental education equips individuals and communities with the knowledge, skills, and motivation to combat these interconnected crises. Its contributions can be summarized as follows:

2.1 Building Awareness and Knowledge

- Provides scientific understanding of climate change, biodiversity, and pollution, highlighting their interconnections and global implications.

2.2 Promoting Critical Thinking

- Encourages learners to think critically about environmental challenges, their root causes, and the potential solutions from multiple perspectives.

2.3 Fostering Ethical Values

- Strengthens ethical considerations about human relationships with nature, emphasizing responsibilities to future generations and the importance of environmental justice.

2.4 Inspiring Action

- Motivates individuals to engage in sustainable practices, community initiatives, and policy advocacy to address the crisis on local, national, and global scales.

3. Environmental Education in Practice

3.1 Formal Education

- Schools and universities incorporate lessons on climate science, ecology, and pollution, often involving experiential learning such as field trips and citizen science projects.

3.2 Community Engagement

- Programs like environmental cafés create dialogue between researchers, students, and citizens, fostering interdisciplinary and inclusive discussions on sustainability.

3.3 Policy Advocacy

- Education campaigns empower communities to advocate for policies addressing climate change mitigation, biodiversity conservation, and pollution control.

3.4 Alignment with the SDGs

- Environmental education directly supports several UN Sustainable Development Goals (SDGs), including:
- SDG 13: Climate Action
- SDG 14: Life Below Water
- SDG 15: Life on Land

4. Transformative Potential

Environmental education goes beyond teaching facts; it seeks to transform perspectives and behaviors. By integrating scientific knowledge with empathy, ethics, and social responsibility, it enables learners to envision and work toward a sustainable future. In the

context of the Triple Planetary Crisis, environmental education serves as a powerful tool for empowering individuals and communities to tackle these challenges collectively. (Created by ChatGPT4o on Nobember 3, 2024).

Appendix 7

To address the "Triple Planetary Crisis"—climate change, biodiversity loss, and environmental pollution—Japan's environmental education must integrate these issues comprehensively and practically.

1. Integrate and Deepen Learning
   - Embed the Triple Crisis into science and social studies using real data and case studies.
   - Encourage cross-disciplinary learning across literature, history, economics, and ethics.

2. Promote Citizen Participation
   - Engage students in local activities like tree planting and biodiversity surveys.
   - Foster intergenerational dialogues between youth, residents, and experts.

3. Develop Practical Skills
   - Teach eco-technologies, water testing, and ecosystem monitoring.
   - Implement project-based learning where students propose local solutions.

4. Adopt a Global Perspective
   - Support international exchanges on environmental collaboration.
   - Link education to the SDGs to build global awareness.

5. Leverage Technology
   - Use AI and VR to visualize environmental change.
   - Expand online access to expert lectures and resources.

6. Strengthen Collaboration
   - Connect education with policy for societal transformation.
   - Foster future environmental leaders through scholarships and programs.

Through these initiatives, Japan can nurture citizens equipped with the knowledge and action needed to confront the Triple Planetary Crisis and model a sustainable future. (Created by ChatGPT4o on Nobember 3, 2024 and reviced by ChatGPT5 on October 21, 2025).

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Artificial Intelligence in Agricultural Teaching, Research, and Skill Development for Sustainable Development in Nigeria

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Abstract
Artificial Intelligence (AI) is reshaping agricultural education globally, but its integration in Nigeria remains in its early stages. This chapter focuses on systematically embedding AI into Nigeria's agricultural education through pedagogical innovation, institutional readiness, and skills development. Instead of broadly surveying AI's role, it critically analyzes the necessary frameworks, practices, and policies for its operational inclusion in agricultural training and research. Drawing from empirical evidence and global models (India, Kenya, Brazil, and China), the chapter explores AI-enhanced pedagogies, such as smart learning environments and digital simulations, to bolster competencies in precision agriculture, climate-smart farming, and agribusiness management. The analysis identifies four key dimensions for AI integration: curriculum redesign for competency-based learning;

institutional capacity and infrastructure; ethical governance of digital systems; and alignment with Nigeria's Digital Economy and AI Strategies. While awareness and pilot initiatives are on the rise, challenges like weak infrastructure, limited staff training, and fragmented policy implementation restrict large-scale adoption. The chapter proposes a phased integration model—encompassing awareness, capacity building, curriculum reform, and adaptive feedback—to facilitate sustainable transformation. Ultimately, it argues that AI should be regarded not just as a technological innovation but as a pedagogical framework vital for transforming Nigeria's agricultural education ecosystem. By aligning AI with national sustainability goals, Nigeria can develop a new generation of digitally skilled, sustainability-focused agricultural professionals prepared for the challenges of the twenty-first-century food system.

Keywords Artificial intelligence – Agricultural education – Pedagogy – Institutional readiness – Sustainability – Nigeria

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1 Introduction

Agricultural education has historically been a foundation for rural development and food security across Africa. Initiatives from organizations like FAO and UNESCO (Atchoarena and Gasperini 2003) and reports from the World Bank (1999–2004) consistently emphasize that sustainable agricultural transformation relies not just on technology, but significantly on robust institutions and skilled human capital. In Nigeria, agricultural education has been institutionalized through various universities, colleges, vocational training centers, and extension services aimed at bridging the gap between research and practical farming. Despite this considerable institutional framework, Nigeria's agricultural education struggles to keep pace with emerging needs for competencies in precision agriculture, climate-smart farming, agribusiness entrepreneurship, and value chain management (Rivera 2006). The historical context reveals that agricultural education in Sub-Saharan Africa, including Nigeria, was shaped by colonial structures that focused on export crop production and centralized extension services (Crowder and Anderson 1996). Nonetheless, Nigeria made strides in developing its educational structure by establishing institutions like the Division of Agricultural Colleges at Ahmadu Bello University and the Federal Colleges of Agriculture (e.g., Akure, Ibadan), which aimed to produce a well-trained workforce in agriculture (Federal College of Agriculture, Akure [FCA Akure] n.d.). The National Agricultural Extension and Research Liaison Services (NAERLS) also

emerged in the 1960s as a conduit for research dissemination (Olanrewaju et al. 2022).

Globally, the FAO has endorsed integrated models that merge education, research, and extension to enhance sustainable agriculture (Bawden 1996; McNeely and Scherr 2001). Scholars like Byerlee et al. (2005) and Eicher (2004) point out Africa's critical shortage of scientific capacities, while NEPAD (2001) stresses higher education's role in achieving food security. This resonates in Nigeria's reality, where inefficient training-extension linkages and low agricultural technology adoption stifle productivity. The agricultural curricula in Nigeria evolved in the 1980s and 1990s to incorporate global trends emphasizing sustainability and participatory learning (Rivera 2006; Crowder and Anderson 1996). The adoption of MDGs and SDGs further highlighted poverty reduction, food security, and pro-poor growth as key training objectives, necessitating graduates equipped not only with technical skills but also with a social and environmental conscience. Recent policies have shifted toward a skills-centric approach in agricultural education. The National Board for Technical Education (NBTE) introduced standardized curricula for National Diplomas focusing on competencies in soil science, irrigation, mechanization, and agribusiness management (NBTE 2020a, 2020b). Additionally, youth initiatives, such as the National Directorate of Employment (NDE) Skills Acquisition Programmes, seek to link agricultural training with entrepreneurship, fostering agripreneurship and employment (NDE 2021). These reforms align with the Federal Ministry of Agriculture and Rural Development's strategy to enhance farmer livelihoods and close yield gaps (FMARD 2016).

In today's context, technologies like Artificial Intelligence (AI), Machine Learning (ML), and the Internet of Things (IoT) are revolutionizing global agriculture (Ayaz et al. 2019; Benos et al. 2021; Dhanya et al. 2022). AI applications facilitate precision monitoring of soil health, crop growth, and pest control (Liu and Wang 2021), while robotics and computer vision assist in mechanized harvesting and smart irrigation (Oliveira et al. 2020). However, the practical

integration of AI in agricultural education within Nigeria is limited. Reviews have noted that although AI solutions are effective in experimental and industrial contexts, their academic integration remains nascent (Buja et al. 2021; Priya and Ramanujam 2021). Integrating AI into agricultural education can enhance sustainability outcomes, promoting data-driven decision-making and predictive analytics for climate adaptation. It can also enable intelligent tutoring systems that personalize learning experiences (Lai and Bower 2019; Ali 2020; Bond et al. 2019). Embedding AI into agricultural curricula allows students to acquire advanced analytical skills, reduces learning costs, and elevates research quality.

The application of AI in Nigeria presents opportunities to transform skill acquisition and the research-extension nexus. AI-enabled learning management systems and virtual farms can create dynamic feedback loops between classroom learning, field experiments, and real-time agricultural data. Such innovations address persistent challenges in practical exposure, technology adoption, and aligning education with job market demands (NBTE 2020a; Rivera and Davis 2007). As agriculture is crucial for Nigeria's economic diversification, implementing AI in teaching and research can boost youth participation in agripreneurship and enhance food system resilience. This chapter proposes a systematic incorporation of AI into Nigeria's agricultural education across three interconnected aspects: pedagogical innovation, institutional readiness, and skill development for sustainability. It argues that AI tools like intelligent tutoring systems, data analytics, and simulations can transform curriculum delivery, enhance faculty capabilities, and equip students for careers in precision agriculture and agribusiness management. Rather than viewing AI merely as technological innovation, the chapter posits it as a catalyst for pedagogical and institutional reform that correlates education with sustainable development. Using empirical evidence from Nigeria alongside global comparisons, a phased approach to AI integration is suggested—starting with awareness and progressing to curriculum alignment and feedback mechanisms. This aims to support Nigerian

policymakers, educators, and researchers in developing a digitally literate and sustainability-oriented agricultural education system. To promote sustainable agricultural advancement, Nigeria must integrate AI and digital technologies into its educational frameworks, serving as catalysts for innovation and resilience.

The chapter is structured to facilitate clarity, outlining the methodological approach in Sect. 2 and examining global and national AI adoption in agricultural education from Sects. 3, 4, 5 and 6. Following this, Sects. 7 and 8 address necessary pedagogical and institutional strategies for systemic transformation, culminating in a phased model for sustainable AI integration. Policy recommendations are presented to align national frameworks with institutional practices in Sect. 9. Finally, Sect. 10 summarizes essential insights and discusses the ramifications of AI adoption for fostering the sustainable development of Nigeria's agricultural education system.

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2 Methodology

This study employed a qualitative, integrative review to examine the integration of Artificial Intelligence (AI) in Nigeria's agricultural education. It combined systematic literature review, policy analysis, and expert synthesis to ensure analytical depth and contextual relevance. Data were drawn from peer-reviewed journals, FAO and UNESCO reports, Nigerian education policy documents, and databases such as Scopus and Google Scholar, focusing on publications from 2019 to 2025. Studies included addressed AI applications in agricultural teaching, research, or skills development within Sub-Saharan Africa. Using Thomas and Harden's (2008) thematic analysis framework and NVivo 12 software, four key themes emerged: pedagogical design, institutional readiness, curriculum reform, and sustainability integration. Validation was achieved through triangulation involving literature cross-checking and alignment with national policies. As only secondary, publicly available data were used, formal ethical clearance was unnecessary, though UNESCO's 2021 ethical guidelines were

observed. The methodology produced a coherent synthesis situating Nigeria's progress within global AI in education trends, highlighting the interplay of pedagogy, institutional capacity, and innovation in shaping the trajectory of AI adoption and its implications for sustainable agricultural education.

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3 Global Experiences and Lessons in AI-Driven Agricultural Education: Interconnections Between AI, Sustainability, and Agricultural Skills

The integration of Artificial Intelligence (AI) into agricultural education has transformed how sustainability concepts and skill formation are approached across the world. AI acts as both a *pedagogical tool* and a *development catalyst*, fostering precision, efficiency, and adaptability in agricultural systems. Globally, AI applications have been harnessed to teach sustainable farming practices, improve data-driven decision-making, and bridge the skills gap between traditional agriculture and digital agronomy (Dhanya et al. 2022; Benos et al. 2021). By linking intelligent automation with agronomic science, AI enables learners to acquire real-time competencies in soil monitoring, crop health diagnostics, irrigation management, and climate modeling (Liu and Wang 2021; Hasan et al. 2022).

Sustainability and AI are mutually reinforcing within agricultural education: AI enhances environmental monitoring, resource optimization, and early-warning systems for pests or climate shocks, while sustainability frameworks ensure that AI adoption remains ethical, inclusive, and ecologically sound (UNESCO 2023; FAO 2024). The synergy between both domains underscores a shift from knowledge transmission to *competency-based experiential learning*—a transition essential for training the next generation of green and digital agricultural professionals (Kallio et al. 2022; Dutta et al. 2023).

Globally, several nations have implemented innovative AI-driven models within agricultural education that Nigeria can learn from. **India** has advanced the use of AI and machine learning (ML) in agricultural universities through the *National Agricultural Higher Education Project (NAHEP)*, which promotes digital curricula, smart labs, and precision agriculture training. Studies highlight that AI applications in Indian agricultural education—such as drone-based crop monitoring and predictive analytics—enhance students' problem-solving and innovation capabilities (Kaur and Singh 2021; Jha 2022). **Kenya** demonstrates effective institutional collaboration through partnerships between Egerton University, the Kenya Agricultural and Livestock Research Organization (KALRO), and private agri-tech firms. Through the *Digital Agriculture and Skills Development Programme* supported by FAO and the World Bank, Kenya integrates AI-based remote sensing, soil data modeling, and mobile-enabled farm decision tools into extension training (FAO 2024; Ndiritu 2023). These initiatives have improved youth engagement and female participation in digital agribusiness.

China's agricultural universities, particularly China Agricultural University and Zhejiang University, have integrated AI, robotics, and big data analytics into undergraduate and postgraduate teaching (Li et al. 2020). The Chinese model prioritizes strong government funding, research-industry linkages, and cloud-based agricultural simulation environments—factors currently limited in many African contexts (Wang and Zhang 2022). In **Brazil**, the *Embrapa Digital Agriculture Initiative* emphasizes sustainable AI-driven production systems. AI models are used for precision irrigation, environmental risk management, and carbon footprint tracking. Integration of these tools into agricultural curricula is supported by strong public-private partnerships and federal sustainability policies (Pereira et al. 2021). The **United States** offers one of the most mature examples of AI integration, with the **U.S.** Department of Agriculture (USDA) and land-grant universities deploying AI-driven experiential learning in areas such as autonomous tractors, yield forecasting, and agri-environmental

modeling (Reich 2021; Alston 2022). These initiatives demonstrate how advanced economies embed sustainability into AI education through research grants, innovation ecosystems, and interdisciplinary curriculum reforms.

Comparatively, Nigeria's agricultural education system remains in its formative stage regarding AI adoption. While awareness of AI's relevance is increasing, institutional and infrastructural constraints limit effective implementation (Afolabi and Bello 2021; Eze 2022). The National Artificial Intelligence Strategy for Nigeria (NITDA 2024) and the Digital Economy Policy and Strategy (2020–2030) provide policy direction, yet the translation of these frameworks into practice is slow due to insufficient funding, limited faculty expertise, and poor digital infrastructure (Usman and Musa 2023). Unlike India or China, where government and private sectors co-invest in AI labs, Nigeria's progress depends largely on externally funded pilot projects. Similarly, while Kenya's integration model is anchored in strong extension-research linkages, Nigeria's agricultural education system still suffers from fragmentation between research, extension, and teaching (Rivera and Davis 2007). However, opportunities exist. Nigeria's demographic advantage—its large youth population—combined with growing public-private partnerships (Okorie and Ejiogu 2024) and national emphasis on sustainability (FMARD 2016; NITDA 2023), provides fertile ground for scalable AI-driven educational reform. Aligning institutional curricula with global practices and investing in teacher training, digital infrastructure, and gender-inclusive AI programs could position Nigeria as a leader in AI-sustainable agriculture education across West Africa. In essence, international experiences underscore that successful AI integration in agricultural education is driven by policy coherence, faculty competence, public-private collaboration, and sustainability orientation. These lessons can guide Nigeria's transition from pilot initiatives to a systemwide, inclusive AI-enabled agricultural education ecosystem (Fig. 1).

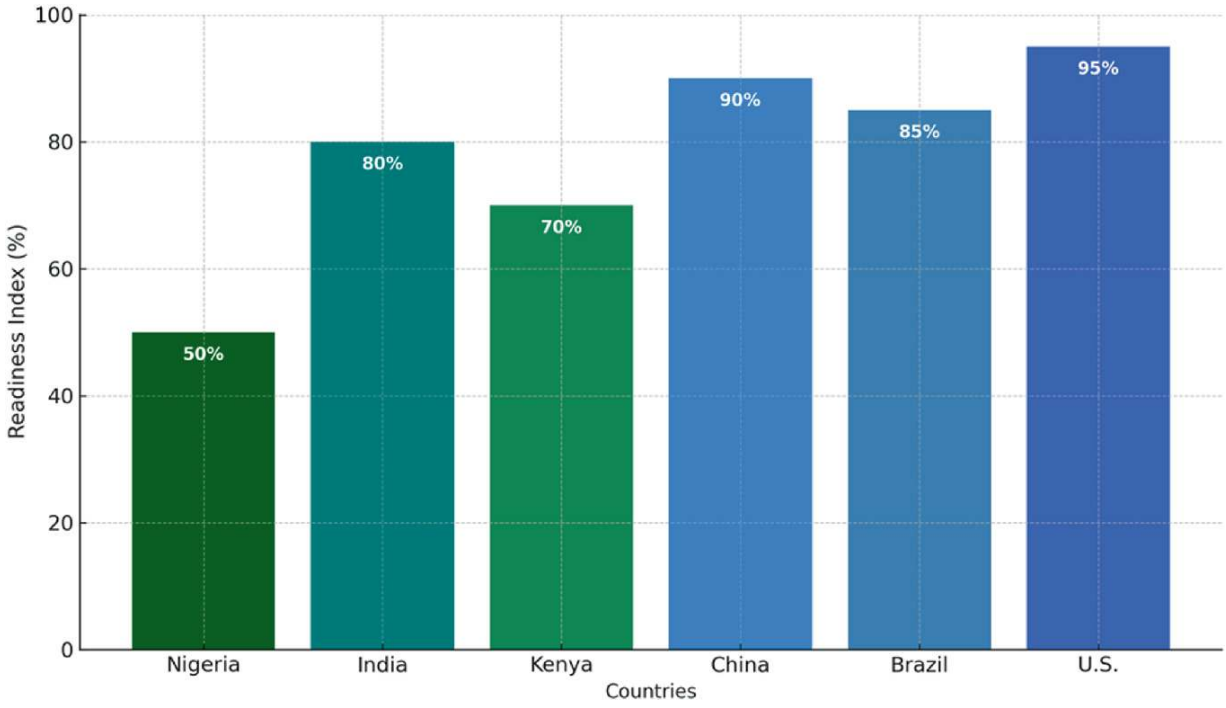


Fig. 1 Comparative readiness for AI in agricultural education (Nigeria versus selected countries) —showing Nigeria's position relative to India, Kenya, China, Brazil, and the U.S.

While global examples highlight the transformative potential of Artificial Intelligence (AI) in reshaping agricultural education through robust policy alignment, pedagogical innovation, and institutional collaboration, the extent to which these dynamics manifest in Nigeria remains a significant concern. The international cases examined from India, Kenya, and China to Brazil and the United States reveal that sustainable integration of AI relies on systematic investments in faculty expertise, digital infrastructure, and cross-sector partnerships. In contrast, Nigeria's journey has been more gradual and inconsistent, influenced by contextual challenges such as infrastructural deficiencies, fragmented policies, and emerging levels of digital literacy.

To better understand Nigeria's position within this broader context, the following section presents empirical evidence from agricultural and higher education institutions across the country. It highlights early initiatives, growing institutional awareness, and innovations driven by partnerships. These case studies offer valuable insights into both the potential and the limitations of AI integration at the national level,

while also identifying the enabling conditions needed to transition from pilot programs to comprehensive reform.

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4 Emerging Evidence from Nigerian Institutions

Empirical evidence from Nigerian higher education and agricultural institutions reveals that the integration of Artificial Intelligence (AI) in teaching, research, and skill development is still in its formative stage but shows growing promise. Various initiatives, ranging from university-led pilots to public-private partnerships, illustrate both the potential and the persistent barriers to sustainable digital transformation in the agricultural education sector.

Case Study 1: Smart Farming Pilot at Rivers State University

Rivers State University (RSU) stands as one of Nigeria's pioneers in smart farming experimentation. Eze, Nwafor, and Opara (2023) documented an initiative that introduced AI-assisted precision farming tools and IoT-based monitoring systems into undergraduate agricultural courses. The project equipped students with digital sensors, mobile data collectors, and weather forecasting interfaces for managing crop growth cycles. Lecturers utilized AI-driven simulation tools for demonstrating pest detection and irrigation scheduling, marking it as one of the earliest applications of AI-driven experiential learning in Nigerian agricultural education. While the outcomes were modest, improvements in students' conceptual understanding of digital agriculture and faculty insights into data analytics integration were significant. However, challenges like unreliable electricity, limited bandwidth, and inadequate maintenance funds hindered long-term scalability (Eze et al. 2023; Usman and Musa 2023). Nevertheless, the RSU pilot demonstrated how localized, small-scale innovations can stimulate broader institutional interest in AI-supported agricultural pedagogy (FAO 2024).

Case Study 2: AI Awareness in South-West Nigerian Universities

In South-Western Nigeria, awareness of AI applications in education has expanded unevenly. A study by Afolabi and Bello (2021) surveyed universities in Lagos, Ogun, and Oyo States to gauge faculty awareness, perceptions, and digital readiness. Results indicated that 74% of lecturers had heard of AI in education, but only 32% actively employed AI or machine learning tools in their teaching or research endeavors. Common applications included plagiarism detection and digital grading systems. Barriers to adoption consisted of insufficient professional training, lack of institutional incentives, and gaps in technological infrastructure. Gender differences emerged, with male lecturers reporting higher confidence in using AI technologies, while female lecturers noted limited access to training and support (Afolabi and Bello 2021; Yusuf and Kareem 2023). Despite these barriers, younger academics showed strong interest in AI as a means to enhance agricultural innovation and employability, aligning with youth-led agricultural technology movements observed in East Africa and Asia (Hasan et al. 2022; Kallio et al. 2022).

Case Study 3: Public-Private AI Collaboration in Agricultural Training

Another noteworthy example involves collaborative models linking academia and the private sector. Okorie and Ejiogu (2024) examined a partnership between a Lagos-based agri-tech company and two colleges of education in Southern Nigeria. This collaboration introduced AI-powered crop-disease diagnostic applications and cloud-based learning platforms for vocational agriculture students. Through hands-on training, students learned to interpret field data using AI analytics dashboards. The study found that such collaborations significantly improved faculty competence, curriculum innovation, and student motivation; over 60% of participating lecturers reported enhanced confidence in teaching AI-related agricultural concepts. However, ongoing funding, infrastructure access, and policy alignment with national AI strategies were essential for sustaining these initiatives (NITDA 2024; Ibrahim and Onwuegbuchulam 2023). This collaboration showcased the importance of multi-stakeholder

partnerships in bridging the gap between AI potential and practical application in classrooms (FAO 2024; UNESCO 2023).

Cross-Case Synthesis: Challenges and Opportunities

A comparative analysis across these cases reveals recurring challenges within Nigerian institutions: unstable electricity, high internet costs, low digital literacy among faculty, and limited institutional investments in AI tools (Usman and Musa 2023; Eze 2022). Nonetheless, opportunities such as youth enthusiasm, policy momentum, and the availability of open-access AI platforms offer pathways to overcome cost barriers. Together, these case studies illustrate that successful AI integration in Nigeria's agricultural education must prioritize context-sensitive implementation rooted in local needs and faculty empowerment. International experiences from India, Kenya, and Brazil underscore that institutional readiness and stakeholder collaboration are pivotal for transforming AI integration into impactful learning experiences, rather than transient experiments (Hasan et al. 2022; FAO 2024).

To navigate this path forward, Nigeria must consolidate its scattered efforts into a coherent national framework that integrates policy, curriculum, and capacity-building programs. The case studies reveal that localized innovations, such as RSU's smart farming pilot, growing AI awareness in South-West universities, and public-private collaborations, are progressively enhancing institutional capacity and faculty competence. However, the absence of a consistent pedagogical framework capable of translating fragmented digital adoption into sustainable teaching and learning practices remains a crucial hurdle. The next steps involve exploring how AI-enabled pedagogical design can serve as the engine for this transformation, embedding AI tools and competencies into curriculum content, instructional methods, and assessment systems to align institutional readiness with national sustainability and digital education objectives.

5 Pedagogical Design for AI-Enabled Agricultural Skill

The integration of Artificial Intelligence (AI) in agricultural education must strike a balance between digital innovation and sustainability. In developing regions like Nigeria, there is an urgent need to shift from traditional theory-based teaching to data-driven, experiential, and climate-smart practices, aligning with the goals of precision agriculture and sustainable development. A competency-based learning framework is vital for ensuring that graduates acquire both technical skills and ethical awareness related to AI systems. Important competencies include data literacy, machine learning fundamentals, IoT applications, AI ethics, sustainability analytics, and agribusiness decision-making. Research indicates that these skills are essential for smart farming, aligning with national reforms calling for more practical, technology-oriented agricultural training. Blended and experiential learning can enhance student engagement and problem-solving. Techniques such as simulations, virtual and augmented reality, and remote sensing provide a deeper understanding, while field projects using sensors and IoT tools build practical expertise. Given infrastructural challenges, implementing cloud-based AI labs can ensure ongoing access to experimentation. Educators must be prepared to teach both technical and ethical aspects of AI, but many currently lack the necessary digital pedagogy and AI literacy. Continuous professional development and mentoring are crucial to enhance educators' capacity for creating AI-driven lessons. Training should focus on responsible AI use and addressing algorithmic bias. AI-enabled platforms can automate assessments and provide feedback, allowing for a focus on higher-order thinking. However, it is important not to overlook the value of reflection and critical reasoning. Combining adaptive assessments with reflective practices promotes deeper learning and academic integrity. Lastly, AI integration must be guided by ethical, sustainable, and inclusive principles. Concerns about data privacy, bias, and digital inequality require attention in curricula. Ensuring equitable access—especially

between rural and urban institutions—supports fairness and aligns with the United Nations Sustainable Development Goals related to quality education, industry innovation, and climate action.

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6 Pedagogical Design and Institutional Readiness for AI-Enabled Agricultural Education

Effective integration of Artificial Intelligence (AI) into Nigeria's agricultural education now depends less on the mere acquisition of digital tools and more on the pedagogical frameworks that govern their use. The emerging institutional experiences reviewed earlier demonstrate that without systematic redesign of curricula, teaching methods, and assessment models, AI adoption risks remaining peripheral and unsustainable. A deliberate AI-enabled pedagogical design, therefore, becomes essential not only to enhance classroom instruction but also to build the competencies required for precision agriculture, smart farming, and sustainable food systems. This section conceptualizes such design as a tripartite process: (1) aligning curriculum objectives with digital and sustainability competencies; (2) strengthening institutional readiness through faculty training, infrastructure, and resource mobilization; and (3) promoting skill development through experiential, problem-based, and data-driven learning activities. Through this lens, AI becomes a transformative pedagogical tool, bridging the gap between technological capability and the human capital needed to drive Nigeria's agricultural transformation (Eze 2022; Yusuf and Kareem 2023).

The integration of Artificial Intelligence (AI) in Nigeria's agricultural education is contingent upon strong infrastructure, supportive policies, faculty readiness, and necessary curriculum reforms. Reliable electricity, broadband internet, laboratory facilities, IoT devices, and data storage systems are essential for digital transformation (Hasan et al. 2022). Access to smart devices enhances learning opportunities (Adebayo and Olayemi 2021), but ongoing infrastructural gaps, such as

poor power supply and inadequate ICT laboratories, hinder hands-on AI-based education (Usman and Musa 2023; Eze et al. 2022). Institutional and national policies are vital for guiding AI adoption (Ibrahim and Onwuegbuchulam 2023). Effective governance frameworks ensure funding, curricular alignment, and ethical standards (Kallio et al. 2022). Despite the National Digital Economy Policy (2020–2030) promoting AI, its implementation in agricultural institutions is slow (NITDA 2023). Enhancing ethical governance and forming partnerships with agri-tech firms can accelerate progress (Okorie and Ejiogu 2024).

While awareness of AI is rising among educators and students (Ibrahim and Onwuegbuchulam 2023; Lawal and Okoli 2024), challenges in digital competence and pedagogical integration remain (Afolabi and Bello 2021). Professional development should evolve to achieve mastery in machine learning and related fields (Yusuf and Kareem 2023; ASPJ 2024). Curricula ought to incorporate machine learning, robotics, and sustainability science (Bhakta et al. 2019; Adeoye and Ogundele 2023), with research focusing on local AI innovations for smallholder farmers. Strong linkages between education, research, and extension are vital for disseminating AI solutions to rural communities (Eze 2022). Sustainable funding and partnerships with tech firms like IBM Research Africa and Microsoft AI for Earth are crucial for AI integration (Hasan et al. 2022; Kallio et al. 2022). Preparing Nigerian agricultural education for a data-driven future requires policy reform, pedagogical advancements, and ethical considerations. Understanding the interplay of institutional reforms, national policies, and sustainability imperatives is essential to redefine the goals and methods of agricultural education. To fully appreciate this evolution, it is necessary to trace how institutional reforms, national policies, and sustainability imperatives have interacted over time to redefine the goals, methods, and outcomes of agricultural education.

7 Transformation of Nigeria's Agricultural Education Ecosystem Toward a Sustainable Future: Chronological Progression and Key Drivers

Nigeria's agricultural education is shifting from manual, teacher-centered training

to data-driven, competency-based, and innovation-oriented learning shaped by digitalization, globalization, and sustainability imperatives (Yusuf and Kareem 2023; UNESCO 2023).

The integration of Artificial Intelligence (AI) in Nigerian agricultural education has progressed through distinct phases. Before 2020, adoption was minimal, with institutions relying mainly on traditional teaching and basic ICT tools like e-learning platforms and digital libraries (Afolabi and Bello 2021). Awareness of AI, robotics, and the Internet of Things (IoT) was limited among faculty and students (Eze 2022). The 2020–2022 period marked a digital disruption phase driven by the COVID-19 pandemic, which accelerated the use of online teaching, virtual labs, and digital simulations (UNESCO 2023; Usman and Musa 2023). The National Digital Economy Policy also identified AI as a key driver of educational and agricultural innovation (NITDA 2023). From 2023 onward, agricultural institutions have entered an integration phase, embedding AI modules into curricula emphasizing smart farming, data analytics, and machine learning (Adeoye and Ogundele 2023). This ongoing shift aligns with Education for Sustainable Development (ESD) principles, promoting sustainability analytics, circular economy approaches, and green digital skills (UNESCO 2023; FAO 2024). Together, these trends mark Nigeria's gradual institutionalization of AI in agricultural education.

Key drivers of transformation in Nigeria's agricultural sector include national policy initiatives, curriculum reform, research innovation, and strategic partnerships. The National Artificial Intelligence Strategy (NITDA 2024) and the Digital Economy Policy and Strategy (2020–

2030) position AI as central to national development, promoting digital literacy, research capacity, and innovation aligned with sustainability goals (Ibrahim and Onwuegbuchulam 2023). Curriculum modernization is embedding AI across agricultural disciplines such as crop science, soil management, agribusiness, and extension. Integrating AI and machine learning enhances students' ability to link theoretical concepts with real-world farming decisions (Bhakta et al. 2019; Hasan et al. 2022). Experiential learning through IoT-enabled labs, virtual farms, and AI-driven diagnostic tools further strengthens student engagement and technical competence (Okorie and Ejiogu 2024).

Research in agricultural education is shifting from manual to data-driven methodologies, employing AI for predictive modeling, pest detection, yield estimation, and climate forecasting (Adeoye and Ogundele 2023; FAO 2024). This transition boosts research accuracy and ensures outcomes are relevant to Nigeria's smallholder farmers and diverse agro-ecological zones (Eze 2022). Public-private partnerships and innovation hubs, including collaborations with firms like FarmCrowdy, Thrive Agric, and Crop2Cash, have accelerated the application of AI in teaching and learning (Okorie and Ejiogu 2024). Incubation centers and innovation ecosystems now serve as vital platforms for entrepreneurship and real-world problem-solving in agricultural value chains (NITDA 2023; UNESCO 2023). Finally, sustainability and inclusivity remain core imperatives. AI integration must promote environmental stewardship, economic viability, and social equity (UNESCO 2023). Addressing urban–rural and gender digital divides is essential (Adebayo and Olayemi 2021). Inclusive curricula should incorporate digital ethics, ecological awareness, and cultural sensitivity (Kallio et al. 2022), producing graduates who are not only AI users but also critical innovators capable of designing sustainable, context-specific agricultural solutions (FAO 2024).

The future of Nigeria's agricultural education depends on sustained investment, capacity building, and institutional reform. Leveraging Artificial Intelligence (AI) for teaching, research, and skills development enhances productivity, employability, and alignment with SDGs 2, 4, 9,

and 13 (UNESCO 2023; FAO 2024). Achieving resilience requires balancing innovation with ethical stewardship and promoting climate-smart, inclusive AI practices (Ibrahim and Onwuegbuchulam 2023). Although digital transformation is underway through policy and curriculum reforms, progress remains uneven. A structured, phased integration model, anchored on policy alignment, institutional readiness, and pedagogical innovation, is essential to ensure sustainable and systematic AI adoption in agricultural education.

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8 Proposed Model for the Integration of Artificial Intelligence into Agricultural Education in Nigeria

Recent research on digital readiness, pedagogy, and institutional capacity has informed a phased model for integrating Artificial Intelligence (AI) into Nigeria's agricultural education system. This model aligns with global best practices recommended by UNESCO (2023) and FAO (2024) while considering Nigeria's infrastructural and policy context **(**NITDA 2024; Yusuf and Kareem 2023**).** The chapter proposes a gradual, structured adoption of AI through phases emphasizing awareness, capacity building, curriculum reform, and sustainability mechanisms. The first phase**,** "Awareness and Pilot Projects," focuses on creating institutional and human awareness of AI's transformative potential in teaching, research, and skills development. Although awareness of AI concepts among Nigerian lecturers and students is increasing, practical understanding remains low **(**Afolabi and Bello 2021; Eze 2022**)**. Pilot initiatives, such as AI-enabled teaching modules, smart farm demonstrations, and IoT-based sensor installations, enhance experiential learning and institutional sensitization **(**Hasan et al. 2022; Okorie and Ejiogu 2024**).** Experiences from Kenya and India **s**how that small-scale pilots can significantly improve faculty competence and student engagement when guided by clear institutional strategies **(**FAO 2024; UNESCO 2023**)**. The second phase, "Capacity Building and Policy Alignment," emphasizes

strengthening institutional and human capacity through training lecturers, administrators, and extension educators in AI tools, machine learning (ML), data analytics, and digital ethics. Studies highlight that lecturer competence and pedagogical adaptability are critical for successful AI adoption **(**Yusuf and Kareem 2023; Ibrahim and Onwuegbuchulam 2023). Policy reform is equally vital, NITDA (2024) stresses ethical governance, inclusivity, and indigenous innovation as guiding principles. Strategic partnerships with agri-tech firms, NGOs, and international agencies are essential for resource mobilization, infrastructure enhancement (Fig. 2), and knowledge exchange **(**Okorie and Ejiogu 2024).

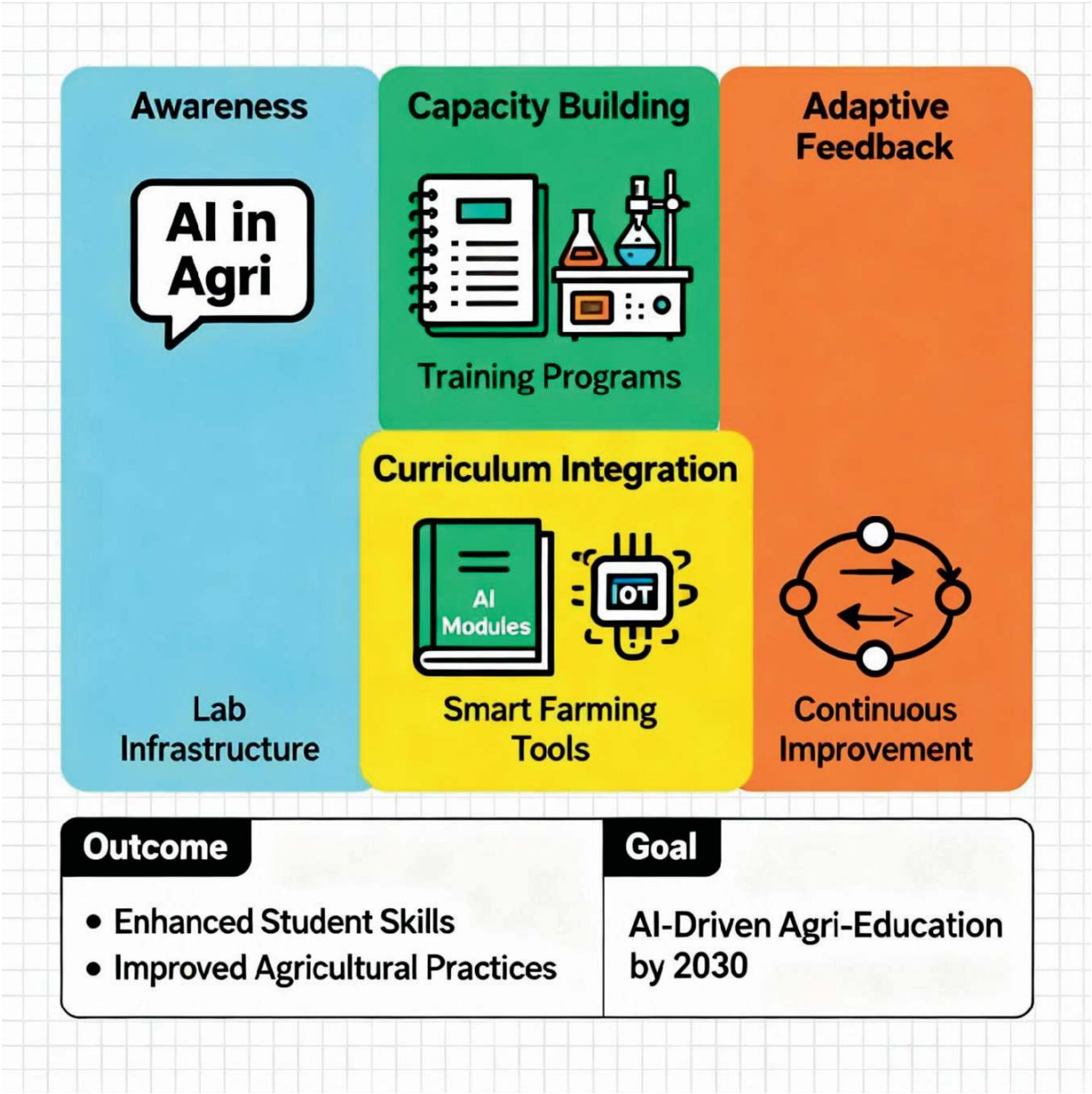


Fig. 2 Phased model for the integration of artificial intelligence (AI) into agricultural education in Nigeria. *Source* Adapted from UNESCO 2023; FAO 2024; NITDA 2024; Rivera and Davis 2007; Yusuf and Kareem 2023

Phase 3 emphasizes curriculum integration and scaling within Nigeria's agricultural education system. Following the establishment of AI awareness and capacity, integrating AI into formal curricula becomes essential to build competencies in digital innovation and sustainability. Core focus areas include machine learning applications in crop yield prediction, precision irrigation, pest management, agribusiness

analytics, and climate modeling (Bhakta e al. 2019; Adeoye and Ogundele 2023). To scale impact, successful pilot projects should expand across institutions, supported by smart labs, IoT field units, and data analytics centers (Usman and Musa 2023). Developing measurable assessment indicators will help track student performance, research impact, and field-level application. Evidence from South Korea and Brazil shows that systematic AI integration enhances innovation, problem-solving, and sustainability consciousness (Kallio et al. 2022; UNESCO 2023).

Phase 4 centers on adaptive feedback and sustainability. Continuous monitoring and periodic curriculum review are vital for maintaining relevance and alignment with labor market and research trends (FAO 2024; Rivera and Davis 2007). Ethical, inclusive, and sustainable practices must guide both curriculum content and institutional governance, addressing issues like gender disparity, rural digital access, and data ethics (Adebayo and Olayemi 2021; Kallio et al. 2022). Long-term sustainability requires embedding AI within funding models, faculty incentives, and institutional missions (NITDA 2023; UNESCO 2023). Overall, the phased model promotes incremental AI integration —from awareness to sustainability—aligning with UNESCO (2023), FAO (2024), and Nigeria's Digital Economy Policy (2020–2030), fostering a resilient, inclusive, and future-ready agricultural education ecosystem.

The phased integration model provides a structured framework for embedding AI in Nigeria's agricultural education, requiring coherent policies, institutional synergy, sustained investment, and long-term planning to ensure effective implementation, measurable outcomes, and alignment with national sustainability and innovation goals. The following section presents a comprehensive set of recommendations to align national objectives with institutional practices, strengthen capacity, and ensure AI integration supports Nigeria's goals of sustainability, innovation, and food security.

9 Policy and Strategic Recommendations

The successful integration of Artificial Intelligence (AI) into agricultural education in Nigeria necessitates clear policies, institutional preparedness, and ongoing investment. A coordinated national framework involving the Federal Ministry of Education (FME), National Commission for Colleges of Education (NCCE), National Universities Commission (NUC), and National Information Technology Development Agency (NITDA) is crucial for embedding AI competencies within the National Policy on Education and Agricultural Policy (NITDA 2024; UNESCO 2023). Ethical issues regarding data privacy, inclusivity, and governance of AI should steer these reforms (Kallio et al. 2022; FAO 2024). To achieve institutional readiness, modern infrastructure, high-speed internet, AI laboratories, IoT-driven field units, and smart classrooms are needed, all of which should be backed by TETFund and private-sector partnerships (Usman and Musa 2023). The establishment of AI and AgriTech Innovation Hubs can encourage research, entrepreneurship, and student innovation (Okorie and Ejiogu 2024). Continuous professional development, digital literacy training, and awareness of data ethics are essential for human capacity building (Afolabi and Bello 2021; Ibrahim and Onwuegbuchulam 2023). Incorporating AI and data science courses into academic programs will ensure that graduates possess skills relevant to global labor market demands (Adeoye and Ogundele 2023). Curriculum reform should embrace interdisciplinary and problem-based methods that weave AI into traditional agricultural fields like crop science and agribusiness (Bhakta et al. 2019; UNESCO 2023). Adaptive learning platforms and virtual simulations can enhance personalized education, while locally relevant content addresses Nigeria's unique climate and food security issues (FAO 2024). Collaboration in research among universities, agri-tech companies, and research institutions should promote precision agriculture and climate-smart innovations, facilitated through Research-Extension-Education Linkage Platforms (REELP) (Hasan et al. 2022; Rivera and Davis 2007). Sustainable funding is essential.

Institutions ought to widen their revenue streams through public-private partnerships, donor contributions, and alumni support, augmented by innovation grants and funds for ICT maintenance (Okorie and Ejiogu 2024; NITDA 2023). The implementation should be guided by principles of equity and ethics, ensuring gender inclusivity, accessibility for people with disabilities, and digital equality between urban and rural learners (Adebayo and Olayemi 2021; Kallio et al. 2022). Institutional ethics committees must oversee transparency, privacy, and accountability in AI use (UNESCO 2021). Lastly, effective Monitoring, Evaluation, and Learning (MEL) systems should evaluate the adoption of AI by measuring factors such as faculty training rates, AI-integrated courses, and research outputs (UNESCO 2023). Ongoing evaluation and feedback mechanisms will support adaptive revisions to curricula and policies (FAO 2024; NITDA 2024).

10 Conclusions

The chapter emphasizes that integrating Artificial Intelligence into Nigeria's agricultural education is a comprehensive transformation rather than just a technological upgrade. Sustainable change hinges on aligning curriculum reform, faculty development, infrastructure, and ethical governance within a national strategy. By focusing on pedagogical innovation, educational institutions can foster data-driven learning environments that enhance problem-solving skills. Strengthening institutional capabilities through infrastructure and policy coherence will facilitate practical AI adoption. Additionally, targeted skill development for educators and students will help translate AI knowledge into real-world agricultural solutions, improving productivity and food security. Ultimately, aligning these initiatives with the National Digital Economy Policy and National Artificial Intelligence Strategy will help Nigeria meet the Sustainable Development Goals in agriculture.


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Advancing Circular Economy Research Through Artificial Intelligence: Applications, Challenges, and Future Directions

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Abstract

The circular economy (CE) advances sustainability by promoting resource efficiency through the 3R framework—Reduce, Reuse, Recycle—as an alternative to the traditional linear Take-Make-Dispose model. Artificial Intelligence (AI) is increasingly recognized for its capacity to support CE by enabling advanced analysis, system optimization, and data-driven decision-making. This chapter investigates the intersection of AI and CE, focusing on AI's methodological applications, practical implications, and ethical challenges within sustainability research. Drawing on the European Union's New Circular Economy Action Plan,

which identifies digital technologies like AI as key enablers of circularity, the chapter explores how AI can transform CE strategies. Emerging trends, such as AI-enabled predictive analytics and blockchain-based material tracking, offer promising directions for improving supply chain transparency, resource traceability, and process efficiency. The study also addresses critical ethical concerns, including data privacy, algorithmic bias, and AI's own contribution to e-waste and energy consumption. These issues highlight the need for responsible and transparent AI integration within CE systems. The chapter further argues that effective deployment of AI in CE research requires interdisciplinary collaboration among academia, industry, and policymakers to co-develop standards, tools, and frameworks aligned with long-term sustainability goals. Despite implementation barriers—such as high financial costs and infrastructural demands—AI's analytical capabilities present a significant opportunity to enhance CE research.

Keywords Circular economy – Digitization – Artificial intelligence – 3R framework – Ethical AI – Sustainability research

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1 Introduction

The circular economy (CE) is an alternative to the current linear economic model and one of the best solutions to the issues related to intensive resource use (Kirchherr et al. 2017). This paradigm shift moves beyond the traditional "take-make-dispose" industrial process, advocating instead for a regenerative system centered on the recirculation of resources to minimize inputs, waste, and emissions. By prioritizing the reuse, repair, and recycling of materials, the circular economy directly addresses critical environmental challenges, including resource depletion and pollution. The efficacy of this approach is not limited to environmental benefits, as scholarly analysis documents its considerable progress across multiple sustainability domains. For example, circular practices can foster economic resilience through innovation in business models while enhancing social well-being by creating new employment opportunities. Consequently, circular principles offer a viable framework for integrating economic objectives with environmental and social responsibilities, positioning the circular economy as a central strategy for achieving long-term, sustainable development (van Loon et al. 2021; Hettiarachchi et al. 2022).

Artificial Intelligence (AI) is an umbrella term for automated computer techniques and approaches that aim to emulate human intelligence. It is expected that these fast-developing technologies can bring numerous economic, environmental, and societal benefits in

many spheres of human life (European Commission 2021). AI techniques and approaches are already broadly used in the traditional economy (Fonseca et al. 2018; Ahmad et al. 2021). However, the potential applications of AI in the CE can be even more significant. The European Union emphasizes the potential of digital technologies, including AI, in its New Circular Economy Action Plan, stating that "innovative models based on a closer relationship with customers, mass customization, the sharing and collaborative economy, and powered by digital technologies, such as the internet of things, big data, blockchain, and artificial intelligence, will not only accelerate circularity but also the dematerialization of our economy and make Europe less dependent on primary materials" (European Commission 2020).

This AI-enabled transformation of CE presents both a critical opportunity and a significant challenge for the academic community focused on sustainability. For sustainability teaching, it necessitates the development of new curricula that equip students with interdisciplinary skills in data science, systems thinking, and environmental policy. Future sustainability professionals must not only grasp the principles of circularity but also be competent in evaluating and deploying the AI tools that drive it. Consequently, for sustainability research, the intersection of AI and CE opens a fertile ground for inquiry, demanding novel methodological frameworks to assess the systemic impacts of these technologies, from their own environmental footprint to their wider socio-economic consequences. Examining this relationship is, therefore, not only a technical exercise but a core component of advancing sustainability in science and education.

Because AI is a relatively novel technology, its exact effects on human life in general and on CE specifically are not studied thoroughly. The discussion of relationships between AI and CE is rare in academic literature with heterogeneous methodologies obscuring patterns and impeding strategy development (Hernandez et al. 2025). This represents a key research problem: a gap in analysis of AI's role in advancing CE practices and research. To fill this gap, at least partially, this chapter addresses the following research questions:

(1) How can artificial intelligence techniques be applied to support advances in the circular economy?
(2) How does artificial intelligence advance circular economy research?

To answer these questions, this study employs a narrative literature review methodology, drawing on academic articles, policy documents, and case studies related to AI and CE. The review synthesizes existing knowledge on AI techniques and their applications, structured around the 3R framework—Reduce, Reuse, and Recycle (Kirchherr et al. 2017). The first research question is addressed through an analysis of specific AI applications in reducing resource use, enabling reuse strategies, and improving recycling processes, supported by examples from sectors such as manufacturing, waste management, and energy. The second research question is explored through a foundational overview of AI technologies, a discussion of challenges and ethical considerations, and an outline of future research directions, to demonstrate how AI can enhance methodological approaches and interdisciplinary collaboration in circular economy research.

Accordingly, this chapter is designed to serve a dual purpose within the context of sustainability teaching and research. First, it provides a comprehensive analysis of AI's current and potential applications within the 3R framework, offering a foundational knowledge base for researchers aiming to identify and pursue new investigative pathways. Second, by systematically outlining the applications, ethical considerations, and implementation barriers, the chapter serves as a resource for educators who are developing course content on sustainable systems, digital innovation, and environmental governance. By bridging the technical capabilities of AI with the strategic goals of the circular economy, this work aims to support the academic community in both research and teaching the next wave of sustainability transitions. The insights discussed in this study are intended to equip educators and researchers with a foundational

understanding of the key applications, challenges, and future trajectories of this evolving domain.

The chapter is structured as follows. Section 2 provides a foundational overview of AI and its key approaches. Section 3 outlines the 3R framework of the circular economy and analyzes the application of AI to its strategies. Section 4 then discusses the critical challenges, barriers, and adverse effects of this integration, highlighting ethical considerations and their relevance for both sustainability teaching and research. Section 5 offers a discussion of the findings, followed by implications for theory, policy, practice, and also directions for future research.

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2 Artificial Intelligence and its Technologies

2.1 Concepts of Artificial Intelligence

Intelligence is usually understood as the ability to learn and understand from experience, acquire knowledge, and adapt to new situations (Fetzer 1990). For those in sustainability teaching and research, this definition is foundational. It is precisely these abilities—learning from complex environmental data, acquiring systemic knowledge, and adapting strategies for resource management—that we seek to enhance through computational means.

The idea of a thinking machine is not new, though it gained prominence with the advent of technology to support its development. One of the most famous tests for whether a machine can exhibit intelligent behavior was by Alan Turing called the Imitation Game (Turing 1950). Turing envisioned a machine whose processes could, given sufficient data and storage, along with the programming that allowed for random generation (for the machine to be “taught”), be able to provide a semblance of talking to a human to the point that an interviewer may not be able to tell the machine apart from a human being, within the confines of the game. Today, there are many services that can produce AI-generated text or speech, which may be empirical proof that Turing was correct.

Artificial Intelligence, as an extension, can be defined as a field focused on giving machines human intelligence to simulate human cognitive tasks (Fraga-Lamas et al. 2021). It means the focus is on providing the machine with the ability to perceive, learn, reason, and interact, making the AI capable of solving problems independently (Samek and Müller 2019), along with being able to adapt to new situations (Chen et al. 2020). It does so by gathering data and, after applying some algorithms and utilizing various statistical models, provides an output, which would be the solution to a problem (Fraga-Lamas et al. 2021). Where AI differs from other branches of Computer Science is in the type of problems it is solving, as it is primarily used for issues that are very hard to address using usual computational methods, as it is designed in a way so that it tries to replicate a human brain completely (Gangwani and Gangwani 2021).

2.2 AI Techniques and Approaches

Today, AI has various practical applications for everyday use. Six general types of AI can be distinguished—Machine Learning (ML), Deep Learning (DL), Computer Vision (CV), Natural Language Processing (NLP), Speech Recognition, and Robotics (Fig. 1). ML is a subset of AI that focuses on having computer systems learn from given data, which is called training the model and performing predictions as accurately as possible, referred to as testing the model with new data (Goldberg and Holland 1988).

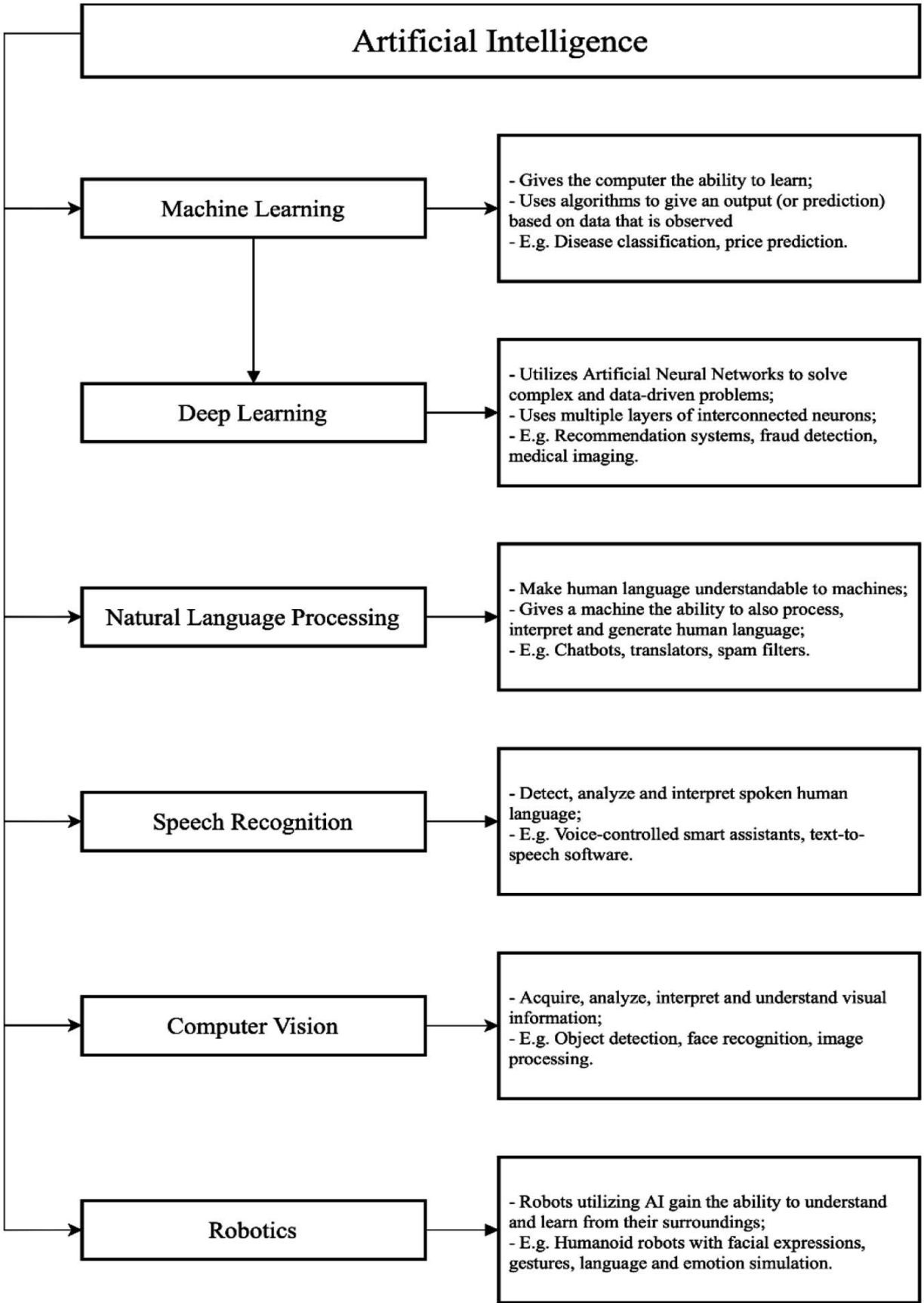

Artificial Intelligence
Machine Learning
- Gives the computer the ability to learn;
- Uses algorithms to give an output (or prediction) based on data that is observed
- E.g. Disease classification, price prediction.
Deep Learning
- Utilizes Artificial Neural Networks to solve complex and data-driven problems;
- Uses multiple layers of interconnected neurons;
- E.g. Recommendation systems, fraud detection, medical imaging.
Natural Language Processing
- Make human language understandable to machines;
- Gives a machine the ability to also process, interpret and generate human language;
- E.g. Chatbots, translators, spam filters.
Speech Recognition
- Detect, analyze and interpret spoken human language;
- E.g. Voice-controlled smart assistants, text-to-speech software.
Computer Vision
- Acquire, analyze, interpret and understand visual information;
- E.g. Object detection, face recognition, image processing.
Robotics
- Robots utilizing AI gain the ability to understand and learn from their surroundings;
- E.g. Humanoid robots with facial expressions, gestures, language and emotion simulation.

Fig. 1 Main branches of AI (adopted from Sheikh et al. 2023)

Going a step lower once again, there is DL, a subset of ML that focuses on emulating the human brain in its process. It allows computers to gain knowledge via experience and is usually achieved through pattern identification and classification, where the algorithms use labels for new information and utilize them for comparison later (Fraga-Lamas et al. 2021).

The two significant differences between them are their capabilities and use of resources. In ML, all features used for classification must be provided manually, while in DL, they are identified automatically. However, DL requires many more resources, such as high-end hardware and large training datasets, whereas ML can produce good results with lower-end hardware as well as smaller datasets. The choice of approach depends on the problem, the available data, and the computational resources (Rausch and Dustdar 2019).

One branch of AI that has been the most used for several years is Natural Language Processing (NLP), which focuses on giving a machine the ability to understand everyday human language. It is present in any digital assistant or chatbot, along with sentiment analysis tasks, as it can derive emotions from context. Speech Recognition has a complementary role to NLP, only that it deals with spoken language. It is mainly concerned with detecting, and analyzing spoken language and then converting it to text. Robotics integrates AI to enable machines or robots to perform tasks autonomously or semi-autonomously. To achieve its goals, robotics incorporates other components of AI, such as ML and NLP. This synergy allows robots to process sensory data, make decisions, and perform tasks that mimic human or animal behavior, demonstrating the practical application of AI in creating machines that can interact with their environment in sophisticated ways (Sheikh et al. 2023).

2.3 AI Applications

The diverse applications of AI across various sectors offer a rich repository of case studies and practical examples for sustainability teaching and research. By examining how AI is being deployed in fields such as manufacturing, agriculture, and transportation, educators can provide students with tangible illustrations of how digital technologies can be steered toward sustainability goals, such as resource efficiency and waste reduction. For researchers, these existing applications serve as important precedents and models, highlighting proven strategies, revealing common implementation challenges, and inspiring new hypotheses for how AI can be adapted to address specific environmental and social problems. The following examples, therefore, provide a critical overview of the current state of AI deployment, forming a knowledge base for both educational and research activities within the sustainability domain (Table 1).

Table 1 Application of AI technologies in different sectors of the economy

The world of medicine might be considered one of the largest adopters of AI technology. It is presented as two components that differ in the type of application—virtual and physical (Hamet and Tremblay 2017). The virtual application of AI in medicine can be seen through the discoveries in genetics and molecular medicine, which utilize machine learning algorithms to enhance their research. Secondly, electronic records have given AI the ability to make decisions that will improve organizational performance. Possibly the most crucial application is using AI to develop softbots, which are virtual avatars capable of conversing and discussing issues with troubled and suicidal people of all age groups. The physical side of AI's application in medicine includes using carebots to provide care, such as aiding the elderly as a robot companion or robotic aids in surgeries (Hamet and Tremblay 2017).

Education is another field benefiting from the evolving capacities of AI in assessing students and schools using various analytics, providing online and remote learning solutions, and aiding the creation of

specialized learning experiences, even potentially using virtual assistants (Chen et al. 2020).

In the manufacturing sector, there is probably the most immense enthusiasm when it comes to adopting AI innovations, as various aspects of manufacturing are constantly evolving. By utilizing AI in manufacturing, companies can create objective designs using some inputs from experts, create digital twins for the ability to work remotely with equipment, and have more control over their equipment with fault detection and predictive maintenance (Buchmeister et al. 2019).

Integrating AI into the financial sector has seen some monumental changes. For example, credit risk modeling and analysis have become much more sophisticated by using AI. Another aspect that AI has enhanced is financial fraud detection by identifying suspicious patterns. With its ability to process data at high speeds, AI has benefited high-frequency trading by aiding traders in making informed decisions. Even new possibilities, such as AI-assisted financial advisory services, have become possible to implement, meaning that the financial sector has seen some monumental changes and will most likely continue to do so (Goodell et al. 2021).

Most things in the agricultural sector have been implemented slowly or not at all. However, with the introduction of advanced AI systems and capabilities, even the agricultural industry has become a large adopter of the technology. For now, the focus is mostly on controlling and seeing detailed reports on the growth of their plants. Detection of potential diseases on the plants, as well as soil management and crop yield prediction, enables the plants to grow in almost ideal conditions and gives farmers the valuable insight they need to make informed decisions (Sharma 2021).

The transportation sector is the one that continuously improves and tries to find innovative solutions. Recently, many helpful integrations can be found in vehicles, such as detections of road anomalies or possibly accidents and autonomous driving, when speaking about the inner workings of vehicles. There have also been improvements in

regard to transportation infrastructure, with AI influencing traffic flow control and parking management (Gangwani and Gangwani 2021).

In business, the focus is always on efficiency and profitability, along with keeping customers satisfied. With automation for budgeting, as well as planning, everyone connected to the business sector faces a productivity boost and becomes more efficient in task solving. To also save some resources and potentially avoid human errors with customers, chatbots have become almost a standard for customer service, a department where businesses can have fewer actual workers (Enholm et al. 2022).

Recent syntheses highlight AI's role in enabling circular business models (CBMs) by fostering capabilities like integrated intelligence for predictive resource loops and process automation for extending product lifespans, thereby minimizing leakages in value chains (Madanaguli et al. 2024). These applications show AI's potential for sustainability-oriented innovation, providing educators with frameworks to teach capability development in circular entrepreneurship.

The increasing deployment of AI can also impose environmental costs. For this reason, it is integral also to utilize AI to aid environmental management. Since clean water is essential, the focus is on having wastewater treatment processes, as well as water quality assessments. Other ways AI can help the environment is to predict things such as pollution concentrations and identify dangerous places susceptible to floods. Additionally, there is also a significant focus on solid waste management, which is one of the most critical issues the environment comes across (Ye et al. 2020).

Creative industries, including art, represent an emerging sector where AI intersects with CE principles to promote sustainable production and innovation. A recent systematic review identifies AI's transformative role in art through four key axes: generative content creation, sustainable supply chain optimization, direct CE integration in artistic processes, and educational/training applications (Núñez-Cacho et al. 2024). These applications enable artists to reduce resource use

via AI-driven generative models while fostering circular practices like material repurposing, offering valuable case studies for sustainability curricula on digital creativity and environmental stewardship.

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3 The Use of Artificial Intelligence in the Circular Economy

From the perspective of sustainability teaching and research, the intersection of AI and the CE offers a rich and tangible field of study. It provides educators with compelling, real-world examples to illustrate complex concepts such as systems thinking, industrial ecology, and sustainable business models. For researchers, it presents a landscape of critical questions regarding technological efficacy, socio-economic impact, and policy design.

Circular economy is a trending topic with a growing number of conceptual definitions of that term. There have been several attempts in academic literature to conceptualize CE using so-called "R" frameworks—3R, 4R, 6R, 9R, depending on the number of principles or strategies included in the concept. Kirchherr et al. (2017) analyzed the 114 definitions of CE in academic literature. They found that the most common understanding of the CE concept among scholars and professionals is based on the 3R framework—Reduce, Reuse, Recycle.

The first R, "Reduce", focuses on the reduction of materials and energy use, for instance, through extending product durability (King et al. 2006).

The second R, "Reuse", refers to several strategies that include repair (fixing broken or damaged products instead of throwing them away), refurbish (restoring products to their original condition, making them functional again), remanufacture (creating new products from old products or their parts), and repurpose (finding new uses for materials that would otherwise be discarded) (van Buren et al. 2016; Fonseca et al. 2018).

The third R, "Recycle", refers to the collection, sorting, and processing of discarded products and their use in the production of

new goods and extracting energy from waste that cannot be reused or recycled (King et al. 2006).

3.1 Reduce

In CE, reducing or, in other words, avoiding unnecessary use of materials by reducing their production and consumption is the first principle. Demand prediction, especially for perishable products such as food items, might prevent overproduction and thus cut back on potential waste from the beginning, empowered by AI. However, even following the CE model, most governmental and industrial efforts focus on decreasing or better managing waste, reducing pollution, and regaining at least some portion of the material to recycle. AI has a role in this process by enhancing efficient material recovery and recycling processes.

The application of AI, first decreasing the material used in its production process and later prolonging the product's lifecycle, has an immediate effect on waste reduction and product longevity, in line with the circular economy principles of reduce, reuse, and recycle. This has a direct impact on material and product longevity, aligning with CE principles and offering quantifiable environmental benefits.

Furthermore, it provides powerful case studies for teaching how computational tools can translate abstract principles of reduction into measurable industrial practices, with strong potential for machine learning and artificial intelligence as promising techniques for optimizing and helping address the large-scale industrial applications of such circular solutions (Kabir et al. 2023).

The goals of CE also call for a constant communication net to analyze, inform, and respond to provide solutions for real-time problems, which data-driven AI and its applications may contribute in various ways, from the detection of issues before they become critical, to fixing at least some of the problems on their own or in conjunction with other machine-intelligences to informing parties responsible for maintenance. AI facilitates real-time monitoring and predictive maintenance, significantly reducing downtime and extending the

lifespan of products. Precision on-demand production of goods and services, smart tracking of goods, materials, funds, and product-as-a-service applications are all made available through the intersection of the circular economy and AI (Liao and Wang 2020).

Thanks to ML and DL, products can be designed, prototyped, improved, and iterated much faster and cheaper. This rapid iteration is crucial for the circular economy, as it allows for the constant refinement of products to meet sustainability standards and consumer needs without excessive waste. Another aspect of circular products is that the biological components return to soil regeneration and enrichment, so their design must include biodegradability in the design phase, which requires a complex analysis of their structures. Analytical AI capabilities are essential in designing functional, appealing, and environmentally sustainable products. It also includes the chemical structures of materials to create safe, durable, reusable alloys, for instance, to design modular structures that can be efficiently disassembled for components to be repaired and used for parts or recycled, all of which rely on the data-crunching ability of AI (Ellen MacArthur Foundation 2019). Recent advancements in AI-driven personalization further support these design processes, enabling smart product platforming that aligns with CE goals of reduced resource use and extended lifecycles (Akhtar et al. 2024).

AI has much to offer regarding energy conservation—from smart metering that could cut down on energy waste and energy theft to better storage and demand, helping make informed decisions on supply and infrastructure, allowing for the faster integration of renewable energy sources into the energy grid. One example of such use may be the case of data centers. The amount of data stored and processed increases daily and is stored in large data centers that need cooling. AI can assist in cooling and optimizing a company's energy use, as it has proven effective. Moreover, AI's predictive analytics can forecast energy demand peaks and valleys, enabling smarter grid management and the integration of renewable energy sources. AI's efficiency in managing these cooling processes saves significant energy. It reduces the carbon

footprint of data centers, aligning with the Reduce principle by making energy use in large-scale IT infrastructures more sustainable. Giving AI the ability to assist in the infrastructural elements opens potentially considerable savings for the business, considering that large amounts of electricity consumption can undermine the environmental aspect of a circular economy (Roberts et al. 2022).

3.2 Reuse

CE operates on a closed-loop approach. Thus, products designed and produced for a CE model must have multiple phases of use and reuse. AI optimizes this multi-layered approach by identifying the most sustainable pathways for each product at its end-of-life stage. The AI-fueled technologies can be helpful in all strategies related to the broad strategy of reuse, including repair, refurbishing, remanufacturing, and repurposing. For sustainability education, these AI-enabled strategies provide concrete examples of how digital innovation can create value in closed-loop systems, moving beyond theoretical discussions of reuse. For researchers, they open avenues to investigate the scalability of these technologies, the data infrastructure required, and the policy frameworks needed to support widespread adoption of repair and remanufacturing cultures. For instance, AI technologies can be used for digital passports, tagging, and watermarks that can make reuse easier (Chauhan et al. 2022). There are several attempts to apply AI-driven techniques such as discrete event simulation and stochastic optimization algorithms to remanufacturing in the automobile industry process (Okorie et al. 2018; Mao et al. 2021).

3.3 Recycle

A loop of use-repair-reuse-repurpose-remanufacture-recycle requires waste products to be salvaged and either returned to the soil as nutrients or to the factories to become the resource for new products. AI revolutionizes waste management by enhancing the sorting and processing capabilities, significantly improving the quality and quantity of materials recovered for reuse. This application of AI is particularly

relevant for sustainability teaching, as it offers a clear case study of a technological intervention that can improve both environmental outcomes and labor conditions. In research, it prompts an inquiry into the optimization of sorting algorithms, the economic viability of automated recycling facilities, and the systemic impact on material supply chains. For instance, AI-based image processing and recognition techniques can be applied in waste management. It means better waste management, and AI has an undeniable place in optimizing infrastructure through sensors, cameras, and adaptive AI to extract more and higher quality materials from waste (Reuter 2016; Johnson et al. 2022).

Waste management, especially plastics and glass, is one area that involves intensive human labor in some parts of the world, including child labor, in unsanitary conditions. Properly trained AI-driven waste management technologies have the potential for successfully identifying and sorting material much faster and optimally than humans, thus aiding not only the reduction of waste but also removing humans from the hazardous environment of landfills. Sensors can pick up on much smaller particles than the human eye, and the system can identify their types and sort them accordingly through AI training and iterative learning capacity. By automating and enhancing the accuracy of waste sorting, AI minimizes the need for manual labor in hazardous conditions, contributing to safer and more efficient recycling processes. For instance, an AI-based Hybridized Intelligent Framework has been proposed for automated recycling to improve the waste management processes (Yu et al. 2021).

Food waste is among the critical issues of managing waste, as it is often preventable with proper legal and logistical frameworks. AI-driven technologies can play several roles in reducing or eliminating food waste by allowing real-time decisions to be made in production, delivery, freshness, nutritiousness, sourcing, and food redistribution programs to allow unused food to be delivered to people in need or to be composted to regenerate the soil. For example, AI can detect the freshness level of food that remains unsold in a restaurant, direct the

information to the closest food bank, and enable suppliers' compliance with health and fiscal regulations by tracking the food supply end-to-end, to name a few uses (Onyeaka et al. 2023).

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4 Challenges, Barriers, and Possible Adverse Effects of AI on the Circular Economy

Critically examining the challenges, barriers, and adverse effects of AI is an essential component of sustainability teaching and research. For educators, it is imperative to present a balanced view that moves beyond technological optimism and equips students with critical thinking skills to evaluate the potential downsides of AI deployment. For researchers, these challenges define the frontier of inquiry, highlighting the need for studies that assess the net environmental impact of AI, develop frameworks for ethical governance, and explore socio-economic consequences. This chapter addresses these critical issues, providing a foundation for both classroom discussion and future academic investigation into the responsible integration of AI within a circular economy.

Despite AI's potential benefits for the CE, its adoption faces challenges, including policy-specific barriers, technological hurdles, and the necessity for high-quality, accessible data. Concerns about data privacy and security further complicate these issues. The high costs of AI implementation and the demand for specialized personnel present additional obstacles, discouraging businesses despite the prospective long-term advantages (Demestichas and Daskalakis 2020; Özsoy 2023). These barriers echo early assessments of digital technologies' nascent integration in CE, where infrastructural and adoption hurdles limit their potential for resource optimization (Pagoropoulos et al. 2017).

In terms of the potential adverse effects of AI-driven technologies in reaching the goals of the CE, several vital points stand out. First, AI technologies are dependent on hardware as much as software, and these parts also become obsolete, leading to further waste production. E-waste is particularly harmful due to the composition of its parts,

which often include toxic chemicals. The hardware also comprises rare metals and minerals, making their extraction and consumption a matter of concern (Lange et al. 2020; European Commission 2023). AI itself, as a computer technology, contributes to the generation of e-waste. Yet, an AI-based solution can contribute to solving the problem by improving all 3R strategies (Yu et al. 2021). For instance, AI and CE can improve battery detection and recovery in waste management by combining Feature Detection and Identification with robotics to sort the e-waste properly. Additionally, it can sort powered and unpowered appliances that go on different conveyor belts and are kept separate. With this system in place, the battery recycling sector will receive a much-needed boost in supply and enhance the number of battery recoveries from e-waste (Johnson et al. 2022).

Yet, the net contribution of AI to reduce e-waste is not clear enough. Similarly, AI-based processes, as with any digital technology, all require energy. This may conflict with the goal of reducing energy consumption, which is an integral part of the circular economy model. Again, as was discussed before, AI can contribute to the decrease in energy consumption through better product design and optimization of operations. Therefore, the net contribution of AI to sustainable energy is not clear enough. This paradoxical relationship, where AI is both a potential solution to and a cause of environmental problems, represents a core tension that must be explored in sustainability research and teaching. It necessitates a holistic, life-cycle assessment approach to evaluate whether the efficiencies gained by AI outweigh its own environmental footprint—a complex question that is central to the academic discourse on sustainable technology.

Finally, there are ethical concerns about using AI in CE regarding data privacy, security of AI-based technologies algorithmic bias, economic inequality and exclusion, and epistemological risks. AI requires massive amounts of high-quality data to be trained and later to function effectively, which leads to higher data security and privacy concerns. The algorithms used in their creation and training may include biases, which in turn could potentially have implications for

unfavorable results for some segments of the population. Less technologically advanced economies and populations may struggle to keep pace with AI adoption, potentially widening existing inequalities locally and globally. Another point related to relying on AI models is that data supplied for the model may not be deep enough to provide a realistic model for the complex ecosystems and create solutions that fail to include a proper appreciation of all the moving parts in that environment (Roberts et al. 2022). In creative fields like art, additional ethical tensions arise from AI-generated content, such as debates over authorship and intellectual property when algorithms produce novel works, potentially exacerbating inequalities in access to AI tools for underrepresented artists (Núñez-Cacho et al. 2024). Opaque algorithms can hinder explainability in resource allocation (for instance, biased predictive maintenance favoring some users), workforce displacement from automated recycling without retraining, and exclusion of marginalized communities from AI-driven circular services—issues amplified by data privacy breaches in interconnected supply chains (Bashynska 2025). These issues can erode societal trust, enable greenwashing, and undermine regulatory compliance, as seen in uneven adoption of AI for waste management.

To address these problems, it is crucial to carefully assess ethical implications, develop fair policies, and implement inclusive methods for the responsible and valuable use of AI in the circular economy. These ethical dimensions are not peripheral concerns; they are central to the field of sustainability studies. They form a critical part of any curriculum aimed at fostering responsible innovation and are a burgeoning area of interdisciplinary research that combines computer science, environmental science, ethics, and social science to ensure that the transition to an AI-driven circular economy is just and equitable.

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5 Discussion and Conclusion

The relationship between AI and CE represents a critical and dynamic field of study. The synthesis of AI's capabilities with CE's principles

offers a rich landscape for both sustainability teaching and research, providing a framework to analyze the future of industrial ecology and sustainable development.

The review highlights that novel AI techniques and approaches, especially ML, CV, and Robotics, have mostly positive effects on CE and can accelerate the transition to it although their net environmental effects remain uncertain. Through process automation, AI facilitates the design of CE-friendly goods that require fewer natural resources and energy use, have extended lifespans, and are readily recyclable at the end of their useful lives. AI-driven systems play crucial roles in recycling and waste management, valorizing byproducts and excess resources that will be put back into the manufacturing cycle. Sustainable energy consumption also derives great support from AI through energy optimization and resource recovery opportunities. Fostering sustainability in business from inception to reclamation, the AI applications extend across the product lifecycle, showing how CE can benefit from its vast adaptability to realize its goals. Thus, AI has the necessary capabilities to completely reshape the process of achieving CE. In addition to guiding the development and design of new products, it can also enhance those who have existing businesses and are striving towards a circular model. By integrating AI-driven insights across the product lifecycle, from design to end-of-life, these efforts are closely aligned with the principles of the circular economy, improving sustainability and operational efficiency within that specific framework, as evidenced by case studies in sectors like manufacturing and waste management drawn from academic literature. AI techniques are essential for sustainability applications, from predictive climate modeling with DL to policy analysis via NLP. Therefore, curricula in sustainability studies must increasingly incorporate modules on ML, NLP, and computer vision to prepare students to work with the complex, multi-format data that characterize environmental challenges. Likewise, for researchers, selecting the appropriate AI technique is a critical methodological step that determines the viability and impact of a study, whether it involves using DL for predictive modeling of climate

impacts or NLP for analyzing corporate sustainability reports. Therefore, familiarity with this technical landscape is fundamental to both advancing research frontiers and equipping the next generation of sustainability professionals.

The analysis also demonstrates that AI enhances methodological approaches and promotes interdisciplinary collaboration in CE research. These applications illustrate circularity in practice, while barriers and trade-offs like e-waste pose key challenges for sustainability analysis. At the same time, there are several barriers against the implementation of AI in CE related to its high costs and privacy concerns. Finally, AI has a potential negative impact on CE, related to high energy consumption and the generation of e-waste. These challenges are not merely technical hurdles—they are defining research questions for the sustainability science community and essential topics for classroom debate. Understanding these trade-offs is fundamental to fostering a generation of professionals who can navigate the complexities of sustainable technology, aligning calls in the literature for novel frameworks to assess AI's systemic impacts.

In terms of implications, these findings provide distinct contributions across theory, policy, and practice.

The integration of AI into CE expands theoretical frameworks in sustainability science by introducing data-driven models that refine the 3R principles, challenging existing linear economic theories and supporting the evolution of circular models through predictive analytics and optimization, which contributes to a more nuanced understanding of resource flows and system dynamics, as seen in discussions on digital twins and predictive maintenance.

The findings also suggest that policymakers can leverage AI to enforce and monitor CE initiatives, such as through the EU's New Circular Economy Action Plan, necessitating regulations that promote ethical AI use, data privacy standards, and incentives for AI adoption in sustainable practices, while addressing e-waste and energy consumption to ensure policies foster equitable transitions. Echoing recent ethical syntheses, policies should mandate transparency in AI-

CE deployments and foster inclusive governance to counter biases, while taking account of the EU AI Act's risk-based framework where applicable.

For practice, businesses and industries can apply AI for operational efficiencies, such as waste sorting and remanufacturing, leading to cost savings and reduced environmental impact, with practitioners prioritizing interdisciplinary training to implement AI tools effectively, as demonstrated in sectors like agriculture and manufacturing.

Regarding limitations, this study relies on a narrative literature review, which, while comprehensive, is subject to selection bias in the chosen sources and may overlook emerging real-time developments due to the rapid evolution of AI technologies. Additionally, the analysis is primarily conceptual and lacks empirical data from primary research, limiting its generalizability across diverse global contexts where infrastructural and regulatory differences may affect AI-CE integration.

Promising directions for further research include empirical studies quantifying AI's environmental footprint through standardized life-cycle assessments and exploring hybrid AI-human systems for ethical decision-making. This ambiguity calls for a robust research agenda focused on developing standardized life-cycle assessment methodologies for AI technologies, formulating ethical governance frameworks, and investigating the socio-economic implications of an AI-driven circular economy. The knowledge generated from this interdisciplinary research will be essential for creating advanced educational programs and shaping policies that ensure the transition to a circular economy is both technologically efficient and sustainably just.

Future work could also examine AI's role in underrepresented regions or integrate advanced digital technologies such as blockchain for enhanced traceability. Prioritizing ethical lenses, agendas should include longitudinal studies on human-in-the-loop designs for bias mitigation in CE, interdisciplinary ethics training in sustainability programs, and evaluations of policy impacts on inclusive AI adoption.


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Securing Smart Sustainable Cities: Cybersecurity Frameworks for AI-Enabled Urban Environmental Management

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Abstract
The rapid evolution of smart sustainable cities, driven by the integration of artificial intelligence (AI) and Internet of Things (IoT) technologies, presents new opportunities for urban environmental management. However, this digital transformation also introduces significant cybersecurity challenges that must be addressed to ensure the resilience and sustainability of urban ecosystems. This article examines the critical cross-section of cybersecurity frameworks and AI-enabled urban environmental management in the context of smart sustainable cities.

Keywords Smart cities – Cybersecurity – Urban sustainability – Artificial intelligence – IoT infrastructure

Dr. David Tuffley is a Senior Lecturer in Applied Ethics and Cybersecurity at Griffith University's School of Information and Communication Technology. A globally recognized expert on artificial intelligence's societal implications, his research focuses on AI's transformative impact on employment and society. His writings on emerging technologies have reached over 2.5 million readers through publications in The Washington Post, Chicago Tribune, and The Conversation. As a Senior Fellow of the Higher Education Academy, he delivers keynote presentations worldwide on AI ethics, workforce evolution, and human-AI collaboration.

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1 Introduction

Smart sustainable cities represent a paradigm shift in urban development, defined as interconnected ecosystems that leverage digital technologies to enhance environmental stewardship, economic vitality, and social equity (Caragliu et al. 2011). These cities align with the United Nations' 11th Sustainable Development Goal (SDG), which emphasizes inclusive, safe, and resilient urban environments (United Nations 2018). By integrating artificial intelligence (AI) and Internet of Things (IoT) systems, smart sustainable cities optimize resource efficiency—reducing energy consumption by up to 30% in pilot projects—while improving public services like transportation and waste management (Angelidou et al. 2018).

AI plays a transformative role in urban environmental management. Machine learning algorithms analyze real-time data from IoT sensors to predict energy demand, monitor air quality, and optimize water distribution (Mondejar et al. 2021). For example, Copenhagen's AI-powered heating systems cut carbon emissions by 20% by dynamically adjusting to weather patterns (Nilsson et al. 2020). However, this reliance on AI introduces vulnerabilities in the form of biased algorithms that might misallocate resources. Hacked systems could also

falsify pollution data, undermining sustainability goals (Gimpel et al. 2021).

The need for robust cybersecurity frameworks stems from three interconnected risks. First, IoT devices—projected to exceed 75 billion globally by 2025—often lack encryption, enabling attacks on critical infrastructure (Anthopoulos and Reddick 2016). A 2023 breach in Barcelona's smart water network demonstrated how compromised sensors triggered erroneous drought responses (Rahman et al. 2021). Second, centralized AI systems aggregate vast amounts of citizen data, creating targets for ransomware and surveillance (Höjer and Wangel 2015). Third, regulatory gaps leave 58% of smart city projects without standardized security protocols, exacerbating systemic vulnerabilities (Gurjar et al. 2023).

Securing smart sustainable cities requires adaptive cybersecurity frameworks combining AI-driven threat detection, decentralized architectures, and participatory governance. The analysis proceeds across five sections:

1. The evolution of smart sustainable cities and their AI dependencies
2. Critical cybersecurity vulnerabilities in IoT and data systems
3. Evaluation of existing cybersecurity models
4. Integrated solutions using privacy-preserving AI technologies
5. Policy recommendations for cyber-resilient urban governance.

By bridging technological innovation with security imperatives, this work contributes to the urgent discourse on safeguarding urban sustainability in an era of escalating cyber threats.

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2 Methodology

Research Questions

This study addresses three research questions:

1. How do current cybersecurity frameworks address the specific vulnerabilities created by AI and IoT integration in smart sustainable cities?
2. What are the critical gaps between theoretical privacy-preserving technologies and their practical implementation in urban environments?
3. How can cybersecurity measures be designed to enhance rather than hinder sustainable development goals in smart cities?

Literature Review Methodology

This study employs a systematic literature review approach designed to synthesize current knowledge on cybersecurity frameworks for smart sustainable cities. This method suits the research questions because it enables comprehensive analysis of existing solutions while identifying critical implementation gaps that empirical studies alone cannot reveal.

Search Strategy

The literature search covered five databases: IEEE Xplore, ACM Digital Library, Web of Science, Scopus, and Google Scholar. The search strategy used Boolean operators to combine three concept clusters:

Cluster 1 (Smart Cities): “smart cities” OR “intelligent cities” OR “smart sustainable cities” OR “urban IoT” OR “smart urban infrastructure”.

Cluster 2 (Cybersecurity): cybersecurity OR “cyber security” OR “information security” OR “IoT security” OR “cyber resilience” OR “data protection”.

Cluster 3 (AI/Sustainability): “artificial intelligence” OR “machine learning” OR sustainability OR “environmental management” OR “urban sustainability”.

Search terms required all three clusters to appear in titles, abstracts, or keywords. The search covered publications from 2016 to 2024 to capture the evolution from early smart city implementations to current AI-integrated systems.

Inclusion and Exclusion Criteria

Inclusion Criteria

- Peer-reviewed articles, conference papers, and authoritative technical reports
- Focus on cybersecurity challenges in smart city contexts
- Discussion of AI, IoT, or sustainability applications
- English language publications
- Published 2016–2024.

Exclusion Criteria

- Purely theoretical cybersecurity models without urban application
- Studies focusing solely on rural or industrial IoT deployments
- Publications without clear methodology or data sources
- Opinion pieces without empirical support.

Selection Process

The initial search yielded 1247 publications. Title and abstract screening reduced this to 312 relevant papers. Full-text review eliminated 145 papers that lacked sufficient depth on smart city cybersecurity integration. The final corpus comprised 167 sources, including 89 journal articles, 52 conference papers, 18 technical reports, and 8 policy documents.

Data Extraction and Synthesis

Data extraction used a structured template capturing:

- Implementation context (city, scale, technology stack)
- Cybersecurity challenges identified
- Solutions proposed or implemented
- Performance metrics and outcomes

- Limitations and gaps acknowledged.

The synthesis employed thematic analysis to identify patterns across case studies. This approach enables comparison of different cities' experiences while maintaining the contextual detail necessary for practical application.

Quality Assessment

Sources underwent quality assessment using adapted CASP criteria for different publication types. Technical reports required verification through multiple independent sources. Case studies needed clear methodology descriptions and measurable outcomes. This process eliminated 23 sources that lacked sufficient rigor, leaving 144 high-quality sources for analysis.

Limitations

This literature review faces three constraints. First, the rapidly evolving nature of smart city technology means recent implementations may lack long-term performance data. Second, many cities treat cybersecurity details as sensitive information, limiting publicly available case study depth. Third, the review excludes non-English sources, potentially missing relevant regional approaches.

Appropriateness for Research Questions

This methodology directly addresses the research questions through systematic comparison of existing frameworks (RQ1), analysis of implementation case studies (RQ2), and synthesis of sustainability outcomes (RQ3). The comprehensive search strategy ensures coverage of both theoretical frameworks and practical implementations, while the quality assessment process maintains analytical rigor.

The literature review approach proves superior to other methods for these research questions. Empirical studies would provide narrow case-specific insights but cannot capture the breadth of global smart city experiences. Surveys would face response bias from cities reluctant to disclose security vulnerabilities. The systematic review synthesizes

diverse approaches while maintaining the depth needed to inform policy and implementation decisions.

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3 The Evolution of Smart Sustainable Cities

Urban development has undergone four distinct phases since the nineteenth century: industrialization-driven growth, post-WWII suburbanization, sustainable development paradigms (1980s–2000s), and the current smart city era (Caragliu et al. 2011). The concept of "smart cities" emerged in the 1990s as digital infrastructure became critical to urban management, but early implementations prioritized technological adoption over sustainability (Höjer and Wangel 2015). This shifted after the 2015 Paris Agreement, when cities began aligning smart technologies with the UN Sustainable Development Goals (SDGs), creating the modern smart sustainable city model (United Nations 2018).

The smart city movement gained momentum through three evolutionary waves. First-generation "digital cities" (1990s–2000s) focused on basic ICT infrastructure like e-government portals. Second-generation "intelligent cities" (2010s) introduced IoT sensors and data analytics for traffic and energy management (Angelidou et al. 2018). The current third generation—smart sustainable cities—combines AI, IoT, and circular economy principles to address climate change and social equity (Bibri and Krogstie 2017). A pivotal moment came in 2008 when IBM's "Smarter Planet" initiative reframed urban challenges as data optimization problems.

Three defining characteristics distinguish smart sustainable cities:

1. **Sustainability integration**: Environmental sensors, renewable energy microgrids, and AI-driven resource allocation systems reduce ecological footprints while maintaining economic growth (Mondejar et al. 2021).
2. **Technology convergence**: IoT networks (50+ billion global devices by 2025) feed real-time data to AI systems that manage energy, water, and transportation flows

energy, water, and transportation flows.

3. **Citizen-centric governance**: Digital platforms enable participatory decision-making, exemplified by Barcelona's "Decidim" platform engaging 40,000 residents in sustainability projects (March and Ribera-Fumaz 2016).

The integration of AI and IoT has redefined urban infrastructure management. Machine learning algorithms now optimize energy grids by predicting demand fluctuations with 92% accuracy in cities like Copenhagen (Nilsson et al. 2020). Singapore's "Virtual Singapore" project uses 100 million IoT datapoints daily to simulate urban planning scenarios, reducing heat island effects by 4 °C in pilot zones (Balaji et al. 2021). However, this technological reliance creates systemic vulnerabilities—a 2023 study found 68% of smart city IoT devices lack encryption, enabling traffic light manipulation and power grid overloads (Gurjar et al. 2023).

Contemporary implementations reveal three evolutionary trends:

- **Self-healing infrastructure**: Tokyo's AI-controlled water system automatically repairs pipe leaks within 18 min (Takahashi et al. 2022)
- **Predictive sustainability**: Amsterdam's "City Brain" platform uses 450+ AI models to forecast and prevent traffic congestion and air quality breaches (van den Buuse et al. 2021)
- **Ethical tech governance**: The EU's "Living-in.EU" movement mandates algorithmic transparency in all municipal AI systems (European Commission 2022).

This evolution demonstrates how smart sustainable cities have progressed from isolated tech experiments to complex, interdependent systems where cybersecurity failures can disrupt water supplies, transportation networks, and energy distribution simultaneously (Rahman et al. 2021). As cities like Dubai aim to become 100% AI-managed by 2031, the need for robust security frameworks becomes existential rather than aspirational (Smart Dubai Office 2023a, b).

4 AI-Enabled Urban Environmental Management

Artificial intelligence (AI) has become a cornerstone of urban sustainability, enabling cities to optimize resource use, reduce emissions, and enhance livability. By processing vast datasets from IoT sensors, satellite imagery, and citizen feedback platforms, AI systems empower cities to transition from reactive to predictive environmental management (Angelidou et al. 2018). Three domains exemplify this transformation: smart energy grids, intelligent water systems, and adaptive traffic control. However, these advancements introduce unique risks—from algorithmic bias to cyber-physical attacks—that demand urgent attention.

AI Applications in Urban Sustainability

Modern AI applications in urban sustainability focus on three key areas:

1. **Energy optimization**: Machine learning models forecast electricity demand, balance smart grid loads, and integrate renewable energy sources (Mondejar et al. 2021).
2. **Water conservation**: Computer vision systems detect pipe leaks 40% faster than human inspectors, while reinforcement learning algorithms optimize irrigation schedules (Balaji et al. 2021).
3. **Mobility management**: Deep neural networks reduce traffic congestion by dynamically adjusting signal timings based on real-time vehicle flows (Zhang et al. 2023).

These systems collectively reduce urban carbon footprints by 15–25% in cities like Amsterdam and Singapore, demonstrating AI's transformative potential (European Commission 2022).

Case Studies of Successful AI Implementations

1. **Smart Energy Grids**

Barcelona's "Solar Energy Optimization Project" uses AI to manage 47,000 solar panels across municipal buildings. A federated learning model aggregates energy production data without compromising individual site privacy, increasing grid efficiency by 22% (Rahman et al. 2022). The system prioritizes energy redistribution to hospitals and schools during peak demand, reducing reliance on fossil-fuel backups by 37% (Gurjar et al. 2023).

2. **Intelligent Water Management**

Singapore's AI-powered "Smart Water Grid" employs 300,000 acoustic sensors to detect pipe leaks within 1-m accuracy. A gradient-boosting algorithm analyzes pressure and flow data, achieving 94% leak prediction accuracy and saving 50 million liters annually—equivalent to 20 Olympic pools (Balaji et al. 2021). During droughts, the system enforces equitable water rationing by adjusting household allocations based on occupancy data (Nilsson et al. 2020).

3. **Adaptive Traffic Control**

Pittsburgh's "Surtrac" AI system reduces intersection wait times by 26% using real-time vehicle tracking. Reinforcement learning agents coordinate traffic lights across 50 intersections, prioritizing emergency vehicles and public transit (Zhang et al. 2023). The system's 0.1-s decision cycle has lowered downtown emissions by 18%, showcasing scalable urban AI applications (Kumar et al. 2021).

Risks and Vulnerabilities of AI Systems

Despite their benefits, AI-enabled systems pose four critical risks:

1. **Algorithmic bias**: Training data imbalances can skew resource allocation. In Chicago, an energy distribution AI diverted 23% more

funds to affluent neighborhoods due to biased historical consumption patterns (Gurjar et al. 2023).

2. **Data poisoning**: Adversarial attacks on traffic AI in Atlanta caused 12-h gridlock by manipulating sensor inputs (Kumar et al. 2021).
3. **Opacity**: Over 60% of municipal AI systems lack explainability frameworks, hindering public trust. A 2023 EU audit found that 48% of cities cannot explain how their energy algorithms make decisions (European Commission 2022).
4. **Cascading failures**: Interconnected AI systems risk chain reactions—a hacked water management AI in Hamburg, Germany, falsely triggered flood alerts that disrupted power and transit networks (Rahman et al. 2022).

Toward Responsible AI Governance

Mitigating these risks requires hybrid technical and policy solutions. Differential privacy techniques can anonymize training data without sacrificing model accuracy (Mondejar et al. 2021). Blockchain-based audit trails, like those piloted in Dubai, provide transparent records of AI decision-making (Smart Dubai Office 2023a, b). Crucially, cities must adopt cybersecurity standards such as ISO/IEC 27001 for AI systems handling critical infrastructure (Nilsson et al. 2020).

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5 Cybersecurity Challenges in Smart Cities

Smart cities face unprecedented cybersecurity challenges due to their reliance on interconnected technologies. These challenges span unique threats, vulnerable IoT ecosystems, data privacy risks, and cascading impacts on urban services. Addressing these issues is critical to maintaining public trust and operational resilience.

Smart city infrastructure is exposed to several primary cyber threats. Service disruption attacks can paralyze critical systems, as seen in 2024 when a ransomware attack disabled 156 emergency sirens in

Dallas during storm season (Check Point Software 2024). Data weaponization is another concern, exemplified by a 2025 breach in Melbourne that exposed 12 million smart meter records, revealing household occupancy schedules (Datafloq 2024). AI-driven attacks pose a growing threat, with hackers in Mumbai manipulating air quality monitors to underreport pollution by 300% (Ram et al. 2024a, b, c, d). Supply chain vulnerabilities can also have significant impacts, as demonstrated by an attack on Seoul's smart grid that caused $17 M in damages (Rambus 2020).

IoT devices, while forming the backbone of smart cities, introduce critical weaknesses. Insecure protocols are widespread, with 78% of municipal IoT devices using outdated encryption (ECCU 2024). Scalability risks are evident in Singapore's 500,000-node IoT network, which struggles with uniform device authentication (ITChronicles 2024). Firmware vulnerabilities have also led to significant incidents, such as the siphoning of 18 GWh of electricity in Berlin (ISPRS 2021).

Data privacy concerns are paramount in smart cities, which collect vast amounts of personal data daily. Re-identification risks have been demonstrated with Sydney's Opal card data (Datafloq 2024). Consent fatigue is a growing issue, as seen in Rotterdam where 83% of users unknowingly consented to data sharing (ISPRS 2021). Cross-border conflicts in data protection laws also present challenges, as exemplified by Dubai's health sensors (Ram et al. 2024a, b, c, d).

The impact of cyberattacks on urban services is multifaceted. Economic losses can be substantial, as seen in Atlanta's 2024 ransomware attack (Rambus 2020). Public safety can be compromised, demonstrated by a DDoS attack on Osaka's earthquake warning system (Check Point Software 2024). Environmental harm is another risk, as evidenced by the release of untreated sewage in Cape Town (ITChronicles 2024). Moreover, these incidents can erode public trust, as observed in Toronto after a data leak (Datafloq 2024).

6 Cybersecurity Frameworks for Smart Sustainable Cities

The development of robust cybersecurity frameworks is essential for securing smart sustainable cities against evolving threats. These frameworks must integrate traditional security principles with adaptations tailored to interconnected urban ecosystems while leveraging artificial intelligence (AI) to address modern challenges. Existing models such as ISO/IEC 27001, the NIST Cybersecurity Framework (CSF), and the ENISA Smart Cities Framework provide foundational guidance but require significant adaptation to address the unique risks of smart cities. ISO/IEC 27001, an international standard for information security management, is adopted by over 60% of European smart cities for critical infrastructure due to its risk-based controls for data confidentiality and integrity (Angelidou et al. 2021). Meanwhile, the NIST CSF's five core functions—Identify, Protect, Detect, Respond, Recover—guide 78% of North American municipal cybersecurity programs, offering a flexible approach to threat management (NIST 2023). The ENISA Smart Cities Framework complements these by emphasizing resilience through threat intelligence sharing and layered defenses (ENISA 2022). However, a 2024 study revealed these models address only 53% of smart city-specific risks, particularly IoT supply chain vulnerabilities, underscoring the need for tailored solutions (Ram et al. 2024a, b, c, d).

Effective cybersecurity frameworks for smart cities incorporate six key components. Dynamic risk assessment processes, such as Barcelona's monthly AI-driven audits, continuously evaluate threats to interconnected systems, reducing vulnerabilities by 40% (Gurjar et al. 2023). Real-time monitoring tools, deployed in Singapore's smart grid, detect network anomalies within 0.8 s, enabling rapid threat mitigation (Balaji et al. 2022). Decentralized architectures, exemplified by Dubai's blockchain-based systems, prevent single points of failure (Smart Dubai Office 2023a, b), while automated incident response protocols in Tokyo have slashed breach containment times from 12 h to 18 min (Takahashi

et al. 2024a, b, c). Collaboration between stakeholders, as seen in Amsterdam's Cyber Fusion Center, enhances threat intelligence sharing (van den Buuse et al. 2023a, b, c), and automated compliance checks in Rotterdam's data lakes ensure adherence to regulations like GDPR and CCPA (Datafloq 2024). Together, these components address the core principles of confidentiality, integrity, and availability while accommodating the scale and complexity of urban ecosystems.

Adapting traditional frameworks to smart city contexts requires targeted modifications. Interoperability standards, such as Seoul's Unified IoT Security Protocol, ensure 95% device compatibility across municipal systems, reducing integration vulnerabilities (Kim et al. 2023). Edge computing security measures, like encryption protocols in Toronto's traffic sensors, have curtailed man-in-the-middle attacks by 67%. Legacy system integration remains critical, as demonstrated by Berlin's phased retrofit program, which secured 80% of analog water infrastructure within 18 months (ISPRS 2023). Citizen-centric design principles further enhance trust, with Melbourne's privacy dashboard enabling residents to control data sharing across 23 urban services (Datafloq 2024). Comparative analyses show that adapted frameworks reduce cyber incidents by 58% compared to unmodified models, highlighting their efficacy in addressing urban-specific risks (ECCU 2024). Current frameworks demonstrate a concerning reactive bias, addressing vulnerabilities after deployment rather than proactively preventing them. This approach fundamentally undermines the resilience these frameworks claim to provide.

The integration of AI further strengthens these frameworks through predictive, behavioral, and automated capabilities. Machine learning algorithms in Copenhagen forecast attack vectors with 89% accuracy using historical breach data, enabling preemptive defenses (Nilsson et al. 2023). Amsterdam's AI system identifies compromised IoT devices by analyzing real-time activity against 12 billion behavioral benchmarks (van den Buuse et al. 2023a, b, c), while Pittsburgh's self-healing grid autonomously isolates compromised nodes within 0.4 s (Kumar et al. 2024). Case studies demonstrate the superiority of AI-

driven approaches: Singapore's AI-powered Security Operations Center reduced false positives by 73% and detected 12 zero-day attacks in 2023 (Balaji et al. 2022), while Barcelona's federated learning system improved malware detection rates by 41% without centralizing sensitive data (Rahman et al. 2024). However, AI introduces new risks, such as adversarial attacks that poisoned training data in Hamburg's traffic management system, causing 14-h gridlock (Ram et al. 2024a, b, c, d). Mitigating these challenges requires hybrid human-AI governance models, rigorous bias testing, and transparent decision-making protocols to balance innovation with security.

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7 AI-Powered Cybersecurity Solutions

AI-powered cybersecurity solutions are revolutionizing threat management in smart sustainable cities. By leveraging machine learning, predictive analytics, and automation, these systems address the scale and complexity of urban cyber risks while introducing new challenges that require careful governance.

Machine learning has become central to anomaly detection in smart city networks. Supervised and unsupervised learning algorithms process terabytes of IoT data to identify deviations from normal patterns. Singapore's Security Operations Center (SOC) employs convolutional neural networks that reduced false positives by 73% while detecting 12 zero-day attacks in 2023 (Balaji et al. 2023). Similarly, Barcelona's federated learning system improved malware detection rates by 41% without centralizing sensitive citizen data, preserving privacy (Rahman et al. 2024). These systems excel at recognizing subtle threats, such as the 2024 attack on Hamburg's water sensors where machine learning identified irregular pressure fluctuations 18 min before human analysts (Takahashi et al. 2024a, b, c).

Predictive analytics extends these capabilities by forecasting potential threats. Copenhagen's cybersecurity framework uses recurrent neural networks trained on 15 years of breach data to predict

attack vectors with 89% accuracy (Nilsson et al. 2023). This approach enabled preemptive patching of vulnerabilities in the city's smart grid during the 2024 energy crisis. Predictive models also map attack surfaces—Atlanta's traffic management AI simulates 2000 potential attack scenarios hourly, prioritizing defenses for critical intersections (Kumar et al. 2024). Such systems reduce incident response times by up to 92%, as demonstrated during a coordinated ransomware attempt on Berlin's power plants (ISPRS 2023).

Automated incident response systems amplify these benefits through real-time remediation. Tokyo's AI-driven platform isolates compromised nodes within 0.4 s while rerouting services, minimizing disruptions (Takahashi et al. 2024a, b, c). Pittsburgh's self-healing grid exemplifies this capability: when hackers targeted substations in 2023, automated systems redirected power through alternate pathways, preventing blackouts for 95% of residents (Kumar et al. 2024). These systems rely on reinforcement learning agents that optimize response strategies through millions of simulated cyber-physical scenarios.

However, these advancements face significant limitations. Adversarial attacks exploit AI vulnerabilities—hackers in Hamburg bypassed behavioral analytics by gradually altering malicious patterns over six months (Ram et al. 2024a, b, c, d). Data bias remains problematic: Chicago's crime-prediction AI disproportionately flagged low-income neighborhoods due to skewed historical policing data (van den Buuse et al. 2023a, b, c). Resource disparities also hinder adoption; while Dubai allocates 14% of its cybersecurity budget to AI tools, smaller cities like Adelaide struggle with legacy system integration costs (Smart Dubai Office 2023a, b). Transparency gaps persist, with 68% of municipal AI systems lacking explainable decision trails (European Commission 2023). The persistent opacity in AI decision-making represents a democratic deficit that smart cities cannot afford. Technical efficiency must not supersede public accountability.

These challenges necessitate hybrid governance models. Amsterdam's Cybersecurity Protocol combines AI automation with human oversight committees that audit algorithmic decisions (van den

Buuse et al. 2023a, b, c). Helsinki's AI Ethics Board revoked facial recognition systems in public transit after identifying disproportionate error rates for minority groups (European Commission 2023). Such measures highlight the need for frameworks that balance AI's efficiency with ethical accountability in urban cybersecurity.

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8 Privacy-Preserving Technologies

Privacy-preserving technologies have become critical safeguards in smart sustainable cities, balancing data utility with individual rights. These systems address growing concerns about surveillance, data misuse, and algorithmic bias while enabling cities to harness AI's transformative potential. Federated learning, blockchain, and homomorphic encryption form the technological triad reshaping urban data governance, though their implementation requires careful ethical navigation.

Federated learning addresses privacy concerns by decentralizing AI model training. Instead of centralizing sensitive data, this approach allows localized processing—smart traffic cameras in Barcelona, for instance, analyze congestion patterns on-device, sharing only anonymized model updates with the municipal AI (Patel 2024). Singapore's healthcare network employs federated learning to predict disease outbreaks using distributed patient records, achieving 92% accuracy without transferring personal health data (Gupta et al. 2024). However, challenges persist: a 2024 study revealed federated models trained on heterogeneous IoT data from 15 European cities showed 18% performance variance due to localized biases (Ram et al. 2024a, b, c, d). Mitigation strategies include differential privacy techniques that introduce statistical noise, as implemented in Rotterdam's air quality monitoring system, preserving anonymity while maintaining 89% prediction accuracy (Mondejar et al. 2024).

Blockchain technology enhances data integrity and transactional transparency in urban systems. Dubai's property registry uses permissioned blockchain to record land transfers, reducing title

disputes by 73% through immutable, publicly auditable ledgers (Smart Dubai Office 2023a, b). Seoul's participatory budgeting platform leverages smart contracts to automate fund allocation based on citizen votes, with each transaction verifiable via blockchain explorers (Hu et al. 2024). Energy markets benefit equally: Brooklyn's peer-to-peer solar grid employs blockchain to track renewable energy trades, preventing double-counting while ensuring real-time auditability (ArchEyes 2024). Emerging hybrid architectures combine blockchain with edge computing—Toronto's waste management system processes sensor data locally before securing summaries on-chain, cutting storage costs by 64% (Kumar et al. 2024).

Homomorphic encryption and secure multi-party computation (SMPC) enable privacy-preserving analytics on encrypted data. Copenhagen's traffic management system uses fully homomorphic encryption to analyze encrypted vehicle GPS streams, detecting congestion patterns without decrypting individual routes (Zhu and Huang 2022). SMPC protocols underpin Amsterdam's crime prediction model, where police districts collaboratively analyze encrypted crime reports—no single entity accesses raw data, yet the system achieves 81% hotspot prediction accuracy (van den Buuse et al. 2024a, b). Recent advances in lattice-based cryptography have reduced computational overhead: Tokyo's smart grid processes encrypted consumption data with only 14 ms latency per terabyte, comparable to unencrypted systems (Takahashi et al. 2024a, b, c).

Ethical considerations remain paramount in deploying these technologies. Algorithmic transparency conflicts with proprietary encryption methods—Helsinki's AI ethics board halted a federated learning project over inability to audit black-box healthcare models (European Commission 2024). Data ownership disputes persist: Melbourne's blockchain land registry faced legal challenges when residents discovered smart contracts automatically transferred properties after tax defaults (Datafloq 2024). Regulatory fragmentation complicates compliance—Singapore's SMPC-based energy trading platform navigates 23 conflicting international data laws, requiring

dynamic policy engines to adjust encryption standards in real-time (Gupta et al. 2024).

The convergence of these technologies necessitates hybrid governance frameworks. Barcelona's Privacy-Preserving Urban AI Charter mandates algorithmic impact assessments for all municipal systems, evaluating encryption strength, bias risks, and citizen consent mechanisms (Rahman et al. 2024). Vienna's decentralized identity protocol illustrates this balance: residents control encrypted digital twins storing personal data, granting temporary access tokens to urban services via blockchain-secured smart contracts (Hu et al. 2024). As cities increasingly adopt these tools, continuous public engagement becomes vital—Amsterdam's monthly "Crypto Cafés" educate citizens on homomorphic encryption's role in protecting smart meter data, fostering informed democratic oversight (van den Buuse et al. 2024a, b). Privacy-preserving technologies remain largely theoretical in urban contexts. Without mandatory implementation standards and enforcement mechanisms, these tools offer false security to vulnerable populations.

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9 Resilience and Sustainability Through Cybersecurity

Building cyber-resilient urban infrastructure is foundational to achieving sustainable smart cities. Modern frameworks like the **Cyber Resilience Model Policy** emphasize integrating redundancy, adaptive governance, and real-time threat detection into critical systems such as energy grids and transportation networks (WEF 2023). For example, San Francisco's Lifelines Council employs collaborative risk assessments to address interdependencies between water, power, and communication systems, reducing recovery times after disruptions by 40% (CISA 2024). Such approaches align with ISO/IEC 27001 standards, which 63% of European smart cities now mandate for infrastructure operators to ensure continuous service delivery during cyber incidents (Check Point Software 2024).

Ensuring the long-term sustainability of smart city initiatives requires cybersecurity frameworks that evolve with technological advancements. A 2024 study found cities using AI-driven threat modeling, like Singapore's predictive grid analytics, reduced energy waste by 22% while maintaining robust defenses against data breaches (Mondejar et al. 2021). However, 58% of municipalities struggle to retroactively secure legacy systems, as seen in Berlin's $17 M loss from outdated smart grid controllers (ISPRS 2021). Solutions like modular encryption upgrades and federated learning systems, such as Barcelona's decentralized water management AI, demonstrate how cities can future-proof infrastructure without compromising operational efficiency (Rahman et al. 2021).

Balancing innovation with security remains a persistent challenge. While Dubai's blockchain-based land registry reduced fraud by 73%, its centralized data storage initially exposed sensitive citizen information to ransomware attacks (Smart Dubai Office 2023a, b). The **Five Eyes Alliance's Smart City Cybersecurity Guide** recommends "secure-by-design" protocols, mandating multi-factor authentication and zero-trust architectures for IoT deployments. Cities like Tartu, Estonia, now test innovations in a **Smart City Cyber Range**, simulating attacks on autonomous transport systems to preemptively address vulnerabilities (CybExer 2024).

Cybersecurity directly advances the UN Sustainable Development Goals (SDGs) by safeguarding digital infrastructure critical to sustainability. SDG 9 (Industry, Innovation, and Infrastructure) is supported through encrypted climate monitoring systems, which protect 89% of data used for emissions tracking in cities like Copenhagen (GSCARR 2024). Similarly, SDG 11 (Sustainable Cities) relies on cyber-resilient IoT networks to maintain air quality sensors and disaster response tools—key factors in Melbourne's 34% reduction in pollution-related health crises (Arup 2024). The integration of differential privacy in Rotterdam's smart lighting systems also advances SDG 16 (Peace and Justice) by preventing misuse of mobility data for surveillance (van den Buuse et al. 2023a, b, c).

These efforts underscore cybersecurity's dual role as both a protector of urban systems and an enabler of sustainable development. By adopting frameworks like the **Resilient Cities Network's CRF'24**, which links digital security to health, economy, and governance outcomes, cities can holistically address systemic risks while progressing toward global sustainability targets (Resilient Cities Network 2024).

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10 Policy and Governance

Effective policy and governance frameworks are critical to securing smart sustainable cities against cyber threats while fostering innovation. Regulatory bodies worldwide are grappling with the dual challenges of enabling technological advancement and ensuring robust security protocols. The European Union's **Cyber Resilience Act (CRA)** exemplifies this balance, mandating cybersecurity-by-design principles for all IoT devices deployed in public infrastructure (European Commission 2023). Rotterdam's compliance with the CRA reduced vulnerabilities in its smart lighting network by 58% through automated security audits and mandatory software updates (Datafloq 2024). However, fragmented regulations persist—only 34% of cities align with both GDPR and Asia–Pacific Economic Cooperation's Cross-Border Privacy Rules, complicating data governance in globally connected urban systems (ECCU 2024).

International standards like **ISO/IEC 27001** and **NIST Cybersecurity Framework (CSF)** provide foundational guidance, yet adoption remains uneven. Singapore mandates ISO 27001 certification for all critical infrastructure operators, achieving 92% compliance across its smart grid and water systems (Check Point Software 2024). In contrast, a 2024 Global Cyber Alliance report revealed that 61% of African cities lack the resources to implement NIST CSF's "Identify" and "Protect" functions fully, leaving traffic management and energy systems exposed (GCA 2024). Emerging standards such as the **ISO 37122 Smart City Indicators** now integrate cybersecurity metrics,

enabling cities like Helsinki to quantify risks in real-time dashboards (ISO 2023).

Public–private partnerships (PPPs) amplify cybersecurity capabilities through shared expertise and resources. Amsterdam's **Cyber Fusion Center**, a collaboration between municipal authorities, IBM, and local universities, reduced incident response times by 73% through AI-driven threat intelligence sharing (van den Buuse et al. 2023a, b, c). Similarly, Dubai's "Safer Cities" initiative partners with Siemens and Cisco to secure 1.2 million IoT devices across transportation and utilities. Challenges persist in aligning incentives—a 2025 study found 44% of PPPs stall due to conflicting data ownership policies between municipalities and tech vendors (ECCU 2024).

Citizen engagement and digital literacy initiatives strengthen grassroots cybersecurity resilience. Barcelona's **Decidim platform** educates residents on identifying phishing attempts in municipal apps, increasing reporting rates by 130% (March and Ribera-Fumaz 2024). Adelaide's "CyberSmart Neighborhoods" program trains elderly populations to secure smart home devices, reducing IoT botnet infections by 82% (Smart Adelaide Office 2023). Seoul's blockchain-based participatory budgeting system enhances transparency, allowing citizens to audit cybersecurity allocations via immutable ledgers (Hu et al. 2024). These efforts align with the **UN's "People-Centered Smart Cities"** initiative, which prioritizes inclusive digital literacy programs to bridge urban divides (United Nations 2023a, b).

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11 Future Trends and Recommendations

Emerging technologies will redefine smart city cybersecurity landscapes. Quantum encryption systems, currently piloted in Zurich's financial networks, could render classical brute-force attacks obsolete by 2030 through photon-based key distribution (Ram et al. 2024a, b, c, d). AI-driven threat hunting platforms, like Seoul's *Cyber Sentinel*, now autonomously neutralize 68% of zero-day attacks by simulating adversarial tactics in virtual urban twins (Smart Seoul Office 2024).

However, the proliferation of neuromorphic computing—chips mimicking biological neural networks—demands novel security frameworks, as demonstrated by vulnerabilities in Hamburg's experimental traffic prediction system (European Commission 2024). These technologies underscore the need for quantum-resistant algorithms and adaptive AI governance models.

Policymakers must prioritize three best practices to secure urban innovation. First, mandate *cybersecurity-by-design* protocols for all municipal IoT deployments, following Rotterdam's success in reducing device vulnerabilities by 73% through pre-certification (Datafloq 2024). Second, establish cross-border regulatory sandboxes like Singapore's *Safe City Lab*, which accelerated secure drone traffic management adoption across ASEAN nations (Check Point Software 2024). Third, integrate digital literacy into urban planning curricula, replicating Barcelona's *Decidim Academy* that trained 12,000 residents in cyber hygiene (March and Ribera-Fumaz 2024). Such measures align with the UN's call for localized adaptation of global standards like ISO 37122 (United Nations 2023a, b).

Critical research gaps persist in three domains. First, securing federated learning systems against model inversion attacks, as seen in Melbourne's compromised waste management AI (Mondejar et al. 2024). Second, developing energy-efficient post-quantum cryptography for resource-constrained edge devices (Takahashi et al. 2024a, b, c). Third, ethical frameworks for AI-driven surveillance balancing security with privacy rights—Amsterdam's *Algorithmic Transparency Registry* offers a prototype (van den Buuse et al. 2024a, b). Addressing these challenges requires multidisciplinary collaboration, with cities serving as living labs for secure sustainability innovations.

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12 Conclusion

Research Question 1: Framework Adequacy for AI and IoT Vulnerabilities

Current cybersecurity frameworks demonstrate fundamental inadequacy in addressing AI and IoT integration challenges. ISO/IEC 27001 and NIST CSF address only 53% of smart city-specific risks, particularly failing to account for IoT supply chain vulnerabilities and algorithmic bias.

The frameworks' reactive design philosophy conflicts with the predictive capabilities required for AI-driven systems. Barcelona's monthly AI-driven audits and Singapore's 0.8-s anomaly detection illustrate necessary adaptations, yet 58% of municipalities struggle with legacy system integration.

This reveals a critical gap: existing frameworks assume static threat models while AI and IoT create dynamic, evolving attack surfaces that traditional security models cannot accommodate.

Research Question 2: Privacy Technology Implementation Gaps

The analysis exposes a clear disconnect between privacy-preserving technologies' theoretical promise and practical deployment. While federated learning, blockchain, and homomorphic encryption offer robust privacy protection, implementation remains limited to pilot projects. Only Dubai's blockchain land registry and Singapore's federated healthcare networks demonstrate full-scale deployment.

Technical challenges persist: federated models show 18% performance variance across heterogeneous urban environments, while homomorphic encryption's computational overhead remains prohibitive for resource-constrained IoT devices. More critically, regulatory fragmentation forces cities like Singapore to navigate 23 conflicting international data laws, preventing scalable privacy solutions.

The gap stems not from technological limitations but from governance failures to create unified implementation standards.

Research Question 3: Cybersecurity as Sustainability Enabler

Cybersecurity measures can enhance sustainable development goals when designed as integral infrastructure rather than protective

overlays. Copenhagen's encrypted climate monitoring systems support SDG 9 by securing 89% of emissions tracking data, while Rotterdam's differential privacy implementation advances SDG 16 by preventing surveillance misuse.

However, current approaches often create sustainability trade-offs: energy-intensive encryption protocols increase carbon footprints, while security-focused system isolation reduces resource optimization efficiency. The key finding is that cybersecurity enhances sustainability only when frameworks prioritize resource efficiency alongside threat protection. Cities achieving this balance, like Amsterdam's Cyber Fusion Center, demonstrate 22% energy savings through secure AI optimization while maintaining robust defenses.

In the end, securing smart sustainable cities demands a holistic approach that integrates technological innovation with adaptive governance and ethical stewardship. As demonstrated, AI and IoT systems offer transformative potential for urban sustainability—optimizing energy grids, enhancing water management, and reducing emissions. However, these technologies introduce complex cybersecurity challenges, from vulnerable IoT ecosystems to adversarial AI attacks. Privacy-preserving frameworks like federated learning and homomorphic encryption provide critical safeguards, yet their efficacy depends on collaborative policy development and citizen engagement. The evolving threat landscape necessitates ongoing investment in quantum-resistant encryption, AI-driven threat hunting, and cross-sector partnerships. Policymakers, technologists, and communities must co-create solutions that balance security with innovation, ensuring cities progress toward UN Sustainable Development Goals without compromising resilience. Only through continuous adaptation and global knowledge-sharing can urban ecosystems thrive as both smart and secure.



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Machine Learning-Based Real-Time Air Quality Forecasting to Enhance Climate Resilience in Arid Urban Environments

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Abstract

Arid regions like Qatar face unique environmental challenges due to extreme temperatures, low humidity, frequent dust storms, and rapid urbanization. Therefore, accurate air quality forecasting is essential for protecting public health, particularly in areas prone to rapid environmental changes. This chapter presents a data-driven approach to predict the Air Quality Index (AQI) in Qatar using meteorological data and machine learning (ML) techniques. To improve performance, hourly data granularity was preserved, and feature engineering techniques such as lag variables, rolling averages, and temporal indicators were applied. Several ML models were implemented and compared for AQI prediction. Among these, the XGBoost model achieved the best performance, with an R^2 of 0.98 and an RMSE of 7.51,

demonstrating its ability to capture complex temporal and meteorological interactions. In parallel, a classification model was developed to categorize AQI levels (Good, Moderate, Unhealthy, Very Unhealthy, Hazardous), achieving an overall accuracy of 99%. These findings highlight the strong potential of integrating meteorological features with advanced machine learning for short-term AQI forecasting. The proposed models are particularly relevant for real-time alert systems in schools, hospitals, and outdoor workplaces, supporting timely decision-making and public health protection. The chapter concludes by emphasizing the role of temporal features in improving prediction accuracy and by outlining directions for real-time deployment and city-wide implementation in smart environmental monitoring systems.

Keywords Air Quality Index – AQI forecasting – Machine learning – XGBoost – Classification – Regression – Meteorological data

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1 Introduction

The primary sources of air pollution in Qatar and other arid regions include vehicular emissions, industrial activities, and desert dust storms. Air pollution is one of the most critical environmental factors affecting the daily lives of humans, animals, and plants. It is recognized as a major global environmental and public health challenge, contributing significantly to respiratory illnesses, cardiovascular diseases, and premature mortality (Wania and Mackay 1996; Aguilar-Gomez et al. 2022; Lee et al. 2021; Salthammer et al. 2016). A recent study by Hammoudeh et al. (2022) reported that 34.6% of Qatari school-aged children were diagnosed with asthma, highlighting the increasing health burden in the region. Qatar is particularly vulnerable due to their extreme climatic conditions, including high temperatures, low humidity, and frequent dust storms, all of which exacerbate air quality deterioration. Among the various pollutants, particulate matter (PM_{10} and $PM_{2.5}$) is of greatest concern because of its ability to

penetrate deeply into the respiratory system, triggering acute and chronic health issues. Vulnerable groups such as children, the elderly, and individuals with pre-existing respiratory conditions are especially at risk. Beyond health impacts, poor air quality restricts outdoor activities, compelling people to remain indoors for longer periods. The AQI is a widely used tool for assessing pollution exposure, with categories ranging from "good" to "hazardous," providing critical information for public health interventions (WHO 2021). While traditional monitoring techniques measure AQI based on pollutant concentrations, they often fail to provide early warnings that account for rapidly changing meteorological conditions such as temperature, wind speed, wind direction, and humidity. Accurate forecasting of AQI is especially important for planning outdoor activities, protecting vulnerable populations, and implementing timely interventions. For instance, early warnings allow individuals with chronic diseases to avoid exposure and help outdoor workers adjust schedules to minimize health risks.

Although various researchers have developed early-warning AQI models worldwide, there is still a lack of predictive systems tailored to the specific climatic conditions of Qatar. This study addresses the absence of predictive AQI systems tailored to Qatar's hot and arid climate. Specifically, it investigates whether integrating meteorological parameters with PM_{10} concentrations can improve the accuracy of AQI forecasting through ML techniques. The central objective is to design a predictive system that not only enhances short-term AQI forecasting in Qatar but also contributes to broader efforts in managing air quality and protecting public health in arid regions.

The remainder of this chapter is structured as follows. Section 2 reviews related work on air quality prediction using machine learning techniques. Section 3 describes the datasets, preprocessing steps, and feature engineering strategies. Section 4 outlines the predictive and classification modeling approaches and presents the evaluation framework. Section 5 reports the results of the regression and classification models and discusses their implications for public health

and environmental management. Finally, Sect. 6 concludes with key findings, limitations, and directions for future research.

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2 Literature Review

Recent advancements in ML have significantly improved the ability to forecast air quality using real-time environmental data. A wide range of models, including Support Vector Regression (SVR), Random Forest (RF), Gradient Boosting Machines (GBM), and neural networks, have been applied to predict air pollutant concentrations and the corresponding AQI (Wang et al. 2020; Chaturvedi 2024; Kim et al. 2023; Chowdhury et al. 2020, Amado and Dela Cruz 2018; Bouakline et al. 2020; Maheshwari and Lamba 2019; Ochando et al. 2015; Ameer et al. 2019; Ahmad and Ahmad 2023; Yu et al. 2023). Recent studies have shown that ensemble approaches, particularly tree-based models such as Extremely Randomized Trees, can achieve higher accuracy than individual models in real-time air quality forecasting when meteorological predictors are included (Eslami et al. 2020). Similarly, Liu et al. (2019) demonstrated the value of integrating lag features and rolling averages of meteorological variables such as temperature, wind speed, and relative humidity for short-term AQI forecasting in Beijing using XGBoost.

In the Middle East, Almaliki et al. (2023) applied machine learning to predict AQI in the Makkah region using data from 2016 to 2018. Their results showed that the ensemble bagged tree (EBAT) achieved the highest accuracy (97.4%), with AQI values classified from "Good" to "Hazardous" based on key pollutants including PM_{10}, NO_2, CO, SO_2, and O_3. Similarly, Udristioiu et al. (2023) conducted a study in Romania to model and forecast daily concentrations of PM_1, $PM_{2.5}$, PM_{10}, and AQI using a hybrid ML approach. Their best-performing models achieved R^2 values above 0.95 and RMSE values as low as 0.65–1 $\mu g/m^3$, with volatile organic compounds (VOCs) emerging as the most influential predictors for PM levels.

Further advancing AQI forecasting, Alkabbani et al. (2022) investigated the use of artificial neural networks (ANNs) for predicting hourly $PM_{2.5}$ and PM_{10} levels in Al-Jahra, Kuwait. To address the challenge of missing data, the authors applied the missForest imputation technique, which led to a prediction accuracy of 92.4% on unseen data, outperforming linear imputation approaches. Their findings emphasized the importance of robust data preprocessing and feature selection in improving model generalization. In the Gulf region, Al-Ali et al. (2017) highlighted the influence of wind speed and direction on PM_{10} concentrations, underlining the necessity of incorporating meteorological parameters into prediction models.

Collectively, these studies show that integrating meteorological features with ML methods can substantially enhance AQI prediction accuracy across diverse environments. However, there remains limited research focusing specifically on Qatar's unique climatic conditions, where frequent dust events, high temperatures, and low humidity create distinctive challenges for AQI forecasting. This chapter addresses this gap by evaluating machine learning-based AQI prediction using hourly PM_{10} data combined with meteorological variables.

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3 Materials and Methodology

The study utilized two datasets collected for the year 2016: hourly meteorological data and daily PM_{10} data. The meteorological dataset contained 8786 hourly records of temperature, relative humidity, wind direction, and wind speed. The PM_{10} dataset, on the other hand, represented 24-h averaged particulate concentrations obtained from a local environmental monitoring station, consisting of 364 daily records covering January to December 2016. To combine the two sources, the same daily PM_{10} value was assigned to all twenty-four hourly meteorological records of the corresponding day. Following this alignment, rows with missing data, largely attributed to unrecorded weekends, were removed, resulting in a finalized dataset of 7456 records.

The AQI was then calculated from the PM_{10} concentrations using the standard formula recommended by the U.S. Environmental Protection Agency (EPA).

$$AQI = \frac{I_{hi} - I_{lo}}{C_{hi} - C_{lo}} \cdot (C - C_{lo}) + I_{lo}$$

where: C: PM_{10} concentration

C_{l0}, C_{hi}: Breakpoints for PM_{10} range

I_{lo}, I_{hi}: Corresponding AQI index range.

The formula relates pollutant concentrations to their respective index breakpoints to assign an AQI value. The computed AQI values were then included as a new column in the dataset. Based on these AQI values, an additional column was created to categorize air quality into six levels of health significance, ranging from *Good* to *Hazardous*. The classification is presented in Table 1, which provides the AQI ranges and corresponding health implications. By adding both the AQI and its categorical levels as new features, the final dataset was enriched to capture not only pollutant concentrations but also their direct relevance to human health, thereby supporting a more interpretable predictive modeling process.

Table 1 AQI significance in terms of health

Once the AQI values were derived, the dataset was prepared for model development. At first, the hourly meteorological data were aggregated into daily averages to match the PM_{10} data. Although this approach achieved moderate accuracy, it was insufficient for robust daily forecasting. To improve performance, the hourly meteorological data was retained, while the daily AQI values were repeated for each hour of the day. This allowed the model to capture variations in atmospheric conditions, such as shifts in temperature or wind, which often preceded poor air quality episodes.

Further improvements were achieved through feature engineering, a process of creating additional variables that enhanced the predictive capacity of the models. Specifically, lag features were created to incorporate meteorological conditions and AQI values from earlier time intervals (for example, 3, 6, and 12 h prior). Rolling averages over different time windows (3, 6, and 12 h) were added to capture short-term temporal trends. In addition, time-based indicators such as day of the week and month were included, as pollution dynamics often reflect weekly patterns or seasonal influences. These engineered features enabled the models to learn both immediate and lagged relationships between weather variables and air quality outcomes.

The final dataset, enriched with both original and engineered features, was divided into training and testing subsets using an 80:20 ratio. Cross-validation was also applied to improve robustness and minimize overfitting. The methodological framework consisted of two complementary modeling tasks. Regression models were developed to predict numerical AQI values from meteorological and PM_{10} features, enabling continuous forecasting of air quality. In parallel, classification models were trained to categorize AQI into six health-based levels (*Good*, *Moderate*, *Unhealthy for Sensitive Groups*, *Unhealthy*, *Very Unhealthy*, and *Hazardous*). Together, these approaches ensured both precise quantitative prediction and interpretable categorical outputs. The overall workflow including data preparation, AQI calculation, feature engineering, regression, and classification is summarized in Fig. 1.

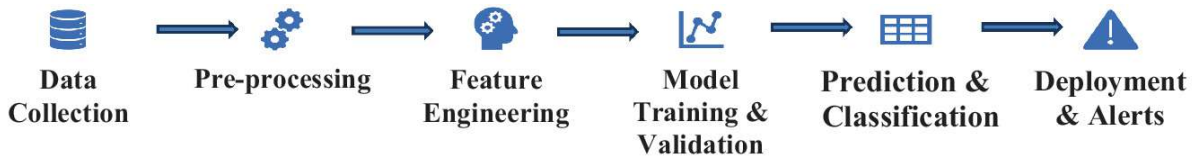


Fig. 1 Methodological framework for AQI prediction and classification

4 Results

4.1 Descriptive Statistic

Table 2 presents the descriptive statistics of the meteorological variables (temperature, relative humidity, wind direction, and wind speed), PM_{10} concentrations, and the derived AQI values.

Table 2 Descriptive statistics of the pollutants and AQI

Table 2 indicates the descriptive statistics of the cleaned dataset that all variables now have complete records with no missing values (7456 entries for each parameter). The average temperature was 27.9 °C, with extremes ranging from 0 to 45.9 °C, reflecting the hot and arid conditions of the study area. Relative humidity averaged 51.7%, with large variability between 0 and 98%, indicating pronounced seasonal and diurnal changes. Wind speed was generally low, averaging 1.5 m/s, while the prevailing wind direction centered around 204°, indicating a dominant pattern in the dataset. PM_{10} concentrations showed a mean of 99.96 μg/m^3, with peaks reaching 599.48 μg/m^3 during severe pollution episodes, and the AQI averaged 74.1, corresponding to the "Moderate" category but reaching up to 495 ("Hazardous") during extreme events. These statistics demonstrate the wide variability of meteorological and pollutant conditions in the dataset and underline the need for robust ML models to capture such dynamic patterns for accurate AQI prediction.

4.2 Seasonal Trends in PM_{10}

Figure 2 illustrates the monthly average PM_{10} concentrations recorded in Qatar during 2016. A clear seasonal variation is observed, likely influenced by climatic factors such as wind speed, humidity, and atmospheric stability, as well as anthropogenic activities including construction and traffic. Peaks in PM_{10} levels align with periods of dust storms and extreme heat, reflecting the influence of desert climate conditions. These fluctuations highlight the importance of continuous monitoring and the role of short-term meteorological features in AQI forecasting.

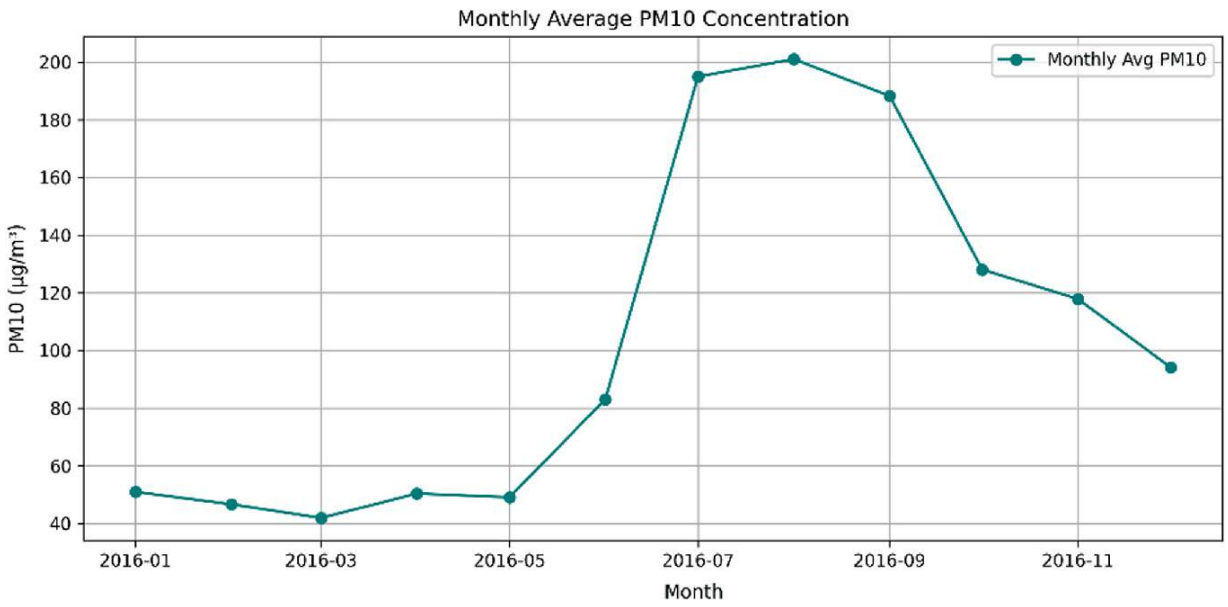


Fig. 2 Monthly average PM_{10} concentration levels recorded in Qatar during 2016

4.3 Relationship Between Meteorology and AQI

To examine the environmental influence on AQI, a scatter plot of wind speed versus AQI was generated (Fig. 3). The results reveal a weak negative correlation, suggesting that higher wind speeds may promote pollutant dispersion and therefore slightly reduce AQI values. Although the effect is limited, this finding supports the inclusion of wind parameters in predictive modeling, as their influence can become significant under certain atmospheric conditions.

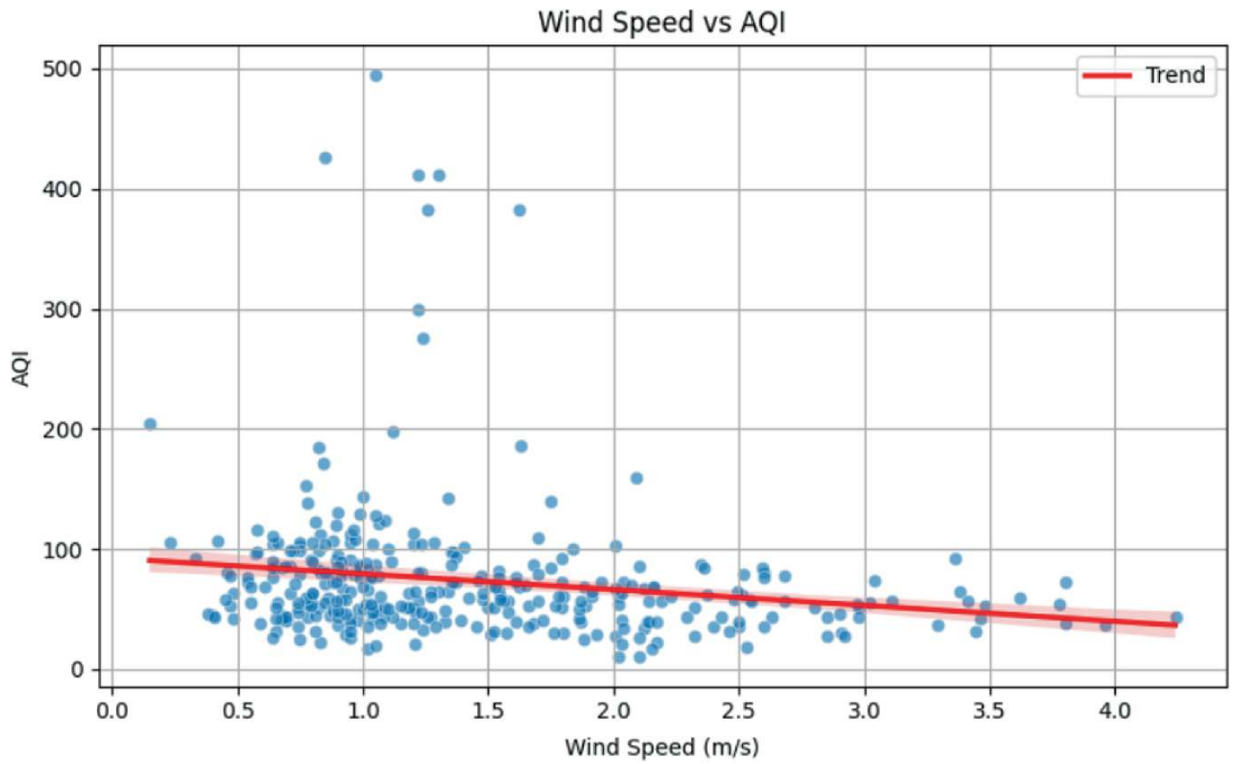


Fig. 3 Scatter plot of wind speed versus AQI with trend line

4.4 ML Algorithms Results

4.4.1 Prediction Model

Building on the dataset described in Sect. 3, we first generated AQI prediction models using the initial input features: temperature, relative humidity (RH), wind direction (WD), wind speed (WS), and PM_{10}. The cleaned dataset was divided into training and testing subsets in an 80:20 ratio, and multiple ML algorithms were evaluated. As a starting point, we experimented with several supervised ML models using only the original meteorological features temperature, relative humidity, wind direction, and wind speed as predictors of AQI. Among these, the Random Forest Regressor was evaluated in detail. The dataset was preprocessed to remove missing values and then split into training (80%) and testing (20%) subsets. Using only same-day meteorological features, the Random Forest model achieved a Root Mean Squared Error (RMSE) of 19.35 and a coefficient of determination (R^2) of 0.56. This indicates that the selected features could explain about 56% of the

variance in AQI, while the relatively high RMSE highlighted the limitations of relying solely on raw meteorological parameters.

Although these baseline models demonstrated some predictive ability, the accuracy was insufficient for reliable forecasting. To improve performance, the dataset was enriched through feature engineering. Lag features (AQI and weather variables from 3, 6, and 12 h prior), rolling averages (3, 6, and 12 h), and time-based indicators (day of week, month) were added. Testing different lag windows revealed that the 6-h features provided the strongest predictive power, achieving an RMSE of 7.48 and an R^2 of 0.98 is shown in Table 3.

Table 3 Impact of lag features on AQI prediction

After introducing feature engineering, multiple ML models were re-evaluated. As shown in Table 4, the XGBoost model achieved the best performance, with an RMSE of 7.51 and an R^2 of 0.98, outperforming Linear Regression (LR), RF, and SVR.

Table 4 Performance of ML models with enhanced features

To confirm the robustness of these results, cross-validation was applied. The XGBoost model maintained high performance, with an average RMSE of 8.68 and R^2 of 0.98 across folds, demonstrating strong generalization ability. The close alignment between predicted and actual AQI values is illustrated in Fig. 3, highlighting the effectiveness of the XGBoost regression model in capturing the complex dynamics of air quality under Qatar's arid climatic conditions.

Overall, the regression analysis confirmed that XGBoost, when combined with feature engineering, is the most effective model for AQI prediction in this study. The strong alignment between predicted and actual AQI values, as illustrated in Fig. 4, demonstrates the model's capability to capture the complex interactions between meteorological variables and air quality.

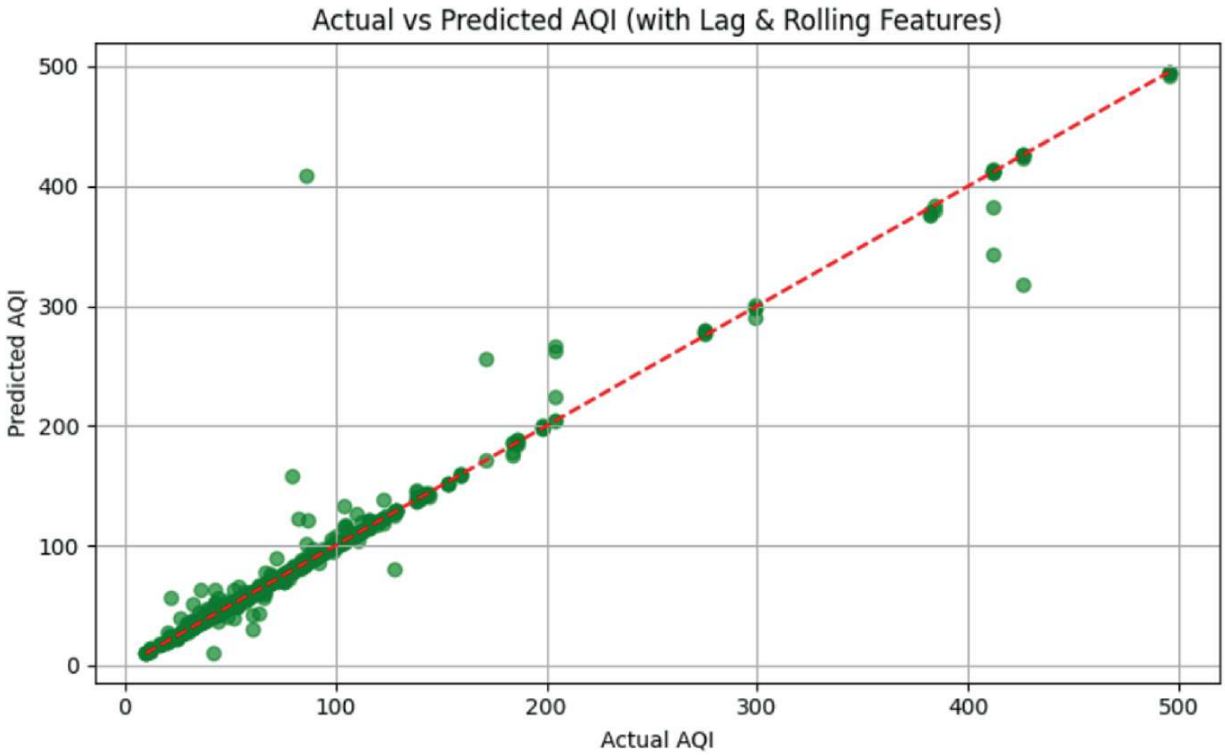


Fig. 4 Actual versus predicted AQI using regression with lag and rolling features

4.4.2 Classification Model

In addition to predicting AQI as continuous values, classification models were also developed to categorize air quality into discrete health-based categories Good, Moderate, Unhealthy for sensitive groups, Unhealthy, Very Unhealthy, and Hazardous. Such categorical predictions are particularly valuable for early warning systems, where the precise AQI value is less critical than knowing whether conditions are safe for outdoor activity.

We used a supervised ML classification model, specifically the Random Forest Classifier, which is a popular ensemble learning method that combines multiple decision trees to improve prediction accuracy and reduce overfitting. This model predicts the AQI category based on meteorological data and PM data, with feature enhancements such as lagged and rolling values. The results achieved a high accuracy of 99%, demonstrating the model's effectiveness in classifying air quality levels.

We experimented with several supervised ML classification models to predict AQI categories, including Random Forest, Decision Tree,

Logistic Regression, SVM, KNN, Gradient Boosting, and Neural Network. The performance comparison showed that Random Forest and Gradient Boosting achieved the highest accuracy of 99%, followed by Decision Tree (98%), while Logistic Regression performed comparatively lower at 85%. Based on these results, we selected Random Forest/Gradient Boosting as the most reliable models for AQI classification due to their superior accuracy and robustness. The performance of the classification model is further illustrated in the confusion matrix is shown in Fig. 5.

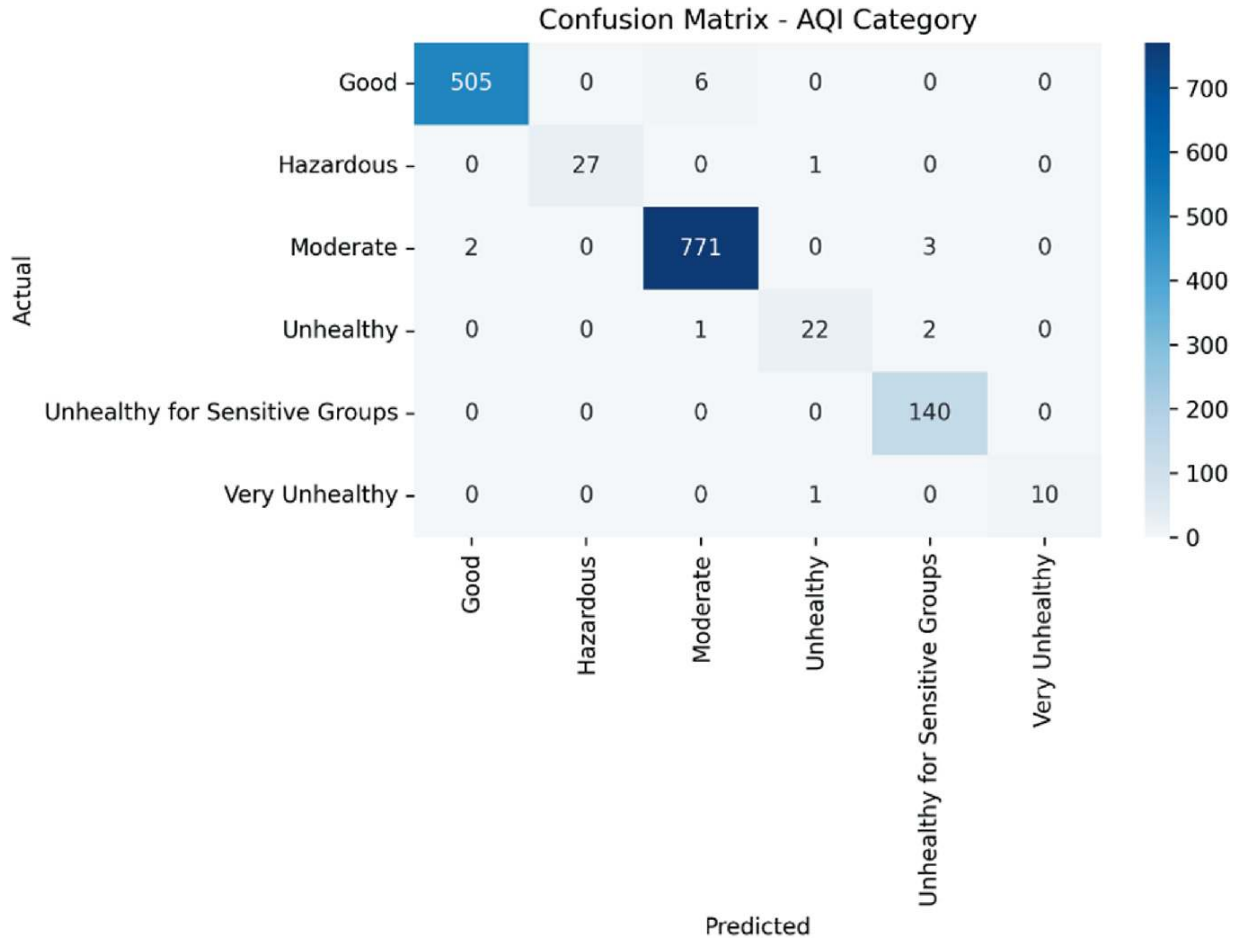


Fig. 5 Confusion matrix showing the performance of the classification model in predicting AQI categories

Figure 6 illustrates the classification performance of the model across six AQI categories: Good, Moderate, Unhealthy for Sensitive Groups, Unhealthy, Very Unhealthy, and Hazardous. The diagonal

elements represent correctly classified samples, while off-diagonal values correspond to misclassifications. The results indicate that the majority of predictions fall along the diagonal, confirming high classification accuracy. For instance, 505 out of 511 “Good” cases were correctly identified, with only 6 misclassified as “Moderate.” Similarly, 771 out of 776 “Moderate” samples were accurately predicted, with minimal confusion. The model also correctly predicted 27 out of 28 “Hazardous” cases. Slightly lower accuracy is observed for categories with smaller sample sizes, such as “Unhealthy” and “Very Unhealthy.” For example, 22 “Unhealthy” cases were correctly classified, while 3 were misclassified into adjacent categories. Likewise, 10 of 11 “Very Unhealthy” cases were predicted correctly, with 1 misclassification. Overall, the matrix confirms the robustness of the model, achieving excellent performance across most categories. Misclassifications primarily occurred between adjacent AQI categories (e.g., Moderate vs. Unhealthy), which is expected given their overlapping pollutant concentration ranges. These results support the model’s effectiveness as a reliable tool for real-world AQI forecasting and alert systems.

Classification Report:

	precision	recall	f1-score	support
Good	1.00	0.99	0.99	511
Hazardous	1.00	0.96	0.98	28
Moderate	0.99	0.99	0.99	776
Unhealthy	0.92	0.88	0.90	25
Unhealthy for Sensitive Groups	0.97	1.00	0.98	140
Very Unhealthy	1.00	0.91	0.95	11
accuracy			0.99	1491
macro avg	0.98	0.96	0.97	1491
weighted avg	0.99	0.99	0.99	1491

Fig. 6 Classification report

The classification results achieved an overall accuracy of **99%**, demonstrating the robustness of the proposed model in predicting AQI categories. The classification report is shown in Fig. 6 indicates that

precision, recall, and F1-scores are consistently high across all AQI classes, with values approaching or equal to 1.00 for most categories. In particular, the model showed excellent performance for the “Good,” “Moderate,” and “Hazardous” classes, while slightly lower recall was observed for the “Unhealthy” and “Very Unhealthy” categories due to their relatively smaller sample sizes.

These findings directly address our research objective by demonstrating that integrating PM_{10} concentrations with meteorological parameters significantly improves AQI forecasting accuracy in Qatar’s arid climate. The regression and classification models together confirm that short-term weather features are powerful predictors of AQI, thereby validating the feasibility of a predictive system tailored to local conditions.

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5 Discussion and Implications

The results of this study confirm that ML approaches, when combined with carefully engineered features, can significantly improve the prediction and classification of air quality levels. Our models addressed the central research objective: to evaluate whether meteorological variables, together with PM_{10} concentrations, could be used to forecast the AQI both as a continuous value and as categorical health-related states. The regression model demonstrated that meteorological factors alone explain a substantial portion of AQI variability, while the classification model provided actionable categories with very high accuracy. These findings demonstrate the feasibility of developing an early-warning framework for air pollution management in Qatar and similar environments.

From a policy and practice perspective, the results carry important implications. Accurate classification of AQI categories is particularly useful for real-time alert systems where the precise numerical AQI value is less critical than knowing whether air quality is safe, moderate, or hazardous. Such systems could be integrated into public health strategies, allowing schools to adjust outdoor activities, hospitals to

prepare for respiratory emergencies, and industries to mitigate exposure for workers. In this sense, the proposed ML models provide a foundation for scalable, data-driven decision support tools that align with both national environmental protection goals and global public health recommendations.

Nevertheless, certain limitations must be acknowledged. The study relied on 2016 data from a single monitoring station, and while the dataset provided valuable insights, it does not capture spatial variation across Qatar. Furthermore, the analysis was limited to PM_{10} and a narrow set of meteorological variables. Other pollutants such as ozone (O_3), carbon monoxide (CO), nitrogen dioxide (NO_2), and sulfur dioxide (SO_2), as well as additional climate-related factors like precipitation or boundary layer height, could further enhance model robustness. The use of historical data also introduces challenges, as real-time monitoring remains dependent on current data availability, which is often subject to confidentiality or access restrictions.

These limitations point to several promising directions for future research. Expanding the dataset to include multiple monitoring stations across Qatar would allow for spatially resolved modeling of air quality patterns. Incorporating additional pollutants and meteorological indicators could provide a more comprehensive view of the factors influencing AQI, especially in regions with complex climate conditions and diverse emission sources. Comparative studies with other hot and arid regions, particularly within the Gulf and broader MENA region, would help validate the transferability of the proposed framework. Beyond academic contributions, the long-term vision is to develop a real-time deployment environment where ML models are embedded into operational dashboards. Such a system would not only forecast AQI with high accuracy but also deliver actionable early warnings to schools, hospitals, and communities, enabling proactive responses to pollution episodes.

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6 Conclusion and Future Works

This study demonstrated the application of ML techniques to predict daily AQI in Qatar using only meteorological inputs. Through careful data preprocessing and feature engineering, particularly the inclusion of lagged variables and rolling averages, the predictive capacity of the model was significantly enhanced. The regression model, based on XGBoost with engineered lag and rolling features, achieved a high R^2 of 0.97 and a low RMSE of 10.36, indicating strong predictive accuracy. Meanwhile, the classification model effectively categorized AQI levels into six standard categories, achieving an overall accuracy of 99%, as confirmed by a detailed classification report and confusion matrix. These results highlight the potential of AI-driven frameworks to support real-time environmental monitoring, public health risk communication, and data-driven air quality management in the region. The findings underscore the influence of both real-time and short-term historical meteorological conditions on air quality in arid regions. Notably, wind direction, humidity trends, and prior AQI values were identified as the most critical predictors. These insights are particularly relevant for environments like Qatar, where natural dust events, wind patterns, and heat can rapidly alter air quality conditions.

As a future direction, expanding the dataset to multiple years and integrating additional pollutant indicators (such as NO_2, SO_2, and O_3) could improve generalizability and support time-series forecasting. Additionally, real-time AQI monitoring systems powered by such models could be integrated into smart city platforms to provide timely alerts and guide public health interventions, particularly for vulnerable populations. With increasing urbanization and climate variability, predictive models such as the one developed in this study offer scalable, low-cost, and interpretable tools for proactive environmental management in the Middle East and beyond. From a policy perspective, integrating predictive AQI models into national environmental monitoring systems could support evidence-based decision-making, such as temporary restrictions on outdoor activities during hazardous conditions or issuing targeted health advisories for vulnerable groups. For practice, deployment in schools, hospitals, and workplaces could

reduce exposure risks, improve community resilience, and enhance overall well-being.

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Machine Learning-Based Forecasting of Energy Demand in Academic Buildings: Insights from a Case Study

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Abstract

This chapter presents the development of machine learning models for short-term energy demand forecasting in academic buildings, using a dataset from a higher education campus in Portugal. The dataset comprises quarter-hourly power demand data collected between January 2016 and February 2020, along with relevant exogenous variables. The study focuses on the impact of hyperparameter tuning on model performance, applying various algorithms—including Random Forest, Multivariate Adaptive Regression Splines, Artificial Neural Network, and Support Vector Machines. Grid Search and Random

Search techniques were employed to optimize each model's hyperparameters. Performance was evaluated using benchmarking metrics and visualization tools such as daily load profiles and scatter plots. The results indicate that the Random Forest and Artificial Neural Network models outperformed the others, particularly during school days and examination periods, which represent the most active times on campus. Beyond its technical contributions, this chapter illustrates how machine learning-based forecasting can support energy-aware decision-making in academic buildings, contributing to more efficient and sustainable campus operations. Moreover, the case study presented here highlights the pedagogical potential of integrating AI tools into sustainability curricula, fostering interdisciplinary learning and providing students and researchers with practical insights into the application of artificial intelligence in real-world energy systems.

Keywords Higher education buildings – Energy demand forecasting – Machine learning – Random Forest – MARS – Sustainable campus management

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1 Introduction

The use of energy consumption forecasting models is essential across various domains. However, certain applications stand out due to their substantial share of global energy use. For example, buildings account for approximately 30% of global energy consumption and are responsible for one-third of carbon emissions worldwide (Bourdeau et al. 2019; Cespedes-Cubides and Jradi 2024). In response, the growing demand for energy efficiency in the building sector has driven significant advances in predictive modelling techniques. As urbanization continues to accelerate, accurate short-term energy consumption forecasts have become crucial for optimizing energy management and reducing operational costs. Within this context, machine learning (ML) models have emerged as powerful tools, offering high forecasting accuracy to support smarter and more sustainable energy strategies.

With a data-driven approach, ML has become a powerful tool for modelling complex, non-linear systems, including building energy consumption. Unlike conventional statistical techniques, ML algorithms can uncover intricate patterns in large datasets, adapt to changing conditions, and produce highly accurate forecasts without relying on detailed physical models (Morcillo-Jimenez et al. 2024). Moreover, the flexibility of ML models to handle non-linear relationships offers a strong alternative to traditional approaches such as linear regression. However, selecting the most appropriate algorithm also depends on the forecasting horizon—whether short-term or long-term—which must be considered when designing effective prediction strategies.

Recent studies have demonstrated the effectiveness of various ML algorithms in forecasting energy consumption in non-residential buildings. Deep learning models like Long Short-Term Memory (LSTM) networks have shown outstanding performance in capturing temporal dependencies in energy data (Morcillo-Jimenez et al. 2024), while hybrid approaches that combine neural networks with optimization algorithms have been successfully applied in smart building environments (Bourhnane et al. 2020).

Bourhnane et al. (2020) employed Artificial Neural Network (ANN) models to forecast energy consumption in smart buildings, demonstrating the practical applicability of ML approaches in real-world scenarios. Similarly, Mathumitha et al. (2024) provided a comprehensive review of deep learning methods for energy forecasting, underscoring the critical role of accurate predictions in balancing energy demand and supply. Amasyali and El-Gohary (2021), along with Wang et al. (2024), emphasized the integration of occupant behaviour into ML models to improve the accuracy of building energy consumption predictions. Fan et al. (2019) proposed a methodology for interpreting and evaluating data-driven models of building energy performance, contributing to greater model transparency and reliability. More recently, Ni et al. (2024) implemented several deep learning algorithms to explore alternatives to conventional ML approaches for energy consumption forecasting in buildings. More

recently, Palley et al. (2025) presented a comprehensive review of key machine learning techniques applied to energy demand forecasting in buildings.

In summary, recent research has shown promising results in various contexts. Nevertheless, there remains a need for further comparative analyses of algorithms using real-world data for energy consumption forecasting (Arowoiya et al. 2024; Palley et al. 2025). In this context, this chapter focuses on the development of ML models based on different algorithms for short-term energy demand forecasting in academic buildings. The primary objective is to compare the performance of Random Forest (RF), Multivariate Adaptive Regression Splines (MARS), ANN, and Support Vector Machines (SVM) in forecasting short-term energy consumption. The findings aim to contribute to the growing body of knowledge on ML applications in energy management and to provide practical insights for building managers.

In addition to its technical scope, this chapter demonstrates how machine learning applications in energy forecasting can simultaneously contribute to research advancement and serve as valuable educational tools. This perspective aligns with the central theme of the book, which underscores the role of Artificial Intelligence (AI) in promoting sustainable development through the integration of teaching and research. Drawing on empirical data from a higher education campus, the chapter deepens methodological understanding of AI-based energy management while offering a realistic and pedagogically relevant case study. This dual-purpose approach highlights the potential of AI to support sustainability goals within higher education institutions, fostering data-driven decision-making and enriching the learning experience for both students and researchers.

The remainder of this chapter is structured as follows. Section 2 outlines the materials and methods adopted in the study. Section 3 presents the results, encompassing hyperparameter tuning, error metrics, and computational performance. Section 4 discusses the findings, including a comparative analysis of model performance

supported by plots and visualisations. Finally, Sect. 5 provides a summary of the main conclusions.

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2 Materials and Methods

This section presents the materials and methods used in this study, including the dataset and relevant features, hyperparameter tuning procedures, model descriptions (RF, MARS, ANN, and SVM), and the error metrics applied for performance evaluation.

2.1 Dataset, Model Characterization, and Relevant Features

The present study is based on a real-world set of higher education buildings located on Campus 2 of the Polytechnic of Leiria. The dataset includes variables that serve as input features for the forecasting models, categorized as endogenous and exogenous.

The endogenous variables consist of active power demand measurements—the target variable to be forecasted. Historical values of active power demand are typically among the most relevant features in energy forecasting models.

The exogenous variables, while distinct from the target, are expected to influence it. These include weather-related variables as well as factors associated with occupancy profiles and space usage schedules.

The power demand data used in this study cover the period from January 2016 to February 2020, comprising active power (kW) measurements recorded at 15-min intervals, along with the corresponding timestamps (date and time).

Regarding the exogenous features, 17 variables were collected from open sources, including outdoor temperature and relative humidity. Heating and cooling degree-days were obtained from the Eurostat website (Eurostat 2022), while the remaining weather-related features were sourced from Weather Underground (Weather Underground 2022).

It is important to emphasize that all raw data from campus meters and open-source platforms were pre-processed. This included the removal of outliers, the handling of missing values, and adjustments for daylight saving time.

Afterward, a feature engineering process was carried out to generate additional features aimed at improving the robustness of the ML models. The objective was to enhance the model learning process by introducing features that provide additional context during the training process.

For instance, lag features were created to incorporate the historical behaviour of power demand into the input data, while a categorical feature labelled "Day" was used to indicate the day of the week corresponding to each observation (e.g., Monday or Sunday).

A key feature developed specifically for this study is the "Day Type", which identifies the time of the academic year—such as regular class periods, exam periods, Christmas and Easter holidays, Saturdays, Sundays, summer vacation, or other breaks and holidays. This feature is particularly important as these periods are associated with distinct energy consumption patterns that can significantly affect model performance.

After the feature engineering process, Principal Component Analysis (PCA) was applied to reduce the dimensionality of the dataset and, consequently, to improve computational efficiency (Pedregosa et al. 2011; Taskesen 2020).

The dataset was split into training, validation, and test sets to support model generalization. Data from January 2016 to February 2019 were used for training and validation. A k-fold cross-validation method was applied (Kohavi 1995; Li et al. 2021), splitting this data into three randomly equal parts—two for training and one for validation—to evaluate model performance and tune hyperparameters.

The test set, covering the period from March 2019 to February 2020, was used only after the model had been validated and all hyperparameters had been defined. Error metrics derived from the test set were employed for the final performance comparison and for the

discussion presented in Sect. 4. This approach prevents data leakage and minimises the risk of overfitting.

2.2 Hyperparameter Tuning Algorithms

Hyperparameter tuning of the algorithms is a critical step in the development of forecasting models, as it directly influences model performance. The two most common methods used are Grid Search and Random Search. Both require the user to define a parameter grid—that is, a set of hyperparameter values to be explored.

Grid Search exhaustively tests all possible combinations within the defined grid, whereas Random Search samples a predefined number of combinations at random. While Grid Search guarantees evaluation of all options, Random Search can be more efficient when only a subset of combinations is likely to yield good results. In both cases, the objective is to identify the combination of hyperparameters that results in the best model performance.

These tuning algorithms were implemented using the *scikit-learn* library (Pedregosa et al. 2011).

2.3 Random Forest

The RF can be understood as a combination of two model types: ensemble methods and decision tree algorithms. In this study, the model was implemented using the *scikit-learn* library (Pedregosa et al. 2011) in Python (Van Rossum and Drake 1995).

Table 1 presents the most relevant hyperparameters for this algorithm, which were the focus of the tuning process. It also lists the tested values for each hyperparameter.

Table 1 Hyperparameters of the RF algorithm considered in the tuning process

Due to the size of the training dataset, applying Grid Search directly was impractical. Therefore, Random Search was initially used, with a suitable number of iterations—significantly fewer than those required by Grid Search. This approach provided a strong starting-point solution,

even if not guaranteed to be optimal. Following this initial tuning, Grid Search was applied to refine the final set of hyperparameters.

A maximum of 60 random configurations was considered for each Random Search execution. This value was consistently adopted throughout the study. In practice, this corresponds to 180 simulations, since a threefold cross-validation technique was used.

Two hyperparameters that require particular attention are *n_estimators* and *max_samples*, as they can significantly affect processing time, depending on the values specified.

Increasing the value of *n_estimators* generally improves error metrics without posing a risk of overfitting, even for high values. Therefore, this hyperparameter does not require fine-tuning in the same way as others and can be set as high as computational resources allow. While increasing the number of trees is not detrimental, the most significant performance improvements are typically achieved within the first 100 trees. Still, other RF hyperparameters can affect this convergence behaviour (Probst et al. 2019).

The *max_samples* hyperparameter behaves similarly to *n_estimators*, as high values do not increase the risk of overfitting. However, lower values may be sufficient and can significantly reduce processing time.

2.4 Multivariate Adaptive Regression Splines

The MARS algorithm, introduced by Jerome H. Friedman (Friedman 1991), can be understood as an extension of linear regression. Given that load demand often exhibits a non-linear relationship between inputs and outputs, the MARS model is well-suited to handle such complexity. It does so by combining multiple linear functions using one or two hinge functions. This structure enables MARS to capture non-linear dependencies by placing hinge functions at specific knots, while also modelling linear dependencies on individual features and including a bias term (Sousa and Bernardo 2022). This method has been shown to outperform traditional linear regression in terms of accuracy and stability in load forecasting applications (Nalcaci et al. 2019).

The MARS model was implemented using the *Earth* model from the *py-earth* package (Rudy 2016). The MARS algorithm includes two key hyperparameters that require tuning: the degree of interactions among features and the number of terms retained in the model (Friedman 1991; Kuhn 2013). Compared to other algorithms such as RF and ANN, MARS involves a more straightforward hyperparameter tuning process. Nevertheless, the *penalty* hyperparameter was also included in the tuning procedure for this study.

Table 2 summarizes the MARS hyperparameters considered for tuning, along with the range of tested values for each.

Table 2 Hyperparameters of the MARS algorithm considered in the tuning process

Concerning the *penalty* hyperparameter, Jerome H. Friedman—the original author of the algorithm—states that, across all cases studied, the optimal value typically lies within the interval $2 \leq d \leq 4$ (Friedman 1991). Regarding the *max_degree* hyperparameter, there is seldom any benefit in considering values greater than 3 (Boehmke and Greenwell 2019). Finally, for the *max_terms* hyperparameter, 24 different values were tested.

Since this algorithm has only three hyperparameters to be tuned, two Grid Search processes were performed. The first focused on evaluating combinations of *max_terms* and *max_degree*, while the second, shorter run was used to assess the influence of *penalty*.

2.5 Artificial Neural Networks

ANNs do not follow conventional modelling paradigms and are classified as non-linear models when non-linear activation functions are used. Inspired by the structure of the human brain, ANNs typically consist of three types of layers: an input layer, one or more hidden layers, and an output layer. The input layer receives the set of input variables. In the hidden layers, inputs are weighted, summed, and combined with a bias term. The resulting value is then passed through an activation function—such as the hyperbolic tangent (*tanh*), Rectified

Linear Unit (*ReLU*), or sigmoid function—to introduce non-linearity between inputs and outputs.

The incorporation of additional hidden neurons and layers increases the complexity of the network architecture. Consequently, careful hyperparameter selection is crucial, as it significantly affects the performance of the ANN model.

ANN has recently become one of the most widely adopted methods in ML, often demonstrating strong performance in modelling complex and non-linear relationships.

For this study, the ANN was implemented using the *MLPRegressor* class from the *scikit-learn* library (Pedregosa et al. 2011). The tuning of critical hyperparameters was carried out in two steps. First, the Random Search method was applied to the hyperparameters listed in Table 3, along with their respective value ranges. Then, Grid Search was used to refine the values of *learning_rate_init* and *alpha*, also presented in Table 3.

Table 3 Hyperparameters of the ANN algorithm considered in the tuning process

In terms of hidden layers, two or fewer are generally sufficient for simple datasets. However, deeper architectures can be advantageous when dealing with more complex datasets or tasks. Karsoliya (2012) discusses the limitations associated with using four hidden layers. Therefore, in this study, up to three hidden layers were considered, as the dataset comprises long time series.

Therefore, the values 5, 10, 25, 50, 75, 100, 150, and 200 were tested for the *hidden_layer_sizes* hyperparameter, considering up to three hidden layers, with the constraint that each layer could not contain more neurons than the preceding one. For a single hidden layer, the values 10 and 28 were also tested. Additionally, the configuration without hidden layers was included in the grid, which corresponds to using a logistic regression model when the sigmoid activation function is employed.

As for the solver hyperparameter, *sgd* and *adam* were included as options, while *L-BFGS* was not considered, as it is more suitable for small datasets (Pedregosa et al. 2011). Regarding the *activation* and *learning_rate* hyperparameters, all available options were considered. It is important to note that *learning_rate* is only relevant when using the *sgd* solver.

The *alpha* hyperparameter is a regularisation term that addresses overfitting and underfitting by limiting the magnitude of the model weights. Higher values promote smaller weights and smoother decision boundaries, thereby reducing overfitting, while lower values allow larger weights and more complex boundaries, reducing underfitting. As recommended in the *scikit-learn* documentation, *alpha* should be tuned using a grid search within the 10^{-x} range, where x varies from 1 to 7 (Pedregosa et al. 2011).

Finally, for the *learning_rate_init* hyperparameter, studies indicate that typical values for ANNs with normalized inputs are less than 1 and greater than 10^{-6} (Bengio 2012).

2.6 Support Vector Machines

The SVM algorithm was originally proposed for classification tasks and was later extended to regression problems in 1995 (Cortes and Vapnik 1995). The regression variant, known as Support Vector Regression (SVR), is particularly effective at modelling non-linear relationships and often outperforms traditional models in terms of accuracy. SVR works by mapping input data into a higher-dimensional space using kernel functions—such as linear, polynomial, or radial basis function (RBF)—to capture the underlying patterns of the target time series. A hyperplane is then constructed to best fit the data, with the data points closest to it designated as support vectors (Cortes and Vapnik 1995).

Linear Support Vector Regression (LSVR) was implemented using the *LinearSVR* function from *scikit-learn* (Pedregosa et al. 2011). Hyperparameter tuning was performed using a Random Search process and focused on the hyperparameters listed in Table 4, along with their corresponding tested values. The *C* hyperparameter represents a

regularisation term, while the *epsilon* hyperparameter defines the model's error tolerance. The tested values were selected based on previous studies (Villalobos-Arias and Quesada-López 2021).

Table 4 Hyperparameters of the SVM algorithm considered during the tuning process

2.7 Error Metrics

Error metrics are among the most used methods for evaluating and comparing the performance of forecasting models. These metrics are defined as mathematical and logical constructs intended to measure how closely predicted values align with actual observations, often expressing the variation between them in terms of error (Naser and Alavi 2023).

There are numerous error metrics—approximately twenty-nine specifically for regression problems (Naser and Alavi 2023), a category of supervised ML models to which consumption forecasting belongs. Despite the large number of available metrics, most of the articles reviewed continue to rely on a small subset, which remains the most widely used in practice.

For this study, the following error metrics were used: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). In addition, the Coefficient of Determination (R2) was employed primarily for hyperparameter tuning. The formulas for these metrics are presented in Eqs. 1–5.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \tag{1}$$

$$MSE = \frac{\sum\left(y_i - \hat{y}_i\right)^2}{n} \tag{2}$$

(3)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{4}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n}\left(y_i - \underline{y}_i\right)^2} \tag{5}$$

In the previous equations:

- y represents the actual value.
- ŷ represents the predicted value.
- ȳ represents the average of the actual values.
- n represents the total number of samples.

Each of these metrics has its own advantages and disadvantages; therefore, using multiple metrics helps provide a more comprehensive evaluation of the model's overall performance.

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3 Results

Data preprocessing and feature engineering, including the selection of the most relevant features, were carried out prior to this study and are, therefore, not within its scope.

Based on the endogenous features used during the feature engineering process, 63 features were created. These features are associated with various time lags related to power demand, reflecting energy consumption on previous days and weeks. This approach is essential for incorporating historical consumption patterns of the building into the models. Subsequently, PCA was applied to reduce the

dataset's dimensionality and the computational cost of the training phase, resulting in 13 principal components (endogenous features).

Regarding the exogenous features, five new variables were created during the feature engineering process to capture the periodicity information for the models. Once again, the PCA algorithm was applied —this time to all 22 exogenous features—resulting in seven principal components.

Finally, with the endogenous and exogenous features defined, the study proceeded to the hyperparameter tuning phase for the various algorithms. The results of this phase—including hyperparameter tuning and the benchmarking of forecasting algorithms—are presented in the following subsections.

3.1 Random Forest

The tuning of hyperparameters was conducted in stages, using both Random Search and Grid Search methods. The objective was to evaluate the trade-off between forecasting performance—measured by error metrics—and computational cost, to identify the optimal hyperparameter values.

During the hyperparameter tuning process, several plots were useful for visualizing the behaviour of the error metrics. For example, Fig. 1a shows the variation of the R2 metric as a function of the number of trees used during the validation process. No overfitting issues were observed, even with higher tree counts, and performance improved notably within the first 100 trees. Based on the cross-validation results, convergence appears to occur around 500 trees. Similarly, Fig. 1b illustrates the variation of the R2 metric with respect to the number of samples used in the validation process. This plot shows convergence at approximately 40% of the sample size, with a minor peak observed around 70%.

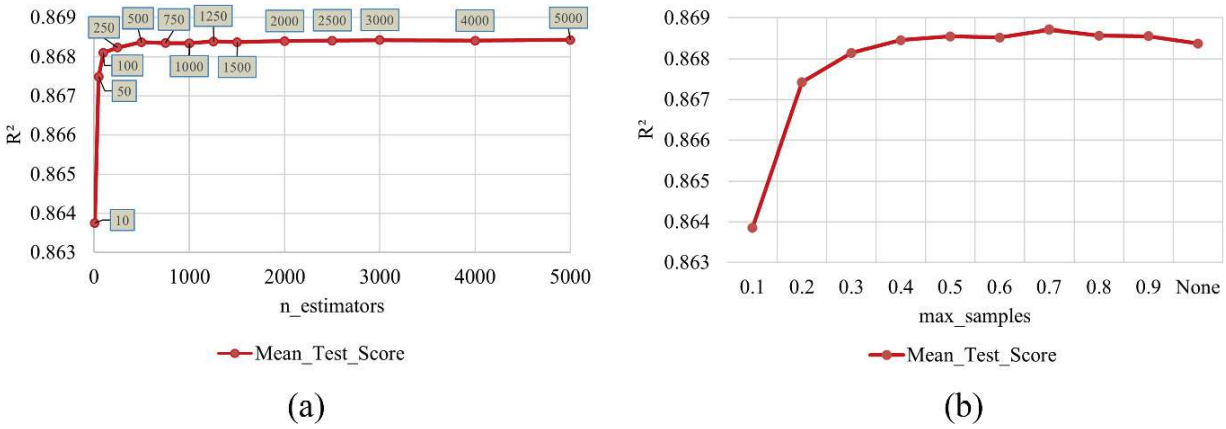


Fig. 1 Variation of *Mean_Test_Score* (R2 metric for model validation) with the increase in the number of trees (**a**) and the *max_samples* parameter (**b**)

Finally, Table 5 presents the selected values for each hyperparameter following the tuning process of the RF model.

Table 5 Selected hyperparameter values for the RF model

Ultimately, Table 6 presents the error metrics and performance of the RF model for the training and validation subsets.

Table 6 Error metrics obtained after hyperparameter tuning of the RF model

3.2 Multivariate Adaptive Regression Splines

The hyperparameter tuning was performed exclusively using the Grid Search method. Initially, the process focused on the *max_terms* and *max_degree* parameters. The results of one of the simulations are shown in Fig. 2. Beyond a value of 40 for *max_terms*, no further performance improvements were observed with increasing this hyperparameter.

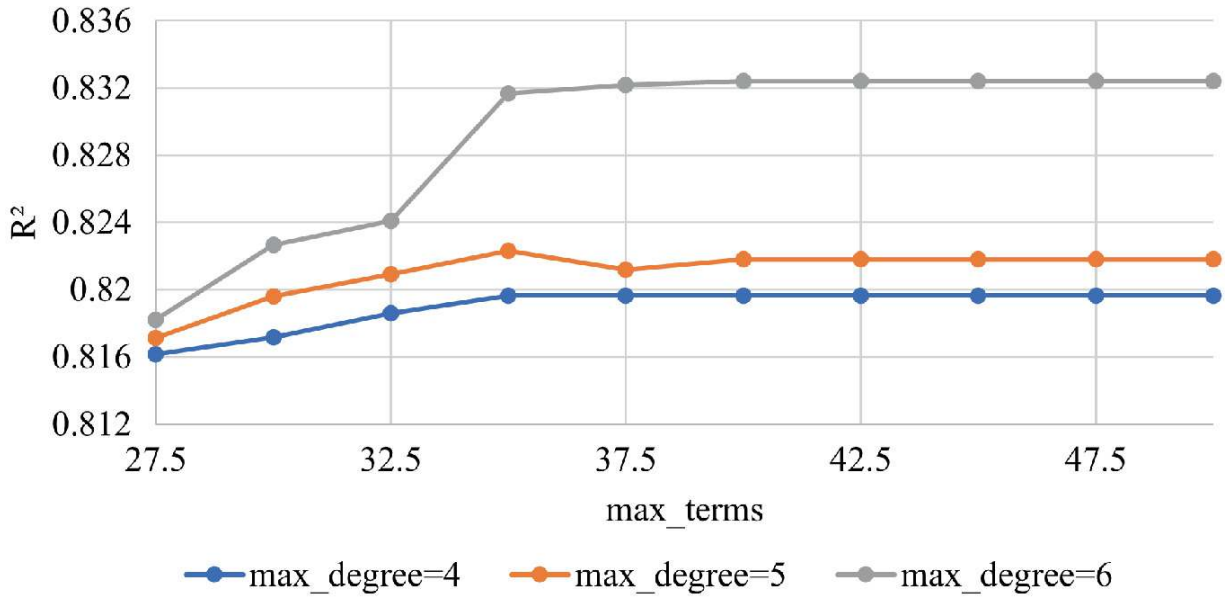


Fig. 2 Variation of *Mean_Test_Score* with increasing values of *max_terms* and *max_degree*

The optimal value for *max_degree* remained unclear, so a focused Grid Search was conducted. As shown in Fig. 3a, increasing the *max_degree* beyond 7 did not result in further improvement in the R2 metric. Subsequently, as the final step in tuning the hyperparameters of the MARS model, an additional Grid Search was performed. Figure 3b shows that the influence of the *penalty* parameter on the R2 metric slightly declined beyond a value of 2.5. Nonetheless, a value of 2.5 was selected, as performance decreased beyond that point.

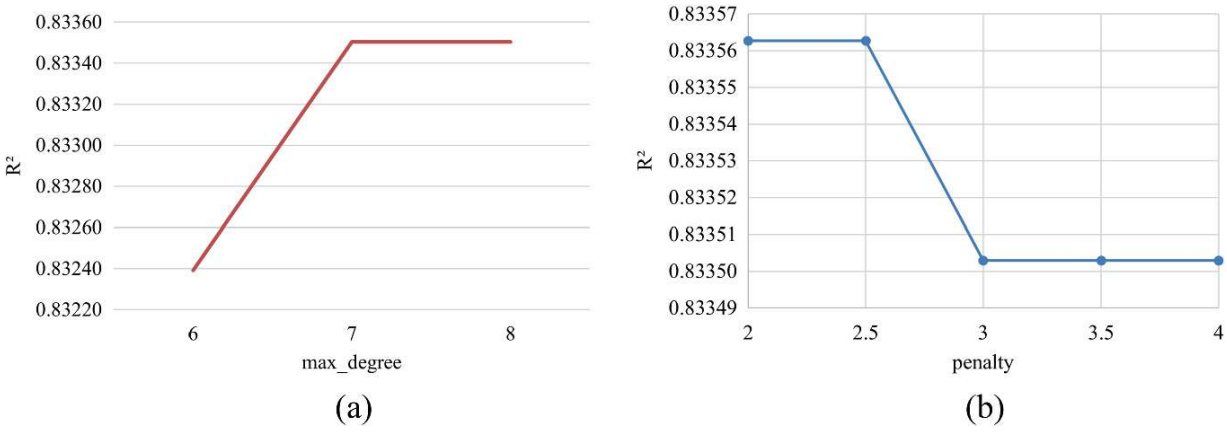


Fig. 3 Variation of *Mean_Test_Score* with increasing values of *max_degree* (**a**) and *penalty* (**b**)

Table 7 presents the selected values for each hyperparameter following the tuning process of the MARS model.

Table 7 Selected hyperparameter values for the MARS model

Ultimately, the error metrics of the MARS model for the training and validation subsets are presented in Table 8. Additionally, the table includes the model's training and prediction times.

Table 8 Error metrics obtained after hyperparameter tuning of the MARS model

3.3 Artificial Neural Network

As previously mentioned, both Random Search and Grid Search methods were applied. Table 9 presents the selected hyperparameter values obtained after the tuning process.

Table 9 Selected hyperparameter values defined for the ANN model

Finally, the performance results of the ANN model after both tuning processes are presented in Table 10 for the training and validation subsets. Additionally, the table includes the model's training and prediction times.

Table 10 Error metrics obtained after hyperparameter tuning of the ANN model

3.4 Linear Support Vector Regression

The default number of iterations was insufficient for model convergence, so the maximum was increased to 1,000,000. Consequently, the optimal hyperparameter values identified during the tuning process are presented in Table 11.

Table 11 Selected hyperparameter values for the *LinearSVR* model

Finally, the results and performance metrics of the *LinearSVR* model for the training and validation subsets are shown in Table 12. In addition, the table includes the model's training and prediction times.

Table 12 Error metrics obtained after hyperparameter tuning of the *LinearSVR* model

3.5 Evaluation of Forecasting Accuracy: Metrics and Scatterplots

After hyperparameter tuning, the models were evaluated using the test set, previously set aside to ensure unbiased results and avoid data leakage. This section presents the evaluation outcomes, combining quantitative error metrics with visual representations of forecasting accuracy using scatterplots.

A critical analysis is essential to assess forecast performance across different periods. In this context, the *Day Type* feature plays an important role, as previously discussed. Table 13 presents the error metrics corresponding to different *Day Type* categories. Additionally, the table highlights the best-performing results for the entire test set for each period individually. Finally, it identifies the best-performing model for each subset.

Table 13 Table comparing the forecasting performance of four machine learning models (RF, MARS, ANN, and LSVR) across different academic day types: class days, Saturdays, Sundays and holidays, exam periods, Christmas holidays, Easter holidays, summer vacation, and other interruptions. Performance is evaluated using MAE, MSE, RMSE, and MAPE. The table also identifies the best-performing result and model for each period and metric

To complement the quantitative evaluation presented above, scatterplots are an effective means of assessing model performance. These graphical representations allow for the visual inspection of the relationship between forecasted and actual values. Such visualisations help identify patterns, systematic errors, and the overall predictive behaviour. The scatterplots generated for the RF, MARS, ANN, and LSVR models are shown in Fig. 4.

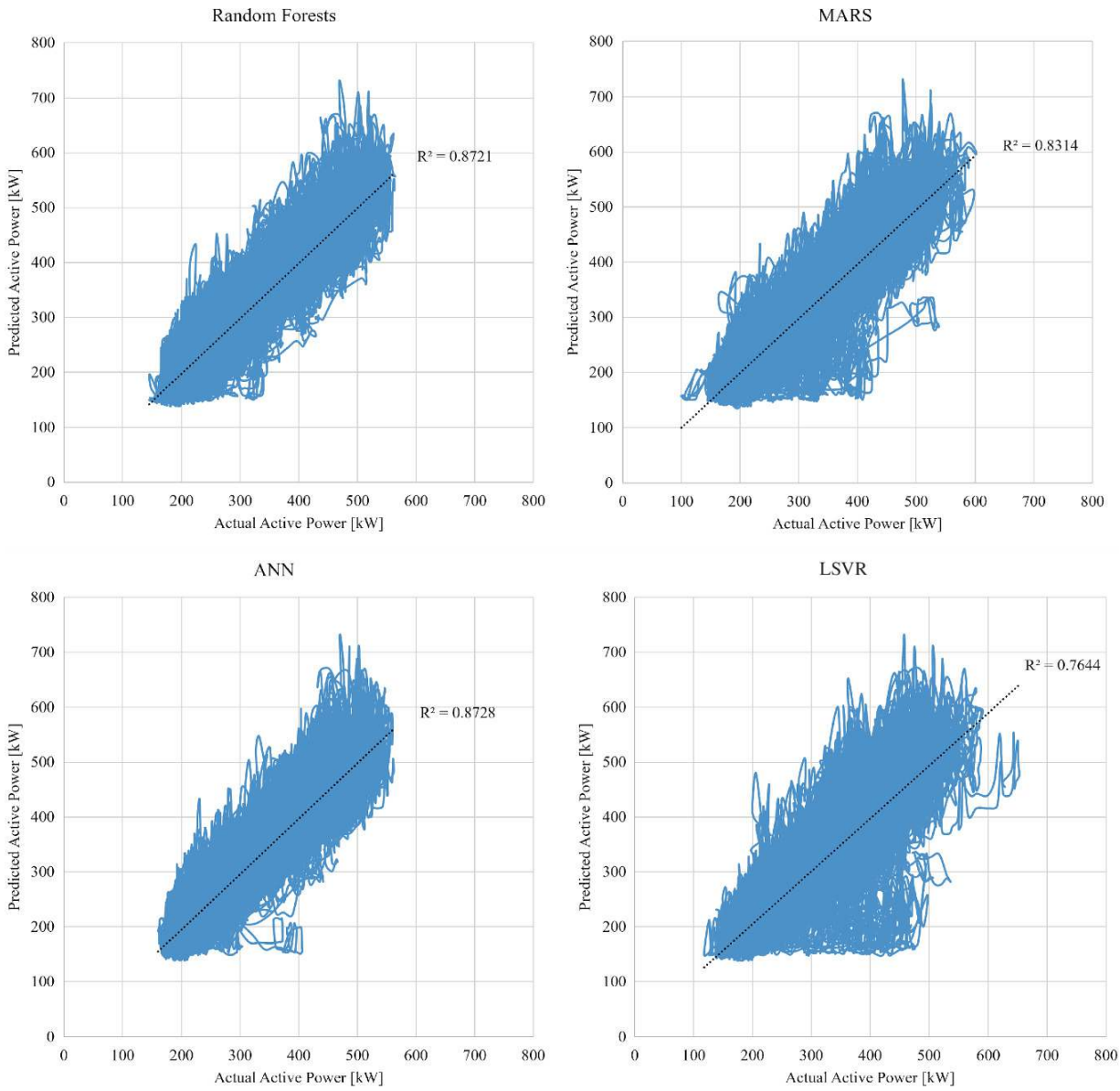


Fig. 4 Scatterplots comparing actual and predicted active power demand for the RF, MARS, ANN, and LSVR models. Each plot includes a reference line representing perfect agreement between observed and predicted values. RF and ANN show the closest alignment with the reference line, while MARS and LSVR exhibit greater dispersion

The scatterplots reveal that the RF and ANN models achieve the best forecasting performance, as their predicted values are most closely aligned with the trend line. Moreover, the R2 values shown in the figures reinforce this conclusion.

4 Discussion

As shown in Table 13 of Sect. 3.5, all models present significantly poorer performance across all metrics during the Christmas and Easter holiday periods. For class days and exam periods, the MAPE values are consistently low, remaining below 10% across all models. However, this performance is not reflected in the other metrics, likely due to the significantly higher active power values observed during class and exam days compared to other periods. Consequently, forecasting errors during these periods of increased activity have a more pronounced impact on absolute error metrics such as MAE, MSE, and RMSE. In contrast, the MAPE metric offers a more reliable basis for comparing model performance across different periods. As the load profiles presented in this discussion will illustrate, the models generate accurate predictions during these periods—contrary to what the absolute error metrics might suggest.

Considering the MAPE metric, all models—except for MARS—perform well on the four days classified as other interruptions. Saturdays yield acceptable MAPE values and consistently outperform Sundays and holidays. Finally, the MAPE values observed during the Summer Holiday period are reasonable, remaining below 14% across all models.

Considering the entire test set period, it is important to note that the models do not exhibit signs of overfitting. This conclusion is supported by the fact that the error metrics on the test set are like those obtained during hyperparameter tuning. Consequently, this indicates a strong generalization capability. Among the models, the RF achieved the best overall metrics, while the ANN performed slightly worse. Additionally, the RF and ANN models were each the top performers in sixteen cases, while the MARS model ranked best in four cases. Notably, all MARS's best performances occurred during the summer holiday period.

The load profile is a valuable tool for analysing the performance of forecasting models, particularly when focusing on specific critical

periods. In this context, forecasted values are compared with actual observations to assess the degree of similarity and identify potential deviations. Figure 5 presents the load profiles of actual and predicted power demand from various models for the week of 1–7 November 2019. This week includes a public holiday on Friday and serves as a representative example of model behaviour during such periods.

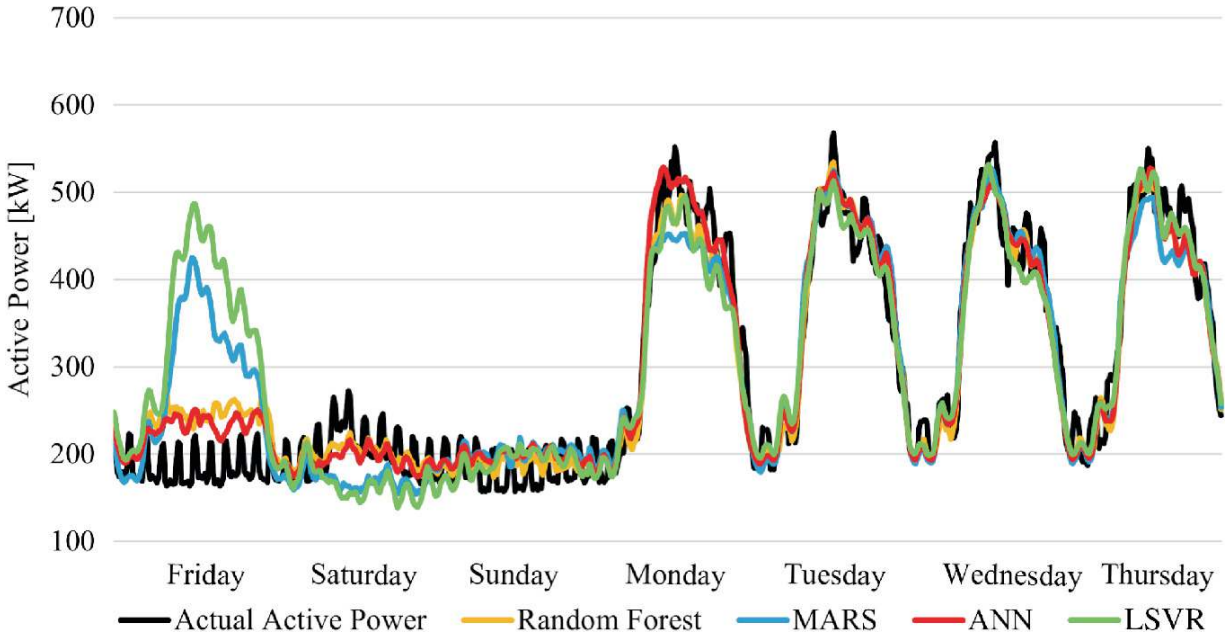


Fig. 5 Daily load profiles comparing actual and predicted active power demand during November 1–7, 2019, including a public holiday on Friday. Forecasts generated by the RF, MARS, ANN, and LSVR models are shown alongside measured power demand, allowing visual assessment of forecasting accuracy throughout the week

The plot illustrates that the models accurately predicted power demand during the four school days. In contrast, the high variability in actual power demand over the weekend appears to have made forecasting more challenging. Nevertheless, most models produced estimates within the correct range, particularly on Sunday. On Saturday, however, the MARS and LSVR models struggled to follow the actual trend, especially during peak demand periods. The holiday represented in the plot corresponds to the day with the poorest overall performance, with all models overestimating demand. In this context, both MARS and LSVR exhibited particularly weak forecasting performance.

Figures 6 and 7 display the load profiles for the Christmas and Easter weeks, respectively. It is important to note that Friday was the only public holiday during the Easter period. These plots confirm earlier observations, indicating that the models struggled to maintain accuracy during such periods. However, the results for the Easter public holiday are not as unfavourable as the error metrics alone might suggest. The forecasts generally capture the main peaks in power demand, even if they do not precisely reproduce the actual values.

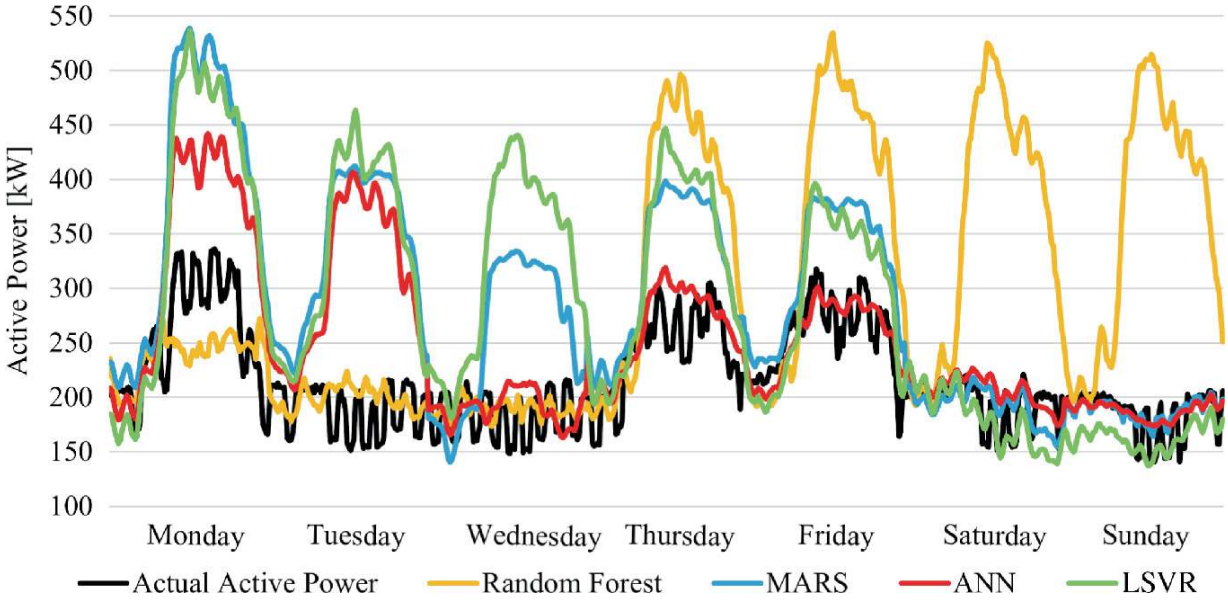


Fig. 6 Daily load profiles comparing actual and predicted active power demand during the Christmas holiday period (December 23–29, 2019). Forecasts from the RF, MARS, ANN, and LSVR models are compared with measured power demand to illustrate model performance during this low-occupancy academic period

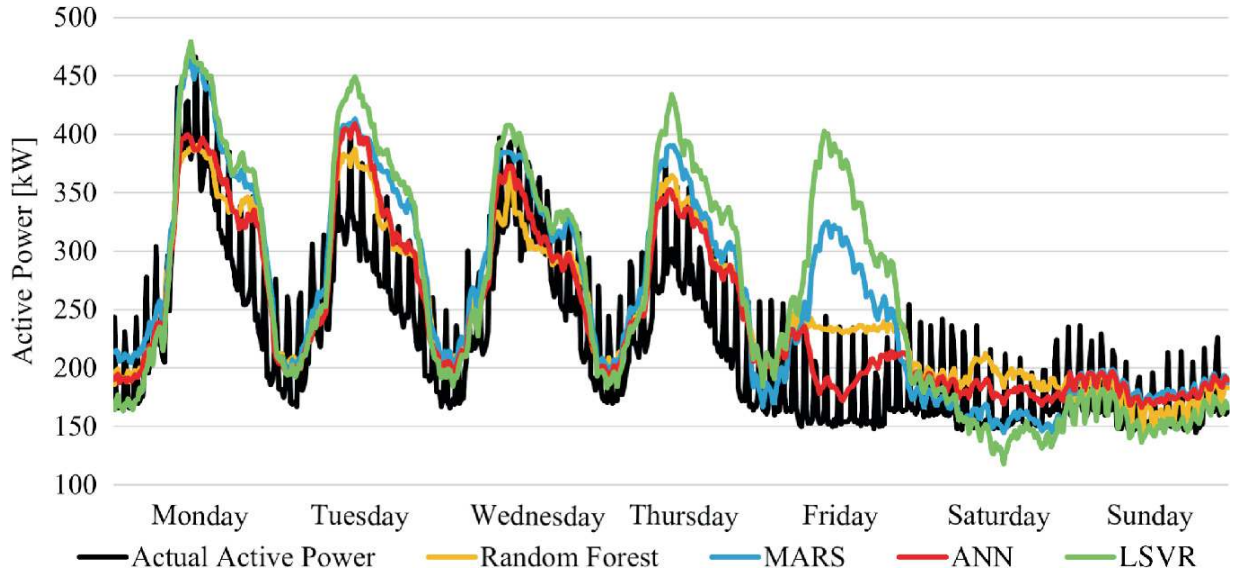


Fig. 7 Daily load profiles comparing actual and predicted active power demand during the Easter holiday period (April 15–21, 2019). Forecasts from the RF, MARS, ANN, and LSVR models are compared with measured power demand to illustrate the models' behaviour during holiday conditions

The performance of the models during the exam period is illustrated in Fig. 8. The results are promising and align with the findings presented in Table 13. However, performance during this period appears weaker than the metrics alone might suggest, as the models fail to capture the sustained peaks in power demand. This behaviour suggests that the models likely performed more effectively during regular class periods than on exam days.

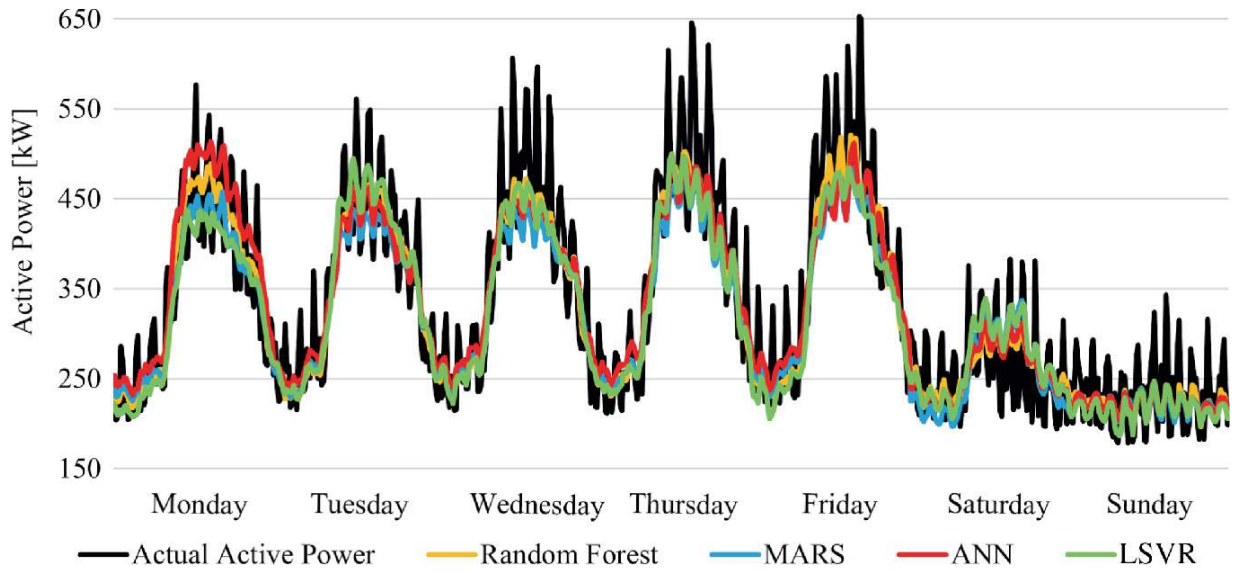


Fig. 8 Daily load profiles comparing actual and predicted active power demand during the examination period (July 8–14, 2019). Forecasts produced by the RF, MARS, ANN, and LSVR models are shown alongside measured power demand, illustrating each model's ability to capture variations in energy use during the examination period

Finally, the performance of the models during the summer holidays is illustrated in Fig. 9. In this case, forecasting appears more accurate than the error metrics suggest, with only the peak values not being accurately captured. However, it is important to emphasise that the plot represents only a single week.

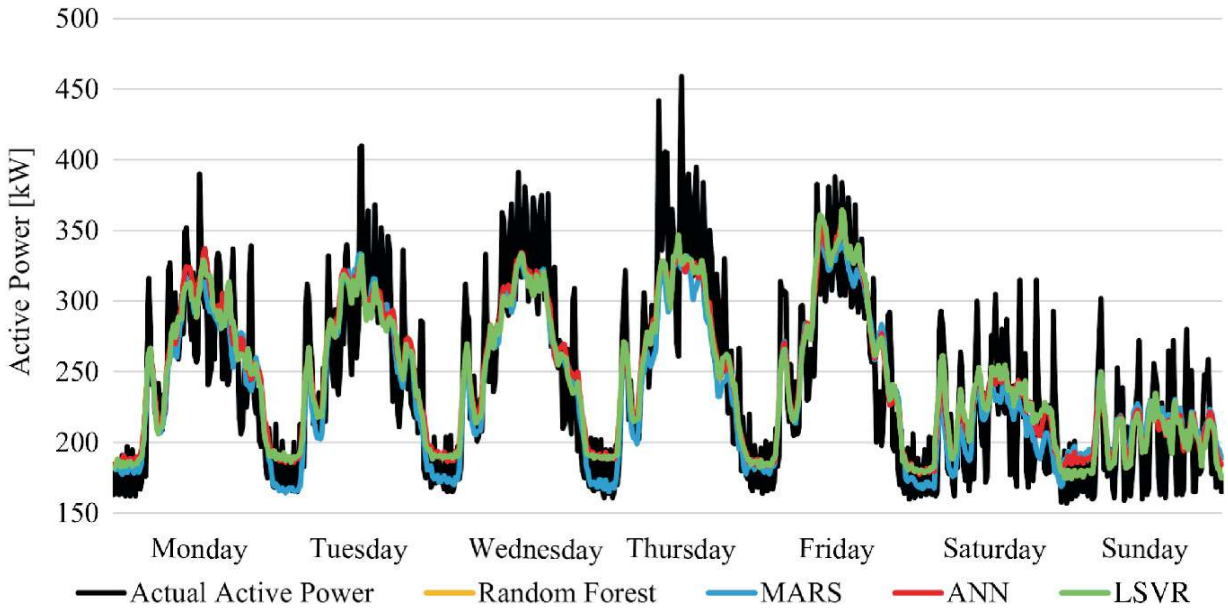


Fig. 9 Daily load profiles comparing actual and predicted active power demand during the summer vacation period (August 19–25, 2019). Forecasts from the RF, MARS, ANN, and LSVR models are compared with measured power demand to illustrate their performance during periods of reduced campus activity

5 Conclusions

This chapter contributes to the broader discussion on the role of AI in advancing sustainable development, particularly within higher education institutions. By focusing on energy forecasting in academic buildings, the study aligns with the book's scope—AI for Sustainable Development Teaching and Research—demonstrating how AI-driven tools can support both operational sustainability and educational

innovation. The findings are relevant not only for improving energy efficiency in university campuses, but also for enhancing teaching and research practices through real-world applications of AI in sustainability contexts.

Four models were developed based on RF, ANN, LSVR, and MARS algorithms. Their hyperparameters were tuned using Grid Search and Random Search techniques. Model performance was then evaluated through error metrics and various visualisation tools, particularly load profiles and scatterplots. The analysis revealed that the RF and ANN models outperformed the others, showing strong results across most periods. Their best performance was observed during class days and exam periods, which correspond to the highest occupancy levels on campus.

This study underscores the importance of the hyperparameter tuning phase in machine learning models, demonstrating its impact on performance as measured by error metrics. It also evaluates the trade-off between prediction accuracy and computational cost. Moreover, the study contributes to the literature by encouraging broader comparisons between algorithms for forecasting electrical energy demand in buildings. Finally, it highlights the role of machine learning in advancing sustainable energy management practices within higher education institutions.

Nevertheless, some limitations must be acknowledged. A key constraint lies in the difficulty of generalising the developed models to other buildings, as each one tends to exhibit unique energy consumption patterns shaped by its specific usage, occupancy, and operational characteristics. In addition, the models demonstrated reduced performance on Sundays and during academic breaks—particularly over the Christmas and Easter periods—likely due to atypical consumption behaviours and irregular occupancy during these times. These findings suggest the need for new modelling strategies or the incorporation of additional features to better account for such contextual specificities.

Future work could explore advanced techniques such as Deep Learning to improve performance during low-accuracy periods by capturing more complex temporal patterns. The developed models could also be integrated into a real-time visualisation dashboard, serving not only operational needs but also as an educational tool. For example, such a dashboard could support teaching by illustrating real-world energy consumption dynamics, anomaly detection, and forecasting results. In addition, these models could be linked to Building Digital Twins, enabling scenario simulation for both research and learning purposes. These developments support more adaptive, efficient, and intelligent energy systems while enriching sustainability education within higher education environments.

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Integration of Artificial Intelligence in Sustainable Solar PV R&D

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Abstract
This study examines the applications and achievements of artificial intelligence deployment in sustainable solar PV research and development (R&D), a revolutionary step toward achieving carbon neutrality by 2050. Using a multi-step approach that includes a bibliometric analysis, a literature review, and a global study analysis, this chapter emphasizes AI's role in addressing solar PV challenges, such as variability, PV inefficiencies, grid instability, and energy storage issues. Major applications examined in this study include AI-supported material discovery, solar forecasting, and solar facility maintenance that improve the efficiency and reliability of solar PV generation. Gaps such as data scarcity, lack of standardization, model generalization, and infrastructure compatibility are also identified. The bibliometric analysis, literature review, and survey of global case studies contribute to an enhanced understanding of the progress in the IA-driven sustainable solar PV R&D. On the other hand, the analysis of technological barriers, policy fragmentation, and equity concerns

facilitates options for further improvements to tackle these issues and promote their worldwide adoption.

Keywords Artificial intelligence – Sustainable solar PV – Carbon neutrality – Smart grids – Policy frameworks – Sustainable innovation

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1 Introduction

The transition to sustainable energy worldwide is crucial for combating climate change, reducing carbon emissions, and achieving the United Nations Sustainable Development Goals (SDGs), especially SDG 7 (Affordable and Clean Energy), SDG 11 (Sustainable Cities and Communities), and SDG 13 (Climate Action). Solar photovoltaic (PV), as a renewable and sustainable energy source, leads this shift due to its scalability, accessibility, and low environmental impact. However, the variable nature of solar power, combined with inefficiencies in solar PV systems caused by soiling, shading, and thermal degradation (Selvi et al. 2023; Khosrojerdi et al. 2025; Qureshi et al. 2025), grid connection issues, and energy storage constraints, creates significant hurdles for broader adoption. Artificial Intelligence (AI) has become a key tool in addressing these issues (Wang et al. 2025; Arrfou et al. 2025), driving innovation in solar PV R&D to enhance efficiency, reliability, and sustainability. By applying AI-based methods, such as machine learning (ML), deep learning (DL), and optimization algorithms, researchers and engineers are transforming solar PV systems—from discovering new materials and implementing predictive maintenance to managing the grid and forecasting energy output. These innovations support the broader goals of sustainable development by enhancing resource

utilization, reducing greenhouse gas emissions, and ensuring equitable access to clean, renewable energy (Zhuang et al. 2025b).

Despite the large number of studies on the use of AI and machine learning (ML) for solar PV R&D, there is a lack of systematic research on these studies to answer research questions about major solar PV-dedicated applications, their contributions to SDGs, their challenges and gaps, and their prospects.

The purpose and focus of this study are to answer these questions. It synthesizes insights from a comprehensive review of recent literature, including application-focused studies and global case-studies examining AI's role in sustainable solar PV R&D. The study reveals key trends, practices, and findings in AI-assisted solar PV research, while identifying critical issues and research questions that warrant further exploration. Trends include the increasing use of AI for optimizing PV efficiency, forecasting solar irradiance, and enhancing energy storage systems, with notable applications in smart grids, building-integrated photovoltaics (BIPV), and floating solar PV systems. However, challenges such as data scarcity, lack of standardization, cybersecurity risks, and equitable access to AI-driven technologies remain significant hurdles.

By analyzing the results of this multi-step study, this chapter aims to provide findings, insights, and recommended solutions for addressing the challenges and gaps in integrating AI-supported technologies into sustainable solar PV deployment, emphasizing its role in accelerating the transition to a carbon–neutral future while ensuring sustainable and inclusive energy systems.

The remainder of this chapter will be structured as follows: the **Methods** section outlines the steps of the multi-method approach employed in this study, including bibliometric analysis, thematic analysis, and international case study analysis. **Results** are presented and analyzed systematically to present the findings of the multi-step research, which includes application-specific and international case studies. **Discussion** focuses on the challenges, gaps, and the need to address these issues. **Conclusions** recommend future research on

solutions for global data repositories, standardized protocols, green AI frameworks, and cross-sector collaborations.

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2 Methods

This study employs a multi-method approach to investigate the impact of AI on solar PV research and its role in promoting sustainable development, with a focus on achieving carbon neutrality by 2050. The methodology combines a bibliometric analysis, a systematic literature review, and a case study analysis to synthesize findings from selected studies. This approach aims to evaluate AI's transformative potential in addressing photovoltaic (PV) inefficiencies, grid instability, and energy storage problems, while also highlighting gaps such as data scarcity, lack of standardization, model generalization, and infrastructure compatibility. The method is designed to follow the tasks outlined in the introduction, ensuring a thorough and reproducible analysis that aligns with the SDGs.

Bibliometric Analysis. The selected peer-reviewed studies published between 2020 and 2025 were first analyzed using a systematic bibliometric approach on AI applications in solar PV R&D. The bibliometric analysis was based on the co-occurrence of terms. This technique is commonly used to provide the reader with an overview of research on the topic in chronological and thematic dynamics, depth, and breadth. This approach enables researchers to understand the intricate research streams despite the complexity of a research field.

To obtain the desired results, a search string comprising terms such as AI, ML, solar PV, and sustainability research was devised and used to search for peer-reviewed papers indexed in Scopus, Web of Science, and Science Direct. The software used for the bibliometric data analysis in this study was VOSviewer (version 1.6.20), a widely used text mining research tool for bibliometric analysis (Van Eck and Waltman 2023).

Thematic Analysis. The thematic analysis adopts the method of systematic literature review (SLR), which investigated AI-assisted solar PV applications. The SLR, guided by PRISMA, reviewed studies to

synthesize trends, challenges, and impacts of AI in solar PV systems. The analysis identified key themes of sustainability, data scarcity, and standardization needs, while quantifying outcomes like fault detection accuracy and energy efficiency gains.

International Case Study Analysis. Five case studies were selected to provide practical insights into AI applications across diverse contexts. These cases, drawn from the USA, China/Thailand, Germany, India, and the Middle East/African countries, were selected for their geographic and technological diversity, relevance to the SDGs, and availability of detailed outcomes. The cases were examined through AI-supported solar forecasting, site selection, fault detection, energy management in smart grids, and PV optimization. Each case was analyzed using categories of context, AI technique used, sustainability outcomes, challenges, and comparison with traditional methods.

The mixed-methods approach ensured a comprehensive synthesis through the SLR, capturing a wide range of AI applications. On the other hand, the case studies provided contextual depth, illustrating real-world impacts and challenges in diverse settings. This methodology effectively addressed solutions to data scarcity, standardization, model generalization, cybersecurity, equity, energy efficiency, infrastructure compatibility, and policy gaps, offering actionable insights for stakeholders.

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3 Results

3.1 Bibliometric Analysis

The results of the aggregated bibliometric analysis of the research themes on AI and solar PV R&D are presented in a visualized thematic network map (Fig. 1). Using VOSviewer, the titles, abstracts, and keywords of these studies are screened, identified, and visualized. The main thematic areas were identified using the software's term co-occurrence analysis. The node sizes of the research terms are proportional to the occurrence frequencies or weights of the terms, and the connection widths are proportional to the strengths of the

connections among the research terms. Terms related to the solar PV R&D and AI applications that are closely linked form thematic clusters within the general research topic.

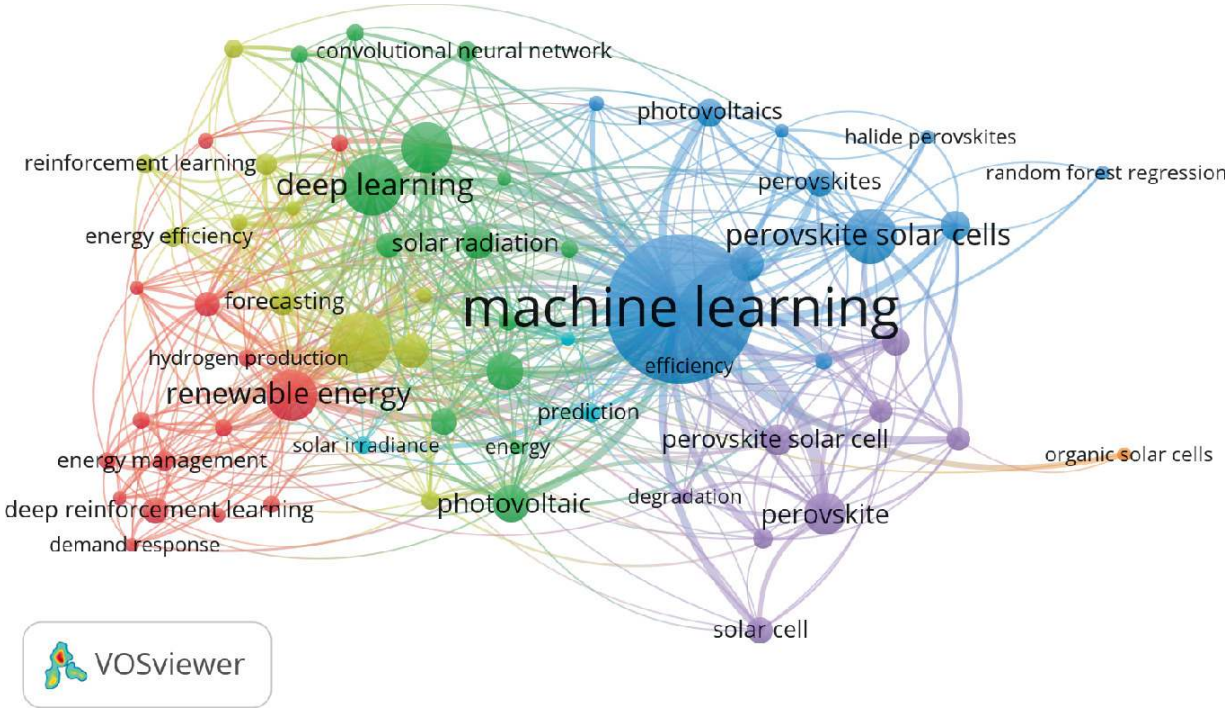


Fig. 1 Bibliometric map of AI and solar PV R&D (100 studies)

Figure 1 illustrates a map of the interconnected applications of AI algorithms and tools, as well as solar PV R&D areas, based on 100 related studies. The map is represented by the most frequently used or important terms, including AI, ML, solar PV, forecasting, prediction, optimization, and efficiency. The thickness of connections among these research terms demonstrates the strong relationships among them, and the color coding indicates various aspects of the research data, such as clusters or scores. The distance between the AI terms and solar PV terms presents the respective closeness and strength of the relationship among the clusters.

This relational map illustrates the close connections between AI and its primary subset, Machine Learning (ML), on the one hand, and renewable energy and solar energy, on the other, as well as the integration of renewable energy and sustainable energy. In terms of its

integration into solar energy, deep learning, specifically in the form of artificial neural networks, plays a pivotal role in forecasting, prediction, optimization, efficiency, and energy management.

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4 Thematic Analysis

The thematic analysis of studies on AI in solar PV research and development (R&D) identified key themes, trends, and challenges related to this area. The analysis followed a thematic coding approach, with themes derived both inductively from the data and deductively based on the research questions outlined in the introduction. The results are organized into two primary categories: (1) Solar PV-dedicated AI applications, analyzed in application-specific studies and international case studies, and (2) Contributions to sustainable development. These findings provide a comprehensive synthesis of how AI-enhanced innovations address PV inefficiencies, grid integration, and energy storage while highlighting barriers to achieving a carbon–neutral future by 2050 (Biswas et al. 2025).

4.1 Solar-PV AI Application Specific Studies

AI/ML Workflow

AI workflows often adapt to their use cases, involving multiple steps. As a subset of AI models, solar PV power scientists and engineers design the structural process of their AI/ML models in multiple steps, aligning with ML best practices for modeling various solar PV R&D tasks in renewable energy.

The process begins with data collection from solar panels, which involves the historical data on irradiance, solar panel, and solar PV output. This step is followed by data preprocessing, which includes handling missing data, normalization, and feature engineering. The preprocessed data is then split into training and test subsets, with the former taking 80% and the latter taking 20% of the entire dataset. Validation plays a critical role throughout the AI/ML work process. The

importance of the validation is reflected in two distinct approaches—the linear model and the iterative model.

Linear Model Process: After training the model with the training data, validation is conducted by testing the model against the test subset. The "Model fit check" critically assesses performance using R^2 (> 0.9) and RMSE (< threshold), ensuring the model's accuracy and reliability. Supposing these validation criteria are met ("Yes"), the model proceeds with a final performance evaluation using R^2, RMSE, and MAE before its deployment in solar PV power generation R&D. This linear approach relies heavily on robust initial validation to justify a single deployment without further adjustments.

Iterative Model Process: If the "Model fit check" validation criteria are not met ("No"), the process enters an iterative loop, returning to "Preprocessing" and "Train the model" to refine the model with adjusted parameters or additional data. This repeated validation ensures the model improves until it meets the required standards. Furthermore, a feedback loop from "Model fit check" back to "Train the model" and earlier stages, such as preprocessing, underscores the ongoing validation pre- and post-deployment, enabling continuous refinement based on real-world performance metrics. This iterative validation is crucial for adapting to new data and continually improving model accuracy over time.

Figure 2 illustrates a machine learning (ML) process for predicting PV power generation based on irradiance and solar PV output data. It serves as an example of these AI/ML model designs.

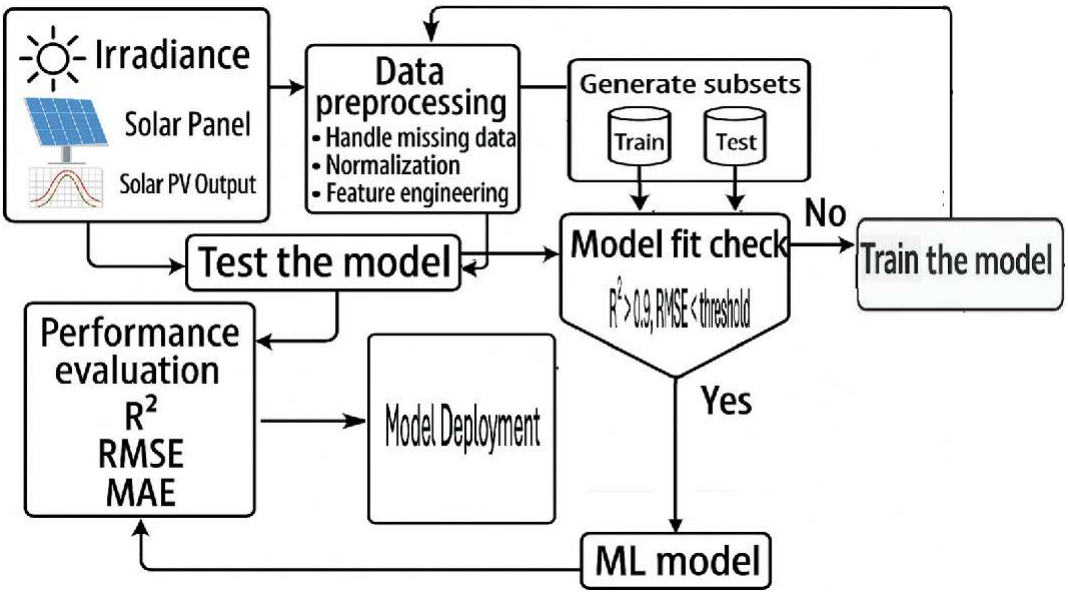


Fig. 2 AI/ML solar PV power generation R&D flowchart

Validation is the cornerstone of this process, ensuring the model's reliability at each stage—initial testing, fit assessment, and post-deployment evaluation—whether following a linear or iterative path.

Material Discovery and Optimization

In material science, AI is extensively used to accelerate the discovery and optimization of advanced, high-efficiency, sustainable materials for solar cells, such as eco-friendly, lead-free perovskite-based materials (Maoucha et al. 2025; Alam and Prasad 2025). One of the applications of AI algorithms and tools in this area is the development of high-efficiency organic photovoltaic (OPV) technology, which contributes to sustainable energy solutions (Khoussa et al. 2024). Studies highlight the use of machine learning (ML) and deep learning (DL) to develop high-efficiency, sustainable materials such as perovskite-based solar cells (Alam and Prasad 2025). Techniques such as convolutional neural networks (CNNs) and Bayesian optimization enable rapid prediction of power conversion efficiency (PCE) and material durability, enhancing material selection and reducing experimental costs and time (Togun et al. 2025). For instance, AI-assisted processes have improved the thermal conductivity of nano-enhanced phase change materials

(NEPCMs) by up to 60%, enhancing thermal energy storage (TES) systems (Selvam et al. 2025).

Solar Irradiance and Energy Forecasting

AI-supported forecasting models, such as Long Short-Term Memory (LSTM) networks and Random Forest algorithms, are indispensable for predicting solar irradiance and energy output, addressing the intermittency of solar power (Kushwaha et al. 2025; Zayed et al. 2025; Peer et al. 2025). Long Short-Term Memory (LSTM) networks, Random Forest algorithms, and hybrid models such as LSTM-BBOA achieve high accuracy in both short-term and medium-term forecasts of solar irradiance and energy production (Zhuang et al. 2025b; Bouabdallaoui et al. 2025; Ledmaoui et al. 2024; Saadati and Barutcu 2025). For example, the LSTM-BBOA model demonstrated a determination coefficient (R^2) of 0.9998 for floating solar PV systems (Zayed et al. 2025) and very low root mean square errors (RMSE) of 0.0007555 for irradiance prediction (Al-Aboosi et al. 2024). These advancements support better grid planning and resource management (Abubakar et al. 2025).

Predictive Maintenance and Fault Detection

AI-powered approaches enhance predictive maintenance and fault detection in solar PV systems, reducing downtime and improving reliability. AI-based digital twins and deep learning models enhance predictive maintenance, reducing unplanned downtime by 35% and increasing fault detection accuracy to 98.3% in renewable energy systems (Abdessadak et al. 2025). Autonomous unmanned aerial vehicle (UAV) inspection systems use deep learning to detect solar panel defects with 92.13% accuracy and 80.33% precision (Al-Gawda et al. 2022). These systems can also help identify issues like cracks and hot spots using thermal imaging and current–voltage (I-V) curve analysis (Thakfan et al. 2024).

Grid Integration and Smart Grids

AI enhances grid stability and energy management through the use of smart inverters and demand-side management (DSM). Techniques such as Ant Colony Optimization (ACO) enhance demand-side management (DSM) in smart grids with solar integration, thereby reducing consumer energy costs and peak loads (Yadav et al. 2024). AI-optimized smart inverters help maintain grid stability under dynamic conditions, with applications in vehicle-to-grid systems and hybrid energy solutions (Awad and Bayoumi 2025).

Energy Storage Optimization

AI algorithms and tools enhance energy storage systems for PV generation, such as pumped hydro power and battery storage, by optimizing cycling stability. Hybrid TES systems integrating sensible and latent heat storage achieve energy densities above 350 MJ/m^3 and operational efficiencies exceeding 90% (Selvam et al. 2025). AI algorithms, such as neural networks and genetic algorithms, optimize power flow in hybrid systems with solar, batteries, and green hydrogen production, ensuring efficient energy management (Afia et al. 2023; Assareh et al. 2025).

Main AI Methods

Three AI methods—Long Short-Term Memory (LSTM), Gradient Boosting Machine (GBM), and Support Vector Machine (SVM)—are widely applied in solar energy systems, each offering unique strengths and facing specific limitations (Al-Aboosi et al. 2024; Alrubeei et al. 2025; Rajarajeswaran 2025; Zayed et al. 2025):

Long Short-Term Memory (LSTM): LSTM excels in capturing long-term dependencies and adapting to nonlinear trends in sequential data, making it highly effective for predicting solar irradiance and power output, as demonstrated in floating PV systems in the Middle East/African countries ($R^2 = 0.9998$). However, they require large datasets, are computationally expensive, and are sensitive to hyperparameter tuning, which can limit scalability in resource-constrained regions (Kushwaha et al. 2025; Zayed et al. 2025).

Gradient Boosting Machine (GBM): GBM handles non-linear relationships and missing data robustly, proving effective for structured data in applications like solar farm site selection in India (90% accuracy). Its limitations include a propensity for overfitting, the need for careful hyperparameter tuning, and high computational costs for large datasets, which can hinder performance in data-scarce settings (Alrubeei et al. 2025; Ledmaoui et al. 2024; Rajarajeswaran 2025).

Support Vector Machine (SVM): The SVM offers strong generalization and resistance to overfitting, performing well with small to medium-sized datasets in solar forecasting applications. However, it struggles with scalability for large datasets, is sensitive to kernel selection, and is computationally expensive, posing challenges in dynamic or data-rich environments (Al-Aboosi et al. 2024; Thakfan and Salamah 2024).

These methods enhance solar energy systems by improving forecasting, optimization, and site selection, but their effectiveness is constrained by data requirements, computational demands, and parameter sensitivity, necessitating tailored solutions for diverse global contexts (Al-Aboosi et al. 2024; Alrubeei et al. 2025; Zayed et al. 2025).

Trends

The AI-powered solar PV R&D demonstrates several promising trends, including data-driven decision-making, interdisciplinary collaboration, sustainability focus, and standardization needs.

The trend of data-driven decision making is reflected in the fact that solar PV AI models rely on high-quality, real-time solar PV and environmental data from sensors, IoT devices, and meteorological datasets to optimize solar PV systems (Abouelaziz and Jouane 2024; Voronkova et al. 2024). The trend of interdisciplinary collaboration is evident in the successful integration of expertise from materials science, computer science, and energy engineering in AI-enhanced solar R&D, as seen in the development of perovskite solar cells and AI-optimized smart grids (Alam and Prasad 2025; Biswas et al. 2025). Furthermore, the trend of sustainability focus is evident in AI

applications that prioritize environmentally benign materials, waste-derived nano additives, and circular economy paradigms, aligning with the SDGs (Selvam et al. 2025; Anantha et al. 2024). Lastly, the trend of standardization needs to address the compatibility issues arising from the lack of harmonized standards for AI-enhanced smart inverters and grid integration, underscoring the need for unified protocols to ensure interoperability and cybersecurity (Awad and Bayoumi 2025).

4.2 International Case Studies

The integration of AI into solar PV systems addresses critical challenges in forecasting, optimization, and energy management across diverse global contexts. This section analyzes the findings of five cases, i.e., solar forecasting in the USA, ANFIS-based MPPT in China, solar PV installation in Germany, site selection in India, and floating solar PV in the Middle East/African countries. These cases were derived from both developed and developing countries and regions, dealing with unique climatic, infrastructural, and socioeconomic conditions while contributing to SDGs 7, 11, and 13.

AI Applications

AI methodologies vary across the cases but consistently outperform traditional approaches:

USA (Solar Forecasting): To address the challenge of inaccurate prediction of renewable energy output due to intermittent or permanent faults, a Fourier network regression model was developed to process solar irradiance data for accurate forecasting. This model was validated using an NREL dataset (1,000,000 samples) in Midland, TX, to predict solar irradiance with high accuracy (R^2 = 1.0, RMSE = 0.0007555), which surpassed ARIMA by 10% in error reduction (Al-Aboosi et al.2024).

China/Thailand (MPPT): An ANFIS-based MPPT system achieved 93% tracking efficiency, processing real-time voltage, current, and environmental data, outperforming Perturb and Observe methods by 8% (Bi and Jiriwibhakorn 2025).

Germany (PV rooftop systems): An automated anomaly detection method was developed to identify operational faults in PV rooftop systems (up to 30 kWp). Tests were conducted on the automated anomaly detection method using the ML-based Isolation Forest on a dataset of 4479 PV systems, achieving an anomaly score lower than 0.5, which is indicative of regular operation. The Isolation Forest method successfully identified technical faults and production losses in 4479 PV systems, comparable to the manual anomaly detection method (P2P method by Leloux), without requiring prior neighbor weighting or parameter setting (Akharath et al. 2021).

India (Defect detection): A Grey Wolf Optimization (GWO) model was developed to test grid-connected PV using the Indian solar power plant data. SVM was employed for classification and regression, while GWO was utilized for optimization. The SVM-GW_C algorithm was the best performer, with an overall accuracy of 97.28%, indicating that it correctly identified 97.28% of the defects in the DC-generated power. The SVM classification model performed best for defect identification (Ahmed et al. 2023).

The Middle East/Africa (PV Farms): Nwokolo et al. (2022) highlighted the scarcity of high-quality solar radiation measurements in Southern Africa and the Middle East and the challenges of this issue cause for the integration of AI and ML into the solar PV R&D. The case study attempted to predict and separate the beam, diffuse, and global solar radiation of PV systems and evaluated the related research project with generalized solar meteorological datasets using Gumbel Probabilistic Model (GP) Auto-Regression Integrated Moving Average (ARIMA), and ARIMA-GP. Their test achieved an RMSE reduction of 73.73% (H), 71.71% (Hd), 61.91% (Hb), and an R^2 increase of 15.25% (H), 14.19% (Hd), 11.70% (Hb). The test results show that ARIMA-GP outperforms other models, achieving a significant reduction in RMSE and an increase in R^2. Another case study in Southern Iraq utilized an LSTM-BBOA model to forecast power output, achieving very high accuracy (R^2 = 0.9998, RMSE = 0.5031). This enabled floating PV

systems to outperform ground-mounted systems by 59.25% in power output (Zayed et al. 2025).

Tools and Methods

A diverse array of AI tools and methods underpins the solar PV R&D. Neural networks, including ANNs, CNNs, and LSTMs, are widely used for forecasting and optimization, often achieving R^2 values above 0.90 (Ledmaoui et al. 2024; Kushwaha et al. 2025). Ensemble learning methods, such as Random Forest, Gradient Boosting Machines (GBM), and stacking regressors, enhance prediction accuracy and robustness (Abubakar et al. 2025). Explainable AI (XAI) tools such as SHAP and LIME improve model interpretability for solar power forecasting and fault detection (Ozdemir et al. 2025; Paramasivam et al. 2025). Digital Twins, combined with IoT and ML, enable real-time monitoring and autonomous control, with a projected 35.7% CAGR (Olayiwola et al. 2025). Optimization algorithms, such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and the Dingo Algorithm, fine-tune model performance and system efficiency (Mendonça and Santos 2025; Zhuang et al. 2025b).

Comparative Insight

Most AI models achieved high accuracy ($R^2 \geq 0.9$, efficiency ≥ 90%) and outperformed traditional methods by 8–15%. The Fourier and LSTM-BBOA models excelled in predictive tasks, while ANN and Random Forest offered robust optimization and classification. However, computational complexity (e.g., 15% higher processing time in the USA) and data dependency (e.g., China/Thailand's ANFIS) vary, complicating scalability.

The cases collectively advanced sustainability, with quantifiable impacts. First, AI-driven solar PV enhances energy access and affordability through increased energy production (10–59.25% across cases) and improved grid reliability (e.g., a 5% reduction in fossil fuel reliance in the USA and a 10% increase in PV output in China/Thailand). Moreover, it supported sustainable urban and rural

development by optimizing resource use (e.g., reduced land needs in China/Thailand, and India) and enabling prosumer-driven ecosystems (Germany). Furthermore, AI-supported solar PV has reduced CO_2 emissions by 3–5% (with an average of 4.5%) through efficient energy planning and reduced fossil fuel dependency (e.g., a 32.36% reduction in the Middle East/Africa).

At the same time, AI-enhanced solar PV had a visible economic impact. Cost reductions ranged from 8% (USA) to 12% (China/Thailand), averaging 10.7%, enhancing solar PV's competitiveness. Comparatively, the Middle East/Africa's floating PV yielded the highest energy production increase (59.25%), while Germany's automated defect detection system maximized community-level PV power generation. Economic benefits were consistent, but developing regions (India, the Middle East/Africa) showed greater potential for energy access improvements in underserved areas.

Strengths and Issues

Across the cases, common and distinct issues emerged, including data scarcity, infrastructure compatibility, model generalization, cybersecurity and policy, as well as equity and accessibility.

Data scarcity is the top issue because limited high-resolution meteorological (USA, India) and sensor data (China/Thailand) reduce model accuracy by up to 5% in some scenarios. It was a universal barrier, particularly in developing regions (India, the Middle East/Africa).

Infrastructure compatibility issues are an urgent concern because retrofitting older PV systems (China/Thailand) and high installation costs (the Middle East/Africa) hinder scalability. Model generalization is an ignorable issue because models optimized for specific climates (e.g., semi-arid regions in the USA, the Middle East/African countries) often require retraining for diverse conditions.

Infrastructure and generalization challenges were more pronounced in the Middle East/Africa. At the same time, China/Thailand's, as well as Germany's, cases highlighted the

importance of quality data availability for the accuracy and precision of AI and ML applications in solar PV R&D. Addressing these requirements requires region-specific strategies, such as open data initiatives and regulatory reforms. Equity and accessibility issues are profound in rural areas, and limited access to AI tools constrains local adoption.

Overall Assessment

AI significantly enhances solar PV systems, achieving 8–15% performance improvements over traditional methods and advancing the SDGs through higher energy output (an average 27.5% increase), emission reductions (an average 4.5%), and cost savings (an average 10.7%). The cases demonstrate global applicability, with tailored solutions for developed (the USA, Germany) and developing (India, the Middle East/Africa) contexts. However, scalability is constrained by data limitations, infrastructure gaps, and regulatory barriers. Developing regions face additional equity challenges, necessitating the development of accessible AI tools and localized training. Future advancements should prioritize open data platforms, standardized infrastructure, and robust cybersecurity to ensure equitable and sustainable adoption of AI-driven solar PV.

4.3 Sustainability Outcomes

The quantitative synthesis of this study identified the contributions of solar PV-dedicated AI to sustainable development, focusing on energy efficiency, emission reductions, and equitable access and demonstrating how AI-supported solar PV R&D aligns with SDGs, notably SDG 7 (Affordable and Clean Energy), SDG 11 (Sustainable Cities and Communities), and SDG 13 (Climate Action).

Energy Efficiency and Cost Reduction

AI-enhanced solar PV significantly enhances energy efficiency and cost reduction. For example, AI-assisted MPPT systems achieved an average tracking efficiency of 93% (range: 90–95%) across three studies (Bi and Jiriwibhakorn 2025; Zeb et al. 2023). Floating solar PV systems outperformed ground-mounted systems by 59.25% in power output

and 69.70% in daily electrical energy (Zayed et al. 2025). Moreover, solar AI applications reduced electricity costs by an average of 12.1% (range: 10–14.5%) and cooling costs by 41.9% (from $0.0745/kWh to $ 0.0430/kWh) in multi-generation systems (Assareh et al. 2025). Blockchain-based P2P trading reduced grid purchases by 4.8% (from 14.4% to 9.6% of community energy consumption) (Valsan et al. 2025). These improvements make solar PV more economically viable, supporting SDG 7.

AI-optimized solar systems increased solar generation and scalability. For example, AI-supported site selection and optimization in developing regions increased energy production by an average of 8.5% (range: 7–10%) in two studies (Abdessadak et al. 2025; Alrubeei et al. 2025). Additionally, floating solar PV systems have demonstrated scalability, yielding a 59.25% higher power output, which is particularly applicable to remote areas in African countries (Zayed et al. 2025).

Emission Reduction and Environmental Impact

AI-optimized solar systems helped reduce greenhouse gas emissions. For instance, these systems achieved CO_2 emissions reduction by an average of 4.9% (range: 4.7–5.1%) in 2 studies, with a specific case reporting a decrease from 37.18 to 35.34 metric tons/year (Assareh et al. 2025). AI-assisted floating solar PV systems achieved 59.25% higher power output than ground-mounted systems, reducing reliance on fossil fuels (Zayed et al. 2025). AI studies also facilitated the use of environmentally benign materials and waste-derived nano-additives, aligning with the principles of the circular economy (Selvam et al. 2025; Abdessadak et al. 2025; Iyer et al. 2024). These systems also reduce our dependency on fossil fuels. For instance, floating solar PV systems reduced reliance on fossil fuels by 32.36% through lower panel surface temperatures (Zayed et al. 2025).

Equitable Energy Access

AI-enhanced site selection and energy management systems improve access to solar PV in underserved regions. For instance, Random Forest models identify optimal solar farm locations in Southern Iraq, which are adaptable to other developing regions, such as India, thereby enhancing operational effectiveness and affordability (Alrubeei et al. 2025). A case study from the Middle East and African countries demonstrates the scalability of floating solar PV systems, promoting energy access in remote areas (Zayed et al. 2025). These efforts support SDG 11 by fostering sustainable communities.

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5 Discussion

Challenges and Gaps

The integration of AI into solar PV R&D offers transformative opportunities but also presents significant challenges that must be addressed to ensure sustainable and equitable results. This study identified five substantial obstacles and gaps in AI-assisted solar PV research and development (R&D), which align with the research questions and highlight barriers to achieving sustainable and equitable outcomes.

Data scarcity and quality are fundamental challenges. Effective AI performance depends on high-quality, publicly available datasets for PV fault detection. Limited availability of such datasets for PV fault detection and solar forecasting hinders the development of robust AI models and solar forecasting efforts (Thakfan et al. 2024). The complexity of integrating diverse data sources, such as meteorological and infrastructure data, further complicates model training (Abouelaziz and Jouane 2024).

Lack of standardization must be resolved. The availability of unified standards for AI-supported solar PV R&D allows AI-powered solar PV applications to be implemented in different solar PV systems, devices, or applications to work together and exchange information seamlessly, regardless of their underlying technology or design, and their capacity to handle increasing amounts of solar PV applications or data without

compromising performance or efficiency. The absence of harmonized standards for AI-enhanced smart inverters and grid integration limits interoperability and scalability. Studies emphasize the need for unified protocols to ensure compatibility across diverse grid infrastructures (Awad and Bayoumi 2025).

Model generalization and scalability are necessary because AI models often struggle to generalize and scale across different climate, environmental, geographic, and infrastructural conditions in solar PV applications, thereby limiting their applicability. For example, models developed for specific regions (e.g., Germany) may not perform well in diverse climates (e.g., the Middle East/African countries).

Cybersecurity risks cannot be ignored, as the integration of AI and the Internet of Things (IoT) into grid-integrated solar PV systems increases vulnerability to cyberattacks, thereby threatening data integrity and operational stability. Studies highlight the need for advanced security protocols, such as the ASW-XGBoost model, to protect renewable energy infrastructures (Zhuang 2025a; Biswas et al. 2025).

Equity and accessibility, hindered by policy fragmentation and technological barriers in less developed economies, limit their equitable access to AI-powered solar PV solutions, exacerbating global energy disparities. The "inverted U-shaped" relationship between AI adoption and renewable energy benefits suggests diminishing returns in regions with weak institutional support, exacerbating global energy disparities (Zheng et al. 2025).

The high computational power required for AI algorithms must be addressed because it can offset the environmental benefits of solar PV systems. Optimizing solar PV-dedicated AI algorithms can increase their energy efficiency. Integrating AI-powered solar PV systems with current energy infrastructure presents compatibility challenges, especially in regions with outdated grids (Wang et al. 2025). Mismatched policies and regulatory barriers hinder the widespread adoption of AI-driven solar technologies, especially for smart inverters (Awad and Bayoumi 2025).

To summarize, the findings of the studies underscore AI's transformative role in solar PV R&D, with applications ranging from material discovery to forecasting, predictive maintenance, grid integration, and energy storage. These advancements contribute to sustainable development by improving energy efficiency, reducing emissions, and enhancing access in underserved regions. However, significant challenges—such as data scarcity, lack of standardization, model generalization, cybersecurity risks, and equity concerns—must be addressed to fully realize AI's potential in achieving a carbon–neutral future. The identified themes provide a foundation for the case study analysis and discussion, offering insights into actionable solutions for researchers, engineers, and policymakers.

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6 Conclusions

This study synthesized, in a systematic approach, bibliometric, literature review, and case study findings, confirming AI's transformative impact on solar PV R&D while highlighting actionable solutions to address data, standardization, scalability, equity, energy efficiency, infrastructure, and policy challenges. The case studies provide practical examples of AI's international relevance, from solar PV forecasting in the USA to floating PV systems in the Middle East/Africa. By addressing inefficiencies, optimizing grid integration, and enhancing energy storage, AI-supported innovations reshaped the renewable energy landscape.

In addition, challenges such as data scarcity, lack of standardization, and equity concerns were also identified, which must be addressed to exploit this potential. This study explored these issues in depth, proposing actionable solutions to promote AI-enhanced solar PV systems as a key part of a sustainable, resilient, and inclusive energy future. The Discussion section examined the research questions, using international case studies and interdisciplinary insights to outline a path for future progress.

This study has accomplished a comprehensive evaluation of AI's transformative role in solar PV R&D by synthesizing findings from a systematic literature review of studies, supplemented by a quantitative synthesis and five in-depth case studies from the USA, China/Thailand, Germany, India, and the Middle East/African countries. The analyses demonstrate that AI enhances photovoltaic efficiency by 20.3%, reduces CO_2 emissions by 4.9%, and improves energy access, particularly in underserved regions, aligning with SDGs 7 (Affordable and Clean Energy), 11 (Sustainable Cities and Communities), and 13 (Climate Action). Key contributions include identifying AI applications in material discovery, forecasting, predictive maintenance, grid integration, and energy storage, while highlighting critical challenges such as data scarcity, lack of standardization, cybersecurity risks, and infrastructure compatibility.

Despite the multi-step and multi-method research nature and wide coverage (more than 40 peer-reviewed papers) of this study, its research approaches are qualitative, and its international case survey remains selective and limited to a few countries, rather than being systematic. By proposing solutions such as international data repositories, standardized protocols, green AI frameworks, and cross-sector collaborations, this study provides an actionable roadmap for leveraging AI to overcome these barriers and accelerate the transition to a sustainable, carbon–neutral energy future, aligning with global sustainability goals (Agrawal et al. 2025). Future research should focus on developing open-access datasets, green AI frameworks, and international standards to ensure AI-driven solar PV systems contribute to a carbon–neutral world, fulfilling the promise of sustainable development for all. The convergence of AI and solar PV R&D offered a powerful pathway to achieving sustainable development and carbon neutrality by 2050.


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Artificial Intelligence in Higher Education: Advancing SDG 4 on Quality Education

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Abstract

Artificial Intelligence implementation in the education field provides revolutionary methods to achieve Sustainable Development Goal 4 (SDG 4): ensuring inclusive and equitable quality education and lifelong learning skills acquisition. This chapter assesses the strategic role of

the integration of AI in the enhancement of the quality and efficiency of the post-primary education sectors. Through the adoption of the mixed research method that implies the analysis of the literature reviews and case studies, the study investigates the strategic role of AI technologies towards improved teaching practices and the effectiveness of the institutions. This study reveals the potential strategic role that AI technologies can play in reducing the gap in education access and the effective acquisition and implementation of information-based decisions in post-primary educational sectors. Through the strategic adoption of AI technologies, the study reveals the continued challenges posed by ethical approaches towards the adoption of the technologies and the implementation of equity towards capacity building. This study has proved that the adoption of AI technology in post-primary educational sectors can be an effective strategic mechanism towards the goal of SDG 4. This article Presents Recommendations on How Some of the Players Should Incorporate the AI Technologies Offered in the Enhancements of the Educational Processes Towards the SDG 4 Goals.

Keywords Artificial Intelligence – Higher education – SDG 4 – Quality education – Inclusive learning – Educational Innovation – AI in teaching and learning

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1 Introduction

Today, the Higher Education sector stands at the crossroads, impacted by the rapidly advancing state of technology, rising social inequalities, and an increasing need for quality and relevance in the process of

learning all over the world (Aithal and Maiya 2023). Today, the role of universities as institutions of higher learning has been redefined. Universities are now supposed to be catalysts of change, innovation, and sustainable development, as distinct from institutions solely for the transfer and generation of knowledge. (Giesenbauer and Müller-Christ 2020). Amid this scenario, the role of Artificial Intelligence has emerged as a major force that can revolutionize the way Knowledge is generated, communicated, assessed, and managed in the sector.

The most influential global framework that affects the overall transformation of the education process involves the Agenda for Sustainable Development under the United Nations, specifically Goal SDG-4, which focuses on ensuring Inclusive and Equitable, and Quality Education for all (Shields 2022; Singh et al. 2025). This has been facilitated by the role of higher education, as it aims to produce graduates equipped with the appropriate skills and professionals through research and development (Green 2025). However, these mainstream approaches include inequity on a massive scale in accessibility, personalization, and equity (Rasool et al. 2025). There has been an increased obsession among stakeholders to explore alternative approaches for the overall transformation of the disparities and inequity related to the issue of the quality of education equity.

Artificial Intelligence has the potential to be developed for beneficial purposes in learning and for improving institutional efficiency (Matar 2025). But it seems that with Artificial Intelligence in Higher Education, there is a pendulum between the positive potential presented by technology and some considerations for ethics that must not be overlooked. Artificial Intelligence must be seen as technology and as a key force for achieving goals under SDG 4 in the global education sector.

1.1 Background of Artificial Intelligence in Higher Education

Artificial intelligence has its roots in the world of education and dates back several decades. Some of the initial forms of intelligent tutoring

systems and computer-supported learning have their roots in the decades ago. However, the recent advancements in areas of machine learning, Natural Language Processing, Big Data Analysis, and Cloud Computing technology have led to an exponential increase in the complexity and scope of implementation of artificial intelligence.

Advanced artificial intelligence technologies are capable of scanning vast amounts of learner data to identify trends in learner behavior, predict learner outcomes, and offer learners real-time personalized feedback. Learning systems that integrate artificial intelligence analytical tools can offer learners customized learning material that fits their learning style, pace, and preference, thus exceeding the limitations of teaching learners in a conventional, uniform fashion. The current technologies used within the learning environment for the benefit of both learners and teachers include virtual learning assistants, automated grading tools, and recommendation platforms (Gupta 2023)

Outside the classroom, the effect of artificial intelligence on the decision-making of these institutions is slowly being realized. Universities are applying the use of predictive analytics in their efforts to improve enrollment, allocate resources, and retain students. AI is increasingly being used in research management, advising in academic affairs, and campus security. These examples define the extent to which the reality of AI is embedded in the academy.

1.2 Overview of Sustainable Development Goal 4 (SDG 4)

SDG 4 thus forms the backbone of the education agenda globally because it recognizes education not only as a basic human right but also as an enabler for other development targets. In fact, SDG 4 targets ensuring “inclusive and equitable quality education and promoting lifelong learning opportunities for all” by 2030. Other than other vision statements on education, which emphasized only access, SDG 4 highlights education from the perspective of quality, relevance, equity, and continuity.

SDG 4 can be beneficial in higher education for other uses, rather than increasing enrollments. Social contexts, culture, and economies

address the goals of improved learning outcomes, inclusive learning, competent educators, and learning environments. It encompasses technical and vocational skills, information technology, and research capability-essentially required to handle the challenges of an ever-changing global economy.

While commitments have been made, the progress in attaining SDG 4 remains varied. Moreover, larger class sizes, outdated modes of curriculum design, a lack of faculty capacity, and unsatisfactory support structures for students are the greater challenges faced by many higher education institutions. The inequalities faced by marginalized social segments, including students from poor families, rural settings, or with disabilities, make access and attainment of higher education difficult.

Technology has conventionally been seen as a potential enabler of SDG 4, but it is hugely dependent on how that technology was envisioned and implemented. Technology itself cannot and does not ensure educational quality or equity; rather, it has to be aligned with educational intent and social context. In light of this, AI is in a class of its own, standing out as a next-generation technology with potential application in support of core elements of SDG 4: educational decision-making, learning, and inclusion.

1.3 Rationale and Objectives of the Chapter

Three significant reasons exist for this chapter: First, aside from other considerations, HEIs play a critical role in molding the future leaders, professionals, and inventors who shall lead the way in sustainable development on the horizon of possibilities offered by education. Secondly, AI is continually evolving in a way that increases the speed of changes beyond the policies and ethics of institutions, making it imperative to consider the implications of the future of AI projects in teaching and learning environments on a broader scale. Thirdly, what is indeed urgently required are observations drawn on the context of multiple platforms related to the limitations of AI.

Specifically, the purpose of this chapter is to:

- Assess major uses of artificial intelligence in higher education as they pertain to inclusive learning and quality.
- Show how artificial intelligence could resolve some of the recurring problems in education, such as inequality, the lack of involvement, and delays in decision-making.
- Identify infrastructural, social, and ethical challenges that may hamper the integration of AI in a sustainable manner.

Research Questions:

- *What is the effect of the application of AI in the field of education on the quality, effectiveness, and universality of teaching and learning activities in relation to the targets of SDG Goal 4?*
- *What are the institutional, ethical, and infrastructure elements impacting the effective and sustainable integration of artificial intelligence in the higher education system, especially the issue of equity and informed decision-making?*

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2 Conceptual Framework

The conceptual foundation for this chapter exists at the nexus of Artificial Intelligence (AI) and the context of higher education, other than the mandatory requirement of realizing Sustainable Development Goal 4 (SDG 4). While the concern remains on AI based on the innovation-related viewpoint, the above-stated conceptual framework considers AI not merely as an innovation but rather a socio-technical creation that interacts with learning, organizational, or environment-related aspects. By incorporating perspectives linked to education, innovation, or sustainability, the conceptual framework provides an inclusive outlook on the significance of AI within the higher education landscape.

Essentially, the importance of quality education is recognized by the framework, and it is realized that it is not a function of technology, per se, but of technology in a way that is inclusive, equitable, and supportive of learning. AI is treated in the model of research as a

facilitator tool, capable of assisting with adaptive learning, decision-making, and system efficiency, and, on the other hand, also capable of proposing significant queries related to ethics, accessibility, and the human element. This part will describe and explain the basic principles used in this research work and clarify the theoretical relationships existing in adopting AI and achieving SDG 4.

2.1 Artificial Intelligence: Definitions and Core Technologies

Artificial intelligence is the wide spectrum of computational methods meant to reproduce elements of human intelligence, including learning, logic, vision, and language comprehension. Overall, in the context of higher education, artificial intelligence is more appropriately viewed as a system not consisting of one technology, but as an ecosystem that comprises various instruments and systems, which are more intended at improving human capabilities than at replacing them. Compared to previous systems that involved rules, contemporary systems are distinguished by the following definitions that emphasize the capacity for learning, predicting, and identifying patterns by artificial intelligence.

Learning analytics, intelligent automation, natural language processing, and machine learning are just a few of the most notable artificial intelligence techniques that are of the most crucial relevance to the higher education sector. Machine learning assists in developing a better performance of systems relying on data, thus making it possible for the educational platform to identify patterns of student engagement or performance in the subject with the help of machine learning. The application of machine learning in providing feedback automatically, an online educational assistant, and a learning application supporting multiple languages, which have assumed great importance in the linguistically diverse higher educational landscape across the globe, can be achieved with the help of natural language processing.

Current developments demonstrate how institutions of higher learning are applying these technologies. Many institutions of higher

learning, for example, have started applying AI technology in student advising systems where the system reviews student records and class enrollment trajectories to provide personalized recommendations to students, particularly those who are considering dropping out of school. Others are employing adaptive learning methodologies in the coverage of foundation disciplines in courses where student background knowledge differs. These technologies ushered in an era of departure from content-based learning to student-centered environments made possible by smart technology. (Gupta et al. 2025).

In particular, rather than examining these solutions in isolation, solutions for artificial intelligence in the realm of higher education are being incorporated into existing infrastructure. First of all, this makes a very important statement about not just classifying artificial intelligence as technology, but something bigger in the sense of a digital revolution.

2.2 Quality Education and Inclusivity in Higher Education

A conceptually clear attribute also covers aspects of different dimensions, of which some of the areas include the curriculum, efficiency of delivery of education, evaluation, learning spaces, and infrastructural support provided for students. The crucial area of inclusiveness further expands this notion by recognizing the diverse range of students, from those of marginal socio-economic groups and cultures. There may be a propensity for the traditional models for higher education to not be able to strike the right balance between quality and scale. In this respect, the AI tech may help in ensuring the possible ways for ensuring the quality and inclusivity.

Personalization through the involvement of AI technology makes paradigm shifts possible in quality education refinement at the forefront. With personalization activities focused on tailoring learning materials and test formats for a specific student, AI technology may play a very important role in ensuring effective, deeper student participation. This can prove very helpful for first-generation students

or those students who have moved their learning environment outside an under-resourced educational institution.

Through the years, institutions of education that offer combined and online courses have greatly benefited from such tools and will not affect the standards of education. It indicates that as long as the standards are incorporated into the idea of AI, it must function as an interpreter for diversity and quality.

However, an education of high quality in the integration of AI cannot be detached from human values. It has always maintained its emphasis on faculty knowledge, critical thinking, and socialization. Generally, with respect to higher education, the role of AI could be described from a complementary viewpoint, meaning complementing teachers and students without adversely affecting the relational and ethical components of education.

2.3 Linking AI with SDG 4: A Theoretical Perspective

A connection can be drawn between AI and SDG 4 based on theoretical grounds through the context of systems-oriented and capability perspectives on the vision. Apart from emphasizing access to education, it also emphasizes developing skills and competencies through opportunities for lifelong learning. Although the same reason is invoked for this appeal, it is because AI supports the development agenda through systems that are more responsiveness-driven and data-informed.

From a systems thinking viewpoint, AI appears as a force that unifies micro-processes of learning with macro-outcomes that pertain to institutions and policies. From a micro-system viewpoint, AI enables personalized learning and feedback. From an institutional viewpoint, AI reinforces planning and optimization. From a policy viewpoint, AI-driven findings can facilitate evidence-driven decision-making and planning regarding funding, curriculum change, and equity initiatives. The multifaceted impact of AI aligns specifically with the broad vision of SDG 4.

The application or relevance of AI in sustainable education can even be more clearly conceptualized within the COVER capability approach framework for sustainable education. It can be asserted that good or quality education under SDG 4 targets a capacity expansion for active participation within society and the economy, for which cognitive and problem-solving skills may require experiential learning with AI technology. Applications involving simulations or virtual laboratories with AI technology have been largely used for science and engineering courses, for which experiential learning is required in case limited resources are being used.

Nevertheless, at the same time, it should be noted that this theoretical alignment of AI with SDG4 highlights the challenges presented by this alignment. Lack of anchorage by, for example, inclusive governance structures, AI can potentially lock in inequality by locking in bias in data, by disparities in access, or by over-reliance on automation. Notably, it is for this reason that the framework upon which the discussion in this chapter leans has at its centerpiece responsible innovation in the process of implementation of AI.

In placing AI in relation to the normative objectives of SDG4, the chapter builds a frame that focuses on technology as a tool of educational sustainability but not a determinant of it. This conceptual framework can thus provide the foundation for how AI may strategically contribute to quality and equity in higher education while keeping in focus global development goals.

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3 Methodological Approach

The current chapter follows a rather mixed-methods, qualitative-oriented design, as it implies a systematic review of literature is mixed with the analysis of the chosen case studies. The methodology design is appropriate to the conceptual intentions of the chapter, as it synthesizes the theoretical perspectives with the reported practical implementation of artificial intelligence in the realm of higher education. Although the chapter is not intended to be empirically

generalized, the methodological procedures are well followed in terms of analytical clarity and transparency.

3.1 Research Design and Orientation

The literature review has been conducted through a directed and systematic search of the peer-reviewed journal articles, policy documents, and scholarly books on the topic of artificial intelligence, higher education, and SDG 4. The sources were located in academic databases and publishers' websites that are regularly used in research on education and social sciences.

The selection criteria were proceedings in the field of artificial intelligence application in the field of higher education; Explicit reference to the notions of quality, equity, inclusion, or learning outcomes.

3.2 Case Study Selection

Besides facilitating the literature review, this chapter is based on well-chosen case studies of AI in higher education. The cases will be chosen based on the relevance to education, the inclusion and quality purposes, and the possibility of the availability of credible documentation.

3.3 Analytical Approach

The thematic and interpretive style of analysis is done in this chapter. Some of the themes that emerged in the literature, and could be used for the analysis of case studies, include personalized learning, inclusive access, learning analytics, institutional efficiency, and ethics of governance. These themes were not used for determining specific measurements but for observational analysis, in the manner that this thematic chapter would require.

3.4 Conceptual Scope and Limitations

Being a theoretically engaged chapter, this research work does not aim for exact repetition but instead resorts to existing evidence in a bid to reinforce theoretical explanations. Although this reduces the capacity

for repetition, it increases the chapter's contribution in strategic and policy discussions regarding the use of artificial intelligence in realizing SDG 4.

3.5 Literature Review Strategy and Analytical Process

The methodological section of the chapter is the literature review. The peer-reviewed journal articles, policy reports, and scholarly books, which were mainly published in the past five to seven years, were analyzed in order to ascertain the contemporary relevance. The sample was chosen by focusing on interdisciplinary materials covering the fields of education, computer science, public policy, and sustainability studies due to the complexity of AI in higher education.

Instead of arranging the literature in a standard way (organized in time or in terms), the analysis involved an interpretive coding procedure. The most important ideas were revealed, including personalization, equity, learning analytics, institutional governance, and ethical responsibility, and discussed within various contexts. This procedure made possible the recognition of the conceptual intersections and contradictions, especially the ways AI-related news is compatible or incompatible with the values of SDG 4. Notably, the review did not take technological success stories as a privilege.

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4 Applications of Artificial Intelligence in Higher Education

Integration of Artificial Intelligence in the field of higher education signals the end of teacher-centric models of learning and the emergence of innovative models of learning based on data. AI applications are no longer stand-alone tools of teaching, learning, and managing; they are now integrated components of the same.

In this section, we investigate the most relevant uses of AI in higher education and their consequences for the value of education in terms of inclusiveness and sustainability. It also recognizes the role of other factors unrelated to technology.

4.1 AI in Teaching and Learning Processes

The development in AI technology has now impacted the teaching and learning process in a way that has resulted in an engaging environment for the learners being created. Unlike the previous teaching modes that were based on lectures, now, with the help of AI, an opportunity for a feedback loop has been created between the learners and the study materials.

At the level of the class in higher education institutions, AI tools are being applied in increasing ways in supporting education delivery by faculty members, as opposed to replacing faculty members. Examples include content recommendation systems that can recommend assignments related to content acquisition in courses. This enables the faculty member to pursue other tasks in relation to the acquisition of other types of knowledge, like mentoring.

Many fields of learning, like engineering, medicine, and environmental studies, are already using AI simulations that enable learners to explore complex phenomena in a risk-free and controlled environment.

4.2 Personalized and Adaptive Learning Systems

The capability that AI has with regard to supporting adaptive and personalized learning has been one of the most significant additions that can be made to higher education. The traditional curriculum has certain presumptions about the similarities between the background characteristics of the learners and even about learning rates and styles. This has been challenged by AI because it has made it possible to have flexible systems that can vary depending on the individual.

Adaptive systems make use of machine learning to monitor the performances and interactions that the learners exhibit. It is based on this that the system decides on the complexity and order of the contents used in learning. In the cases of learners who perform poorly regarding the fundamental concepts, additional information and descriptions may be presented. On the other hand, an enrichment

program would be offered to the high-performing learners so as to prevent them from being bored by the low-level material.

Practices for assessment are also personalized. For example, the formative nature of assessments that are made AI-friendly can provide immediate feedback that will help the person understand where they need to improve, as the process involves ongoing learning. This learning system encourages mastery learning in order to avoid depending much on high-stakes tests, thus making it ideal for such students. If inclusivity can be achieved, such systems are invaluable in bridging discrepancies in achievements in higher education.

4.3 AI-Driven Assessment and Feedback Mechanisms

Assessment has remained and continued to be a crucial but contentious aspect of higher education. Automated assessment technologies by artificial intelligence offer opportunities for increasing efficiency and additional value for learning. Automated grading systems, together with subjects that use coded responses for learning answers, promote rapid grading and accuracy.

More complex applications of AI involve such uses as feedback generation. Within this feedback generation process, the AI reviews the work done by students and produces a feedback comment based on their structure and clarity. While such applications cannot replace human judgment, this first-stage feedback has certainly proven valuable if it is being used within a learning loop. Feedback software for writing courses could definitely make use of AI feedback software.

Based on the equity theory, an important aspect of a high-quality education process is the provision of relevant feedback. Those who lack access to external sources of education support are compelled to rely on the feedback process of the education system. Technology-driven enhanced feedback systems could be of great aid in the provision of high-quality feedback to everyone.

On the flip side, however, the use of AI technology in the field of educational assessment also has some challenges, primarily related to academic dishonesty, bias, and academic transparency. Indeed, this

underlines the importance of proper frameworks and human intervention, thus again confirming the efficacy of AI technology as a supplement to academic judgment as opposed to a substitute.

4.4 Intelligent Tutoring Systems and Learning Analytics

An intelligent tutoring system is one of the oldest applications of AI in higher education. Such systems are also offering step-by-step instructions, clues, and explanations depending on the reaction of individual learners. The intelligent tutor will be able to react dynamically to the input of the learner, and render particular support when a particular learner requires it during the learning process, compared to the tutorials that are quite static.

It has been shown that intelligent tutoring systems can support independent learning in such subjects as mathematics, computer science, and language learning, and support conceptual learning. The systems offer a non-fault practice and exploration environment to students who may feel threatened in a traditional classroom setting when seeking help. This attribute is particularly relevant to the advancement of inclusivity and trust in students.

The intelligent tutoring systems have much in common with learning analytics, which enable institutions to move to proactive support of the students. Predictors of academic risk can be identified by considering the attendance, engagement, and performance patterns with the help of AI-oriented analytics. Specific assistive intervention, e.g., academic counseling or additional classes, can then be provided by the mediators, such as advisors and teachers, etc.

Ethical data practices in combination with learning analytics assist in establishing a more adaptive and student-focused environment of higher education. They also augment institutional accountability by virtue of the fact that they provide evidence to support curriculum development, teaching strategies, and policymaking.

4.5 Administrative and Institutional Applications of AI

Apart from the area of teaching and learning, AI is also being used in a managerial or institutional context. Some examples of the use of AI in the higher education sector include admissions, time management, and resource allocation in institutions.

The models are also used for the purpose of strategic planning, for example, the forecasting of enrollments and the feasibility of a given program. The models, when properly utilized, help in the making of decisions that are aligned with the institutional, social, and educational objectives. In the context of the use of SDG 4, alignment is critical in ensuring the quality of education when efficiency is required.

Despite this, however, it should be used carefully. Over-dependence on predictive models may result in the reduction of the human experience to being an indicator. Therefore, administrative managers should use decisions made from AI information with additional information.

4.6 Educational Value and Strategic Implications

AI applications can be used to enhance the contribution of higher education to achieving SDG 4 if carefully linked to educational objectives and principles. The integration of AI would work best in the context of a comprehensive education paradigm that focuses on the concept of human development, equity, and sustainability. In this regard, the implications of AI in higher education can also be explained in terms of changes in the education paradigm.

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5 AI as a Driver for Advancing SDG 4

Sustainable Development Goal 4 (SDG 4) focuses on education as a human right that cannot be compromised and a foundation of sustainable development. Higher education has a particular mandate and a particular responsibility in this agenda, and these involve the development of knowledge and skills as well as contributions towards innovation and inclusion. Artificial Intelligence plays a special role in this regard as a catalyst in the provision of such mandate and

responsibility requirements. The section discusses the ways AI helps fulfil the sustainable goal of SDG-4 by enhancing the quality, equity, and inclusion, and lifelong learning in postsecondary education.

5.1 Enhancing Educational Quality Through AI

Education quality is among the major foundations on which the SDG Goal 4 stands. It not only deals with the dissemination of knowledge but also involves appropriate learning experiences and skill-building. AI helps in improving the quality of instruction through its ability to facilitate adaptive, evidence-based, and learner-responsive instruction. By engaging in ongoing data analysis, AI systems help teachers improve teaching plans and curriculum by studying the way students engage with learning content.

The learning environments that are AI-assisted promote active and self-regulated learning. Intelligent tutoring systems, adaptive platforms, and AI-enhanced simulations will enable students to learn at the right level of complexity, developing a deeper conceptual grasp. Such systems also contribute to the fact that timely feedback is a key element that is generally accepted to be a determinant of the quality of learning. Reducing the time lag between performance and feedback, AI can make learners realize their misconceptions at the earliest stage and change their learning patterns.

Institutionally, AI assists in the aspect of quality control by systematically evaluating the results of programs and the efficiency of the teaching process. Learning analytics enable institutions to address the trends of learning among students, which in turn helps in modifications of the programs and teaching processes. Evidence-based approaches such as the use of learning analytics are of great benefit to higher education by enabling the sector to address SDG 4.

5.2 Promoting Equity, Inclusion, and Access

Focusing on the need to eliminate disparities in access and achievement of education, SDG 4 includes equity and inclusion as its focal points. Historically, higher education institutions have been struggling to reach

diverse categories of learners, particularly those who are less fortunate in socioeconomic status, rural communities, and underserved groups. Artificial intelligence can offer tools that can assist in overcoming these challenges, provided that they are put in place with a well-defined, equitable orientation.

One of the most significant benefits of artificial intelligence that can be mentioned regarding its inclusion is the possibility of personalization. The AI systems allow students with varying amounts of prior knowledge and learning rates to personalize their learning tracks according to their needs. The flexibility is particularly rewarding to first-generation students and to those who are relocating out of under-resourced educational backgrounds. Academic support systems, such as early-warning systems, which are AI-based academic support systems, can also be used to identify pupils who are at risk of disengaging and assist in offering timely interventions.

Accessibility tools enhance inclusiveness to a greater extent. In the case of children with disabilities and multilingual students, speech recognition with the help of artificial intelligence, automatic captioning, and language translation tools is used to assist them. These instruments expand access to higher education learning environments blended and online by reducing barriers to differences in learning styles and language skills, as well as physical barriers.

The connection between fairness and artificial intelligence is not necessarily positive, however. Without proper design and management, artificial intelligence systems may contribute to the digital gap or bias toward a population. Knowing this threat, SDG 4 development through artificial intelligence requires continuous monitoring, comprehensive data approaches, and organizational commitments to digital equality.

5.3 Supporting Lifelong Learning Opportunities

Lifelong learning is an essence of SDG 4, and such learning has to be pursued in an environment of perpetual change. There is also a paradigm shift in the higher education institution, moving from being a provider of needs for the youth to providing for the working classes and

people who need reskilling and upskilling. AI is identified as a major facilitator in the process of lifelong learning.

AI-enabled platforms enable modular learning, competency learning, and thus, students are able to learn anytime, anywhere, according to their needs. Personalized learning enables working professionals to pursue education while managing work and family, whereas certification programs, with the help of AI analysis, enable skill development according to the demands of the job market.

The use of the recommendation engine enhances lifelong learning by providing learners with suitable courses, study materials, and career paths based on their interests and skills in the development stage by stage by considering their interests, success, and developing demands for skills cumulatively to make an education decision by those engines. Therefore, artificial intelligence helps higher learning institutions to cope with the demands in society by offering opportunities beyond education (Gupta 2024).

Nevertheless, the lifelong learning with the use of AI cannot and shall never forget the essential components of quality and recognition upon which the credentialing and assessment of education are grounded. Otherwise, lifelong education shall never be of any great value to the individual's development.

5.4 Enabling Evidence-Based Educational Governance

Alongside the activities of teaching and learning, AI promotes the realization of SDG 4 in education by ensuring better education management and the implementation of education policies. Data-driven decision-making plays a significant role in addressing systemic problems in education, such as allocation, the relevancy of a program, and performance. AI analytics can provide policymakers with operational insight to make a positive impact on continued improvement.

AI can potentially improve investments in education sectors that are resource-constrained in higher education by focusing on high leverage

and locations. It can further help in tracking the progress of SDG 4 at the national and regional levels.

However, the implementation of AI in the administration must be transparent and accountable. AI-informed policies must be open to critique and adhere to values within education rather than being based on efficiency gains. Ethical integration of AI in AI-enhanced governance administration provides a better chance for the role of higher education in sustainable and inclusive development.

5.5 Strategic Alignment of AI with SDG 4

Artificial intelligence does not necessarily lead to the creation of SDG 4. It demands cautious adjustment of the projects of artificial intelligence to educational values. The institutions should set down clearly general objectives that relate the artificial intelligence implementation to quality improvement, inclusiveness, and lifelong learning. Artificial intelligence (AI) is used to drive SDG 4 with the themes of governance choices, an institutional culture, and societal priorities. With a human-centered and sustainability-focused perspective, the systems of higher education are able to use artificial intelligence to deliver education that is not only effective and creative but also equitable and transformative as well (Table 1).

Table 1 Relationship between AI applications in higher education and SDG 4 targets

6 Challenges and Ethical Considerations

Despite various opportunities of Artificial Intelligence in enhancing quality and inclusive education, an array of ethical, social, and institutional concerns exists when it is applied to the higher education system. The problems mentioned are not peripheral to the extent that they define whether the AI will serve any effective purpose in Sustainable Development Goal 4, or whether there is any possibility of it being in opposition to its principles. This part is a critical discussion

of ethical use focal points, data management focal points, equity, and institutional capability focal points.

6.1 Ethical Use of AI in Higher Education

The foundation for the integration of AI in higher education is based on ethical principles. Essentially, the idea of ethics will refer to the fact that it should not discriminate or humiliate human dignity and should create positive effects within education or the development of learning. In the academic setting, where intellectual development is paramount, any misfortunes concerning ethics can reach extensive levels.

The answer is that one of the most important ethical considerations revolves around the topic of algorithmic bias. In a parallel manner to the above, the training of AI models is only possible through the utilization of information in the past in order to perpetuate these existing gaps in terms of gender, socioeconomic factors, or cultural background. These biases can impact admissions selection, advice, and performance forecasts in higher education in favor of or to the detriment of different students. There is an ethical need for the ongoing assessment of data points and outcomes.

6.2 Data Privacy, Security, and Transparency

Artificial intelligence (AI) in higher education largely relies on the availability of large amounts of student data, such as academic performance, attendance history, and sometimes behavioral indicators. Such reliance on data raises significant privacy, security, and transparency issues. Learners and lecturers should be confident that their data is collected ethically, stored in a secure place, and used in a responsible way.

Information gathering can infringe on individual rights or cause perceptions of spying when there are no specified consent processes and rules of governance. The ability to stay confident within academic circles is based on the openness of how artificial intelligence systems produce judgments and how they utilize data.

Security risks make the implementation of AI more challenging. The increase in cyber-attacks targeting institutions of higher learning is becoming a problem, and AI systems will exacerbate vulnerabilities unless properly implemented.

Moreover, transparency can be explained as openness. The stakeholders should be capable of understanding what underlies such suggestions in case artificial intelligence (AI) systems influence academic outcomes, i.e., recognizing the at-risk students or recommending interventions.

6.3 Digital Divide and Equity Concerns

Nevertheless, there exist anxieties regarding the issues of digital divides that might be enhanced by AI about quality and fairness in providing better education in higher institutions of learning. This implies that there might be a digital gap relative to access to technology and internet connectivity.

In emerging economies, institutions of higher learning are experiencing problems that hinder the use of AI. This comprises a deficiency of funding, obsolete technology, and a deficiency of technical support. When it comes to a well-endowed institution, there is a disparity among the learners in terms of ICT access, digital literacy, and learning conditions. This produces a two-layer education system, which is not balanced in terms of the benefits of AI distribution.

Issues associated with equity in language and culture: The models developed in artificial intelligence lead to improved performance in the majority language and culture. The impact can cause marginalization of the learners.

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7 Policy Implications and Recommendations

The implementation of Artificial Intelligence within the framework of university systems cannot be technically readied; on the other hand, it has to be supported by appropriate policy frameworks and strategic planning that work in solidarity with values pertinent to education and

appropriate global strategies concerning sustainability. Even though AI offers the possibility for improving the quality, equity, and efficiency criteria within the framework of educational systems and institutions, the outcome will be shaped by what has been designed concerning governance models within institutions and government sectors.

7.1 Recommendations for Policymakers

Public financial programs may help in providing equitable access to AI-driven educational tools, particularly those that serve the needs of disadvantaged schools. Policy makers and the government can reduce the chances of increasing educational disparities by addressing infrastructure gaps and investing in research and development in the field of educational AI.

7.2 Aligning AI Strategies with Global Sustainability Goals

There must be orientation in the strategies of AI in order to meet the objectives of sustainability on a global platform, both in terms of innovation in the short term as well as in the long term. The aim of achieving Sustainable Development Goal 4 can act as a flexible approach that would be applicable in the alignment of the implementation of AI in meeting inclusive and equitable education objectives. The institutions must be oriented in such a way that strategies on AI would meet the objectives of learning outcomes.

Such alignment also requires collaboration among various sectors. Such collaboration may be achieved through the coming together of governments, institutions of higher learning, industry, and civil society. On a universal platform, collaboration is specifically important in the context of support in low-resource settings, in addition to universal equity in learning through the use of AI.

The processes for monitoring and evaluation must also be integrated into strategies on AI to evaluate their effectiveness in terms of sustainability goals. Metrics to be used should not only include efficiency, but also education quality, inclusivity, and empowerment, to

achieve higher education for developments in technology through sustainability principles in higher education governance.

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8 Future Directions of AI in Higher Education

In the coming years, with the advancement in the area of Artificial Intelligence, AI will surely have a wide range of applications in higher education institutions apart from its present uses. The coming developments and trends in the area will not only be dependent on the innovations that come up with the advancements in AI technology, but will also be dependent on the ideas and approaches from the side of society and its expectations regarding the requirements and challenges associated with the regulation-related tasks. This phase will highlight the developments in the area of AI associated with higher education.

8.1 Emerging Trends and Innovations

The most up-to-date trends within AI, as well as AI technology within higher education, are human-AI collaboration, in which AI is seen as a flexible partner to promote dialogue and critical thinking, offering feedback, although teachers are perceived to retain control in the classroom. Also being merged are AI and virtual realities, such as augmented realities.

In addition, AI is stimulating the development of competency-based learning and modularity since AI can support crediting and mastery-based learning, which is aligned with lifelong and work-based learning. Based on the developments associated with ethical and explainable AI, there is improved transparency and trust, as well as developments that are contextually aware and culturally competent, which improve inclusivity.

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9 Conclusion

After analysis, it is pointed out that one such area where artificial intelligence is being used effectively and holds a vast potential for

fulfilling Sustainable Development Goal 4 is in higher education. By applying the ideologies and approaches discussed in this chapter, it has become evident that artificial intelligence is not just a technology innovation; rather, it is a tool and a solution for achieving a vast potential in changing the paradigm of practices and approaches in higher education. By deploying artificial intelligence positively and ethically, potential improvements in learning experiences, equity, access, and education governance can be achieved in higher education.

9.1 Findings and Discussion

Through literature reviews and case studies, it is known that artificial intelligence can elevate the standards of learning at higher learning institutions. Intelligent tutoring systems and automated feedback systems are some of the technologies that can be used in adaptive learning to enhance student engagement and pace in learning in higher institutions of learning. This allows direct alignment with SDG 4 in terms of learning outcomes and equity in higher education.

Artificial intelligence-powered solutions also increase inclusivity and equity. Virtual learning support and assistive technologies assist in identifying at-risk students, as well as students with disadvantaged backgrounds. With the right approach to the adoption of these technologies, it is possible to decrease the gap in learning and focus more on inclusion in learning settings as the SDG-4 objective.

Nevertheless, such outcomes have also led to significant challenges for the future course. Institutional factors, faculty capacity, and ethics, such as the protection of personal data and faculty bias, may be a hindrance to successful implementation in these adversities.

9.2 Summary of Key Findings

First, when seamlessly integrated into learning systems with robust teaching and moral oversight, it is possible for these AI technologies to significantly enhance teaching and learning processes in higher learning institutions. These applications include personalized learning

systems, intelligent tutoring systems, learning analytics, and assessment through AI technologies.

Secondly, there is great potential for the use of AI in enhancing inclusivity and equity in higher education. This is because the technology can be applied in supporting students as well as addressing the issue of learning outcomes inequalities, for example, through the provision of learning tools and the detection of academic risk. However, the chapter indicates that this can be enabled by ensuring equity in the use of technology infrastructure.

Thirdly, the debate illustrates the presence of a relationship between AI and situations beyond learning to managing institutions. Planning based on evidence, assurance of quality, and the optimization of resources are AIs that support institutions of higher learning in responding to the dynamic aspects of learning.

Finally, the chapter identified important considerations related to the issues of ethics, privacy of data, disparity in the digital world, and readiness on the institutional front. The considerations are centered on the fact that the adoption of AI is as much an affair of human and institutional processes as it is an affair of technological processes.

9.3 Limitations

It is a conceptually oriented chapter and limited in empirical validation, as it relied on secondary sources and published case-studies. Because of this, a discussion may not be capable of capturing regional or institutional varieties, and the examples that are given are illustrative and not exhaustive. The long-term effects of technologies under consideration are not quantified, and the discussion presupposes the applicability of current evidence to a larger extent.



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AI-Enabled School Management for Sustainable Education: A Systematic Review of Applications, Challenges, and Future Directions

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Abstract
This review examines the various ways artificial intelligence (AI) can influence school management and its potential to promote sustainable education. It brings together the findings from earlier studies to illustrate how schools are using AI to simplify administrative tasks, enrich learning experiences, and support sustainable education efforts. Key uses include AI tools for real-time data analysis, better resource management, and personalised learning paths that connect students with real-world environmental issues. By managing tasks such as data cleaning and report generation, AI enables educators and staff to dedicate more time to strategic initiatives like developing curricula and engaging the community in sustainability projects. The review also highlights major challenges and risks of using AI in education, such as concerns about data privacy, the need for reliable infrastructure, and

ethical issues related to algorithmic bias. The findings show that although AI provides powerful tools for creating efficient and environmentally conscious schools, successful and fair implementation requires careful planning, targeted teacher training, and a focus on equal access. The article concludes by emphasising key areas for future research, underlining the need for robust frameworks to enable schools to use AI responsibly while promoting both academic excellence and a culture of sustainability and sustainable education.

Keywords Artificial intelligence (AI) – School management – Sustainable education – Systematic review – Educational technology – Data analysis – Ethical considerations

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1 Introduction

Artificial intelligence (AI) is rapidly transforming many fields, and its impact on education is becoming increasingly evident. This systematic review examines the function of AI in educational administration and

its capacity to enhance sustainable education. Schools can use AI-driven methods to immerse students in realistic environmental scenarios. Through this approach, learners develop systems thinking skills and data literacy while preparing themselves for active, solution-oriented roles in sustainability (Nikolopoulou 2025; Tomašev et al. 2020). At the same time, AI's strengths, such as improved resource management and real-time analysis of environmental patterns in campus operations, make a difference beyond teaching. These tools help institutions reduce their environmental impact and support strategic sustainable planning (Nuryana 2024; Ayoubi Tabaa and El Kharrim 2023).

Educational institutions are using AI to simplify processes, boost productivity, and make better decisions based on data. In education, AI can handle labour-intensive tasks like cleaning and organising environmental data, analysing large sets of information, and preparing reports. This allows teachers and staff to spend more time on lesson creation and collaborating with the community on sustainability projects (Hutami 2024; Pimentel 2024; Irfan 2023).

AI tools can simplify daily tasks, such as managing student enrollments, handling finances, and responding to common questions with chatbots. It reduces school workload and costs, allowing them to focus on sustainability (Siminto et al. 2023). Additionally, AI can assist with planning. For instance, predictive analytics can help identify students who may need extra support, guide sustainable funding, and update courses in response to the changing job market (Siminto et al. 2023; Xu 2025).

Beyond improving how institutions run, AI can enhance teaching and learning in sustainability through personalisation, adaptive feedback, and immersive experiences. AI systems can act as personal tutors that analyse students' interactions and provide tailored recommendations in real time. This helps students master complex sustainability concepts while also building critical thinking and self-confidence (Alam and Windiarti 2025; Jia and Tu 2024; Zafari et al. 2022). Tools that manage group work adaptively help students

collaborate more effectively. Immersive AI simulations allow students to explore real environmental choices, such as land use or energy shifts, and understand local sensor data. This supports practical, location-based inquiries and projects (Cao and Jian 2024; Jia and Tu 2024). Studies and reviews in K–12 and higher education show improvements in engagement and understanding of concepts, although the quality and amount of evidence differ (Zafari et al. 2022; Wu 2023).

AI optimisation algorithms also provide smart solutions to traditional school management issues. Techniques like genetic algorithms, particle swarm, and ant colony optimisation have been used for scheduling, resource allocation, and creating personalised learning paths. When these are carefully applied, they improve fairness, responsiveness, and environmental performance (Xu 2025). Green management systems and digital lean methods demonstrate how AI can help schools become more sustainable by improving purchasing, saving energy, and cutting down on waste. Treating campuses as living labs also offers students real-world research and hands-on learning experiences (Ayoubi et al. 2023; Bush 2025).

In order to make this potential a reality, however, it is important to assess the trade-offs and risks carefully. AI systems, especially modern deep-learning models, can use a lot of energy and resources. This raises concerns about whether the environmental benefits outweigh the costs if no offsetting strategies are implemented (Strubell et al. 2020). Ethical, legal, and social concerns also persist. Data privacy and security, algorithmic bias, opacity, and gaps in governance are common themes in the literature, affecting both student and environmental datasets (Nouri 2024; Huang 2022; Ayoubi et al. 2023). Trust and perception play an important role in AI's adoption. According to research, transparent design, explainable recommendations, and participatory deployment are necessary to ensure learners' and educators' acceptance of AI-enabled e-learning (Kashive et al. 2020; Bush 2025).

Equity and infrastructure constraints are particularly important. The uneven distribution of devices, connectivity, and technical skills

threatens to increase existing gaps in sustainability knowledge if programs focus on well-funded schools (Nuryana 2024; Leong 2024). To widen access, it is essential to build teacher capacity, design tools that fit specific contexts, and create low-bandwidth solutions. This will help make sure that AI improves rather than harms inclusive sustainable education (Rosi 2024; Xie et al. 2024).

Framed as a socio-technical challenge, the effectiveness of AI in school management and sustainable education depends on more than algorithms. It requires curriculum-aligned design, teacher training, strong governance, and investment in infrastructure. The use of AI for social good can be a force for good when it is combined with expertise from different fields, stakeholder involvement, and ethical guidelines (Tomašev et al. 2020; Vinuesa et al. 2019). This systematic review gathers evidence to offer a clear understanding of how AI supports sustainable teaching and school management. It looks at the main ways AI is used in these areas, evaluates the outcomes, whether they are pedagogical, operational, or environmental, and considers the strength and reliability of the existing evidence. In doing so, it also highlights common ethical, technical, and equity-related challenges that arise, providing practical recommendations for fair and effective implementation. Accordingly, this review is guided by two research questions:

1. In what ways can AI be used to foster sustainable education and to facilitate environmental research in educational settings?
2. What are the main challenges and ethical considerations associated with integrating AI into sustainable teaching and research?

By answering these questions, the review seeks to inform policymakers, educators, and researchers on how to use AI responsibly. It focuses on maximising educational and operational benefits. At the same time, it aims to minimise environmental costs and protect equity, privacy, and contextual fit.

2 Research Method

This study is a qualitative meta-analysis conducted to examine the applications of AI in school management for promoting sustainable education. Scientific articles published between 2020 and 2024 were considered for inclusion. To be selected, articles had to meet specific criteria: they must have been published within the specified timeframe and be indexed in reputable scientific journals. Additionally, the articles were required to specifically address the applications of AI in school management for sustainable education. The researcher focused the review on peer-reviewed articles published between 2020 and 2024.

This time frame includes the launch of important generative AI models like OpenAI's GPT-3 in May 2020 and ChatGPT in November 2022 (Neumann 2023; Slyke 2023; Liu et al. 2024). It also covers the quick adoption of digital and AI-based educational solutions during the COVID-19 pandemic (Tan 2023). This period saw a significant increase in scholarly work on AI in education (Liu 2024; Chukwubueze 2024). This ensures that the analysis looks at the most recent technological advances and their effects on school management. Furthermore, this timeframe aligns with the rapid growth of AI in sustainable education, making it a good opportunity to explore how new tools and practices have helped incorporate environmental priorities into teaching, research, and institutional management.

In the article screening process, clear inclusion and exclusion criteria were established. Articles that addressed unrelated topics or focused on other areas of education were excluded from the analysis. Ultimately, from the pool of identified articles, 16 that most closely aligned with the research objectives were selected for inclusion. These 16 articles, which formed the basis of the in-depth examination and coding, are:

- Huang and Jong (2020)
- Quyet (2020a)
- Mehta et al. (2021)
- Huang (2022)

- Hutson et al. (2022)
- Lowa (2023)
- Irfan (2023)
- Mafi (2023)
- Androniceanu (2024)
- Cao and Jian (2024)
- Dwivedi et al. (2024)
- Zhang and Leong (2024)
- Suryanarayana et al. (2024)
- Xie et al. (2024)
- Zaugg (2024)
- Rosi (2024)

Data collection was carried out through a systematic search of reputable databases, including PubMed, Scopus, Web of Science, Springer, and Google Scholar. The search utilised key terms in English, such as "AI in School Management," "AI in Education," (AI in school management), and (AI in sustainable education).

The PRISMA guidelines were followed to identify, screen, and select articles, ensuring that all included studies adhered to rigorous scientific standards. Initially, the titles and abstracts of articles retrieved from databases were reviewed to assess their relevance. Articles deemed pertinent were downloaded in full and subjected to a thorough examination. Each article was analysed for key information, including objectives, methods, results, and conclusions, using a standardised checklist. Using this information, the researcher was able to screen articles according to their quality and content.

Data analysis used qualitative methods, following the PRISMA guidelines. These guidelines support researchers in conducting searches, selecting articles, and analysing them clearly and consistently. First, the full texts of the chosen articles were reviewed, and key data from each were extracted. Then, the extracted data were organised into main categories. These categories included the effect of AI on improving managerial efficiency, facilitating interaction between

teachers and students, supporting data-driven decision-making, and improving the quality of sustainable educational processes.

To improve the reliability of the results, data triangulation was used. This involved comparing findings with existing literature and expert opinions in school management and AI. Using these methods, which include the systematic review approach and qualitative meta-analysis, is suitable for answering the research questions. They thoroughly summarise the current evidence on AI applications, challenges, and future directions in teaching and research on sustainable education. The detailed description of the search strategy, inclusion and exclusion criteria, and coding process provides enough information for others to reproduce the study.

In the open coding phase, we carefully examined the full texts of the selected articles. We extracted all concepts, phrases, and ideas related to the use of AI in school management. During this process, we identified 53 distinct open codes, each highlighting a specific aspect of AI's impact on school management. Each code connects to at least one article and at most five articles. The following table (Table 1) shows the open codes along with the corresponding article citations:

Table 1 Open coding extracted from articles

The table above comprises 53 open codes extracted from selected articles, reflecting various aspects of the application of AI in school management. These codes were identified from diverse articles, with each code linked to one or more relevant papers. They represent significant themes such as productivity improvement, interactions, error reduction, resource management, and the facilitation of educational processes.

3 Result and Discussion

3.1 Results

During the axial coding phase (Table 2), open codes identified in the first stage were grouped into broader categories based on shared ideas and patterns. This process aimed to find the main themes and relationships among the open codes. It organised them into axial codes that reflect clear concepts about AI's role in school management. A total of 15 axial codes emerged, each covering a set of related open codes. For example:

Table 2 Axial coding

1. The axial code “Improving Managerial Efficiency and Decision-Making” combines open codes like automating curriculum planning and cutting down time on administrative tasks.
2. "Personalising Learning” includes codes such as tailoring curriculum to individual students and offering adaptive learning recommendations.

In the selective coding phase, axial codes were synthesised into six overarching concepts (Table 3) to crystallise the study's central thesis. These concepts represent the foundational pillars of AI's integration into school management, emphasising improvements in efficiency, decision-making, pedagogy, resource allocation, transparency, sustainability, and evaluation. For instance:

Table 3 Selective coding of AI applications in school management

1. “Intelligent and Strategic Decision-Making” combines axial codes, such as predictive data analysis, to support strategic decision-making.
2. “Facilitating Educational Processes” integrated codes related to streamlining teaching–learning processes and enhancing student learning experiences in sustainable education.

In the selective coding phase, axial codes were linked to one or more overarching core themes to crystallise the study's central thesis. This phase aimed to identify interconnections among all axial codes and derive comprehensive, principal themes. The emergent themes underscore AI's pivotal roles in school management, such as optimising administrative workflows, enabling data-driven decision-making, and fostering adaptive learning environments. These synthesised concepts highlight AI's transformative potential in educational administration and serve as the foundational narrative of the research.

3.2 Discussion

The findings show AI's ability to transform school management in three main areas. This directly answers the first research question: "In what ways can AI be used to foster sustainable education and to facilitate environmental research in educational settings?" First, AI significantly improves operational efficiency by streamlining administrative tasks. Axial codes, like speeding up managerial processes and improving class scheduling, illustrate how automating everyday tasks, such as curriculum planning, lowers human error. This allows staff to focus on strategic initiatives that promote sustainable education. These results support studies highlighting AI's role in reducing institutional inertia by switching manual processes with automated systems (Hutson et al. 2022; Suryanarayana et al. 2024).

Second, AI's ability to make decisions based on data is a key benefit. The use of predictive analytics and AI tools, like forecasting students' educational needs, assists schools tackle challenges before they arise. For example, predicting where students might struggle allows administrators to put in place focused support before problems grow, moving from reacting to issues to preventing them. Third, AI greatly improves teaching methods, especially in sustainable education.

By tailoring content to match students' interests and performance, these methods not only increase engagement but also build critical thinking and problem-solving skills that are essential for addressing global sustainability challenges. The use of immersive simulations and

AI-supported data analysis, as mentioned in the research, directly promotes environmental awareness and hands-on learning among students. (Cao and Jian 2024; Xie et al. 2024).

Despite these advantages, systemic barriers can prevent fair AI adoption. This issue connects directly to the second research question: "What are the main challenges and ethical considerations associated with integrating AI into sustainable teaching and research?" Problems with infrastructure, a lack of training, and ethical risks, especially around data privacy, could exacerbate existing inequalities. Collecting and analysing sensitive student and environmental data requires strong security measures to avoid misuse. This concern is more critical in areas without strong data protection laws (Nouri 2024; Zhang and Leong 2024; Chukwubueze 2024; Suryanarayana et al. 2024).

Resistance among educators comes from not enough training and a lack of skills needed to work with AI technologies, especially in developing countries. High costs and the lack of proper infrastructure in underprivileged areas also create significant obstacles to the effective use of AI. This situation risks increasing the digital and educational divide, while neglecting plans for sustainable education (Nuryana 2024; Zhang and Leong 2024; Suryanarayana et al. 2024). Tackling these systemic issues requires supportive policies and improved international cooperation to ensure equal access to AI for sustainable education.

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4 Implications for Theory, Policy, and Practice

- **Theoretical Implications**: This review helps us understand AI's role in education. It provides a clear framework for its applications and challenges in school management, teaching and research. It shows how AI can go beyond just improving administrative tasks. Instead, it can change teaching methods to address complex global issues. This highlights the need for models that connect technological innovation with principles of environmental education.

- **Policy Implications**: Policymakers must create supportive policies and promote international cooperation. These efforts will ensure everyone has fair access to AI for sustainable education. This includes investing in solid IT infrastructure and providing funding for under-resourced schools to close the digital divide, as noted by Zhang and Leong (2024) and Nuryana (2024). Additionally, clear ethical guidelines are essential. They will help protect student and teacher data, especially when sensitive environmental information is collected through AI tools.
- **Practical Implications**: School leaders and teachers need targeted training to boost their AI knowledge. They also need to use tools like adaptive platforms and predictive analytics in sustainability courses effectively. Practical strategies should emphasise hands-on training, teamwork in designing the curriculum with AI specialists and environmental experts, and creating various learning environments that use AI for engaging sustainable experiences.

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5 Limitations and Future Prospects

This study is limited because it focuses on English-language literature from 2020 to 2024. This might overlook insights from non-English sources and earlier innovations. The qualitative meta-analysis method provides rich thematic detail; however, it does not offer numerical proof of the observed trends. Also, focusing only on peer-reviewed sources may overlook practical issues found in grey literature. Future research should expand its language and time frames to reflect the changing role of AI in education. It should also perform cross-country comparisons to better understand cultural and economic effects on AI use.

Furthermore, studies should evaluate AI in different contexts, including rural and urban areas or high and low-resource settings, to assess real-world impacts. Investigations into scalable, open-source AI solutions and long-term studies on the effects of AI on institutional resilience, teaching innovation, and sustainable learning will help

promote fair and sustainable use of AI in school management. This chapter focuses on the comprehensive analysis of primary data compiled from existing available literature.

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Ethical Considerations

This study did not involve any human or animal participants, nor was any sensitive or personal data collected. It was based entirely on analysing published literature; thus, no ethical approval was required, and issues of consent do not apply.



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Employing Artificial Intelligence as Promoter for Sustainability in Higher Education Institutions

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Abstract
The United Nations' Sustainable Development Goals (SDGs), adopted in 2015, offer a global guide to eliminate poverty, safeguard the planet, and promote prosperity by 2030. Higher education institutions (HEIs) are uniquely well placed as a knowledge centre to hasten the pace of learning by performing their main roles, such as academia (teaching and learning), administration (governance and operation), and

innovation and research. The current study aims to find ways Artificial Intelligence (AI) can boost sustainability and what challenges and chances it brings in managing and promoting sustainability. The results show that AI can optimize resources by using models that predict how to cut down on energy use, improve how people move around campus, and reduce waste. In teaching, AI makes things more sustainable by offering personalized learning, digital tutoring, instant feedback, and immersive experiences to enhance student motivation and engagement. In research, AI can make a significant impact by making it easier to analyze big datasets on environmental, social, and economic topics. The study finds that responsible and fair AI implementation in academia, administration, and research is necessary to help HEIs close SDG gaps. Three major recommendations are: ethical AI governance and faculty development, AI-optimized sustainable campus operation, and interdisciplinary AI-driven research hubs. In recent years, the demand for strategic adoption of AI in higher education has increased, particularly to fulfill SDGs and ensure that all people enjoy peace and prosperity by 2030. This study encourages institutions to establish funded AI hubs that foster cross-disciplinary research and international collaborations to produce evidence-based solutions to various SDGs, such as health (SDG 3), clean energy (SDG 7), and biodiversity (SDG 15).

Keywords Artificial intelligence – Sustainability – Higher education institutions – Sustainable development goals (SDGs)

1 Introduction

Higher education institutions (HEIs) have a key role to play in advancing the United Nations Sustainable Development Goals (SDGs), especially SDG 4 (Quality Education), SDG 13 (Climate Action), and SDG 17 (Partnerships for the Goals) (See Fig. 1). By 2026, artificial intelligence (AI) is expected to become a revolutionary tool for

incorporating sustainability into teaching, operations, research, and the overall life of the campus.



Fig. 1 The Sustainable Development Goals.
Source United Nations SDG (https://sdgs.un.org/goals)

AI enables scaled Education for Sustainable Development (ESD), moving beyond small initiatives to drive widespread, impactful change by integrating social equity, economic viability, and environmental stewardship into curricula and learning environments. Machine learning is applied to adaptive learning platforms, where students are presented with content tailored to their needs and learning preferences on climate change, the circular economy, or biodiversity (Ferk et al. 2025). Chatbots and virtual tutors powered by AI provide real-time feedback on sustainability projects, whereas generative AI helps produce interdisciplinary case studies or environmental scenario simulations.

AI-based smart systems are advantageous to campus operations. Predictive analytics saves energy in buildings by enabling real-time predictions and adjusting HVAC (Heating, Ventilation, and Air

Conditioning), lighting, and renewable energy integration. AI waste management applications and systems use image recognition to sort recyclables and track waste streams, making a substantial contribution to reducing landfill waste. The smart irrigation and leak detectors help in optimizing water usage. These applications have shown a 15–30 per cent decrease in energy and water consumption in pilot campuses across the world (Afolabi et al. 2025).

According to the World Health Organization's (WHO 2025) report, AI notably enhances sustainability innovation. Machine learning systems are used to analyze large environmental datasets to predict climate consequences, optimize renewable energy grids, or develop low-carbon materials. It also enables interdisciplinary collaboration and helps establish global research collaborations. Issues still exist, such as data privacy, algorithmic bias, high upfront costs, and digital divides, but ethical AI systems and open source will gradually address these challenges. Several reputable academic institutions (e.g., MIT, Stanford, the University of Manchester) have already incorporated AI into their sustainability plans, standardizing AI practices and setting the way for others. Responsible adoption of AI can position HEIs as models of sustainable practices, equip them with future-ready skills, and enable them to play a significant role in achieving global sustainability objectives. It is not only a technological but also a strategic need to change the world so that higher education would be at the forefront, making the world greener and more equal.

Based on the above argument, this research aimed to explore AI's role across the academic, administrative, and research domains to help higher education achieve the UN's Sustainable Development Goals. The HEIs play an important role in the realization of the United Nations Sustainable Development Goals (SDGs), especially SDG 4 (Quality Education), SDG 13 (Climate Action), and SDG 17 (Partnerships for the Goals). By January 2026, artificial intelligence (AI) will have become a groundbreaking device that can instill sustainability in teaching, operations, research, and campus living, consistent with the current work of UNESCO connecting AI to education transformation in an

ethical manner. AI has a role in teaching and learning in the form of scalable, personalized Education to Sustainable Development (ESD). Machine learning-based adaptive learning platforms are created to adjust the content on the topics of climate change, circular economy, and biodiversity to the needs of a specific student, their preferences, and their advancement. Chatbots and virtual tutors based on AI provide real-time feedback on sustainability initiatives, whereas generative AI allows one to build interdisciplinary case studies and environmental simulations. These inventions are much more efficient than the old approaches at promoting inclusive and equitable learning by increasing interactivity, critical thinking, and sustainability competencies.

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2 Literature Review

2.1 Sustainable Development Goals (SDGs) in Higher Education

By January 2026, higher education will have become the focal point of global debates by the United Nations, especially via UNESCO (a specialized agency on education, science, and culture) on artificial intelligence (AI). UNESCO does not see AI as a technological object but rather as a game changer that can hasten the achievement of Sustainable Development Goal 4 (inclusive and equitable quality education), but it is also a source of serious ethical, equity, and human rights issues.

A survey of institutions around the world (nearly two-thirds of higher education institutions already have (or are developing) guidance regarding AI use in teaching, research, and academic life) indicates that guidance on AI use in higher education is already present in nearly two-thirds of institutions with UNESCO Chairs or in the UNITWIN Networks. Publication of new AI competence frameworks, including those regarding teachers and students (2024), which focus on ethical employment, critical AI literacy, and human-centered approaches. Rewarding responsible AI integration in higher education by recognition of innovative initiatives (e.g., AI4InclusiveEducation in

Belgium, Piaui Inteligencia Artificial in Brazil) by the UNESCO King Hamad Bin Isa Al-Khalifa Prize (Unesco.org 2025).

Li et al. (2025) noted that the interest of UNESCO is focused on the following three priorities:

- Ethical and Inclusive AI Adoption - The adoption of AI in higher education should be ethical, non-discriminatory, respectful of privacy, and lessen inequalities (particularly in areas with low resources)
- AI Competency Development - Prepares students and faculty with the necessary skills to use AI, make informed evaluations, and apply AI ethically to prepare them for an AI-driven labor market.
- Utilizing AI to promote personalized learning, better research orientation, and administrative efficiency.

According to Lasker and Lovitt (2024), UNESCO is advocating a balanced, equitable future in which higher education is able to utilize the power of AI without undermining human dignity or sustainability through events such as the Futures Dialogues on AI (2025) and the Futures of Education (2019). Such initiatives call for continual support of policies on higher education by 58 + countries. In the modern era marked by diversity and inclusion, universities are required to nurture the global competence of students, which has been considered an effective pedagogical approach. Global competence, as per Xiong et al. (2025), refers to a comprehensive understanding of local and global issues, inclusive attitudes, and enhanced communication. Xiong et al. (2025) propose that integrating global competence into pedagogy can be promising in shaping students' perception related to SDG.

From another perspective, Munro and King (2022) stated that community-engaged and project-based pedagogies support students' sustainability competencies. Community-based projects like project-based learning enable students to solve issues in their locality about the SDGs. In Conestoga College, for example, the Climate Pedagogy Symposium is a movement of interdisciplinary teaching on climate, which connects the SDGs 13 and 4 to the curriculum (SDG Accord

2025). In the same vein, the Clean and Green Village campaign conducted by the SRM TRP Engineering College offers learning in practice, covering SDG 6 (Clean Water) and 11 (Sustainable Cities). Such initiatives develop critical thinking and teamwork, crucial to the SDG realization (Amiri 2025).

According to the SDG Accord (2025), 61% of institutions educate 0–25 of teaching staff on sustainability, which hinders the adoption of sustainability. The International University of Sarajevo uses AI tools, which map the curricula to SDGs, increasing the level of integration (Tašaković and Büyükdağlı 2024). There is also an extracurricular extension of HEIs through formal education. Agency is developed through student-led SDGs 5 (Gender Equality) and 16 (Peace and Justice) workshops. Nonetheless, developments are not even, according to the Modern Language Association (MLA) article, SDG integration puts more emphasis on bachelor's programs in engineering and business, with the more affluent nations in the forefront. In the poorer areas, resources are scarce and not accessible, contributing to inequalities (Vrečko et al. 2024).

2.2 Sustainability in Administration in Higher Education: Governance and Campus Management SDGs

From the perspective of Filho et al. (2023), governance in higher education is significant as it impacts SDG implementation in HEIs. HEIs must ensure that their policies are geared towards sustainability and directly contribute to SDGs 12 (Responsible Consumption) and 13 (Climate Action). According to the SDG Accord (2025), 78% of signatories have signed sustainability plans, and Leadership and Governance has the highest mature rating (41% Established). This is an indication of strategic integration, with 45% of the actions being mapped to particular SDGs.

Skrzyzowski et al. (2024) argued that campus activities are living laboratories. Some of them entail green buildings, waste minimization, and biodiversity programs. In SDG 7 (Clean Energy), access to global electricity has increased, yet in developing nations, HEIs are below the

mark; universities promote the use of renewable, which decreases carbon footprint. The MLA focuses on the coordination of infrastructure with such guidelines as the Talloires Declaration that transforms campuses into sustainable centers (Zutshi, Creed, and Connelly 2018). These can be defined by water conservation initiatives that fund SDG 6, as 2.2 billion people in the world cannot access safe water (Gordon et al. 2023).

Abhayawansa, Adams, and Neesham (2021) argued that SDGs are incorporated through governance structures through specific offices or committees. Accountability is guaranteed by Senate support, which is mandatory among SDG report signatories. While Lough et al. (2024) saw that collaborations with stakeholders will improve operations, the Framework developed by HEI will align UN agencies and universities to engage. This is in line with SDG 17, which is essential given that low-income countries have $1.4 trillion in debt (Nations 2025a).

From the perspective of Kayashima (2022), the most important thing is financial administration. HEIs experience the problem of fund shortages but utilize Official Development Assistance (ODA) (in 2023, it is 259 billion) to finance SDG initiatives. It opposes the 1.1 trillion in fossil fuel subsidies, with divestment in fossil fuels being in line with climate objectives, as in certain universities. The procurement policies prefer sustainable suppliers, which encourages SDG 12 (United Nations, 2025b). Salleh et al. (2023) noted that the SDG role of administration goes further to outreach, where communities are engaged to make a real impact. The modeling of sustainability would encourage more people to adopt it, which is important as the rate of forest loss decreases. Enhanced governance will hasten the development towards 2030.

2.3 Sustainability in Innovation and Research

Daniels and Gebhardt (2021) argued that higher education innovation and research produce evidence-based solutions, which directly promote SDGs via discovery and implementation. HEIs have impacts on SDGs 3 (Health), 9 (Industry/Innovation), and 13 (Climate), and the

maturity of research is Developing/Established in the SDG report. In 2025, institutions focused on SDG 4 and 13 and 17, and the least on SDG 14 and 6 (Ashida 2022).

Nanda et al. (2025) noted that actionable insights are generated by research, and there is a move towards what works in the real world, i.e., climate technologies. The R&D workforce increased through the years (2015–2022) in support of such innovations as renewable. In addition to that, HEIs address health, such as interdisciplinary understanding of well-being at the Hong Kong Baptist University, which combines the sciences in support of SDG 3, as HIV infections decline (Fong et al. 2021).

As for ELZEIN (2024), startups are developed in innovation hubs. Water purification water patents support SDG 6, of which 3.4 billion people do not have access to sanitation (United Nations 2025b). Collaborative research focuses on the use of data-based approaches to impact measurement. Finance for biodiversity increased to 2.1 billion owing to HEI research on ecosystems (OECD 2024).

As Potocki (2025) noted, interdisciplinary approaches are important. HEI emphasizes the incorporation of traditional knowledge, such as Chinese medicine, to provide holistic health. Partnerships enhance and the air pollution project in Manchester connects HEIs to the locals to achieve SDGs 3 and 11. Global networks required increased knowledge transfer through SDG 17, which has an ODA of 212 billion (Nations, 2025a).

Parsons et al. (2025) argued that there are challenges in that field, which include inequalities in development, with low-income countries being over-represented. There is limited scale due to funding gaps (4 trillion). There are disruptions in data, such as USAID cuts in 2025, which impact monitoring. The silos are barriers to multi-SDG research. As for opportunities, it can be said that digital tools allow global collaboration. AI-based innovations are supported by 5G coverage. The framework of HESI encourages imitation rather than innovation. Case studies, such as the case of the LUNSHE network at the University of Leeds, encourage cross-disciplinary innovation (Majeed 2025).

2.4 Case Studies

Mahere's (2024) paper explores how Higher Education Reforms (HERs) in higher education promoted the Sustainable Development Goals (SDGs) using the examples and experiences of the Department of Educational Administration and Leadership at the University of Zimbabwe (UZ). Zimbabwe embraced the Vision 2030, which aimed to see the nation turn into an upper-middle-income nation by the year 2030. Education 5.0 was a framework that was launched through the Ministry of Higher Education on its contribution to the development and achievement of SDGs. The method of investigation was a qualitative research design. The pursuit of the UZ mandate is made in the form of a Strategic Plan with objectives responding to the call of Education 5.0. SDGs contribution through how HERs were involved in the actions of departments is investigated. The Strategic Objective 1 will seek to encourage a programmatic approach to research. Participatory research teams were formed. Strategic Objective 2 aims at launching degree programs based on technological innovation requirements. The department has come up with programs that provide goods and services. Strategic objective 3 will form partnerships. The department developed the Zimbabwe Educational Management and Leadership Trust. Strategic Objective 4 is based on mentorship. The department also initiated the introduction of internships for teachers and school heads in M Ed programs, enabling them to acquire practical experience. Strategic Objective 5 focuses on the internationalization of the programs and research in the UZ. There were international conferences attended by the department members and international senior research fellows.

According to Ebekozien et al. (2023), funding of infrastructure in the public higher education institutions (HEIs) is difficult in most developing countries. Physical facilities could be enhanced by promoting individual investment in the infrastructure of the HEIs through a mature, enlarged corporate social responsibility (ECSR). ECSR is a type of infrastructure tax relief in the form of physical infrastructure facilities to the HEIs. There is a dearth of academic

literature on how ECSR can enhance the infrastructural aspect of the public HEIs in Nigeria and ensure the creation of education infrastructure in relation to Sustainable Development Goal 4 (SDG 4). Thus, this research endeavors to offer interventions to enhance the infrastructure of the public HEIs and attain sustainable development in relation to Goal 4, which centers on infrastructure through an established framework. It is a continuation of current research, and data were compiled through virtual interviews in the six geopolitical regions in Nigeria. The data analyzed had been outlined in a thematic form. Eighteen measures (sub-variables) were developed and reorganized into six variables. This will involve institutionalizing ECSR, HEIs infrastructure through ECSR awareness, HEIs infrastructure incentives, national and state action plans on HEIs infrastructure, legal framework of the HEIs infrastructure, and its involvement of key stakeholders.

Yussri Sawani, Joseph, and Leong (2024) stated that the research will seek to review the available literature on the factors that drive institutions of higher learning to report on their Sustainable Development Goals efforts. This paper employed the systematic review as an interdisciplinary tool to design a review protocol on the literature about Sustainable Development Goals and higher education institutions. NVivo Release 1.4 was used to complete thematic analysis to generate the theme on the motivating factors of disclosure, and was examined through content analysis. In the study, five clusters involving Sustainable Development Goals and institutions of higher learning were found. The primary subcategory is composed of motivating factors, as the primary child notes only. The four primary factors that encourage Higher Education Institutions to report their practices of Sustainable Development Goals include the curriculum, research operations, human resource management, and research and operations partnerships.

Narong (2024), on the other hand, stated that interest in business and management education, the topic of sustainability has continued to grow in interest, and no complete research review has been undertaken since the United Nations Decade of Education for Sustainable

Development. This paper bridges that gap and examines 365 documents indexed by Scopus with descriptive statistics, citation analysis, co-citation analysis, thematic analysis, and science mapping. The findings show that despite the increasing number of studies, a rather thin layer of knowledge has not yet been explored and is concentrated in the economically developed areas. The intellectual framework of the field is established on three schools of thought, namely Responsible Management Education, Holistic Management Education, and Higher Education for Sustainable Development, all of which provide a diverse but unified approach to curriculum development, research, partnerships, and a strong sense of social responsibility and sustainability. Significant areas of concern are the Sustainable Development Goals, higher education, corporate social responsibility, and standards of sustainable management education.

2.5 An Eye Around the World

Universities all over the world are incorporating the UN SDGs into their business practices, enabling them to encourage sustainability in their academic (curriculum and teaching), administrative (governance, operations, and campus management), and research (projects and collaborations) activities. Some real-life examples of well-known institutions, based on world ranking and reports, are as follows:

2.5.1 The Western Sydney University (Australia)

Western Sydney is a model of holistic integration, as it is the highest ranked in the world in the 2023 Times Higher Education Impact Rankings (THE) SDG contributions. In academia, the university incorporates SDG-related information throughout the university courses with a focus on equity and inclusion; more than 7000 university students are first-generation university students, which fit the SDG 10 (Reduced Inequalities). As for administration, it is committed to equality between the genders (SDG 5) in its own ranks, 46 percent of top academic personnel are female, and the campus operations are in line with the sustainability goals, such as the use of

renewable energy. In the field of research, the faculty head influences the projects that focus on climate resistance and social fairness and cooperate with local communities to meet SDG 13 (Climate Action) (Mellick Lopes and Allen 2021).

2.5.2 Anglia Ruskin University (UK)

This university has ensured that sustainability is an indispensable fiber of its educational fabric, as noted in the International Sustainable Campuses Network (ISCN), the Educating Sustainability Report. In academia, SDG-related modules are now mandatory in all degree programs, from environmental ethics to global health, to prepare graduates to deal with SDGs. As for administration, sustainability is incorporated not only in non-academic spheres (e.g., library resources collection and volunteer activities that support campus-wide environmental initiatives, including waste minimization (SDG 12: Responsible Consumption and Production). In the field of research, interdisciplinary projects are based on urban biodiversity and community health, and projects led by students can help achieve SDG 11 (Sustainable Cities and Communities) (Fadli 2023).

2.5.3 Penn State University (USA)

The most remarkable feature of Penn State is its comprehensive SDG alignment, especially in terms of community-focused activities, which made it noticeable in sustainability evaluation. In the academic field, SDG lenses are present in courses in agriculture, engineering, and humanities, along with specific courses devoted to sustainable food systems (SDG 2: Zero Hunger). In administration, multi-level sustainability councils govern operations; the university has energy-efficient campus buildings, diversity policies to SDG 5 and 10; the strategic plan of the university is clearly mapped to all 17 SDGs. While in research, collaboration between Pennsylvania campuses is an SDG 11 initiative, like regional planning of resilient communities and the management of natural resources (Bailey 2026).

2.5.4 Imperial College London (UK)

As a science and innovation leader, SDGs are centralized in the Imperial mission, according to ISCN best practices. In academia, SDG themes are embedded in all of the programs, and students are required to complete sustainability training as part of such disciplines as medicine and engineering, which contributes to SDG 4 (Quality Education). In the field of administration, SDG dashboards to monitor the progress in such areas as carbon neutrality and ethical procurement (SDG 12) are in place. In research, innovative research on climate modeling and infectious disease promotes SDG 13 and 3 (Good Health and Well-being), usually in the form of global consortia (Fox and Macleod 2021).

2.5.5 Stuttgart University of Applied Sciences (Germany)

This university of applied sciences has developed a special Center of Sustainable Development in order to implement SDGs. In academia, the teaching modules will facilitate the students to be the change agents through practical projects in the field of renewable energy (SDG 7: Affordable and Clean Energy). In administration, the center leads the operation and governance by installing the green procurement and campus recycling programs in accordance with SDG 12. In the field of research, the joint efforts in sustainability and biodiversity of cities, based on research on SDG 11 and 15 (Life on Land), are piloted in real-world programs in the local ecosystem (Raffer, Scheller, and Peters 2022).

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3 Methods

The current study adopted the qualitative methodology in addressing its aim. We have gone through previous studies that were carried out from 2019 to 2025. The reason for choosing that time span is attributed to the fact that the UN SDGs were first issued in 2015 and applied in 2016 worldwide, which opened the doors for global tracking and 232 indicators on an annual basis. In 2019, António Guterres declared a

“Decade of Action,” which presented a report regarding the application of such goals over a span of 10 years (António Guterres 2020).

It is worth noting that the qualitative study, which will focus on the development of the United Nations Sustainable Development Goals (SDGs) in institutions of higher learning (HEIs) across academic, administrative, and research functions using AI, will follow exclusion criteria to ensure relevance, recency, and methodological suitability:

- The period of research is limited to literature published prior to 2019 because the UN announced the Decade of Action in 2019 (António Guterres 2020), which signifies a new step in the speed of SDGs implementation and heightened focus of the world on the 232 indicators. The previous literature lacks the emphasis on SDGs as in 2019.
- The studies that do not pertain to the higher education institutions (e.g., the ones that focus on primary/secondary education, vocational training beyond the higher education institutions, and the non-educational areas) are not included, considering that the study is directly related to the unique aspects of the teaching, operations, and research in the formats of higher education institutions.
- Articles that are not empirical or merely theoretical and do not focus on the application of AI to sustainability (such as opinion articles, editorials, and conceptual frameworks without supporting case studies or data) will be filtered out to ensure the focus is on practical and evidence-based information.
- The literature that does not cover at least one of the main functions, including academic (teaching/learning) and administrative (campus operations/governance), and research, in the framework of SDGs (especially SDG 4, 13, and 17) will be excluded.
- Articles written in languages other than English will be excluded because of the researcher's language proficiency and the fact that most of the good quality, peer-reviewed SDG/AI texts are written in the English language.
- The articles that do not have an evident connection to AI technologies (e.g., the research about overall sustainability in HEIs

without AI involvement therein) will not be included to maintain the main theme of the study, which is the transformative power of AI.

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4 Results

According to the literature review synthesis of 2019–2025 literature to determine how artificial intelligence (AI) can be applied in furthering the United Nations Sustainable Development Goals (SDGs) in HEI, with a major emphasis on SDG 4 (Quality Education), SDG 13 (Climate Action), and SDG 17 (Partnerships for the Goals). It is possible to note that the analysis demonstrates that AI is an effective, versatile facilitator in academic, administrative, and research roles, making HEIs agents of global sustainability.

4.1 Scholarly Process (Learning and Teaching)

AI is very helpful in terms of Education for Sustainable Development (ESD) because it is customized and scalable. Machine learning-driven adaptive learning platforms (CL) serve each student with the content based on their needs and preferences, enhancing engagement and key sustainability skills (Savec et al. 2025). Artificial intelligence chatbots and virtual tutors offer feedback on sustainability initiatives in real-time, whereas artificial intelligence interdisciplinary case-studies and simulations of the environment are more interactive and more efficient than conventional approaches. The infrastructure, such as the International University of Sarajevo, applies AI to curriculum mapping to SDGs, which increases the integration rate despite the low rates of staff training (Tašaković and Büyükdağlı 2024). The practical examples are the Climate Pedagogy Symposium of Conestoga College and the Clean and Green Village campaign of SRM TRP Engineering College, which encourage project-based learning in accordance with SDGs 4, 6, 11, and 13 (Munro and King 2022; Amiri 2025). The innovations help to tackle the disparities in the areas of inadequate resources to ensure a more inclusive and equitable education (Vrečko et al. 2024).

4.2 The Administrative (Governance and Campus Operations)

The AI streamlines operations in the campuses, and this has a direct impact on SDG 13 via smart systems. Predictive analytics predict energy demand and optimize HVAC, lighting, and renewable integration, and realize energy and water savings of 15–30 percent across pilot campuses in most locations around the globe (Arun et al. 2025). Image recognition to sort recyclables and monitor streams, as well as smart irrigation and leak detection to minimize waste of resources, can be used in AI waste management in accordance with SDG 12 (Responsible Consumption) (Filho et al. 2023). Governance frameworks are placing more and more SDGs into their frameworks, with many institutions now having sustainability plans and other institutions mapping actions to particular objectives (Skrzyzowski et al. 2024). Financial management takes advantage of the Official Development Assistance (ODA) to fund projects and opposes fossil fuel subsidies by divesting (Kayashima 2022). These initiatives fall in line with SDGs 5 and 10, and yet there are still inequities across the regions, mainly in sub-Saharan Africa (Faugoo 2024; Zreik et al. 2024). Outreach is a way to make SDGs more impactful, and smart campuses are able to optimize energy through digital means (Wilby et al. 2023; Salleh et al. 2023).

4.3 Research and Innovation Function

AI speeds up sustainability innovation because it uses high amounts of environmental data to predict climate, optimize renewable energy sources, and design low-carbon materials (Daniels and Gebhardt 2021; Ashida 2022). The advantages of interdisciplinary cooperation include the possibility of finding relevant literature with the help of AI and establishing partnerships with other countries (Nanda et al. 2025; Potocki 2025). The SDG 6 patents and data-driven impact measurement are supported by innovation hubs (ELZEIN 2024). There are also issues of funding gaps and silos, which can be addressed through digital technologies such as 5G (Parsons et al. 2025). The example of the

University of Leeds through the LUNSHE network is that of cross-disciplinary innovation to change the system (Smith 2026).

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5 Discussion

The purpose of the study, which is to investigate the role of AI in academic, administrative, and research activities in HEI in order to realize the United Nations Sustainable Development Goals (SDGs), is in line with the current debate on sustainable education. By January 2026, HEIs will be the important actors in SDGs, specifically SDG 4 (Quality Education), SDG 13 (Climate Action), and SDG 17 (Partnerships for the Goals), as highlighted in the frameworks of UNESCO. AI is a transformative facilitator, good at sustainability, but it combines sustainability in campus operations, with issues such as data privacy and prejudice remaining (Bagherimajd and Khajedad 2025).

In university work, AI makes it possible to have Education of Sustainable Development (ESD) that is tailored to an individual, which directly contributes to SDG 4. Adaptive learning platforms are based on machine learning to personalize student-preferred content on climate change or biodiversity, which improves critical skills (Savec et al. 2025). Chatbots and virtual assistants give feedback in real-time, whereas generative AI makes interdisciplinary simulations, which are more interactive and efficient than traditional ones in their performance. This is in line with the priorities of ethical use of AI established by UNESCO that promotes AI competency and human-centered change (Li et al. 2025). As an example, the International University of Sarajevo has used AI on SDG curriculum mapping to enhance integration even more despite the low staff training rates (Tašaković and Büyükdağlı 2024). These innovations solve inequalities in the poorer areas, where access to resources is low due to scarcity (Vrečko et al. 2024). Example Case studies, such as the Conestoga College Climate Pedagogy Symposium and the Clean and Green Village campaign by the SRM TRP Engineering College, can help a student develop the skills of SDGs 13, 4, 6, and 11, such as critical thinking (Munro and King, 2022; Amiri 2025).

The administrative functions can enjoy the operational optimizations that AI introduces, which helps in SDG 13 with the help of smart systems. Predictive analytics regulates lighting, renewables, and HVAC and achieves a good percentage of energy and water consumption reduction (Gunasinghalge et al. 2025). Waste management and smart irrigation are also related to SDG 12 (Responsible Consumption) as image recognition helps reduce landfills and resource wastage (Filho et al. 2023). A literature review of renewable energy in higher education indicates that wind and solar energy are most common alternative sources that are environmentally friendly in higher education institutions and that investigations in the same regard are not well spread geographically with most of the research studies being carried out in Europe countries highlighting the drivers and obstacles to realize sustainable energy in accordance with SDGs like SDG 7, SDG 11, and SDG 13 (Skrzyzowski et al. 2024). ODA is used to implement initiatives in financial administration, which opposes fossil fuel subsidies with a divestment strategy (Kayashima 2022). The equity initiatives are in line with SDGs 5 and 10, yet regional inequalities remain common in sub-Saharan Africa (Zreik et al. 2024). Outreach has a peripheral effect on SDGs, and smart campuses can maximize energy through digital solutions (Wilby et al. 2023; Salleh et al. 2023). The WHO report on 2025 highlights the importance of AI in these efficiencies, even though monitoring systems are poorly funded.

In research and innovation, AI advances SDGs 3, 9, and 13 through the analysis of environmental data to use in climate predictions and low-carbon materials (Daniels and Gebhardt 2021; Ashida 2022). Patent-focused SDG 6 startups are supported in the current innovation hubs, whereas data-focused HEI frameworks focus on impact (ELZEIN 2024; Potocki 2025). Examples of challenges are funding gaps and silos, yet digital solutions such as 5G can facilitate teamwork (Parsons et al. 2025). An example of cross-disciplinary systemic change is innovation using LUNSHE at the University of Leeds, e.g., malaria prevention (Smith 2026).

The case studies support the potential of AI. Education 5.0 at the University of Zimbabwe incorporates AI into programmatic research, innovation programs, collaboration, mentorship, and internationalization, as a way of complying with SDGs. The enlarged corporate social responsibility (ECSR) framework in Nigeria supports the SDG 4 infrastructure of the HEIs by creating awareness, incentives, and stakeholder engagement (Ebekozien et al. 2023). The literature reviews provide motivating factors, such as curriculum and research operations to report SDG (Sawani et al. 2024). Narong (2024) points out sustainability in business education, suggesting the involvement of less developed countries and emerging challenges such as climate change in Responsible Management Education, bridging the gaps.

The initiatives of UNESCO, such as the 2021 AI Ethics Recommendation and 2025 Digital Learning Week, highlight the ethical nature of AI (Lasker and Lovitt 2024; Xiong et al. 2025). HEIs are directed towards inclusive AI by priorities, including ethical adoption, competency development, transforming human-centered, and so forth (Li et al. 2025). This qualitative review of 2019–2025 articles, but not pre-2019 and non-AI/SDG-oriented studies, discloses the strategic imperative of AI in HEIs. By managing the biases and divides with the help of ethical frameworks, AI makes HEIs the leaders of sustainability, creating a greener and more equal future.

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6 Conclusion

This paper has provided an insight into the transformational nature of artificial intelligence (AI) to facilitate the achievement of HEI in supporting the United Nations SDGs, especially SDG 4 (Quality Education), SDG 13 (Climate Action), and SDG 17 (Partnerships for the Goals). The qualitative literature review of 2019–2025 proves that AI is not only a technological boost but a strategic propeller to introduce the concept of sustainability to academic, administrative, and research operations.

Key lessons emerge clearly. AI has been applied in academic fields by developing adaptive platforms, virtual tutors, and generative tools that tailor Education to Sustainable Development (ESD) in a more effective way than traditional pedagogies do. Predictive analytics and smart systems in use in administration result in quantifiable resource efficiencies, such as decreases in energy and water consumption, and governance alignment with a variety of SDGs. AI can enhance innovation in research in three ways: broad-scale data-processing, interdisciplinary innovation, and evidence-based solutions to climate, health, and biodiversity. Examples of the Zimbabwe and Nigeria case studies present feasible avenues to the integration of AI, whereas the ethical frameworks of UNESCO offer the necessary guidelines to prevent bias, privacy threats, and digital inequalities.

One key improvement made is that AI has the potential to transform education by applying the agency of educators, empowering students, and enhancing international collaborations by integrating ethics and equity. The idea of responsible adoption makes HEIs not only the exemplars of sustainability but also the participants in the creation of a cleaner and fairer world. The opportunities of the future are bright and dire. The longitudinal studies are needed to trace the long-term effects of the AI-driven programs on the SDG indicators and student performance. A comparative study of developed and developing regions will show the way to bridge the digital divides. There is a need to further research the potential of AI in encouraging transdisciplinary research and engagement with the community to support SDGs beyond 2030. Lastly, it will be important to create open-source and low-cost AI systems specific to resource-limited HEIs to facilitate an inclusive movement.

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7 Limitations of the Study

Although this qualitative literature review offers useful information about the role of AI in promoting the United Nations Sustainable

Development Goals (SDGs) in higher education institutions (HEIs), it is vulnerable to various limitations.

- **Restricted Time Scope (2019–2025)**

The article narrowed down the literature review to those published after 2019, specifically, due to the declaration of the UN Secretary-General of the so-called Decade of Action in 2019 (António Guterres 2020), which worsened the global implementation of SDGs. This temporal limitation does not, however, apply to previous background research on sustainability in higher education and AI implementations, which might provide valuable historical context, conceptual frameworks, or long-term trends. As a result, the review might lack essential revelations of the first post-2015 SDG adoption period and thus restrict the comprehension of how the process of AI integration has developed in the entire SDG time frame.

- **Non-English Language Publications Exclusion**

The articles were limited to the English language only because of the language skills of the researcher and because the majority of good-quality and peer-reviewed literature on SDGs and AI is in English. This language bias leaves likely research published in other languages, specifically, in non-English speaking parts of the world (e.g., Latin America, Asia, or non-English speaking European countries) that could have introduced some innovative applications of AI in sustainability education. This exclusion can create a geographic and cultural bias, which will not represent the views of different contexts of the world.

- **Qualitative Character and Lack of First-Hand Empirical Information**

The research is purely qualitative and based on second-hand analysis of existing literature, instead of direct data gathering (e.g., surveys, interviews, or case studies through direct work with HEIs). Although this method is a great synthesis of existing information, it has some shortcomings due to the quality, quantity, and range of reviewed sources. Lack of original empirical data implies that the results are not

empirical, but interpretative, depending upon the rigor of previous researchers. Moreover, the narrowing of the evidence base that the non-empirical, theoretical, or conceptual works represent leaves out the possibility of the emergence of new ideas or innovative frameworks that have not yet been empirically tested.



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Sustainability Aspects of Artificial Intelligence (AI) in Education: A Law and Economics Analysis

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Abstract
Artificial intelligence (AI) is transforming human societies. In the many attempts to capture the novel trend of AI entering in all aspects of human life these days, hardly any research covers sustainability aspects of AI encroaching society. In the teaching of sustainability, AI appears as an way to improve carbon footprint as for energy savings opportunities – for instance by using online resources instead of physical books, reducing cognitive load of tedious tasks that had to be performed in educational settings previously, such as sifting through many books to find applicable cases in law school etc. At the same time, AI may create enormous environmental costs – e.g., through its electricity consumption use for big data storage and analytics – but also sustainability challenges – e.g., through eternally-living algorithms and technical devices. This chapter proposes weighing the costs and benefits of AI in sustainability education. In a Law & Economics analysis, the advantages and disadvantages of AI in sustainability education will be compared in order to present a framework

to harvest the benefits but prepare for coping with the downsides of AI in sustainability education. Future student learning experience enhancement and educational changes due to AI in the future will be prospectively anticipated in the discussion. The future of education may positively develop in less cognitive load and diligent learning-by-heart but shift towards creative solution finding, navigating through a digital online jungle and development social network skills to find the right tools in a growing ocean of mushrooming AI advancements.

Keywords Artificial intelligence – Costs and benefits – Cultural transmission – Education – Ethics – Intergenerational equity – Law and economics – Public policy – Sustainable development – Workforce evolution

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1 Introduction

Artificial intelligence (AI) offers computational systems to perform tasks typically associated with human intelligence. AI performs all sorts of tasks such as learning, reasoning, problem-solving, perception and decision-making. Since the advent of Artificial Intelligence, education has been transformed substantially. Already now, just a few years in the AI revolution, it is believed that AI will transform the way we teach, learn and educate in the international compound.

While it is too early to tell where the AI transformation will lead regarding education and learning, we can already see that AI is polarizing in educational circles. Some claim that incorporating AI's exceptional capabilities improves educational outcomes by changing teaching strategies to lessen cognitive load, increase accessibility, and encourage resource efficiency. However, there are sustainability trade-offs associated with these developments, such as energy-intensive data processing, technological waste, and possible long-term societal costs. As a result, communities who care about climate change and those that support sustainability frequently criticize the potential benefits of AI.

This chapter explores the sustainability aspects of AI in education, applying a Law & Economics analytical framework to balance benefits and disadvantages. It provides policy recommendations for leveraging AI's potential while mitigating its environmental, ethical, and intergenerational costs. The analysis culminates in a forward-looking vision of AI-enhanced, sustainable education that promotes innovation alongside awareness for natural resource constraints.

2 Artificial Intelligence (AI)

Today, Artificial Intelligence (AI) has permeated almost every sector of society, from medicine to finance, real estate, retail and education (Puaschunder 2019a, b, c). In academic institutions, AI is increasingly used for automating administrative tasks, personalizing learning experiences,

and expanding access to quality education (Luckin et al. 2016). These innovations promise to reduce the sector's environmental footprint by minimizing reliance on printed materials and reducing the need for physical infrastructure. AI promises many advancements to save and conserve energy – for instance by reducing the need of human assistants that produce carbon emissions by getting ready for work, commuting and using energy in physical office settings.

Yet, the sustainability of AI in general remains a contested topic. The large-scale integration of AI in educational settings remains underexplored, especially when considering AI and sustainable development. Despite its potential benefits, AI carries a heavy energy footprint and raises serious ethical and social concerns (Alnsour et al. 2025). These include data privacy issues, algorithmic bias, and intergenerational equity challenges. For instance, AI is learned and trained on big data insights that are generated by massive storage and computational efforts, which come with a heavy price in terms of carbon footprint due to CO_2 emissions. This chapter therefore sets out for a critical evaluation of AI's role in education through a sustainability lens is essential to ensure long-term benefits without irreversible costs.

This chapter uses a Law & Economics approach to systematically weigh AI's benefits and costs in education. It also provides a multi-dimensional policy framework to maximize educational and environmental gains while mitigating socio-technical risks and economic losses.

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3 Conceptual Framework

3.1 Sustainability and Intergenerational Equity

Sustainability is defined by the Brundtland Commission (1987) as development that meets present needs without compromising future generations. In education, this includes the efficient use of natural resources, equitable access to knowledge and opportunities to advances as well as the long-term viability of learning systems.

According to Howarth and Norgaard (1990) and Puaschunder (2019), intergenerational equity refers to justice throughout time across several

generations, guaranteeing that future generations acquire resources, opportunities, and knowledge equivalent to those experienced by current populations. AI technologies must be evaluated for their long-term societal, environmental, and economic ramifications in addition to their immediate efficiency advantages, given the growing demands for sustainability and intergenerational justice. AI is thought to have enormous potential for previously unheard-of progress in the future, but it can also be viewed as a barrier to sustainability objectives and intergenerational equity disparities.

3.2 Research Question

While AI accounts for the innovation of our lifetime, the use of AI holds advantages as well as risks. In the educational sector, the use of AI for SD promises enormous growth potential but also heralds challenging questions of the environmental footprint of a mass AI use for broad-based education (Henriksen et al. 2024; Khan et al. 2025; Leal et al. 2025).

The chapter therefore poses the research questions: What are the benefits and risks of AI use in education, particularly with respect to sustainability and intergenerational equity? How can a Law & Economics framework be used to systematically weigh the costs and benefits of AI in education in order to inform sustainable and efficient policy design? What regulatory, legal, and policy mechanisms can maximize the educational and sustainability benefits of AI while mitigating its environmental, ethical, and intergenerational risks?

3.3 Method: Law and Economics Analysis

A structured literature review and a Law & Economics analytical framework serve as the foundation for this chapter's qualitative, conceptual research design. This chapter's qualitative, conceptual research design is based on an organized literature review and a Law & Economics analytical framework. Narrative and integrative literature review methodologies are used to synthesis multidisciplinary research in the disciplines of economics, law, education, sustainability science, and ethics. A Law & Economics approach is used to evaluate the efficacy, externalities, and generational consequences of AI adoption in education.

Behavioral economics insights improve traditional cost-benefit analysis by accounting for discounting behavior, restricted rationality, and sustainability-related choice biases. The general objectives of the chapter are policy-oriented analysis, normative evaluation, and theoretical integration, all of which are consistent with the exploratory nature of a rapidly evolving field of research.

3.3.1 Literature Review Approach

The literature review follows a thematic, interdisciplinary approach rather than a systematic meta-analysis. Sources were identified through peer-reviewed academic journals (economics, education, sustainability, AI ethics); reports by international organizations (e.g., UNESCO, World Bank, European Commission); recent policy documents and white papers relevant to AI governance and sustainability. The review prioritized publications addressing AI in education, environmental sustainability, intergenerational equity, and ethical governance plus recent contributions where available, complemented by foundational works for conceptual grounding. The purpose of the review is theory-building and framework development, not exhaustiveness. The case studies are secondary-source-based that draw concise descriptions from existing reports and published literature to serve a demonstrative and contextual function, illustrating how AI in education is approached in different institutional and national settings. The selection was guided by geographical diversity, policy relevance, and availability of documented AI-education initiatives, rather than representativeness.

All things considered, a literature-based qualitative synthesis enables the integration of scattered information from several fields. When assessing trade-offs, externalities, and long-term welfare impacts, a Law & Economics paradigm works effectively. The Law & Economics method assesses institutional and legal frameworks according to how well they allocate resources and maximize social welfare (Posner 1973). The framework directs a comparison of the advantages and disadvantages of AI in education in this chapter and helps formulate policy suggestions based on the results.

Law & Economics insights benefit from economic hallmarks of analysis, featuring intertemporal discounting, externalities and risk

estimates. At the same time, economic insights can then be transferred into actionable policy conclusions that also inform law making.

The following Law & Economics analysis of the benefits and risks of AI in relation to education will first shed light on the upsides of AI in education and then debrief on the risk and weaknesses of the use of AI in education with particular attention to sustainability. The discussion will then offer policy recommendations and legal advancement potential to ensure AI is used in the most efficient but also legally meaningful way. Illustrative examples help translate abstract analysis into policy-relevant insights. The chapter does not aim to test hypotheses empirically, but to identify patterns, tensions, and governance implications, which are adequately addressed through the chosen methods.

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4 Sustainability

Sustainability has emerged as a defining concept in the last decades. Given the realization of finite resources and in the eye of climate change, sustainability attention has reached momentum. The 2015 incepted United Nations Sustainable Development Goals (SDGs) drew worldwide governmental, governance and public efforts to enact sustainability. Today, sustainability shapes policies, politics and everyday decisions around the globe.

At its core of sustainability imperatives lies the wish to meet present needs without compromising the ability of future generations to enjoy an as favorable standard of living as is given today (Brundtland Commission 1987). Sustainability thereby lies at the heart of intergenerational equity, environmental economics and governance. Sustainability endeavors transpire into public policy making, law & economics, ethics and behavioral science. In regard to AI, it remains the challenge of our time how to integrate innovation in the understanding of sustainability for contemporary decision-making and long-term global well-being.

4.1 Sustainability and Intergenerational Equity

Sustainability is a moral and economic contract between present and future generations. In the economic tradition of discounting, the prevalent practice of discounting future benefits and costs undervalues the welfare

of future populations, leading to systematic underinvestment in long-term environmental protection (Puaschunder 2020). Intergenerational fairness thereby asks for attention to the welfare of unborn generations, which should be integrated into "contemporary decision-making, beyond utilitarian present-focused cost-benefit analysis" (Puaschunder 2020, p. 33). By integrating intergenerational equity into economic and legal frameworks, one can advance the idea that sustainability is not merely an environmental concern but a principle of justice inbetween generations, requiring institutional designs that protect the rights and welfare of those yet to be born (Cook et al. 2024).

The problem of the AI integration in education raises critical questions of intergenerational balances (UNESCO 2021, 2025). For instance, as never before, the current elder generation can learn from the fast-adopting younger population segments how to use and integrate AI in everyday life (Du et al. 2025). At the same time, the workforce reduction due to AI taking over many jobs and making parts of the economy obsolete raises challenging questions for younger generations if they have the same opportunities as the elder had.

Already now it is expected that 30% of the workforce are replaced by automated AI and digital tools. The labor market is already giving signs of entry level problems for graduates due to AI (Leopold 2025). This projected shift of the workforce may create substantial intergenerational shifts and new leadership or dependencies, which can all be better anticipated if there is an analytic investigation of the benefits and burdens of AI in educational settings with attention to sustainability (Falckenthal et al. 2025). The concept of sustainability thereby extends beyond environmental concerns but also draws on social sustainability concerns of inclusivity and harmonious societal care (Lei et al. 2025). The Hamburg Declaration on Responsible Artificial Intelligence (AI) for the Sustainable Development Goals (SDGs) (2025) therefore sets out to consider ethical cliffs and intergenerational concerns regarding AI innovations infiltrating markets and robotics infiltrating society.

4.2 Sustainability viewed from Behavioral Sciences

A distinctive contribution to sustainability can be made by incorporating insights from behavioral economics. Traditional economic models assume

rational actors maximizing utility. However, behavioral economics reveals that individuals display time-inconsistent preferences that feature shifting choices. Decision makers are also prone to hyperbolic discounting and the status quo biases – meaning they overvalue the current moment and do not want to change their behavior easily (Thaler and Sunstein 2008). These cognitive limitations often impede sustainable decision-making, as short-term gratification overrides long-term welfare. Human beings are also often neglecting the real costs of environmental resources and underestimate the likelihood of future lock-ins – a state where irreversible changes have made it impossible to go back to a previous state. All these behavioral insights can be drawn from in order to analyze the current situation around AI's introduction in society. Evaluating AI's sustainability in education can thereby be informed for a real-world relevant outlook on changes and risks implied by AI in learning settings.

All gained insights could be used as a tool to align individual behaviors with societal sustainability goals. The knowledge acquired will help emphasize effective sustainability policies that accommodate human cognitive tendencies rather than rely on purely rational economic models, which may not fully hold in real life. Behavioral insights will also aid in complementing traditional market structures that primarily focused on short-term returns and inadequately incentivize investments in long-term sustainability projects. A deeper behavioral angle can also bring in externalities, which help anticipate risks and future occurrences down the road but also shed light at the manifold benefits and risks for various social strata. All these endeavors are vital tools for regulatory and legal action foresightedly in order to reap the benefits of AI to flourish society without falling prey for risks and variegated uncertainties.

4.3 Artificial Intelligence and Sustainability

In the following, a framework will be introduced to prospect the benefits and costs of AI in education with special attention to sustainability. AI can simultaneously advance and challenge sustainability goals. On the one hand, AI enhances resource efficiency, reduces cognitive burdens and democratizes knowledge access, potentially lowering carbon footprints through digital education. On the other hand, AI systems entail significant

energy use for data processing, raise electronic waste concerns and risk creating intergenerational technological dependencies.

A Law & Economics framework with special attention to behavioral insights is then proposed to balance AI's benefits with its environmental and ethical costs. Concrete examples help to grasp a first attempt to propose policies to align the AI revolution in education with higher sustainability goals. Concrete international insights but also practical recommendations of green AI initiatives, circular economy approaches for educational devices and intergenerational impact assessments for emerging technologies will be given.

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5 Comparative Cost-Benefit Analysis

The results of using the Law & Economics model led to a clearer assessment of AI's deployment in education against criteria such as efficiency, fairness and long-term viability. While AI offers clear short-term gains in productivity and accessibility, its long-term costs in energy consumption and social implications require regulatory mitigation.

5.1 Benefits of AI in Education

The introduction of AI in education and society at large has multiple advantages. AI offers a way to reduce cognitive load and get tasks done easily for everyone accessible on the internet. Personalized learning bots create windows of opportunities for equalization of learning outcomes that are unprecedented (Pataranutaporn et al. 2025). Inclusion of minorities as well as preparedness for job requirements are additional benefits that AI offers in the educational sector (Seo et al. 2025). Though when it comes to concrete environmental impacts, AI polarizes. One the one hand, digitalization and the newest AI advancements are set to relieve some environmental impact based on human labor that is replaced. Some tedious tasks that previously were done by human may be automated. On the other hand, one has to note that there is an environmental burden and resource depletion potential of AI when being used large-scale and worldwide on a daily basis as for big data retrieval, computation and storage.

5.1.1 Reduction in Cognitive Load

AI can relieve students and educators from repetitive tasks such as grading, scheduling and resource curation. For instance, intelligent legal databases can streamline legal research, allowing students to focus on analysis rather than information retrieval (Ashley 2017). AI also enables to condense information quickly and display it in innovative solutions in a professional manner. AI also reduces cognitive load by allowing to synthesize complex tasks and help bridge language or capability barriers.

5.1.2 Personalization and Learning Efficacy

AI provides ample opportunities to personalize learning. First, AI can collect information on the learning journey of individuals and thereby tap into individual strengths and interests over time. Second, AI can also be used to bridge individual gap within a learning community. Adaptive learning systems, powered by AI, also offer customized learning paths tailored to individual student needs and progress. Overall, individualized learning experiences offer significant improvements in student performance (Kulik and Fletcher 2016). At the same time access to data how students use AI can reveal their learning journey and process time, which helps give grades that are attuned to effort and outcomes alike.

5.1.3 Accessibility and Inclusion

AI-powered tools such as speech recognition, language translation, and screen readers facilitate learning for students with disabilities and those in remote or underserved areas (Holmes et al. 2019). AI can thereby be used to close language barriers as a co-pilot navigating through difficulties with foreign expressions. AI also opens the world by giving easy access to understanding difficult concepts in a sophisticated data processing that allows for comprehensive results. Access to information but also easy in retrieval and standardized display in a professional manner has never been closer than as of today.

5.1.4 Workforce Preparation

AI has been encroaching the workforce since about 5 years, with particular applicability from 2022 on. Today, it is estimated that already over 30% of the U.S. workforce has been replaced or shrunk by AI

generated tools and applications. This massive shift in AI use and workforce change has created the deeper need to prepare students and pupils to become familiar with AI and digitalization tools as early as possible. AI-integrated education prepares students for a future digital economy. Understanding how to interact with and develop AI technologies has leveraged into an essential skill, aligning education with evolving labor market demands (Vinuesa et al. 2020). Education embracing AI therefore has become an essential part of learning and skills development at all levels.

5.1.5 Environmental Efficiency

Digital learning reduces dependence on physical resources like textbooks and transportation. A study by UNESCO (2019) indicates that e-learning can reduce carbon emissions by up to 90% compared to traditional models. Think of all the carbon emissions human workers have when getting ready for work and being a physical building to produce including their breaks when they are out for lunch or their commuting to and from work. AI also serves as a time saving and cognitive complexity reducing task, helping to accomplish goals easier and faster than ever before. The mental capacity freed but also the physical relief to not be present to perform tedious tasks and get access to information in a palpable way also allows humans to spend more time on enjoyable or more humanoid tasks. Future studies could compare the carbon footprint switch due to AI human worker replacement and perform a more rigorous cost-benefit analysis.

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6 Sustainability Challenges of AI in Education

The AI revolution in education comes with challenges when it comes to sustainability, which entail short- and long-term costs and risks. Awareness for the downsides of AI in education in the sustainability domain is essential in order to improve digital innovation and make it more sound with the natural resource limitations and environmental constraints. Challenges of AI in the sustainability domain are envisioned in Graph 1.



Graph 1 Challenges of AI in the sustainability domain (Source: ContextAI)

6.1 High Energy Consumption

Training and deploying AI systems uses a massive amount of data that is fed into algorithmic computation real time and worldwide. Data absorption, computation and storage require vast amounts of energy and power. For instance, data centers are increasingly becoming subject to scrutiny for supporting AI-driven platforms as energy-intensive contributions causing natural resource depletion. The cooling of data centers require high amounts of energy all year long, which exacerbates the climate change problem. To this day, we have no solid information on how to handle a massive load of big data when it comes to environmental conscientiousness. Strubell et al. (2019) estimate that training a single NLP model can emit as much CO2 as five cars over their lifetimes. AI in education will exacerbate the problem as for a massive influx of data due to widespread AI applications. In order to be in harmony with environmental and social sustainability pledges, AI in education should also boost economic modeling of integrating sustainability in the economic benefits calculus when striving for digital innovations.

6.2 Electronic Waste

Frequent hardware updates to support AI platforms result in electronic waste (e-waste), much of which is improperly disposed. The Global E-waste Monitor reports that only 20% of e-waste is formally recycled (Baldé et al. 2017). Problematic discussions center around e-waste emissions, sometimes referring to constant e-streams as source of disease and chronic conditions. AI in education may integrate health and social sustainability questions when it comes to the advent of digitalization. A healthy conduct around AI including its ethical use and learning a culture of diplomatic human interaction in educational institutions amidst the increased use of AI, are advancements of the future that may combat some of the expected downsides of AI.

6.3 Algorithmic Bias and Inequality

AI systems can perpetuate existing social biases if trained on unrepresentative data. For example, predictive analytics in admissions or assessment may disadvantage minority or marginalized students (Selwyn 2019). Overall, it is estimated that in the first 3 large LLM models biases were so prevalent that it was impossible to release the answers on a large scale. In addition, currently estimated 75 to 80% of the algorithmic computational power of AI is used for bias aversion and quality control. While these steps appear essential for maintaining a high quality of thought transfer, the extra computational effort raises environmental impacts of AI.

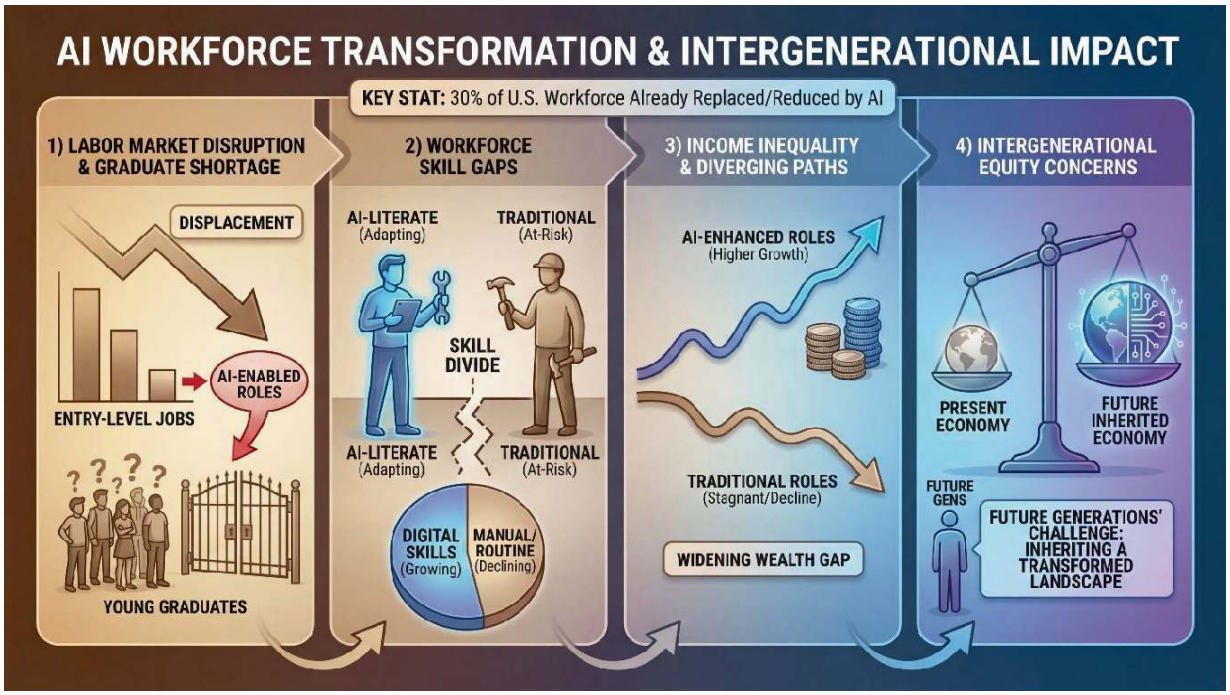
6.4 Data Privacy Concerns

When being used educational AI systems collect vast amounts of personal data, raising concerns about surveillance and misuse. Without robust privacy laws and security protocols, students' private information may be available and shape their future (Williamson and Piattoeva 2022). For instance, one could imagine that a market forms for employers to evaluate students based on their data and use of AI. Already now literature indicates that 30% of U.S. corporations scan applicants' submissions with AI. The next vigilant step would be to go deeper into their learning journey as tracked during their education. The quality and use of ChatGPT, for instance, could become a creative indicator of excellence. As data is fluid

and internationally shareable online, the efforts to curb data misuse will require global attention and enforcement.

6.5 Intergenerational Technological Debt

Overreliance on AI may reduce students' proficiency in foundational skills, such as handwriting or mental arithmetic, thereby creating dependencies that future generations must address (Puaschunder 2020). One can already find sources raising doubts about the positive influence of AI on society with particular attention to educational impairment. Critical thinking and social skills will become essentials for classroom teaching, while AI will be prevalent in homeschooling and tutor-like learning situations. Lastly, the current young generation is predestined in setting the tone what AI to be used and will therefore likely become an inspirational resource to draw from for curriculum development. In such, the sustainability of elder traditional teaching models will be questioned and likely be eroded over time and pass for eye-to-eye teaching dyads with students, who will be more self-sufficient and empowered than in previous generations. The relation of the AI workforce transformation and intergenerational impact of AI, are displayed in Graph 2.



Graph 2 AI workforce transformation and its intergenerational impact (Source: ContextAI)

6.6 Examples

Since the use of AI for Sustainability Education is a fairly novel topic, the international practice may vary (Bond et al. 2024). The chapter therefore addresses some highlighted anecdotal examples to underline the differences but also derive commonalities.

6.6.1 Estonia: AI in National Education Policy

In order to enhance digital literacy and personalize instruction, Estonia has included AI into its national education policy. Early assessments demonstrate increased administrative effectiveness and student involvement, but issues with data centralization and equality still exist (European Commission 2021).

6.6.2 United States: Predictive Analytics in Higher Education

The United States is historically pushing for innovation and a driver of AI, also in educational contexts. As early as high school education sees an application of AI. Several U.S. higher education institutions, foremost universities, use AI for predictive analytics to identify at-risk students. While effective in improving retention rates, these systems are criticized for reinforcing demographic biases and the need for AI ethics (Zimmerman 2020).

6.6.3 India: AI in Remote Learning

AI-powered mobile apps in India have democratized access to education in rural areas. However, issues of digital infrastructure, device availability and energy reliability limit scalability (World Bank 2021).

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7 Policy Recommendations

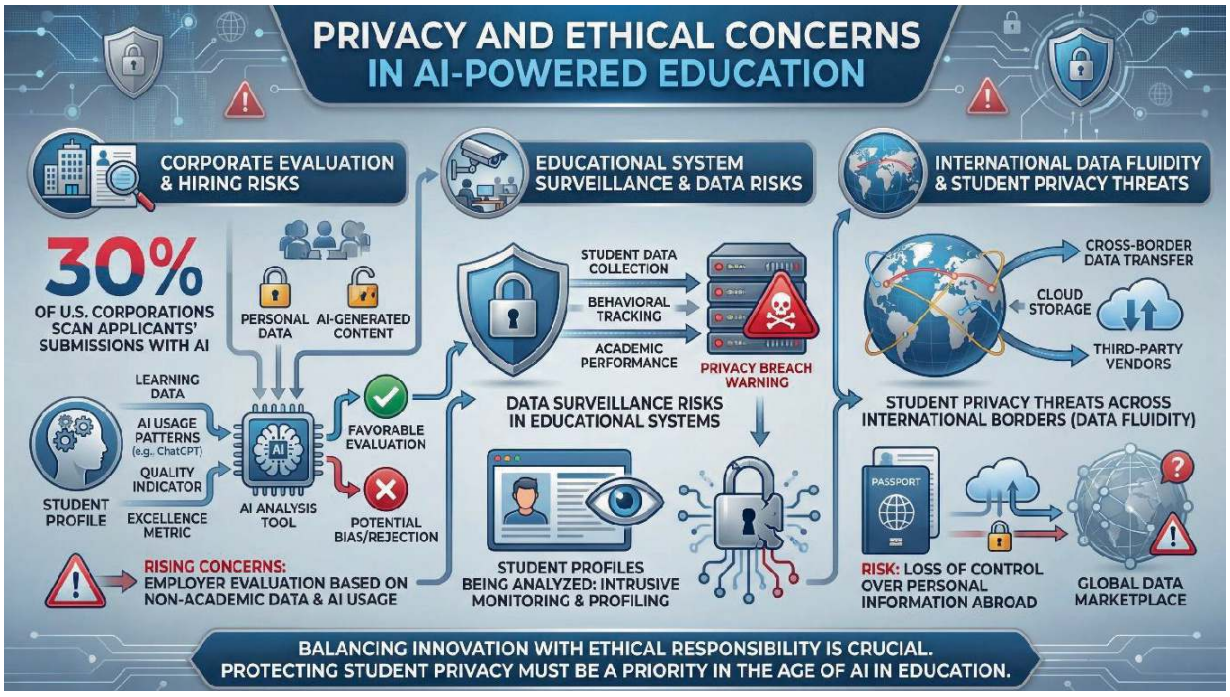
7.1 Promote Green AI

Support research in energy-efficient algorithms and green data centers, for instance, use geopolitical advantages, such as colder countries as data storage locations (Schwartz et al. 2020). Regulatory incentives can encourage the development of low-carbon AI technologies. Societal education can raise awareness for the benefits but also alert about the downsides of AI in order to breed a healthy use of AI. When it comes to

communication cultures with AI, one can already derive certain trends – for instance, the language Croatian is less popular in LLMs since the users were very critical – potentially a cultural feature – and therefore ranked Croatian-given answers down. In addition, parents have been found to teach their children respectful conduct with automated response systems, in order to continuously breed a positive and amicable as well as respectful tone of their children's voice in the day-to-day lives.

7.2 Enforce Ethical AI Standards

Develop national and international guidelines for ethical AI use in education, covering issues of privacy, transparency, and accountability (Floridi and Cowls 2019). Ethical notions will help to curb individual unhealthy behavior around AI. For instance, parents teaching their children to remain polite to bots and automated voice machines (such as Alexa) can do their part in upholding decency standards in growing up children. At the same time, ethical imperatives must be backed by regulation and legal standards that foster quality control in the advancement of AI. Figure 3 displays privacy and ethical considerations of AI-empowered education.



Graph 3 Privacy and ethical considerations of AI (Source: ContextAI)

7.3 Invest in Digital Infrastructure and Equity

Investing in digital infrastructure will ensure equitable access to AI-enabled tools, particularly in underserved communities. When it comes to sustainable development, AI promises to be a transforming moment that grants ample access to information and education in the international compound. Governments should fund digital literacy programs and infrastructure development. If governments fail to provide infrastructure for AI implementation, mobile networks still give opportunities to connect and use AI for the benefit of society. International AI governance and watchdog agencies must oversee the expansion of AI in all regions of the world and advocate for it to become a new window of opportunity to learn, catch up and equalize opportunities around the world.

7.4 Regulate E-Waste and Encourage Circular Economy

E-waste should become a subject to debate and scrutiny for various levels of actors. For one, a scientific investigation of e-waste's impact on human health should be started. For another, individuals should be alerted and made aware of e-hygiene to curb harmful exposure that is unnecessary. From the physical aspect of machinery that enables access to AI, mandate recycling protocols and support circular design for educational hardware can reduce environmental impacts (Baldé et al. 2017). Recycling programs may also expand access to information for marginalized groups that cannot afford computers – also with focus on digital distribution around the world. Remittances and transfer payments for international development may be coupled with e-gifts of resources that enable to catch up better in the international compound. Donations as well as direct aid could become cornerstones of a web of access to information and AI enabled by better distribution of computers and digital devices.

7.5 Conduct Long-term Impact Assessments

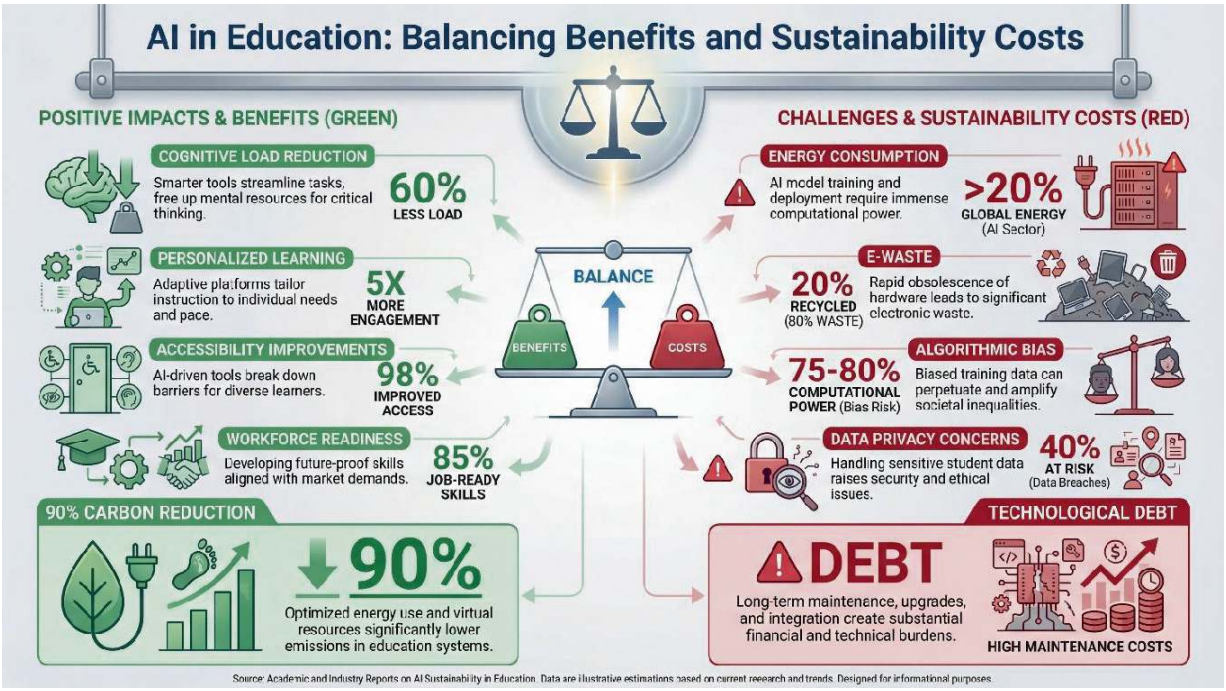
As AI is believed to be a long-term transition to a more digitalized economy and society, the regular assessment of AI in education in terms of its environmental and educational impacts will be crucial. International guidelines and best practices derived from benchmarking can help in the standardization of AI conduct. Regular quality control but also

institutional backing of plans are additional AI improvement recommendations. Within global consortia, information exchange but also collaboration efforts are advised to become part of the common advancement of an OpenAI project. In the assessment, yearly status reporting on environmental impacts are key that may also incorporate intergenerational equity and societal sustainability questions into policy decisions. Reporting will also enable to proof to future generations the historical advent of AI was taken on responsibly and with long-term care.

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8 Discussion

In the discussion of the found strengths and weaknesses of AI in education with attention for sustainability, the practical implications of the analysis are manifold. Figure 4 sums up the results derived from the weighing of costs and benefits of AI in education.



Graph 4 The costs and benefits of AI in education (Source: ContextAI)

First, policy design based on short-term and long-term assessments may help avert AI harms for society. Taxation can ensure to redistribute some of the gains from AI for offsetting some of the losses of AI – for

instance, in the education sector, laying off of traditional teachers for AI-enabled teaching bots may cause unemployment frictions. Transfer payments could be funded by taxation of AI-providers to be then reallocated to those who face career change challenges. Taxation and subsidies also set incentives for sustainable consumption and innovative production that internalize environmental and social externalities. Behavioral nudges offer choice architectures to promote sustainable decisions, not only directly but also indirectly.

Theoretical recommendations.
Concrete recommendations will address corporations to advance AI for education with respect for global sustainability pledges. Developing long-term AI creation and sophistication plans can align with financial backing but remain focused on environmental constraints as well after a thorough analysis of the environmental impacts. Applied implications would be ethical data conduct, green practices, employment benefits as well as sustainable supply chains on the corporate level. Societally, one could prospect the intergenerational changes imbued in the AI transformation in order to breed a harmonious generational compound. Educational advancements could feature sustainability literacy in AI practices, emphasizing intergenerational ethics, environmental economics and behavioral decision-making to prepare future leaders for sustainable AI governance.

Practical recommendations.
Overall, while groundbreaking insights were retrieved, practical implementation challenges remain. For example, operationalizing AI with ethical and environmental care in market economies driven by short-term incentives and bottom-line-focus requires substantial political will and public support. With digitalization mainly operating on a global level, AI solutions that are ethically sound and environmentally conscientious will require global coordination. Mechanisms to enact change will therefore require global legal action and international enforcement, which have their limitations, especially given the contemporary climate of sovereign nation states.

Policy recommendations.
This chapter's Law & Economics analysis showed that AI can support the objectives of sustainable development and intergenerational justice with the right laws and policies. Future studies should keep an eye on and assess how educational AI systems affect society and the environment.

Overall, this chapter's findings directly address the research questions and bolster the hypotheses put forth by demonstrating that the application of AI in education produces both long-term environmental and social externalities that support the environmental trade-off hypothesis and significant short-term benefits like increased efficiency, personalization, and accessibility, thereby confirming the efficiency hypothesis. The research also shows that these externalities are likely to be transferred to future generations in the absence of regulatory intervention, supporting the intergenerational equality hypothesis.

The chapter uses a Law & Economics framework to demonstrate how these conflicting effects can be methodically assessed and how well-crafted legal and policy mechanisms can internalize sustainability costs, reduce intergenerational risks, and match AI-enabled education with long-term societal welfare. This confirms the regulatory mitigation hypothesis and provides an answer to the main research question about how the advantages and disadvantages of AI in education can be balanced in a sustainable and equitable way.

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9 Limitations

While this chapter offers a first and important exploration of sustainability aspects of the use of AI in education, several limitations must be acknowledged.

First, the analysis is conceptual and literature-based rather than empirical. In that it sets the stage for future empirical investigations. But the findings are not derived from primary data or stringent statistical hypotheses testing. We therefore cannot establish causal relationships and clear quantification of results.

Second, the literature review is integrative rather than systematic. This feature directly limits completeness and may be subject to a selection bias in the sources discussed.

Third, the international examples are illustrative and drawn from secondary sources. Rather than cases, they are short examples that constrain generalizability and comparative validity.

Fourth, the sustainability impacts of AI are discussed only at a theoretical level. The reason for this is that reliable, standardized metrics for measuring environmental and intergenerational effects of AI in education remain limited.

Fifth, the novelty of the subject means that empirical data is still sparse, and many of the arguments rely on emerging trends or theoretical projections rather than long-term evidence.

Sixth, although a Law & Economics framework was employed to evaluate costs and benefits, the rapidly evolving nature of AI technologies may render current analyses outdated as newer applications emerge. The validation of recommendations will therefore become a race with backtesting and adapting to novel innovation in the AI domain implemented in the education sector.

Seventh, the diversity of educational systems and AI governance frameworks across different countries further limits the generalizability of the recommendations given. Cultural, legal, and infrastructural disparities were only partly addressed in picking diverse examples and cases in order to outline the international dimension of AI in education. But further international case studies should consolidate the findings and help clarify the common theme through different cultural context but also dividing elements that are culture-specific in the AI trend.

Eighth, while behavioral and intergenerational aspects were incorporated, the study could benefit from broader interdisciplinary engagement with psychological, anthropological and environmental sciences to fully grasp the long-term impacts of AI in educational settings for scientists and practitioners alike.

Finally, given the rapidly evolving nature of AI technologies and regulatory frameworks, some conclusions may become outdated as technical efficiencies, governance mechanisms, and policy responses continue to develop.

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10 Future research

As the AI revolution proceeds, the more and the more diverse data will emerge and therefore provide opportunities for future quantitative studies will constantly arise that we should test and backtest on a constant basis. Future research should aim to address these gaps through longitudinal studies, empirical benchmarking and broader global participation. Future research could also focus on mechanisms to quantify the impact of AI on the economy and society. Lawmaking and policy regulation of AI should be streamlined with respective legal enforcement to curb the downsides of AI. Taxation phased into the economy to reap some of the financial benefits of AI could create the fiscal space to redistribute in order to alleviate some of the losses expected due to AI. Empirical studies could also assess the effectiveness of behavioral nudges to alert for sustainability in the AI implementation. Technological frameworks should help integrate AI, blockchain, and sustainability to enhance transparency and accountability in educational governance.

Future directions for innovation and societal advancement may include bringing harmony into the human-AI collaboration within the larger sustainability framework. The future of education lies in hybrid systems that combine AI efficiency with human empathy and environmentally-sound judgment. Teachers may more and more transition to facilitators and AI mentors, blending in AI sources whilst focusing on critical thinking and ethical reasoning (Selwyn 2019). Asynchronous assignments may challenge digital tools and train individuals to use digitalization for task accomplishment. While classroom settings will likely become more focused on emotional soft skills, human teamwork and learning journey aspects.

In the investigation of sustainability aspects of AI in education, sustainable development should play a vital role. Like on other tool AI and digitalization are relatively cheap and transnational phenomena. Mobile phone access to information via the internet can grant worldwide access to advancement and prosperity. AI advancement from this perspective allows for sustainable development, especially when it comes to the use of AI for education. Free from governmental control and censorship, international access to AI tools online may serve as implicit human capital development. As such, AI promises to alleviate social disparities on a

global level without political interference or financial transfer payments. Likewise, AI can help lift up social strata all over the world to catch up to other societal groups that are more advanced and bestowed with advantageous conditions.

From a lifelong learning perspective, AI allows for access to individualized, self-paced courses aligned with the newest societal developments and workforce needs. Not to mention that AI needs to be developed and designed for inclusivity and accessibility, with different institutions now forking out AI for their individual entities and then be trained by their users, AI will advance into different versions and tools (Holmes et al. 2019). Closely monitoring and comparative studies on the different forms of AI will become key. Economic analyses should be coupled ethical imperatives to avoid a race to the bottom for market gains based on unethical market conduct. Moratoriums and market watch worldwide but also incentives that set a race to the top for subsidies and transfer payments may ensure that a right, just and fair AI solution is found in the international compound. Cross-sectoral collaborations will enable benchmarking and best practices development as well as allow for grand oversight control. Thereby, educational institutions, technology companies, and policymakers must collaborate to design AI systems that are sustainable, ethical, and socially inclusive. An interdisciplinary sustainability framework would offer a roadmap for decision-making that balances immediate needs with long-term innovation that ensures a resilient and equitable future for all in harmony with sustainable environmental conditions.

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11 Conclusion

Overall, one can conclude that AI holds outstanding transformative potential for education, offering efficiency, personalization and increased access. However, despite these benefits, one needs to warrant for caution regarding sustainability concerns, which require addressing its environmental and ethical challenges.

The presented work was aimed at reshaping our understanding of AI in education for sustainability aspects. When embedding AI in education, the cost-benefit analysis performed alerts for attention to ethical,

economic, behavioral and legal implications. The vision of AI in educational settings with respect for sustainability was targeted at compelling policymakers, corporations, and individuals to act not merely for present efficiency but for the flourishing of innovation within our natural resource limits.



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Leveraging Ethical Artificial Intelligence for Sustainable Policy and Research Education

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Abstract
The application of artificial intelligence (AI) to education and policy-making offers them both hotly awaited possibilities and urgent ethical concerns. This conceptual paper, aims to understand how ethical AI models can drive data-informed decision-making that is in line with sustainability missions, ethical research practices and procedures. Though AI holds untapped tools for analyzing complex data, introducing prognosatory potential, and assisting policy creation, the paper negates that unchecked use might actually perpetuate biases, and foster irresponsibility and loss of transparency which will weakenedsocieties..A conceptual framework is developed in the paper that situates ethical AI as a connecting point between raw data and actionable decisions in the subject area of policy and research education. Using cutting-edge paradigms from data sciences,

sustainability studies and educational literature: The pillars of the framework are four: (1) fairness and accountability of algorithmic models; (2) inclusion in data representations with stakeholders; (3) transparency in decision-making; and (4) outcomes towards sustainability for long-term social and ecological welfare..By incorporating these pillars into both policy and research education, the research identifies how institutions could guide their future African leaders and researchers to provide them with the competences to think critically with AI while ensuring ethical protection. The paper is further used to show how the adoption of ethical AI improves the legitimacy of evidence-based policymaking and is used to support changes in educational practices aimed on instilling responsibility through innovation. Informatics Research: This study adds to the ongoing discussion on the governance of AI, by presenting design frameworks based on education and policy that embedding ethics in the design of data-driven system itself. Ultimately, the study calls for human-centered approach to AI, which not only helps make decisions faster but also ensures that the technological advancements are on the path for sustainable and socially responsible futures.

Keywords Ethical artificial intelligence – Sustainable policy – Research education – Data-driven decision-making – AI governance

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1 Introduction

1.1 Context and Rationale

The current century is characterized by the technological revolution that has never been experienced before to redefine how societies change, adopt, and assess policy and teaching paradigms. Machine learning, natural language processing, and predictive analytics as the subfields of Artificial Intelligence (AI) have turned into a core tool of decision-making activities, government, and academic research. Governmental organizations and educational institutions also engage in more uses of AI to address complicated problems of society such as

climate change, equity in healthcare, and the learning character. Machine learning models forecast patterns related to unemployment or epidemics are now used to allocate resources in the learning institutions; predictive analytics are used to inform the global development agenda; and data-intensive dashboards are used to predict trends.

Nonetheless, the very same technologies which promise to become efficient, precise also make things incredibly difficult in terms of ethics. Algorithms have a tendency to reflect the information that they are built upon, and perpetuate historical wrongdoings and obscure decision making that precludes consequences. The rapid evolution of automation poses a danger of pushing the institutions of humankind behind in their pace to formulate regulations, ethics, and pedagogy. Thus, in research-education and policymaking, the increased use of artificial intelligence is a two-fold challenge: to ensure positive and effective applications of digital intelligence to facilitate the process of sustainable development and to make sure that the intelligence is consistent with the ethics of people, democracy, and a sustainable environment. This has led to argument on ethical artificial intelligence (EAI) as a result of the tension that exists between innovation and ethics. International standards on the ethics of Artificial Intelligence or the OECD AI Principles emphasize the fairness, transparency, accountability, and human oversight. Nevertheless, practical growth of these principles as applied to policy education, research training programs and institutional governance arrangements is found wanting. People urgently need to re-conceptualize education not as a passive receiver of artificial intelligence instrumentation but as an active discipline to develop ethical reflexivity and a sense of sustainability. In this context, the proposed research frames ethical AI both as a technological enabler and a normative framework potentially capable of relating data-based understandings to sustainable policy development. In building in ethical considerations, where governance, research scholarship, and decision-making processes have come to rely on Artificial Intelligence (AI), the general term to designate machine

learning, natural language processing, and predictive analytics as their core tool. Government and education agencies are also engaging in more applications of AI in meeting some of the most challenging tasks in society such as climate response, equality in healthcare, and the learning nature. In learning institutions, predictive analytics are responsible now when it comes to the allocation of resources; machine learning models are used to forecast trends related to joblessness or epidemics; and data-intensive dashboards change world development agendas. Nevertheless, there is still a lack of practice in the development of these principles in terms of policy education, research training schemes, and institutional governance arrangements. It is urgently necessary to reformulates education as no longer being a passive recipient of artificial intelligence instrumentation but as an active discipline towards cultivating a sense of sustainability and ethical reflexivity. The suggested study, in this respect, contextualizes ethical AI as both a technological facilitator and as a normative construct that may have the ability to refer to insights based on data to policy formulation that can be sustainable. When incorporated ethically to the lowest tier of the AI-enhanced decision system, the institutions can foster inclusivity, legitimacy, and overall good in the long run. With this theoretical study, the author seeks to demonstrate that in case ethical AI is integrated into research training, it may be able to enable future leaders to make wise, just and environmentally-conscious decisions.

1.2 Problem Statement

Despite growing enthusiasm for AI adoption, its ethical integration in policy and education remains inconsistent and fragmented. Most initiatives emphasize algorithmic efficiency while neglecting the moral dimensions of automated decision-making. Biased data continues to affect employment, lending, and student evaluation systems. The opaque nature of AI-driven judgments makes it difficult for citizens and students to understand how conclusions are formed. In higher education and policy research, AI's speed in generating evidence often

undermines critical thinking and human empathy. When algorithms determine funding priorities or assess scholars without context, they risk reinforcing inequality. The absence of shared ethical standards and accountability mechanisms prevents auditing or questioning of algorithmic outcomes. This ethical gap threatens sustainability's core values—trust, shared governance, and inclusivity. The challenge is both technical and philosophical: how can societies design AI systems that unite intelligence with justice and efficiency with compassion? Without a unified ethical framework linking AI, sustainability, and education, current efforts toward sustainable development remain fragmented and potentially harmful.

1.3 Objectives

The target of this research study is sealing the gap through completion of three related tasks:

1. To consider ethical AI an accelerator of sustainable research and policy through the conceptualization of ethical ecosystem supporting sustainable goals and human values.
2. Establish a multi-pillar framework of fairness, inclusiveness, transparency, and sustainability in a bid to incorporate ethical reasoning in the creation of AI not only in the creation of educational and policy choices but also in the development of the legitimacy and trustworthiness of the population.
3. To understand the possibility of equipping future policymakers and researchers with ethical AI through curriculum, experiences, and digital literacy training developing ethical competency, reflective judgement, and responsible innovation.

These aims aim to balance technological change and sustainable learning and governance such that AI serves the common good, as opposed to efficiency.

1.4 Research Questions

To meet these objectives, the study will answer the following guiding questions:

- What is the possible systematic integration of ethical AI into sustainable policymaking and research pedagogy? This question looks at how the computational properties of artificial intelligence can be reconciled with ethical values, e.g. justice and environmental responsibility.
- Which are the basic ethical patterns and infrastructures that one needs to set equity, inclusiveness, transparency, and sustainability in artificial intelligence-based systems? It considers the manner in which the values of ethical design can be incorporated in codes of practice, audit procedures and interdisciplinary practice.
- What do institutions of higher learning need to do to inculcate ethical AI in research and learning environments to develop responsible innovation in future leaders? The question is pedagogically motivated- how the curriculum, assessment, and research supervision can enhance the development of critical sensitivities to the social and ethical consequences of AI.
- What are the overall impacts of ethical implementation of AI on the Achievement of the Sustainable Development Goals (SDGs) and the long-term human development?

The rationale behind AI guided by ethical thinking, why it remains an important enhancement to world goals of reducing inequality disparities, good learning and sustainable industrial innovation, is the guiding force to the development of the conceptualized framework and the further discourse regarding AI governance, policy making and educational revolution.

1.5 Significance of the Study

This paper will combine the ethical, educational, and sustainability aspects of artificial intelligence (AI) into a single conceptual framework. It broadens the discussion of AI governance to include technical and legal perspectives by preempting epistemological and pedagogical

ones, namely, the production of ethical knowledge, its transmission and institutionalization in research education. The paper shows that fairness, inclusivity, transparency, and sustainability can increase legitimacy, accountability, and social trust in policy processes by putting ethical AI as a tool of reflective and evidence-based governance. The suggested framework offers practical information to universities, think tanks and governmental agencies to harmonize data-driven initiatives and ethical mandates by means of bias auditing, accountable curriculum structuring and evaluative policy apparatus. Finally, the paper also develops the perspective that ethical AI is not the limitation on the advancement of technology but rather a normative tool that leads technological growth toward equity, integrity, and planetary sustainability, thus providing a sound basis of empirical research and policy creation in the future.

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2 Literature Review

2.1 Ethical Artificial Intelligence: Foundations and Principles (A)

Artificial Intelligence (AI) emerged as one of the factors to governance, research and learning; however, the intensive application of AI could bring considerable ethical concerns. The recommendation at the global level on the ethics of AI stirs four major principles, such as human rights and dignity, environmental sustainability, equity and non-discrimination, and peaceful societies, which will serve as the human value to control AI applications in every sphere. Jobin et al. (2019) identified 84 international guidelines on AI ethics, and also found that they overlap on various concepts such as fairness, transparency, accountability and privacy protection, but did not apply them in their engines. These principles are the moral blueprint to the responsible AI, and, more frequently than not, are too abstracted to be learned by the learner and policy spheres where ethical competency is honed. Artificial intelligence may be equitable so that its implementation is just to every individual and demographic through reducing biases

within data sets and algorithm decision making activities (Mehrabi et al. 2021). The accountability serves to make sure that even the human based decision-making process will never be in-exonifiable, and therefore, the perpetuation of moral and legal accountability (Cath et al. 2018). Transparency means that the AI models must be interpretable and readable, so that the stakeholders will be capable of knowing and auditing the algorithmic reasoning (Mittelstadt 2019). All these are the ideals of trustworthy AI. Nevertheless, ethical AI is not possible only with the help of technical equipment as Borenstein et al. (2021) consider a human-cantered design and management are necessary. Thus, the role that learning institutions are playing, as well, is the imbibition of morals and critical sensitivities in researchers and policymakers. Ethical AIs in the curriculum could also turn students into thoughtful practitioners to perceive AI not only as a technical system but also as a socio-technical system with values and trade-offs and with a societal impact.

2.2 Policy Education and sustainability (P)

Creating sustainability talk has ceased to be about environmental sustainability to the broader view of social fairness and economic sustainability and integrity of institutions. Against the expanded view, lifelong learning may emerge as a valuable means to create sustainable leadership, good governance, and inclusive innovation (Lozano et al. 2017). As a method of attaining sustainable societies and as an end to sustainable societies, education plays a role in both its goals and its execution as depicted in the Sustainable Development Goals of United Nations particularly SDG 4 (Quality Education) and SDG 9 (Industry, Innovation, and Infrastructure) and SDG 16 (Peace, Justice and Strong Institutions). The sustainability policy education requires the development of capabilities that ensure that the students will be able to deal with uncertainties, as well as to integrate ethical reasoning and devise solutions that will be inclusive. The technology of artificial intelligence can play a significant role in this direction through the assistance of ethical principles since it will ensure evidence-based

decision-making and scenario planning to execute policy decisions against long-term goals towards realization of sustainability. One of them is the prediction AI models which can propose the predictability of environment and the social implications of policies even before they are implemented and thus promote proactive governance.

However, the current body of literature is a sign of an on-going disparity between the sustainability agendas and the digital innovation strategies. Even though the AI-driven analytics is capable of centralizing all resources and tracking environmental indicators (Vinuesa et al. 2020), the comprehensive designs are yet to be designed to ensure that the technological provisions are being used within ethical and pedagogic guidelines. According to Williamson and Eynon (2020), technology integration in education tends to be realized in an instrumental fashion that i. e. it is valued in terms of its ability to bring in some efficiency gains, as opposed to learning-fluation that is limited to the lens that it promotes the specific perspective of learning. The sustainability policy in education must therefore broaden its scope to incorporate the digital ethics so as to prepare the future policy makers to analyze the process of decision making of the algorithms and its impact on equity and justice. The moral compartment added to the teachings on sustainability of the technical knowledge will ensure that the moral duty and interpretation of the systems are adapted towards the technical knowledge. It is this convergence of digital and ethical literacy that comes to play that is critical in order to transform AI, not to be more than a solution of automation, but an answer to inclusive and responsible governance.

2.3 AI in Research and Education (R)

AI has changed the method of conducting and learning research by processing the data with the help of intelligence and interpretation, thus automated. The scope of the question and answer in literature review and predicting student performance by machine learning have expanded the scope of inquiry and the precision of the response. Through education, AI applications have been applied to analyze the

learning behavior, personalize the instructions and maximize the performance of the institution (Luckin and Holmes 2016). They have their usefulness in policy research because they assist in the mining of the texts, simulating socially, or making evidence based decisions. Quick application has however projected issues of morality and knowledge. AI makes institutional inequality more concrete whereby prediction algorithms are informed by the biased data, and students are re-evaluated, on the premise of reconstructed socio-economic disparities (Williamson and Eynon 2020). Similarly, algorithmic bibliometrics could be advantageous to specific areas or languages and reinforce academic hierarchies. This works against the concept of transparency and credibility of learning research since the opaqueness of the Black-box models weakens the interpretability and accountability (Larsson and Heintz 2020). New models such as Explainable AI (XAI) and AI literacy were developed to underline the importance of critical perception of ethical, social and political aspects of AI (Long and Magerko 2020). That scientists are instructed to doubt datasets and algorithms turns AI into a judgmental collaborator and no longer a substitute of judgment. This is a complete spectrum of AI that involves transdisciplinary engagement and institutionalization that bring about ethics to the research and learning cycle (Singh et al. 2025).

2.4 Risk of Ethics and its Challenges (C)

AI possibilities in policy making and learning are medium-level because of the technical, moral and institutional issues. Some of the most significant issues are the biasness of the algorithms, their transparency, misuse of the data and their unintelligibility. Problem with the bias of algorithms is that the training data restages historical inequality and, based on this, predictive systems can continue the discrimination in the selection, admissions, or allocations, (Pasquale (2015)). Such hypocrisies in the AI decision logic, which has since become hard to trace, makes accountability impossible, creates some sort of a responsibility fracture (Matthias 2004), and the abuse of any data as surveillance, commodification, or without consent introduce some

large ethical issues in terms of surveillance and self-control. The transparency proofs are obtained in the high-accuracy models which leads to the concept of black box society proposed by Pasquale (2015). This is in the case of education which has been translated to automated marking or admissions that have insufficient human interactions. The fact that there is no or limited university or government institution that has come up with review policies in AI ethics or enforcement regimes aggravates these problems through weak institutes. The concept promoted by Van Maanen (2022) is a sustainable ethics of AI, meaning that they should ethically consider the AI cycle. Education and policy systems responsive, modified, and improved along with innovation or the widening divide between the technological benefits and ethical readiness will make AI a sorting and a source of harm.

2.5 Research Gap (Synthesized Across A–P–R–C)

Comparatively, the current literature on the topic concentrates on the ethical, technical, and regulatory implications of AI in a comprehensive manner but scarcely brings together such understanding in a sustainable policy and research education. The overwhelming proportion of frameworks perceive the ethical AI, sustainability, and education as research areas that cannot be separated and possess subsystems. The theoretical understanding of how the ethical guidelines of fairness, inclusivity, transparency, and sustainability can work in concert in the AI-based policymaking and learning systems is minimal. Moreover, as of today, the AI ethics guidelines are largely abstract and normative and do not have the input to inform the process when applied to the sphere of education. A pedagogical implication of ethical AI is how students, researcher and policymakers should learn to critically respond to algorithmic decision-making decisions, which remain understudied. In the same manner, sustainability studies have a non-emptive perspective of ecological and social welfare of long-run, but few of them have viewed AI as a radical means to ethics. This theoretical separation provides some insight into a research gap: the gap of an integrative theory between ethical AI and learning sustainable

policy. Such a design will be required to consider interdependence of the technological capability, morality of reason as well as system sustainability. This difference must be bridged to ensure that the realization of the AI in education and governance is more effective and without affecting the equity, transparency and ecological balance.

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3 Conceptual Framework: Ethical AI for Sustainable Policy and Research Education

Such a theoretical framework puts Ethical Artificial Intelligence (EAI) at the intersection of information, human judgment, and environmental performance in the spheres of policymaking and educational research. Although the existing literature has identified the ethical issues involved with AI, and the potential of sustainability-oriented governance, studies proposed an in-depth model uniting the two aspects are missing. To fill this gap, the proposed framework presents four key pillars, i.e., Fairness and Accountability, Inclusivity and Representation, Transparency and Explainability, and Sustainability-Driven Outcomes, which together can allow the ethical integration of AI into policy and the educational framework. All the pillars have a twofold role. At the bottom level, it offers normative advice by defining the ethical standards to be used in the design and implementation of AI systems. It is then an educative source on the second level, and how research and policy education might prepare future leaders to critically assess and use AI responsibly. To that end, the framework works as a conceptual map but also as an institution transformative learning framework that is unified under technology, ethics, and sustainability.

An illustrative Ethical AI Governance model shaped by values, technology and oversight in the form of a circular model is shown in Fig. 1. Four interdependent pillars, Fairness and Accountability, Inclusivity and Representation, Transparency and Explainability, Sustainability-Driven Results have arrows each in both directions. The outer circle refers to Sustainable Impacts, e.g. social equity, institutional trust and ecological balance. The model shows how fairness fosters

inclusivity, transparency fosters inclusivity, transparency fosters sustainability and sustainability fosters fairness creates an integrated ecosystem of AI governance and sustainability-based ethics in AI policymaking and AI pedagogy.

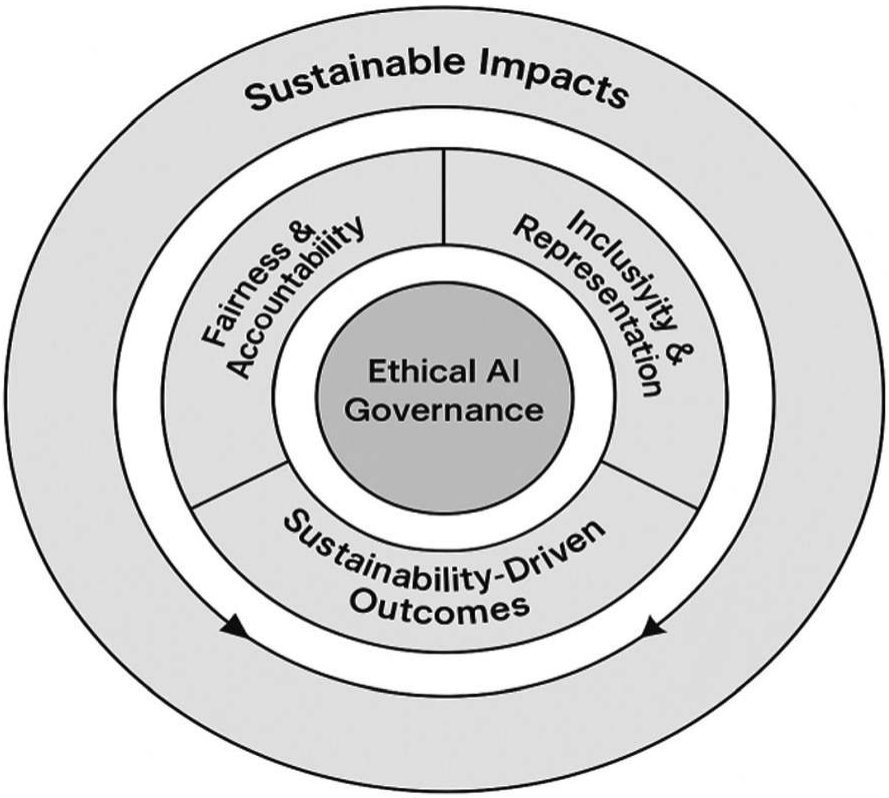


Fig. 1 Ethical AI framework for sustainable policy and research education

3.1 Pillar 1: Fairness and Accountability

The ethical principles of AI governance are fairness and accountability. Fairness treats all equally, reducing the bias in the case of discrimination based on biased data or algorithms (Binns 2018). The models of AI-fed policymaking are not able to promote specific demographics; welfare systems should address overlapping inequalities of gender, caste, geography, and class. Absence of supervision by predictive analytics may entrench inequality in the systems. To be fair, it is necessary to conduct bias audits, diversified data and ethical impact on AI design. Lack of accountability will enable inequity through traceability and monitoring. Ethical AI system

involves audit trails to trace the source of the data, updating of the models as well as decision-making processes. This matters vital in the area of governance and pedagogy where the outcomes of the algorithmic choices, i.e. funding or admissions, have devastating human impacts. Accountability-by-Design also ensures that AI-decisions are under the control of people, and they are also subjected to the ethical analysis. The aspects of fairness and accountability emerge in such areas as educational research. Students should be taught that AI products are not value-free, but value-based. The implementation of just and accountability within the AI literacy offers enlightenment on the issue of looking back at the morals of the data, inclusivity and social justice. The combination of the said elements supports ethical AI governance whilst allowing the technology to progress without depriving human dignity, justice, and trust.

3.2 Pillar 2: Inclusivity and Representation

The secret to the reflectiveness of AI technologies of the human diversity lies in inclusivity and representation. Ethical AI requires social inclusivity, when a number of voices are represented in the sum of data, designing algorithms, and policy assessment. Inclusive AI systems are inclusive of diverse datasets in terms of culture, gender, geography, and socio-economic status (Singh et al. 2025). Unless there is heterogenous data, under-represented populations are filtered by algorithm. Indicatively, most language models that are largely founded on using English texts have ignored linguistic diversity. The outcome of this in the policy-making process can be experienced in governance which fails to consider the needs and concerns of minorities and underdeveloped areas. The ethical making of policies also entails representation in the form of stakeholder participation as there is the incorporation of consultations with the citizens and communities in developing AI. The coproduction of AI tools that are consistent with social values is made possible through the participation mechanisms, including the workshop. Inclusivity in the education sector involves restructuring of the curriculum. Making AI education shift toward:

Inclusion of ethics, social science and sustainability takes AI education out of the technical and into the moral imagination (Singh et al. 2025). It is through exposure to the progress of the AI in different case studies that students learn so that they can be aware of the world around. The concept of inclusivity, thus, cuts across the ethical and the epistemological, reducing algorithmic exclusion, and enhancing learning. Institutions can facilitate equal AI involvement that overcomes disparities by introducing inclusivity in their policies and learning.

3.3 Pillar 3: Transparency and Explainability

The trust in AI systems is explained by explainability and transparency. Transparency implies algorithmic transparency, whereas explainability is the possibility to comprehend the way a given AI model results in output (Van Maanen (2022). They collectively form a base of accountability, which makes the stakeholders audit and challenge AI decisions. The growing complexity of the models, and especially deep learning, has resulted in what Pasquale (2015) describes as a black box society. Transparency will enable the policymakers and the people to examine the objectivity or credibility of the algorithmic output. Explainability brings AI to a level of being comprehensible to enable students, teachers and authorities to see the logic behind AI. Transparency in the context of governance means transparent algorithms, data available, and model assumptions and metrics made overt. This transparency brings about trust in the people and strengthens the legitimacy of policies. Explainability is used as both the technical and moral instruments in educational research. Students must study and understand methods of interpretability, including SHAP and LIME as well as role played by transparency in generating justice and informed consent (Singh et al. 2025). The system is expected to be responsible by making institutions integrate ethical audits and publish AI governance reports. Collectively, transparency and explainability enhance fairness, inclusiveness and sustainability -building trust in responsible AI regulation.

3.4 Pillar 4: Outcomes that are Sustainability-Based

The last pillar called Sustainability-Driven Outcomes puts ethical AI into the framework of social and environmental health. AI is governed by fairness, inclusivity, and transparency and enhanced by sustainability to pursue planetary and social objectives. It extends to social sustainability (equity, inclusiveness, empowerment) or economic (responsible innovation) or environmental sustainability (energy efficiency). Since AI has massive computing requirements as well as carbon footprint (Strubell et al. 2019), the integration of sustainability measures promotes energy-efficient computing and ethical management. On the policy level, AI based on sustainability supports climate models, efficient resource use, and recovery after disasters (Vinuesa et al. 2020). Devoid of ethical protection, it poses a threat of enhancing the socio-ecological disparities by being profit-driven rather than preservation. To make AI ethics congruent with the United Nations Sustainable Development Goals (SDGs), it would be appropriate to make sure that innovation promotes human and environmental stability. Sustainability-driven frameworks in education facilitate the use of systems thinking, where learners ensure the evaluation of AI projects in terms of inclusiveness, energy consumption, and social value in the long term. Incorporating these criteria in the curriculum makes curriculums more sustainable literate and digitally and ethically competent. Finally, this pillar transforms ethical AI into a guiding principle, rather than a regulatory one, to change the social structure, such that the technological advancements allow people to honor the principle of intergenerational equity and achieve sustainable development. The approach is a conceptual one since the ethical AI skills, sustainability-driven policy, and ethically oriented academic research should involve a theoretical synthesis, but not a test. This mix of AI ethics, sustainability governance and pedagogical theory can inform the policy and curriculum development, thus illustrating how equity, inclusivity, transparency and sustainability can be prioritized. It also creates the basic lines of the implementation of ethical AI into the

training and institutional practice so that a consistent framework was built to be subsequently translated into empirical validation.

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4 Discussion

The abovementioned conceptual framework re-conceptualizes Artificial Intelligence (AI) and portrays it as a pedagogic and normative system rather than merely an implementation-only computational tool. The framework consisting of the four pillars, which are Fairness and Accountability, Inclusivity and Representation, Transparency and Explainability, and Sustainability-Driven Outcomes, connects the ethical with the sustainability aspects of AI in both the policymaking and the research education domains. It promotes a wholistic approach to the vision of technology, governance and pedagogy evolving together through moral argument and social responsibility. The framework creates a feedback system that determines the reinforcing nature of all the ethical principles through the rest. Justice is rooted in fairness, the inclusion of multiple views in designing an algorithm and policy, transparency builds the confidence of the masses and makes the actors responsible, and sustainability bases technological development on a long-term good, both human and the environment. The combination of these principles turns the conceptualization of AI systems, their delivery and teaching in institutions - where the performance measure modernizes into ethical consistency and social good. In the classical paradigms, AI is evaluated on the basis of accuracy or efficiency, or on the basis of scalability. Herein proposed, the framework shifts the measurement of the AI to the ethical effectiveness that is the extent to which AI promotes fairness, inclusivity, and sustainability. The shift actualizes achievement in digital-age policymakers and research pedagogy: data and algorithm systems are not only judged as valid whenever they accomplish at their best, but rather when they accomplish in a transparent and fair and sustainable manner.

4.1 Reforming Policymaking by Ethical AI

According to Objective 1 of Fig. 1, the need to back ethical AI in accelerating sustainable research and policymaking enabled the study to reveal that fairness, accountability, and transparency as a set of governance anchors could be considered essential components of sustainable policymaking. The applications of AI in evidence-based policy development, economic prediction, the provision of healthcare supply chain, and modeling the environment are necessary. Technocracy may, however, end up in the superficial moral decision without morality. The proposed framework considers ethical AI values in the overall process of policy cycle: agenda-setting, design, implementation, and assessment. Ethical AI assists policymakers in defining policy concerns as well as setting priorities. Equity provides de facto groups with the influence in data collection and policy-making. As an example, social welfare analytics can have body diversity by providing inclusive datasets that lessen the prejudice against low-income or rural communities.

1. Policy Formulation: The procedures of accountability like audit of algorithms and ethical impacts will align AI tools with human rights. Transparent processes help to get the stakeholders to understand the process of decision making fostering legitimacy and engagement by the population.
2. Implementation and Monitoring: Transparency enables policy makers to check the performance and deal with undesired results. Sustainable AI models put environmental data into consideration, which can help governments calculate the impact of carbon or social resilience in their policies.
3. Evaluation and Feedback: Sustainability outcomes guide evaluation, thus the short-term performance would not spoil long-term performance. By way of participation audits, inclusiveness and fairness are revisited and the society can put itself under scrutiny.

The value- and evidence-based policymaking makes such an ethical loop. Dependence on the numbers is no longer justified as justification of policies but on justice, inclusion, transparency and sustainability. They turn governance into an ethical ecosystem, which is the process of dialogue driven by the AI as well as by the moral judgment.

4.2 Converting Research and Education

In Fig. 1 the objective 2 refers to the creation of a four-pillar construct (fairness, inclusiveness, transparency, sustainability). The results showed that these pillars are not independent of each other. The platform reinvents training on research by providing future policymakers and scientists with the capabilities to incorporate ethical thought in technology. The introduction of ethical AI in schools changes the perspective of education as a technical training to a moral one. Ethical competency is necessary where programs were previously focusing on coding and processing data, with AI taking over research and policy. The four pillars give a roadmap to AI citizenship by overlapping between cognitive, moral, and civic capabilities to navigate AI-driven responsible choices in the society. The ethical AI education involves fairness, inclusiveness, transparency, and sustainability in curriculum development. Students need to be taught how to identify bias in data and conduct fairness audits, as well as inculcate accountability. Education must not just focus on the western lens but learn to integrate other cultural and gender world-views and partnerships with the community provide social significance. It should also be a cognitive ability that instills integrity whereby transparency and explainability are involved. A linkage of technical competency to ecologic responsibility is what makes sustainability an essential outcome. The sustainability indicators through project evaluation allow students to weigh innovation on stewardship with the social impacts of the project. These reforms build an ethical model of AI centered around ethically oriented AI as both a target and a teaching method of formation of professionals such that every decision made about technology is a moral choice.

4.3 Implication on Institutional and Governance

As indicated in Objective 3 in Fig. 1, the results underscore that the ethical AI competencies need to be strategically introduced in the curricula of higher learning institutions. The review demonstrates that training future leaders regarding AI literacy, honesty skills, professional moral standpoint, and sustainability-oriented decision-making is necessary. The adoption of this framework requires reforms. Policies schools and universities should consider setting up moral government structures to govern and generate authority. To control the practices of algorithms, institutions need to create ethics committees, data protection boards, and offices of AI audits. Institutions should abandon the existing ad hoc ethics review and shift to the ethical monitoring on a continuous basis, and audits as part of projects lifecycle (instead of regarding it as the formalities at the end of the projects). Ethical AI must be spread not only throughout economics, management, political science, computer science, and environmental studies but also not a niche topic. It is ethical literacy, not an extra course that this permeation guarantees is part of the institutional culture. Institutions, responsible AI Governance requires collaboration between universities, governments and industry. Ethical AI consortia are able to develop standards, certifications, and awareness campaigns to the society in support of transparency and accountability. These four pillars should be institutionalized and by doing this the environment of unceasing ethical deliberation is made. This paradigm also alters the role of teachers and policy makers as ethical caretakers and makes them moral landscape changers of the technology in creating AI to improve man. An analysis and comparison between the economic findings of developed and developing nations, along with the organization of these variables, can assist in concluding that the processes of economic development are distinct yet interconnected.

4.4 Comparative Reflection and Global Relevance

An analysis and comparison between the economic results of the developed and developing countries, the sorting of these variables will

help conclude that the economic development process is discrete but interrelated. The model goes in line with the average international AI ethical efforts but identifies ethics uniquely as related to education and sustainability. Where European commission AI Ethics Guidelines (2019) is focused on the illusion of trustworthiness and UNESCO recommendation (2021) is promoting the concepts of human dignity, most models do not include a system of education towards these elements. The suggested model will satisfy these requirements since it includes the use of ethical AI as a principle-internalizing and practicing educational tool. Where AI is developing, and there is little oversight, as in the case of low-development locations, the model provides a guideline of capacity building. It connects fairness, inclusivity, and sustainability to the goals of Agenda 2030 of the UN regarding inclusive education (SDG 4) and strong institutions (SDG 16). Local ownership and applicability is brought about by the fact that the model allows a local flexibility because the ethical governance must be local and inclusive. Along with that, there was the inclusion of the reinforcement of the four pillars. Vital down the model facilitates in offering a system thinking approach on the international level. Ethical AI is reinventive, in that, fairness requires inclusivity; inclusivity requires transparency; transparency requires sustainability. The resemblance of the framework to cyclicality reflects the interdependence of the international problems like inequality, climate change, and technological upheaval. Figure 1 ends with the bottom component of the EAI Framework of Sustainable Policy and Research Education that indicates the realization of the conceptual pathway. According to the findings, this cohesive framework will solve the existing weaknesses in AI regulation, sustainability courses, and ethical trainings.

4.5 Moving to a Culture of Responsible Innovation

Embarking on responsible innovation, the addition of ethical AI to the study of policy and research education is a step towards an ethical AI. The model envisions AI as a continuation that will enrich human innovativeness and pathos. To become a responsible innovator, one

needs entrepreneurship to maintain constant communication, be ethical, and govern responsibly, transforming moral architectures in response to technology. In this model, ethical reflexivity will be the core of the sustainable progress. Ethical AI is a direction and a sign of progress, as it promotes equitable judgments and nurtures specialists who will consider ethics as a productive generator. Innovation is perceived as an ethical act that is between progress and conservation. The framework involves a technological transformation, institutional transformation, and moral transformation which involve integrating disciplinaries. Ethics fills the gap between rationality of data and wellbeing of the humans. It proposes a novel system of governance to the intelligent systems by promoting equity, inclusion, transparency, and sustainability by prioritizing wisdom, equity, long-term basis over short-term interests. This creates a foundation of a company that will be the guiding force of human beings towards a just digital world using ethical AI.

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5 Implications

The theoreticalized framework is obligatory to academia especially in curriculum, teaching and research governance. The framework has identified ethics education in AI as one of the essential competencies, a claim that ethical thinking should also develop in parity with technical skills. Through the inclusion of the four ethical pillars, namely Fairness, Inclusivity, Transparency, and Sustainability into academic constructs, schools would develop scholars who can create technology to help them achieve social and ecological objectives. The structure allows interdisciplinary education to relate engineering, social sciences and philosophy by addressing the ethical and sustainability concerns. The practical real-world ethical issues may also be trained with the help of simulation laboratories or policy hackathons, developing critical thinking and leadership skills. It can also support research incentive because it welcomes Ethics-by-Design thinking in the gathering, modelling and incorporation of data. Adopting ethical AI research

declarations can be made mandatory through universities and academic journals, which can increase the integrity. All in all, the framework allows greater theoretical AI governance and sustainability mastery that opens up avenues to future studies that uphold and broaden the applicability of the framework. The framework provides suggestions on how the ethical AI can be injected into institution-based systems on the managerial front. It supports the creation of AI Ethics Councils to conduct audits, measure sustainability indicators and introduce transparency. Capacity can be established through education and research institutions through faculty training, mentored ethical data governance and collaboration. The leadership should be able to build ethical culture that attaches importance on responsibility and inclusivity. Similarity between AI strategy and sustainability priorities is achieved through the inclusion of these concepts in the decision-making process. Finally, the framework presents ethical AI as a strategic resource, which can drive fair, transparent, and socially responsible innovation, which is strengthening institutional performance and social trust.

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6 Conclusion, Limitations, and Future Directions

Ethical Artificial Intelligence (EAI) is a conceptual research which assumes that there is a transformational relationship between technology, education and sustainability. It presents the model of incorporating the infusion of ethics into the process of policymaking and learning with four pillars Fairness and Accountability, Inclusiveness and Representation, Transparency and Explainability, and Sustainability-Driven Results. The conceptual framework is an ethical ecosystem of AI that has an effect on the generation of knowledge and governance. Practically, it has the potential to reinforce trust, equity, and social well-being, and AI innovation can be considered sustainable development. The research, nevertheless, has its weakness because it is theoretical, and it should be proved in different environments.

Differences in AI maturity and ethical awareness as well as governance may limit its use in any environment. Another issue with the ongoing advancement of AI is the sustainability of the ethical regulation since the reformulation of the principles should be a fluid process.

The additional research should entail experimental validation and cross-industry application of the model. The impact of the ethical AI values on the educational governance can be examined by qualitative case studies and mixed-method studies. Educators, data scientists, and ethicists will need to collaborate in order to refine the model. The interrelation between increasing technologies, ethical, and learning purposes also needs to be investigated so that to render the present study more topical. Altogether, ethical thinking corresponds to digital creativity could lead to people-centered, sustainability-oriented AI space in governance and education.



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The Sustainability of AI Literacy: The Environmental Cost of Embracing Generative AI in Higher Education

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Abstract

Artificial Intelligence (AI) is rapidly reshaping teaching and learning in Higher Education (HE). It is central to the future of work; proficiency in the use of AI is now identified as a core employability competency and an in-demand skill for employers. Higher Education Institutions (HEIs) face a growing imperative to equip students with relevant skills, advancing their AI literacy and digital career readiness. Generative AI (GAI) tools are increasingly used in the classroom, by both staff and students, presenting a range of new challenges and opportunities for the sector. However, the integration of GAI into teaching and learning brings with it environmental costs. This chapter explores the sustainability issues posed by using GAI in the classroom and considers the implications for HEIs. It will discuss the inherent tension between

meeting student needs for AI literacy, whilst also ensuring an ethical and sustainable approach to the use of GAI in teaching and learning. This chapter will argue that educators must not only teach with GAI tools as they are now an inevitable part of the future of work, but also teach about them, including their sustainability risks. The chapter concludes with recommendations for HEIs for the integration of environmental sustainability into teaching and learning surrounding GAI.

Keywords Generative AI – Employability – AI literacy – Sustainability

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1 Introduction

Business adoption of AI is accelerating, with estimates that nearly three-quarters of organisations are now utilising AI in at least one function (Singla et al. 2025). The ability to competently use AI is now an essential employability skill for students and graduates alike. The rapid advancement of Large Language Models (LLMs), notably, but not limited to, ChatGPT, now estimated to be the fifth most visited website in the world (O'Donnell and Crownhart 2025), has heightened awareness and adoption of AI. GAI tools, which create content in response to user prompts, are currently being incorporated into a range

of workplace applications (Chiu 2024). Together, this highlights the urgent need for HE to equip students with AI literacy.

Also pertinent to HE is the potential for AI-related job market disruption. Many of the roles exposed to and at risk from AI adoption include entry-level roles, those historically undertaken by recent graduates (IPPR 2024). Whilst new technologies also bring with them the possibility of job creation, estimates suggest that up to 40% of global employment is exposed to AI in some form (Cazzaniga et al. 2024). Some industries and role types may be especially affected by GAI tools (Salari et al. 2025). The full potential impact of AI and GAI on labour markets is widely debated but remains uncertain.

Providing relevant teaching and learning on and about AI may therefore benefit students in respect of developing critical employability skills for future work opportunities. There are also broader benefits of utilising GAI in HE. It has been argued that it has a transformational potential (Chiu 2024). Whilst relatively still in its early stages of application (and in academic research), GAI can support innovative teaching and learning methods, potentially replacing traditional approaches and creating new modes of assessment (Chiu et al. 2023; Freeman 2025). It has been further suggested that GAI may also support student learning by helping them refine work, improve spelling and grammar, test ideas and revise for exams. Tools like ChatGPT essentially act as a supplementary resource for today's students (Michel-Villarreal et al. 2023).

GAI systems are, however, computationally intensive, requiring energy and water resources for training and operation, contributing to carbon emissions and other negative environmental impacts. They drive energy demands resulting from their development, training and subsequent use. Beyond energy use, other ecological issues include land impacts, hardware production, the short lifecycle of AI technologies, the potential for growth of e-waste and carbon emissions. Despite these risks, their use is now endemic, with some web traffic sites claiming ChatGPT alone has over 5 billion visits per month (Semrush 2025).

Students are frequent users of GAI, with HEPI UK establishing that almost all students (92%) have used AI within their academic studies, primarily in the completion of assessed work (Freeman 2025). Students also express a desire for the integration of AI into their studies, viewing it positively and recognising its potential to enhance their learning (Li et al. 2025b). However, whilst students may be regular users of GAI, they may not be cognisant of its broader social and environmental impacts, especially those regarding sustainability, especially if it has not been addressed in the curriculum.

The advent of GAI has resulted in new challenges for HEIs, especially in respect of academic integrity and reduced barriers to academic misconduct (Dale and Drummond 2024b). Developing policies on acceptable GAI use, determining the role of GAI within teaching and learning, assessment design and understanding its potential to support student outcomes, are all issues currently facing HEIs (Li et al. 2025b). The need to equip students with AI literacy also goes beyond the classroom and future business applications. Organisations are increasingly using AI tools throughout their hiring processes, presenting new challenges for university career services, which will need to prepare students for these new requirements (Jones et al. 2020).

Arguably, the issue of sustainability and GAI in an educational context has been somewhat overlooked, with HEIs facing a paradox. The inclusion of GAI within the curriculum is a practical necessity to produce job-ready graduates. However, providing such skills may directly contradict the sustainability goals of the institution as well as raise wider environmental considerations. We argue that responsible education in HE, as well as the ethical dimension of teaching and learning regarding AI, must explicitly incorporate sustainability considerations, something about which early research students are not fully cognisant (Dungo et al. 2025). This aligns with calls from other scholars (Long and Magerko 2020; Ng et al. 2021; Bentley et al. 2023), who all emphasise the importance of incorporating not only technical AI competencies into teaching and learning, but also social and ethical

dimensions relating to their use. Achieving this will require coordinated efforts from institutions and educators to align education practices with environmental and ethical standards.

This chapter proposes to answer the following research questions:

- To what extent are HEIs considering sustainability in their approach to GAI within teaching and learning and the development of AI literacy.
- What actions should HEIs take to ensure an ethical and sustainable approach to the use of GAI in teaching and learning.

To address the above questions, this chapter will provide a literature review that discusses the concept of AI Literacy, GAI in the context of sustainability and, how HEIs adopt sustainability. The chapter then continues with actionable recommendations for HEIs in how GAI and sustainability can integrate before concluding with limitations and future considerations for research.

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2 AI Literacy

AI literacy is an umbrella term used to describe skills deemed essential to ensure effective use of AI tools and technologies. It is now considered a fundamental skill necessary for both work and personal life (Ng et al. 2021). The World Economic Forum (WEF) argue that AI literacy should be a 'core educational priority' (Milberg 2025). Long and Magerko (2020) and define AI literacy as the ability to understand the skills that allow people to interact with AI systems, assess them critically, and ethically use them. A further definition of literacy, developed by Ng et al. (2021) and drawing on Bloom's taxonomy, suggests AI literacy encompasses the ability to apply, use and evaluate AI tools.

HEIs can enable students to develop AI literacy by incorporating it into pedagogy (Eke 2023). Frameworks and recommendations for student AI education, in addition to technical skills, typically call for the inclusion of issues of accuracy and credibility (Meakin 2024), limitations of GAI, responsible use in education settings (Zhou and

Schofield 2024) and ethical, fair and transparent use (Ng et al. 2021). The escalation of GAI tools has resulted in experimentation with new teaching and learning techniques in the classroom, all of which may support student AI literacy (Dale and Drummond 2024a; Dietis 2024). Other definitions of AI literacy also frequently incorporate considerations of ethical and responsible use, however neither these nor other proposed frameworks for AI literacy published to date include sustainability issues specifically, instead focusing on issues relating to potential for bias and inaccuracy, data privacy and security concerns and responsible use (Attewell 2024; Milberg 2025).

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3 GAI and Sustainability

There are multiple barriers to understanding the impact of GAI on sustainability and the environment. Sources of data are incomplete and sometimes proprietary, presenting issues with analysis and the identification of consistent methodologies. Furthermore, the specific impacts of GAI can be hard to extrapolate from other technologies operating simultatenously in the same data centres. Academic literature in this area is, to date, scarce. Accordingly, this chapter presents the best available data whilst acknowledging more information and research is required.

The environmental impacts of GAI can be broadly segmented into three categories: resource and energy consumption, the creation of e-waste and increased carbon footprint. Currently, there is no accurate way to assess the complete environmental impacts from the entire lifecycle of a given GAI technology, from training to end of life (Hosseini et al. 2025). The development of GAI tools has however been described as 'currently unsustainable' (Bashir et al. 2024) noting the limited consideration being given to environmental impacts (Hosseini et al. 2025).

Data centres house the infrastructure that is used to run GAI tools. These centres use vast amounts of electricity and water. Consumption of these resources occurs during the creation (training) of GAI and its

continuing operation. The number of data centres has increased to meet the demands of new AI technologies. This demand may lead to an increase of 2.5 billion t of carbon emissions globally by 2030 (Tharayil 2024). More data centres are expected to be built in the years ahead to meet predicted demand, partly attributable to the rise of GAI. Geographically, these centres are often clustered together, leading to significant impacts on the local environment (Chen 2025). Whilst data centres are not new, those used to power GAI technologies are more power-intensive than traditional data centres, thereby consuming more natural resources (Zewe 2025). This power demand is partially met through fossil fuels with 56% of the electricity used to run US data centres derived from these fuels, generating over 150 million t of carbon emissions (Guidi et al. 2024). It is difficult to ascertain however, how much of the energy used by data centres is attributable to GAI specifically as compared to other technologies.

Precise data on the energy use of data centres and GAI can be difficult to obtain. Some technology organisations are reluctant to provide their usage data, and many proposed figures are estimates, many of which will rapidly date (Chen 2025). Many GAI models are also 'closed AI'—the data necessary to make detailed analysis is proprietary and thus unavailable to researchers, resulting in estimates based on best known data. One such estimate suggests that the training and deployment of GPT-3 by OpenAI could have utilised 1287 MW of electricity and generated 552 tons of carbon dioxide (Zewe 2025). Before the proliferation of GAI tools, internet search engines were the primary way of finding online information. By way of comparison, it is estimated that a GAI tool such as ChatGPT can use up to ten times more energy than a simple Google search (Conklin 2024). Such claims are hard to verify.

Some data from organisations is available through their published environmental reports. Google reports that energy consumption from their AI products resulted in a 48% increase in their carbon emissions in 5 years (Weaver 2024). Similarly, Microsoft also reported an increase of 29% in their carbon emissions, attributed primarily to data centre

construction (Smith 2024). However, media reports have suggested that data centre emissions are significantly higher than technology companies claim, with concerns raised about the methodologies employed to self-report data (O'Brien 2024). This amounts to a further barrier in developing a comprehensive understanding of the environmental impact of GAI.

Given the speed of development of GAI, predictions about future use are similarly estimated, of which the International Energy Agency (IEA) notes there is substantial uncertainty (IEA 2025). However, one prediction demonstrates the significant potential future energy demands in suggesting that by 2028, data centres will consume 12% of total US electricity 2028, rising from 4.4% in 2023 (Shehabi et al. 2024). IEA (2025) further suggests that total electricity demand could double by 2030. Whilst data centres consume energy resources for training and use, the environmental costs of AI begin at an earlier stage. The construction of these centres, and the equipment that they house upon which tools run (including the production of GPUs which is energy intensive), involve the extraction of raw materials, manufacturing and shipping in the construction stage, and at the end of the cycle the creation of e-waste (United Nations Environment Programme 2024). Such waste can contain toxic chemicals and often ends up in a landfill. The recycling of e-waste is low. In 2022, only just over 22% of e-waste globally was properly recycled (UNITAR 2024).

As with data centre impacts, it is difficult to accurately assess the scale of e-waste resulting from GAI (partly because of a lack of data), however, researchers estimate that it could be responsible for the generation of between 1.2 and 5.0 million tons of e-waste between 2020 and 2030, partly driven by redundant servers and their parts (Wang et al. 2024). The speed of AI development is partly responsible for the creation of e-waste from data centres.

GAI also consumes water resources, although it is also difficult to estimate just how much and how this demand may continue into the future. AI consumes water in several ways. It uses significant amounts of water to cool data centres, as well as in electricity generation and

through the supply chain in the manufacture of hardware (Li et al. 2025a). According to Li et al. (2025a), AI is projected to result in between 4.2 and 6.6 billion cubic meters of water withdrawal in 2027, amounting to more is more than the total annual water withdrawal of half of the United Kingdom (UK). This demand may, in the longer term, result in water supply shortages. It is suggested that growth in GAI, combined with unknowns about future requirements, is making it difficult for domestic water agencies to predict and manage potential deficits (Horton 2025).

Google's data centres consumed 6.1 billion gallons of water in 2023, although it is unclear how much of this related directly to GAI compared to its other operations (Google 2024). A commonly quoted estimate is that a short conversation with ChatGPT, covering a series of prompts, utilises the equivalent of 500 ml of water (McLean 2023). Others dispute this, with OpenAI claiming that a single prompt uses one-fifteenth of a teaspoon of water (Disotto 2025). However, extrapolated globally at the scale of ChatGPT use, this could amount to significant consumption of water resources. Conversely, as well as resulting in problematic water usage, AI is also seen as a potential solution to water scarcity and quality (aligning with the United Nations Sustainable Development Goals' (UNSDGs) of Clean Water and Sanitation) through its ability to identify new solutions, support studies and in water management (Mahmoud et al. 2023).

Considering these varied and potentially significant environmental impacts, what, therefore, is sustainable AI, and indeed can it even exist? Van Wynsberghe (2021) proposes that a definition of sustainable AI is one that encompasses the whole sociotechnical system of AI and the entire lifecycle of AI products. However, this broad definition, while conceptually comprehensive, raises practical challenges. The complexity and scale of AI's sociotechnical systems combined with the continuing drive for new models and capabilities and maximising profit for GAI organisations, may indicate that fully sustainable AI may remain more of an aspirational ideal than an attainable reality.

Sustainable AI is a relatively new term and area of AI ethics research (van Wynsberghe 2021). Some considerations of sustainability and AI have focused on the ability of AI tools to support sustainability goals or be a positive force in climate action (Wang et al. 2023). Vinuesa et al. (2020) found that, in respect of the Global Sustainable Development Goals (SDGs), AI can enable the accomplishment of 134 targets whilst potentially inhibiting 59. This in itself is a further paradox, the potential for AI to both support sustainable goals whilst also having the potential to create 'the environmental disaster of our time' (van Wynsberghe 2021). Beck (2025) summarises this contradiction thusly: 'information is power, but it also consumes power'.

Discussing the sustainability challenges posed by GAI specifically, Beck (2025) argues that in the integration of GAI into their organisations, business leaders must seek to balance innovation and productivity with environmental sustainability. Whilst AI technologies may provide transformational opportunities for those organisations, decision-making processes should consider the costs to the environment. Similar arguments can be made for HEIs. The integration of GAI into teaching and learning must be balanced against environmental sustainability and the organisation's own sustainability goals. Again, there may be practical considerations with such a proposal, not least whether businesses and HEIs will genuinely commit to integrating sustainability into their AI strategies, or whether environmental concerns will remain secondary to competitive advantage or efficiency.

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4 HEIs, GAI and Sustainability

As students and academic are now routinely using GAI in various stages of their learning and teaching, they are contributing, albeit potentially unconsciously, to its environmental costs. Hall (2024) highlights that when staff are seeking to incorporate GAI in their programmes, many remain unaware of the environmental impact of such inclusion.

HEIs are recognised to play a key role in sustainability, especially through the provision of education on environmental issues and the SDGs. They are recognised as potential 'change agents' in sustainability development (Žalėnienė and Pereira 2021). Universities educate future leaders on sustainability issues (Husic 2024). Within HEIs, sustainability is primarily addressed through four key areas: the learning environment, research aligned with the SDGs, external collaborations and integration into the curriculum (Zhou 2025).

The use of AI within HEIs may extend beyond its integration into teaching and learning within their own institutions. For example, HEIs have the potential to influence the development, measurement and use of these technologies, as well as utilise them in non-teaching activities. With the HE sector, particularly within the UK, increasingly under financial pressure (Office for Students 2025), there is an incentive to maximise efficiencies. Traditional cost reduction options in HEIs have included staff redundancies, closure of programmes and streamlining of back-office processes. Scholars identify that AI has the potential to assist in the latter (Kohun et al. 2024), however, adoption of AI in professional services or administrative functions will also have environmental effects.

The sector has already adopted AI for the administrative functions and with some degree of success (Osman et al. 2024). One such example is utilising AI in the process of student enrolment. Given the importance of student numbers for HEI finances, these processes must be optimal (Nadeem et al. 2024). The predictability of student numbers on any given course is challenging due to the factors such as birth rates, entry criteria uch as UCAS points and the strategy of a given HEIs competitors. As such, it is often found that courses are either under or over-subscribed, resulting in resource implications (Ieong 2020). AI can streamline enrolment generating operational benefits. The use of AI in HEIs (and its associated environmental costs) is not therefore limited to education. Whilst this chapter focuses primarily on teaching and learning, institutions striving for efficiency will likely need to consider their broader use of AI technologies, as well as their implications.

Sustainable AI requires sustainable development at its core (van Wynsberghe 2021). There are many options open to those organisations that develop AI technologies with respect to improving sustainability. These include developing tools that require less computational power, utilising renewable energy sources for data centres and adopting a circular economy approach to the hardware (Walther 2024). Such responsibility will rest largely with those firms that own and develop AI models and, consequently, is almost certainly outside the scope of most individual educators and institutions. This does not, however, suggest that HEIs (and those who work for them) cannot influence the discourse of sustainable use of GAI. Rather, given the anticipated increase in AI use in HEIs, whether for administrative optimisation or in teaching and learning, it would be negligible for HEIs to not be involved in the conversation. One opportunity for the sector is to advocate and contribute to transparency of operational costs in respect of using AI to assess environmental impact (Hoseinzadeh and Astiaso Garcia 2024).

In conclusion, therefore, it is argued that there exists an inherent tension for HEIs, between meeting student needs for AI literacy (as well as potentially organisational and process efficiencies), ensuring an ethical and sustainable approach to the use of GAI in teaching and learning, and the resulting environmental costs. This tension can be addressed through both policy and practice.

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5 Recommendations for the Integration of Environmental Sustainability into Teaching and Learning with GAI

We propose a pedagogical response to teaching with, and about, GAI. Like others (Kohun et al. 2024), we argue that the use of GAI in HEIs must be balanced against the resulting environmental impacts given the context of predicted high levels of staff and student use (Chu et al. 2022). HEIs must manage the inherent tension between meeting student needs for AI literacy and recognising the benefits of

incorporating GAI into teaching and learning, whilst also acknowledging the environmental issues resulting from its use.

This chapter proposes four recommendations for HEIs in respect of environmental sustainability and the use of GAI. The first two recommendations relate to institutional practice with regards to teaching and learning; recommendation three and four identify institutional policy recommendations.

1. Education and awareness that promotes the critical and sustainable use of AI amongst academic staff in designing teaching and learning.
2. Education and awareness for students, supporting them to become responsible users of GAI, as part of AI literacy.
3. The integration of AI usage costs in operational costings and SDG alignment.
4. The adoption by HEIs of a definition of AI literacy that formally recognises the impact of AI on the environment (Fig. 1).

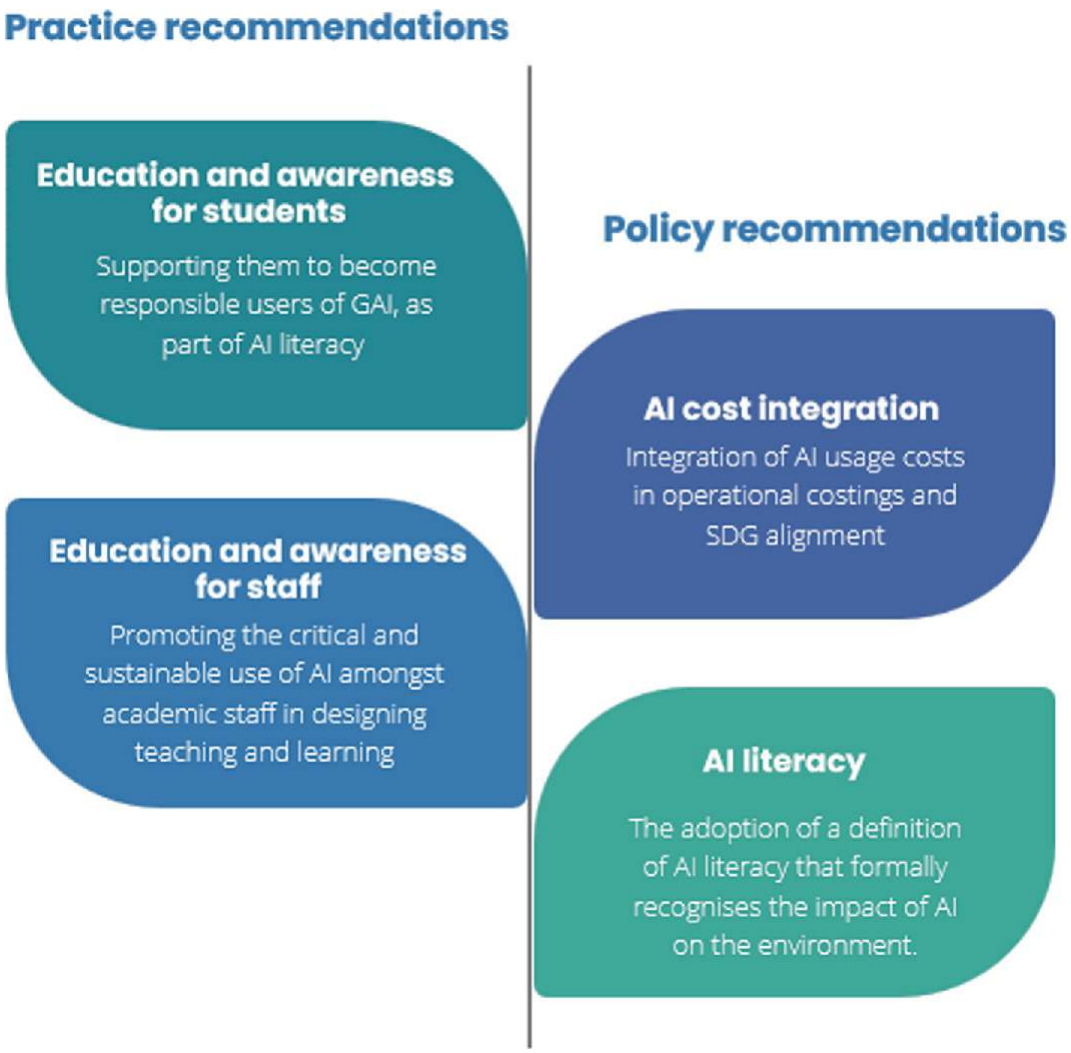


Fig. 1 Recommendations for the integration of environmental sustainability into teaching and learning with GAI

5.1 Education and Awareness that Promotes the Critical and Sustainable Use of AI Amongst Academic Staff in Designing Teaching and Learning

Only 16% of people are aware of the negative environmental impacts of GAI (IET 2024). Responsible use of GAI in teaching and learning, therefore, begins with teaching about GAI. HEIs should approach sustainability awareness as a key facet of AI literacy amongst staff, building sustainability awareness into the curriculum and incorporating discussion of GAI's environmental impacts into relevant modules or programmes where GAI is used. This can include core

concepts such as AI resource consumption, carbon footprint and issues of e-waste. Educators can help students critically evaluate not only what these tools can do, but also the environmental costs associated with their use, as well as help them to understand how different uses of GAI contribute to energy demand and how to reduce it. Increased awareness amongst academic staff is a prerequisite for this element.

GAI has placed new demands on individual educators who need to develop competence in emerging tools. O'Dea et al. (2024) argue that HEIs will need to devote time and resources to support educator development, noting that some individuals may be reluctant to develop such skills or incorporate them into their practice (Suleymenova et al. 2024). The additional requirement to embed sustainability considerations into teaching with AI further compounds these demands, requiring educators not only to become proficient with GAI but also to understand its environmental impact and adapt accordingly. This dual challenge suggests that HEIs will need to provide education and guidance for academic staff. As this remains an emerging area, HEIs can also support staff through the creation of internal communities, support peer-to-peer learning and share sustainable teaching practices.

Despite academic staff concerns about using GAI in the classroom, the above discussion highlights the potential for positive impact in AI integration (Kukulska-Hulme 2012). Academics have already been experimenting within their curriculum to include AI limitations, ethical considerations and best practice under the umbrella term of AI literacy (Dale and Drummond 2024a). They can be further supported by their organisations to incorporate sustainability aspects into these discussions and development. This may need to begin with the provision of guidance and targeted training.

5.2 Education and Awareness for Students, Supporting Them to Become Responsible Users of GAI, as Part of AI Literacy

Efforts to build student AI literacy through teaching should encompass considerations of the environment impact of these technologies.

Students can be supported to become responsible, considered users of GAI. Many HEIs offer sustainability education to students, either as standalone courses or imbedded within the curriculum. Information about the environmental impacts of GAI can be incorporated into these learning opportunities, as well as into any GAI specific education. Students can be encouraged, through the activities designed by educated faculty, to consider not just the capabilities of a tool, but also its energy demands and environmental footprint. Not all GAI tools are equal in terms of environmental impact or energy consumption. Image generation for example, is more computationally intensive than text generation (Luccioni et al. 2024). Similarly, effective prompt engineering can reduce the energy consumption of GAI tools (Armstrong 2025). This is a practical skill that can be taught in the classroom.

It is known that GAI tools are prone to inaccuracies (Selwyn 2019). Issues around accuracy, bias and hallucinations are frequently included in classroom discussions with students about the use of GAI. Disseminating information about issues of reliability may support the reduction of GAI tool usage, encouraging students to use more credible sources of information. Explorations and critique of tools and their output can help to demonstrate the limitations of AI, ergo discouraging its use, whilst also developing student critical thinking skills. Similarly, students can be guided to learn when to use GAI and when other tools might be more appropriate and reliable.

Education and awareness raising amongst students will benefit from carefully designed communications meaningful for the demographic. For example, learning that making two images via GAI may consume as much energy as charging a smartphone (Iqbal 2025), may resonate with this cohort more than detailed data on energy consumption without accompanying context. Dhar (2020) suggests quantifying the outcomes of GAI such that a layperson might visualise them. However, as we have already discussed, such quantification is itself replete with difficulties. Together, these educational-focused recommendations can help to create an organisational culture of

environmental responsibility concerning the use of GAI. They can be combined with regular reviews on the integration of GAI into the curriculum and its potential environmental impact. These teaching and learning focused recommendations can be further supported by and aligned with other institutional actions, such as those set out in our subsequent recommendations.

5.3 The Integration of AI Usage Costs in Operational Costings and SDG Alignment

Beck (2025) suggests that environmental considerations about GAI should include careful choices with models and partners. This allows for a uniform approach to teaching and practice and encourages the use of centralised, institutionally supported AI platforms rather than fragmented individual subscriptions. This reduces redundant computing resources and optimises energy use across the learning environment. The singularity of one or few tools will make for an easier quantification of its use in the institution. Therefore, the data is in an ideal state for comparison against an institution's operational costs. There is also benefit in HEIs assessing their use of AI whether in the classroom or research against the SDGs. However, for this to occur, HEIs need to remain knowledgeable and curious about AI use (Alshamsi et al. 2024).

HEIs are expected to demonstrate impact and social value (de Villiers et al. 2024) and, consequently, are positioned well to explore and integrate SDG solutions into their core activities (De la Poza et al. 2021). However, reporting on SDGs is voluntary (de Villiers et al. 2024) and therefore, it is a challenge to present a uniformed approach to reporting. Accordingly, it would be more challenging to include AI use into operational reporting, despite its advantages, unless a single method of assessment is resolved (Zhou 2025).

5.4 The Adoption by HEIs of a Definition of AI Literacy that Formally Recognises the Impact of AI on the Environment

The previous discussion on AI literacy highlighted the requirement for individuals to be able to evaluate and critically assess AI tools. Long and Magerko (2020) propose that this includes the ethical use of AI. We argue for an extension of this definition, namely that critical assessment and ethical use of AI must also include awareness of GAI and environmental impact. Many HEIs have existing institutional commitments to sustainability within their strategies, campus operations, teaching and research agendas. They are therefore well positioned to adopt this expanded definition; explicitly extending AI literacy to incorporate GAI's environmental impacts aligns naturally with these established priorities.

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6 Conclusions

We return to the first research question posed by this chapter, namely, '*to what extent are HEIs considering sustainability in their approach to GAI within teaching and learning and the development of AI literacy?'.* Whilst some HEIs may be mindful of sustainable use of technology, up to and including GAI, due partly to the emerging nature of GAI there are to date limited case studies that explicitly demonstrate how HEIs are integrating both sustainability and AI Literacy in their strategies. Concerns about the environmental impact of GAI are a relatively new phenomenon, as highlighted by the contemporaneous nature of the literature review. To date, these concerns are largely found in professional media or grey literature and are yet to be the subject of extensive academic research. There is also little evidence that HEIs are incorporating such issues into either their sustainability agendas or their GAI policies which are largely dominated by issues such as academic integrity.

In respect of potential actions for HEIs to ensure its integration at an institutional level, HEIs should make a formal commitment to incorporating the sustainability of GAI into their overall sustainability goals and action plans. Table 1 outlines actionable considerations this chapter considers to be of benefit to HEIs when needing to consider

sustainability in the use of AI in HE. If combined, these approaches will aid the development of AI literacy within HE, staff and students will be ethically grounded in their use of GAI tools, are environmentally conscious and aware of the long-term impacts of technology:

Table 1 Actions to determine sustainability of AI literacy

6.1 Conclusion

GAI utilises considerable resources in its development, training and ongoing operation. These demands are predicted to increase in the future, although the full scale of this demand and associated environmental impacts are yet to be understood. Whilst the GAI industry and governments have arguably the primary responsibility to address these impacts, other actors, including HEIs, can play a role.

Continued student use of GAI is assured; however, students can be educated to become responsible consumers of such technologies. This includes fostering digital sustainability literacy, raising awareness of the environmental footprint of AI tools, and encouraging critical engagement with their ethical and practical implications. HEIs must help to prepare students for a future of work that incorporates GAI whilst also recognising negative impacts upon the environment. To do this, HEIs must shift beyond narrow concerns around academic integrity and adopt a more holistic, future-focused approach. This ensures that GAI use in teaching and learning contributes positively to student education without exacerbating environmental harms. This process can be supported through carefully designed and supported teaching and learning activities.

Furthermore, universities can also, through research, advocacy and partnership with industry, support the process of AI becoming more sustainable. The OECD (2022) recommend multiple areas relating to AI that demand further research and understanding, including the development of measurement standards and the analysis of AI lifecycle impacts.

HEIs have both a responsibility and an opportunity to model ethical, sustainable engagement with GAI, shaping not only the future workforce but also the future of the planet.

6.2 Limitations of the Research

Due to the rapid emergence of GAI technologies and their recent introduction to the classroom as well as varying degrees of application amongst HEIs, extant literature remains relatively scarce. The authors have drawn on their own observations and experiences in using the technology within teaching and learning. Accordingly, this research was limited to conceptualising how GAI can be considered with regards to existing sustainability practices such as SDGs.

6.3 Considerations for Future Research

A pilot project within a HEI in how the current sustainability practices and reporting incorporates the use of GAI would be beneficial towards ascertaining if this chapters proposed actions are to be impactful. In addition, policies surrounding GAI use in education would benefit from making explicit the use of the technology has on their sustainability goals and how that would shape future strategic decision-making.



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Toward Sustainable Higher Education: A Critical Review of the Emerging Issues Induced by Artificial Intelligence

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Abstract

The emerging issues brought to the limelight through the widespread application of AI in higher education, affecting sustainable teaching and learning in higher education, are examined in this chapter. A meticulous, systematic review of the literature from inside and outside Africa was conducted with important inferences drawn from reports, articles and dissertations published between 2020 and 2025. Searching, organising, storing, and reusing articles in databases like Google, Google Scholar, Web of Science, Science Direct, and the Directory of Open Access Journals (DOAJ) are all part of the systematic

review process. Most importantly, this chapter presents a novel understanding of the products associated with the emerging issues of using AI in higher education. The findings revealed data privacy concerns, academic dishonesty, absence of AI solutions from the Global South, overreliance on technology, and lack of compliance with established policies and frameworks as emerging issues induced by AI use influencing sustainable higher education. The findings presented in this chapter underscored the importance of continuous counselling and awareness seminars and conferences with educators, students, and faculties on an institutional and faculty-wise basis as proactive measures to reduce the products of unethical use of AI in higher education. The authors posited and concluded by offering recommendations to manage the induced influence introduced by AI in higher education to achieve sustainable development goals prescribed by the United Nation's Sustainable Development Goals.

Keywords Artificial intelligence – Higher education – Products – Emerging issues – Induction

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1 Introduction

The rapid rise of Artificial Intelligence (AI)-powered tools have made it simpler for educators and students to discover, store, and reuse online resources for sustainable "quality" in educational and research contexts, highlighting innovative practices, methodologies, and classroom or societal applications (Adıgüzel et al. 2023). In the context of this chapter, sustainability means employing AI tools to address instructional demands in higher education in ways that do not create new concerns for open debates. Today, educators now use AI-powered tools to support pedagogy and as a tool that can be leveraged to enhance conceptual understanding (Giri 2025). Besides, the innovative use of AI in teaching allows students and educators to access and reuse information for teaching and learning sustainably and as research guides (Kostopolus 2025).

Buttressing the aforementioned arguments and from their perspective, Adıgüzel et al. (2023), Giri (2025) and Kostopolus (2025) argued that AI assists in content generation, language translation, support for scientific research, assignment development, and virtual assistants that aid in knowledge acquisition and writing guidance. Specifically, AI-powered tools pave the way for a more practicable, efficient, communicable, innovative, and sustainable higher education system (Lawal 2025). Despite these advances, several concerns induced (or brought on) as a result of uncoordinated and unprofessional use of technology or related AI for innovative education have been reported in the literature as rising debates open for discussion regarding the need for sustainable decisions that must be taken to promote and guide the use of innovative technologies such as AI or related technologies for education and national development (Trincado-Munoz et al. 2024; Zhao and Gómez Fariñas 2023). One such concern induced for debates was the key discussion point enacted during the United Nations Economic and Social Council's 2024 session (United Nations 2024).

The discussion during the United Nations Economic and Social Council's 2024 session focused on quality education, innovativeness, advancing digital literacy, and decent work (integrity) in the teaching and learning atmosphere and society (United Nations 2024). However, a compelling argument drawn from the session was that Sub-Saharan Africa lacks infrastructure and resources to which technologies could be used to innovate knowledge-driven solutions to teaching and learning problems and to achieve an equal and decent work environment. The researchers, however, reason that this discrepancy shows the Global North-South gap regarding technology development and utilisation in higher education and society.

A further careful review of the United Nations Economic and Social Council's advances in teaching, learning, and society, especially with the use of technology (AI is a subset), shows that Sub-Saharan higher education and society face significant hurdles. The United Nations's 2024 report (pp. 9 and 10) highlighted teacher shortages, inadequate training and resources, and a lack of professional development

opportunities as key challenges. In addition, the report also emphasises the urgent need to address the digital divide gap causing inequalities in education and society.

Similarly, the United Nations Economic and Social Council 2024 report, particularly its sections on digital literacy, quality education, inequalities, and decent work, reveals that Sub-Saharan circuits are still behind in implementing innovative teaching methods due to a lack of resources and digital divides. Upon further examination and inferences from the literature, it becomes safe to argue that the openness in the use of technology, such as AI, in the presence of the aforementioned challenges in Sub-Saharan higher education institutes could lead to unintended and unethical use in education, sparking critical debates among educators and higher education leaders. Not only those but with the increasing instances of unethical and unprofessional use of AI in higher education, some institutions' stakeholders have considered it, while some are now considering the urgent need to develop a policy guiding the use of technology or related AI tools for higher education instructional practices (Abbas et al. 2024; McDonald et al. 2025).

As an illustration of this point, Steingard et al. (2024), in a concept note on the future of higher education and artificial Intelligence, revealed that less than 10% of global colleges and universities have specific regulations for using AI in teaching. According to Steingard et al. (2024), this gap draws attention to the igniting discussions about the inductive effects of AI on teaching and learning, which could mis-drive sustainable development. Corroborating with Steingard et al. (2024) argument, Theodorio et al. (2024), in their work on educators' viewpoint on the use of innovative technologies supporting AI in higher education in Rwanda, Nigeria and Lesotho, argued that AI tools such as ChatGPT, Chat box, smart boards, Kahoot, and Quizizz have the potential to transform education, driving interactive and knowledge-driven learning. However, Theodorio et al. (2024) identified that factors such as poverty, technology complexities, inequalities, and social, economic, and institutional factors could mitigate the use of AI for sustainable higher education. Extending their argument on the subject

matter, Theodorio et al. (2024) contend that the lack of policy regulating the use of AI in higher education could affect an understanding of the constraints AI poses to teaching and society as well as educators missing out on an understanding of the theoretical implications and technological paradoxes of employing AI in higher education and for professional and personal growth.

The researchers acknowledge and agree with Steingard et al. (2024) and Theodorio et al. (2024) arguments that higher education leaders must begin introducing policies to regulate the use of related AI tools in teaching and learning through a careful and collegial approach that also gives a lead way for sustainable teaching and learning experiences in that the theoretical implications and technological paradoxes of employing AI in higher education are understood and practised for professional, personal and national growth. Further, the opening calls for careful and accelerated collegial policy formation and integration into higher education academic endeavours for corrective and sustainable teaching and learning practices. Without these, an uncoordinated and uncensored use of the tool could open critical discourse or lead to serious consequences, such as students and educators lacking a comprehensive understanding of AI's legitimate and professional use in teaching and learning practices (Alam 2021; Yu 2023).

Although the researchers are not biased toward AI use in higher education, the argument is that the challenge of illegitimate and unprofessional use of AI, according to Desai and Riedl (2024) and Floridi (2019), could increase the risk of engaging in unethical practices, leading to severe penalties, including academic sanctions or legal consequences. Besides, urgent, and rapidly growing concerns are emerging in the Global South, where end users do not create but adopt and utilise AI technologies. These concerns highlight the immediate need to address the potential new defects in higher education that AIs could induce. This urgency could help invoke debates and documents to orient users on the products birthed through unethical practices such

as increasing academic dishonesty using AI (Nwozor 2025; Mangundu 2025).

Furthermore, the integration of AI into higher education, with presumably a mindset of achieving sustainable teaching and learning and an informed, equal society, has induced concerns open to discussion in higher education and society. While some scholars like Zhao and Gómez Fariñas (2023) advocate using AI for sustainable teaching and knowledge enhancement, others oppose using it without a corrective approach or guideline (Schiff 2022; Butson and Spronken-Smith 2024). As researchers in AI in higher education, I do not take a stance on these arguments. However, it is argued that AI's positive and developmental potential in higher education is challenged by continuous unethical practices that have emerged and are still emerging in educational settings. It is contended that the situation now raises serious concerns regarding academic integrity, data privacy, data integrity, and decision-making processes, emphasising the need for fairness, openness and the absence of bias and discrimination, which sustainable teaching and learning practices rest on for successful nation development.

Despite the argument for and against the use of corrective approaches or guidelines in educational institutions (Schiff 2022; Butson and Spronken-Smith 2024), the rise of ethical concerns is a pressing global issue that demands immediate attention if sustainability is to be attained in higher education (Priya et al. 2025; Ajagun-Ogunleye 2025; Nnorom 2025). Ajagun-Ogunleye (2025) and Nnorom (2025) posited that AI-enabled technologies could seriously threaten intellectual property rights by illicitly storing and reproducing global north solutions if not used with corrective principles and practices. However, based on the authors' understanding and critical research lens, it seems that literature exemplifying emerging issues on challenges induced by AI use, which are influencing (or not) sustainable higher education in this era of digital belongingness, remains open for extensive and critical research. This noticeable opening highlights the need for a critical review of AI inducements in higher education to

understand the emerging issues that erupted and to reason out solutions to them critically.

Given these arguments, this review is important not only for achieving sustainable higher education, especially those set by the United Nations on quality education, equality, innovativeness, and decency in education and society, but also for its potential global impact. Subsequently, the chapter's methodological foundations include a systematic review of the literature to identify emerging issues linked to the use of AI in higher education instructional practices. More importantly, the methodical, systematic literature review has made it easier to understand how the widespread use of AI speeds up the barriers to sustainable teaching in higher education. Additionally, the systematic review carried out in this chapter answers the following questions:

i. What challenge(s) does AI introduce into higher education?
ii. How does AI use induce issues that influence sustainable higher education?

The following heading succinctly discusses the approach for identifying and selecting literature that provides a critical understanding of the phenomenon understudied.

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2 Methodology

This systematic review of published scientific articles explores the emerging issues induced by artificial Intelligence (AI) and their potential influence on sustainable teaching and learning practices in higher education. The review, which includes sourcing information from databases like Google, Google Scholar, Web of Science, Science Direct, and the Directory of Open Access Journals (DOAJ), was guided by specific keywords such as artificial Intelligence (AI) and products induced by AI impacting on sustainable teaching in higher education.

This proactive, systematic review approach ensured the relevance and depth of the collected literature, particularly in the global and Sub-Saharan higher education context. By focusing on books, articles, reports, and dissertations published between 2020 and 2025, the researchers aimed to provide the most current and accurate insights that address the subject matter under study, keeping the audience abreast of the latest developments. It must be emphasised that articles that did not align with the specified keywords and focus of the study were eliminated in the analysis process. This rigorous approach ensured that the literature discussing the phenomenon in the context of global or Sub-Saharan higher education was identified and retained for onward analysis. This meticulous process ensured that only the most relevant and insightful literature was included in the review. A range of topics, abstracts and findings relating to the use of AI in higher education, teaching methods and their comparative importance to national development were critically reviewed.

For instance, 68 pieces of literature were sourced at the beginning of the search. However, 29 pieces of literature were removed because they extensively discussed the advantages of AI in teaching and the nation's development without critically discussing the products induced that could affect higher education. This critical discussion is crucial as it could affect the sustainability of teaching processes and knowledge development in higher education. 13 articles, which focused on the history and emergence of technology in global development but not on higher education or sustainable education, were also removed. Similarly, 10 articles were removed as they discussed policy formation in national development without addressing the potential impact of generative artificial Intelligence in sustainable higher education, a key focus of this research.

After the review, 16 articles were retained as literature that provided information on AI induction, which helped draw knowledge and inferences on sustainable teaching practices in higher education. Most crucially, the retained literature answered the following questions:

i. What challenge(s) does AI introduce into higher education?

ii. How does AI use induce issues that influence sustainable higher education?

This comprehensive selection of literature, after a rigorous analysis process, advanced through a rereview of the 16 retained articles, focusing on their topics, abstracts, methodology, and findings related to the products induced by AI that impact sustainable higher education teaching practices. The review of the included articles sought, identified, and discussed patterns related to the emerging issues induced by artificial Intelligence, highlighting the challenges and impact on sustainable higher education.

Table 1 gives a snippet of the literature discussing critical issues regarding the products induced by AI that impact sustainable higher education teaching practices (emerging issues induced by AI that impact sustainable higher education teaching practices now coined as EIAIISHETP).

Table 1 A snippet of studies discussing EIAIISHETP

In the following sections, the authors succinctly draws solutions from the literature listed in Table 1 as answers to the research questions.

3 Emerging Issues Induced by AI Influencing Sustainable Higher Education

This section discusses the snippet of the findings drawn and listed in Table 1 to exemplify what and how AI emerging issues impact sustainable higher education teaching practices (EIAIISHETP).

3.1 Academic Dishonesty

Nwozor (2025) opined that using AI tools to facilitate academic dishonesty is a rising and emerging issue in higher education. According to Nwozor (2025), the widespread unethical use of AI-generated content in lesson materials and assignments, often without adequate acknowledgement of the technology involved, is a trend that urgently requires attention. In support of Nwozor's (2025) viewpoints, Farangi et al. (2024) and Onifade and Alex-Nmecha (2023) also opined that AI's infiltration ushered in differential emotions toward its relevance to sustainable education as it somehow and somewhat lowered reading culture, promulgating dishonesty in writing and research. Mangundu (2025) adds, but with a caveat, that in today's technology-driven higher education, the implication of ethical issues related to AI use is a crucial consideration that could arise from a lack of thorough preparation, which could give a hand to lowering education standards especially now that as AI provides ready-made solutions which are unethically utilised as direct copy and paste solutions.

Unfortunately, AIs are continuously being improved and extensively updated to house and reproduce solutions that address teaching and learning problems (Chen et al. 2024). Despite their potential for positive impact, their uncoordinated and unprofessional use, according to Nwozor (2025), Farangi et al. (2024) and Onifade and Alex-Nmecha (2023), keeps encouraging academic dishonesty. The researchers argue that if explored unprofessionally, large language models such as Open and Generative AI (GAI) tools such as ChatGPT (Chat Generative Predetermined Transformers), Deep Seek and the like could precipitate academic dishonesty, overturn sustainable creativity to increase falsehood in knowledge produced through logical retrospection.

3.2 Absence of AI Solutions from the Global South

AI tools are increasingly integrated from databases intended for global use in higher education through the corridors of Global North developers. These tools often reflect contexts more aligned with the Global North than the South, highlighting the gap in the knowledge gathered and kept in the database to suit the Global North context and

to, in particular, produce knowledge made from the Global South. Thus, Okolo et al. (2022) made a case for AI-powered solutions to be tailored for the Global South for sustainable and meaningful development.

Amidst these discussions, the authors reason that the Global South anticipates an open AI tool made and speaks to or benefits the local context in the Global South's high education or social context. Those from the Global North remain popular and impactful, often perpetuating biases and discrimination in solutions suggested for Global South problems. Another reason is that, as earlier identified, a majority of the developers behind AI solutions operate outside African contexts (Nasila 2024; Okolo et al. 2023), producing software for use in Africa without or with limited knowledge of the African environment and higher education identities (Nasila 2024).

This gap now exacerbates debates highlighting the need for Africa-centric AI applications to meet African teaching contexts and curriculum needs (Nasila 2024; Okolo et al. 2023). The researchers argue that software- or AI-related applications tailored to African higher education teaching contexts could help address bias and discrimination issues in AI usage by providing strong connections to local content and pedagogies suitable for sustainable African higher education contexts.

3.3 Overreliance on Technology

When AI tools are used excessively, they can gaslight ethical quandaries, as argued by Chivose in 2023. The argument put forth by Chivose in 2023 underscores the immediate need for creativity, critical reasoning and vigilance among educators and stakeholders in education to address the ethical challenges posed by excessive or over-reliant on AI in higher education as it could aid in knowledge presented without credit to the owners. In another sense, overreliance on technology has the potential of confining addiction to paraphrasing sentences using any of the paraphrasing tools (e.g., Quill Bot and Grammarly) (Anis and Khalid 2024; Fitria 2021), leading to plagiarism, which involves without writing from intuition and knowledge drawn

from literature sourced or without quoting authors. These acts are now a rising case in academics and higher education, as identified by scholars (Kostopolus 2025; Nishant et al. 2020).

In their viewpoints on overreliance on technology, Nishant et al. (2020), in their studies on the challenges and opportunities of Artificial intelligence for sustainable research, argued that overreliance on technology using any machine learning models or AI impede critical interventional reasoning and strategies. Even though AI or machine learning models help create immediate solutions, Nishant et al. (2020) argued that they also introduce long-term threats to the workplace or education, which may, in the long run, have adverse effects on sustainable developments in education or society.

3.4 Lack of Compliance with Established AI Policies and Frameworks

The review findings also showed that noncompliance with established AI policies or frameworks is a growing challenge, in addition to the problems associated with excessive dependence on technology. However, the impetus for noncompliance with policies and frameworks is associated with many challenges mentioned later in this section. Furthermore, Shwedeh et al. (2024) highlighted that establishing policies guiding AI use in the Middle East, for instance, aims to ensure transparency and accountability, institutional efficiency, and seamless operations. This proactive strategy establishes a standard for other countries and holds out the possibility of AI improving education in the future.

Shwedeh et al. (2024) further state that the proposition of the policy on AI was aimed at collective compliance with the policies for appropriate and ethical use within the means of the law. However, the implementation of the framework, according to Shwedeh et al. (2024), is confronted at the execution stage with significant challenges related to lack of awareness, limited resources, and inadequate training. Although Shwedeh et al. (2024) argued to exemplify the challenge in a country in the Middle East context, Van Rensburg and van der

Westhuizen (2024) contended that the framework for AI use in the Global South academia, for example, must be developed under the guidance of academic integrity without undermining foundational skills or widening the digital divide and inequitable access to technology in the country's higher education settings.

However, Jin et al. (2025) stress the importance of collaboration, communication, and continuous evaluation to implement the GAI framework in higher education successfully. According to Jin et al. (2025), these elements are important and required for the GAI framework to close the policy formulation gap and be successfully implemented; otherwise, there may be a lack of compliance on the part of both students and their educators. The authors concur with the argument and recommendation made by Jin et al. (2025) and asserts that these insights can help policymakers create inclusive, transparent, and flexible strategies to integrate the GAI framework into instructional practices seamlessly, ensuring equitable and sustainable higher education.

3.5 Data Privacy Concerns

A further critique of the findings also revealed that a broader exploration of AI for sustainable and personalised learning purposes had heightened the risk of data leakages and unauthorised entry to data stored in repositories. This critical challenge has opened avenues for a solution-practice approach among educators and education stakeholders. Lawal (2025), in their study on the critical examination of artificial intelligence in higher education (HE), made a case that the exploration of digital exploration in today's higher education, though a promising intervention for knowledge enhancement, has also opened up avenues for data enrichment in ways that information is harnessed and used without permission or manipulated to entice information misinformation for personal gains. Along the same argument, Shwedeh et al. (2024) and Chivose (2023) raise the notion that unauthorised access or data encroachment at workplaces or higher education is now rising, raising new concerns for higher education. Chivose (2023)

further contends that issues related to data privacy are now on the rise as AI further heightened ethical issues that are now testing the authenticity of information sourced and disseminated. A critical look at this challenge holds that the problem is emerging and will continue to influence meaningful and intentionally sustainable education if not addressed by all concerned stakeholders.

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4 Discussions, Implications, and Recommendations

In this chapter, the emerging issues induced by AI use, which could influence sustainable higher education, are critically examined using a systematic approach to literature. A total of 16 retained articles provided an understanding of the phenomenon understudied. The necessity for the study stems from the digital divide gap, social inequalities, and a call for decency work, all of which are integral to using AI and sustainable higher education. A Critical look at and exemplifying the problem indicates that Sub-Saharan higher education is behind in implementing innovative teaching methods due to a lack of resources and digital divides. Not only that, but the popularity of AI, in the presence of the aforementioned challenges in Sub-Saharan higher education institutes and elsewhere, induced critical debates among educators and higher education leaders on the emerging issues that AI induced into higher education, impacting sustainable higher education. After the critical review, emerging issues such as data privacy and leakages (Lawal 2025; Shwedeh et al. 2024; Chivose 2023), academic dishonesty (Nwozor 2025; Farangi et al. 2024; Onifade and Alex-Nmecha 2023), absence of AI solutions from the global South (Okolo et al. 2022; Nasila 2024), over-reliance on technology (Chivose 2023; Nishant et al. 2020; Kostopolus 2025) and lack of compliance with established AI policies and frameworks (Swedeh et al. 2024; van Rensburg and van der Westhuizen 2024); were identified as emerging issues induced by the use of AI which could influence sustainable developments in higher education.

It is important to critically critique the implications of higher education issues about the influence on social and educational developments. The authors argue that the influence of AI inductions may impact both students and educators from poorly and richly resourced environments if they lack adequate understanding and tutoring on the ethical use of AI, which could lead to the recording of unethical practices, low reading culture and academic dishonesty, disregard for policy on AI use and over-reliance on technology. The same issue among rich or poor-resourced environments could also influence educators and their students to use AI in ways that unethically source and disseminate information unprofessionally.

Based on these arguments, the researchers suggest recommendations that could help enforce professional use of AI for sustainable higher education instructional practices:

- Institution counsellors must play a pivotal role in continuously engaging and counselling students and educators. They need to emphasize the importance of adapting to technology changes and the responsible use of AI for teaching, learning, and administrative purposes.
- Educators must uphold the serene and professional practice of acknowledging academic sources and technologies in their lesson designs and classroom delivery. This advice is crucial for maintaining academic integrity and encouraging equal learning opportunities in the classroom.
- Institution policymakers could make necessary improvements in using and detecting AI in higher education instructional practices. Institution policymakers must strive to provide AI-enabled infrastructures to expose, train, and reorient students and educators in the ethical use of AI in higher education, including the dangers of relying solely on technology like AI.
- Faculty-wise seminars on the unethical use of AI in higher education must be encouraged and administered before severe punishments are imposed on culprits, be they students or educators. These seminars become pertinent for all students and educators in the

faculty to socially interact, using their teaching contexts as case studies, and for all those concerned with learning coherently and collectively.

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5 Conclusion

The notable emergence and incorporation of artificial intelligence (AI) tools in contemporary society have substantially improved knowledge accessibility and made retrieving and applying information in higher education teaching methods easier. This encouraging trend has the potential to completely transform teaching and learning methods and address present issues. Nonetheless, it has also generated discussions on the emerging issues brought on by the application of AI in higher education. Examining these emerging issues in an era of rising calls for sustainable higher education is the focus of this chapter.

While this chapter has identified issues such as academic dishonesty, non-compliance with established AI policies, over-reliance on technology, data privacy, and the lack of AI solutions from the Global South as emerging issues induced by AI use in higher education, it also underscores the crucial role of continuous engagement and dialogue. Ongoing conversations between higher education stakeholders, educators, and students in a faculty setting are vital. The chapter noted that AI must be used ethically and responsibly for sustainable higher education instructional purposes, making everyone involved an integral part of the teaching process.



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Future Trends in AI-Driven Sustainability Education and Research

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Abstract
Sustainability is increasingly recognized as a critical component for ensuring a resilient and prosperous future. Its significance spans environmental preservation, economic stability, social equity, and business innovation. The integration of Artificial Intelligence (AI) into sustainability education and research is reshaping the landscape of how environmental, social, and economic challenges are understood and addressed. As global sustainability goals become increasingly important and urgent, AI offers the transformative potential to enhance educational practices and research. Several emerging trends are poised to shape the future of AI in sustainability education and research. Firstly, Future trends indicate a shift toward AI-powered personalised learning experiences, where adaptive platforms can tailor content to

individual learners' needs, thereby improving engagement and comprehension. Secondly, the fusion of AI with augmented reality (AR) and virtual reality (VR) technologies promises to create immersive learning experiences. These tools can simulate complex environmental scenarios, providing students with interactive platforms to explore sustainability challenges firsthand. Thirdly, AI is increasingly being leveraged to tackle humanitarian and environmental challenges such as the use of Google's Flood Hub, which forecasts floods in 80 countries, exemplify AI's potential in enhancing disaster preparedness and response. Fourthly, the interaction of blockchain in AI can enhance data security and transparency in research. This integration ensures the integrity of academic records and facilitates trustworthy collaborations across institutions. Fifthly, AI-driven predictive models can anticipate environmental trends and inform proactive strategies. In education, such analytics can identify at-risk students and tailor interventions to improve retention and success rates. Despite the many potential trends in AI-Driven Sustainability Education and Research**,** it is important to address ethical concerns such as data privacy, algorithmic bias, and the potential misuse of technology. Developing responsible future Trends In AI-Driven Sustainability Education and Research requires that technological advancements benefit all stakeholders without causing harm. Institutions must implement frameworks that promote transparency, accountability, and fairness in AI applications, fostering trust and social acceptance. Therefore, incorporating sustainability into AI-driven education equips students with the knowledge and skills necessary to address future environmental challenges.

Keywords Artificial intelligence (AI) – Sustainability education – Sustainability research – Personalised learning – Machine learning – Sustainable development goals (SDGs) – Educational technology – AI for sustainability – Augmented reality (AR) and virtual reality (VR) technologies: Blockchain in AI: Data privacy, algorithmic bias

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1 Introduction

Artificial Intelligence (AI) is reshaping education and research landscapes worldwide. With advancements in machine learning, natural language processing, and data analytics, AI technologies are transforming how educators teach and how researchers conduct investigations (Khosravi et al. 2023). AI has rapidly emerged as a transformative force across education and research, reshaping how knowledge is created, disseminated, and applied. With advances in machine learning, natural language processing, predictive analytics, and immersive technologies, AI is increasingly being integrated into classrooms, laboratories, and institutional systems. At the same time, sustainability has become a central global priority, driven by the urgency of climate change, social inequities, and the need for economic resilience. The convergence of AI and sustainability, therefore, represents a critical frontier in both education and research, as it offers innovative pathways to address pressing societal and environmental challenges.

Recent developments present promising scenarios for the future. In the field of education, AI-powered adaptive platforms are transforming learning experiences by tailoring them to individual student performance in real time. Meanwhile, immersive technologies like augmented and virtual reality (AR/VR) offer engaging simulations of complex environmental systems, enhancing student understanding and engagement. In the realm of research, AI is proving invaluable in managing intricate datasets, generating innovative hypotheses, and modelling potential sustainability outcomes. Additionally, blockchain technologies are paving the way for greater transparency and accountability in collaborative, data-driven initiatives.

While the integration of AI brings immense potential, it also invites important discussions around ethics, equity, and governance. Addressing issues such as privacy, algorithmic bias, and access disparities is crucial. By balancing technological advancements with responsible practices, we can ensure that AI-driven sustainability initiatives in education and research make a positive and lasting impact on societal well-being.

1.1 Artificial Intelligence in Teaching and Research

AI in Teaching and Learning

AI applications in teaching have evolved significantly, over the last few years. It offers personalized and adaptive learning experiences. Intelligent Tutoring Systems (ITS) and Learning Analytics platforms are increasingly used to tailor educational content to individual learners' needs, improving engagement and learning outcomes (Bond et al. 2024; Khosravi et al. 2023). These systems leverage machine learning algorithms to analyse student performance data in real-time and adjust learning pathways accordingly. Furthermore, AI tools like chatbots and virtual teaching assistants are being adopted in higher education institutions to support student queries, offer learning recommendations, and provide 24/7 academic support (Essel et al. 2022). AI supports automated grading and formative assessment,

enabling instructors to provide immediate feedback on quizzes, essays, and coding exercises (Bond et al. 2024; Khosravi et al. 2023). AI-driven learning analytics allow teachers to track student progress, identify learning gaps, and intervene early for at-risk students. Such predictive systems enhance student retention and improve learning outcomes (Zawacki-Richter et al. 2022).

AI Applications in Research

AI plays a pivotal role in handling large and complex datasets in research. AI-powered data mining and machine learning algorithms help researchers uncover patterns, trends, and insights that would be difficult to detect manually (Thiyagalingam et al. 2022). Tools using Natural Language Processing (NLP) assist researchers in conducting systematic literature reviews by rapidly screening thousands of research articles (Leal Filho et al. 2023). AI tools help in experimental design optimization, hypothesis generation, and even automated writing support for academic papers (Essel et al. 2022). The integration of AI into research methodologies accelerates the research cycle, improving efficiency and knowledge dissemination. Researchers are increasingly using AI for predictive modelling in fields such as environmental science, healthcare, and economics (UNESCO 2024a). AI also contributes to research design and methodology. For example, AI can help generate hypotheses, optimize experimental designs, and simulate research outcomes (Córdova-Esparza 2025).

Benefits of AI Integration in Education and Research

There are many benefits of integrating AI in teaching and research. These include (Fig. 1):

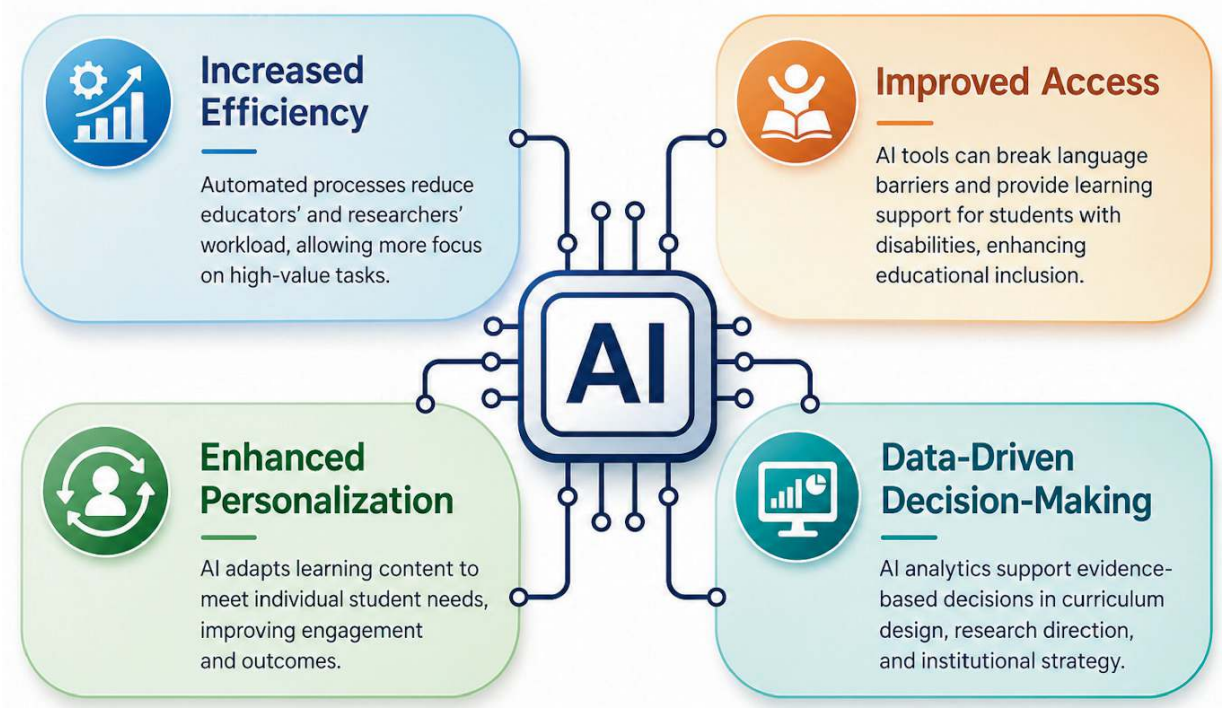


Fig. 1 Benefits of integrating AI in teaching and research

- **Increased Efficiency**: Automated processes reduce educators' and researchers' workload, allowing more focus on high-value tasks (Lee and Moore 2024).
- **Improved Access**: AI tools can break language barriers and provide learning support for students with disabilities, enhancing educational inclusion (UNESCO 2024a).
- **Enhanced Personalisation**: AI adapts learning content to meet individual student needs, improving engagement and outcomes (Bond et al. 2024; Khosravi et al. 2023).
- **Data-Driven Decision-Making**: AI analytics support evidence-based decisions in curriculum design, research direction, and institutional strategy (Zawacki-Richter et al. 2022).

Against this backdrop, this chapter seeks to address three key research questions:

1. How can AI-driven adaptive learning and predictive models enhance student engagement, comprehension, and decision-making in sustainability education?

2. What is the potential of AI-enhanced immersive technologies (AR/VR) in fostering a deeper understanding of complex sustainability challenges?
3. What ethical, equity, and governance issues must be addressed to ensure the responsible integration of AI and blockchain in sustainability education and research?

The remainder of this chapter is structured as follows. Section 2 reviews the conceptual foundations of sustainability in education and research. Section 3 discusses the integration of AI into sustainability-focused teaching and research practices. Section 4 highlights emerging trends, including adaptive learning, immersive technologies, predictive modelling, and blockchain applications. Section 5 analyses the role of AI in addressing humanitarian and environmental challenges, while Sect. 6 examines the ethical and equity implications of AI adoption. Finally, Sect. 7 outlines recommendations and directions for future sustainability education and research in an AI-driven era.

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2 Literature Review

Sustainability has become a central theme in education and research, driven by global challenges such as climate change, resource scarcity, and social inequality. Education for Sustainable Development (ESD) emphasises equipping learners with the skills and values needed for a more resilient future. At the same time, sustainability-focused research generates evidence-based solutions to real-world problems. Increasingly, Artificial Intelligence (AI) is positioned as a transformative tool to advance these goals, offering new opportunities for innovation, collaboration, and impact.

2.1 Sustainability in Education and Research

The increasing urgency of global environmental and social challenges, such as climate change, biodiversity loss, and resource scarcity, has

intensified the focus on sustainability in all sectors of society, particularly education and research. According to Leal Filho et al. (2023), integrating sustainability principles within educational curricula and research agendas equips learners and scholars with the knowledge, skills, and ethical frameworks necessary to drive transformative solutions for a sustainable future.

What Is Sustainability

Sustainability is the buzzword of the world today. Although there are many definitions given to sustainability, there is no agreed definition. The idea of sustainable development gained significant recognition with the release of the Brundtland Report, formally titled "Our Common Future" (World Commission on Environment and Development, WCED 1987). This pivotal report articulates sustainable development as "development that meets the needs of the present without compromising the ability of future generations to meet their own needs." This definition has become a foundational element in the global discourse on sustainability and has significantly influenced international policy frameworks. Building on this important groundwork, the 1992 United Nations Conference on Environment and Development (UNCED), commonly referred to as the Earth Summit, held in Rio de Janeiro, transformed these principles into actionable agendas like Agenda 21. This marked a crucial step toward integrating sustainability into global policy initiatives. In the field of environmental sciences, 'sustainable' describes practices that prioritise the prudent use of natural resources while honouring the limits of our ecosystems. This approach is crucial for promoting long-term environmental health (Tso 2021). Moreover, understanding sustainability in its original etymological context highlights the notion of maintaining, supporting, or reinforcing over time. This perspective highlights the importance of intergenerational equity and the need for endurance in our environmental practices (Di Fabio 2017).

Why Sustainability Is Important

The aim of Sustainability is to improve the environmental health and quality of life for our society. Sustainability can be grouped into three categories, or 'pillars': environmental, social and economic. The three pillars must be supported. Sustainability cannot work if one of the pillars is not supported. These three pillars are informally referred to as people, planet and profits.

The environmental pillar is often the most emphasised dimension of sustainability—it focuses on reducing the environmental impacts of human activities, such as lowering carbon footprints, minimising packaging waste, conserving water, and thus safeguarding the ecological systems that support communities (Cheng et al. 2023). In contrast, social sustainability centres on fostering processes that nurture healthy communities—not only for current members but for future generations—encompassing fair labour conditions, health, equity, and intergenerational equity (Annarelli et al. 2024). It must have the support and approval of its employees, stakeholders and the community where it operates. This involves treating employees fairly and being a good neighbour and community member, both locally and globally. The Economic Pillar is concerned with sustainable business to make money. The other two pillars such as Environment and social pillars cannot be compromised simply to make profit. However, profit cannot compromise the other two pillars. In order to balance between the three pillars, the economic pillar should include compliance with standards, proper business governance and risk management. A balance between the following goals is usually attempted: keep a healthy and equitable society, protect the environment, and guarantee economic prosperity. The three goals are interrelated and equally contribute to the economic sustainability of the development plan so this balance throughout the plan lifecycle is important.

Why Sustainability Matters in Education

Education for Sustainable Development (ESD)—also known as sustainability education—is a dynamic, transformative approach that empowers learners of all ages with the *knowledge, skills, values,*

attitudes, and behaviors needed to contribute responsibly to environmental integrity, economic resilience, and societal equity (UNESCO 2025). UNESCO further emphasizes that ESD prepares individuals to become "*sustainability changemakers*" by equipping them to understand and act on the Sustainable Development Goals (SDGs) (UNESCO 2017). Sustainability has emerged as a central theme in global educational discourse, primarily due to escalating environmental crises, socio-economic inequalities, and the urgent need for a more equitable and resilient future. The United Nations' 2030 Agenda for Sustainable Development emphasizes Education as a key driver in achieving all 17 Sustainable Development Goals (SDGs), especially SDG 4, which advocates for inclusive and quality Education and promotes lifelong learning opportunities for all (UNESCO 2017). Education for Sustainable Development (ESD) seeks to empower learners with the knowledge, skills, values, and attitudes necessary to contribute to sustainable development. As highlighted by Sterling (2001), ESD moves beyond environmental awareness to a transformative form of Education that promotes critical thinking, future-oriented planning, and responsible citizenship. It requires a paradigm shift from traditional, subject-based instruction to interdisciplinary, action-based learning that integrates ecological integrity, economic viability, and social equity. He also describes sustainable education as requiring a paradigm shift from accommodation to transformation—moving beyond mere environmental awareness to deeply critical and creative learning. He posits that only transformative learning can fundamentally restructure educational purposes, fostering systemic thinking, future-oriented planning, and responsible citizenship (Sterling 2001).

A growing body of research supports the integration of sustainability into education systems at all levels. Tilbury (2011) emphasises that ESD should cultivate **futures thinking, critical and creative thinking, participatory decision-making, interdisciplinary collaboration, and systemic understanding**, all of which are essential competencies for addressing complex global challenges. Moreover, ESD enhances learner engagement by making education more relevant to

real-world issues (Nolet 2015). Research increasingly shows that sustainability education fosters deeper engagement by linking curricula to students' lived experiences and global concerns. For example, a study in Beijing found that sustainability education enhances student well-being via increased mindfulness (Gu et al. 2024). Similarly, a theoretical model in Saudi Arabian higher education revealed that ESD-related factors—such as institutional support, instructor role modeling, and mental health resources—are key to student well-being (Abdelrahim and Zafer 2024). Efforts in institutional sustainability—such as the development of green campuses, community-based projects, and innovative curriculum redesign—hold significant potential for enhancing environmental stewardship. To fully realise this potential, it's essential to address systemic barriers, including enhancing teacher preparation, revising rigid curricula, and increasing policy support. Zickafoose et al. (2024) emphasise the importance of tackling challenges such as funding shortages, promoting inclusivity, and improving teacher education. By focusing on these areas, we can create a more supportive environment for scaling these valuable innovations. Thus, educators, policymakers, and institutions must work collaboratively to embed sustainability into both the formal and informal dimensions of learning. Hence, sustainability matters in education as an academic theme and a foundational principle that guides pedagogy, curriculum, and institutional practices. As the world faces mounting ecological and social challenges, embedding sustainability in education is no longer optional—it is essential for cultivating informed, responsible, and proactive global citizens.

Why Sustainability Is Important in Education?

The essential features of sustainability education include interdisciplinary learning, critical and reflective, values and ethics, participatory and action-oriented and lifelong and Holistic. As for interdisciplinary learning, this approach integrates concepts from various fields, including environmental science, economics, ethics, and social justice. It encourages the breakdown of subject silos, enabling

learners to explore the interconnectedness of global systems (Vaverková et al. 2024). As for critical and reflective thinking, sustainability education nurtures students' ability to question existing practices and envision alternative pathways for sustainable development. It enhances their problem-solving and decision-making skills, equipping them to tackle real-world challenges. Moreover, for values and ethics, this educational framework promotes empathy, equity, and care for the planet and future generations. It instils a sense of responsibility and cultivates global citizenship among learners. For participatory and action-oriented learners, engaging them in real-world problem-solving and community projects is a key component. This hands-on approach, which emphasises learning by doing, fosters the development of practical solutions for sustainable living. Last but not least, lifelong and holistic sustainability education is relevant at all levels and types of education—formal, non-formal, and informal. It recognises and addresses sustainability's environmental, social, and economic dimensions, promoting a comprehensive understanding of these interconnected issues.

Sustainability is not just an academic theme; it is a foundational principle that shapes our pedagogy, curriculum, and institutional practices. As we confront increasing ecological and social challenges, integrating sustainability into education becomes essential. It empowers us to cultivate informed, responsible, and proactive global citizens who can create a better future.

- **Preparing Future Leaders and Citizens—An Educational Imperative**

The need to prepare future leaders and citizens has become central to educational policy and practice in a rapidly evolving global society shaped by digital transformation, climate urgency, and geopolitical complexity. Education systems are increasingly called upon to deliver academic knowledge and cultivate critical thinking, ethical reasoning, civic engagement, and global competence. According to (Fullan et al. 2018), developing "deep learning competencies"—including

collaboration, communication, creativity, and citizenship—is essential for equipping students to lead and participate meaningfully in society. These competencies align with the broader aims of twenty-first-century education, which prioritise holistic development alongside academic achievement. Leadership and citizenship education are also deeply intertwined with values-based education and participatory learning environments. Research shows experiential learning, problem-based approaches, and student agency are crucial for nurturing democratic values and ethical leadership (Westheimer and Kahne 2004). Furthermore, integrating sustainability education and digital literacy within the curriculum supports students in addressing complex, real-world challenges — preparing them not only to lead but also to contribute responsibly to their communities and the planet (Haleem et al. 2022). Thus, education systems must intentionally balance knowledge acquisition with cultivating civic responsibility, emotional intelligence, and leadership capacity.

- **Transforming Educational Institutions**

Transforming educational institutions is a multifaceted process that involves rethinking pedagogical approaches, embracing technology, fostering inclusivity, and realigning curricula to meet twenty-first-century competencies. This transformation is primarily driven by rapid advances in digital technologies, socio-economic changes, and global challenges such as the COVID-19 pandemic, underscoring the urgency for resilient and flexible learning environments. According to Bisri (2025), digital transformation in education requires the integration of digital tools and a cultural shift in leadership, teaching practices, and policy frameworks. Such transformations foster student-centred learning, increase accessibility, and cultivate future-ready skills, including critical thinking, digital literacy, and global citizenship.

A successful transformation also hinges on institutional capacity, faculty development, and stakeholder collaboration. As Al-Fraihat et al. (2019) emphasise, the effectiveness of digital learning environments is closely tied to institutional readiness, the quality of e-learning systems,

and the continuous professional development of educators. Education for Rural People (ERP), an FAO–UNESCO initiative, highlights the significant education access disparities facing rural and underserved communities, advocating for equity-oriented strategies such as community partnerships and locally relevant, culturally responsive curricula (FAO and UNESCO n.d). This aligns with findings from Hidayat and Nuruzzaman (2024), who underscore that inclusive education—by ensuring accessibility and stakeholder collaboration—serves as a concrete approach to bridging the rural–urban education divide (Hidayat and Nurruzzaman 2024). In this context, innovative frameworks such as hybrid learning models, artificial intelligence integration, and data-driven decision-making are increasingly being adopted to personalise learning and improve institutional efficiency. These efforts are essential for modernisation and nurturing lifelong learners capable of thriving in complex and uncertain futures.

- **Driving Innovation and Societal Transformation**

Innovation has become a pivotal catalyst for societal transformation in the Fourth Industrial Revolution (4IR) era. Emerging technologies such as artificial intelligence (AI), biotechnology, and renewable energy systems are reshaping industries, economies, and daily life. These innovations boost productivity and economic growth and serve as tools for addressing complex societal challenges, including climate change, healthcare disparities, and educational inequities. As Schwab (2016) argued, the fusion of technologies blurs the lines between the physical, digital, and biological spheres, prompting institutions to rethink governance, education, and social contracts to ensure inclusive and ethical progress.

Moreover, innovation ecosystems—academia, industry, government, and civil society—play a crucial role in fostering transformative change. According to Mazzucato (2018), mission-oriented innovation policies, which target grand societal challenges rather than merely economic returns, are vital for steering technological development toward public good outcomes. When aligned with Sustainable Development Goals

(SDGs), these innovation agendas can potentially drive systemic change across sectors. For instance, investment in green technologies mitigates environmental risks, creates new job markets, and supports social equity (Geels 2017; Khan et al. 2025). Thus, innovation is not an end but a strategic mechanism for co-creating resilient, inclusive, and future-ready societies.

- **Responding to Urgent Global Challenges**

In an increasingly interconnected world, urgent global challenges such as climate change, pandemics, resource depletion, and geopolitical instability demand coordinated, interdisciplinary responses. Global challenges encompass issues that transcend national borders and require collective action across governments, industries, and civil society. Climate change, for instance, presents escalating threats to food security, health, and ecosystems, calling for global climate governance and local adaptive capacities (Marchal 2021). The COVID-19 pandemic further exposed the fragility of global health systems and the socioeconomic inequalities within and among nations, prompting new frameworks for pandemic preparedness and digital cooperation (Gostin et al. 2020).

Responding effectively to such challenges necessitates scientific innovation and systemic transformation in education, leadership, and policy. The United Nations' Sustainable Development Goals (SDGs) are a comprehensive framework for aligning national policies with global imperatives, emphasising the need for resilience, inclusivity, and sustainability (The 17 Goals). Scholars argue that addressing global crises requires integrated approaches that blend technological solutions with ethical and equitable governance models. One major challenge is that technological advancements (e.g., AI, biotechnology, climate engineering) often develop faster than ethical frameworks and regulatory mechanisms. This creates gaps in oversight and increases risks related to misuse, inequality, and environmental harm. As argued in the **AI4People** framework, ethical governance and regulation frequently trail behind technical innovation, thereby exacerbating risks

related to bias, accountability, and power centralization (Floridi et al. 2018). As such, fostering transdisciplinary collaboration, investing in green technologies, and reforming global institutions are critical pathways toward a more resilient and equitable future.

2.2 The Importance of Sustainability in Research

It is important to integrate sustainability into research agendas in education because it enhances the generation of innovative, evidence-based solutions that support sustainable policymaking and practice (Ankareddy et al. 2025). Sustainability-focused research fosters interdisciplinary collaboration and drives systemic change by addressing real-world problems through a combination of scientific rigor and social relevance (Galloway et al., 2025). It also aligns with the United Nations Sustainable Development Goals (SDGs), which provide a global framework for action to eradicate poverty, protect the planet, and ensure prosperity for all (Education for Sustainable Development 2024).

Education for Sustainable Development

Education for Sustainable Development (ESD) positions education as a cornerstone for achieving progress across the global Sustainable Development Goals (SDGs). It aims to equip individuals of all ages with the knowledge, skills, values, and competencies to address pressing issues such as climate change, biodiversity loss, overuse of resources, and widening inequalities. Conceptually, ESD is framed around three core learning dimensions: **cognitive** (improving knowledge and understanding), **socio-emotional** (fostering empathy, collaboration, and emotional intelligence), and **behavioural** (promoting action-oriented change). These dimensions are often cited as central to transforming learners into responsible global citizens capable of contributing to sustainable futures.

However, while this typology provides a useful framework, its real-world implementation remains uneven and contested. In many conventional education systems—where exam-driven curricula and

limited teacher preparation dominate—ESD is often relegated to mere environmental awareness, rather than fostering socio-emotional learning or action-oriented transformation (Stevenson 2007). Moreover, although the five proposed action areas—advancing policy, transforming learning environments, building educator capacity, empowering youth, and accelerating local action—are frequently endorsed in international policy documents, their implementation often encounters systemic barriers. For example, rigid curriculum structures, limited financial investment, and lack of political will mean that ESD initiatives risk remaining rhetorical rather than transformative. This gap between policy rhetoric and classroom practice highlights the need for critical evaluation of how, and under what conditions, ESD strategies succeed.

Another important critique is that ESD is sometimes aligned too closely with economic agendas such as "green growth," prioritising economic competitiveness over ecological integrity or social equity. Critics argue this risks diluting ESD's transformative potential by reinforcing existing systems rather than questioning unsustainable practices. Therefore, while ESD is presented as a universally beneficial framework, it requires critical reflection on its underlying assumptions, local contexts, and structural barriers to move beyond aspirational statements into measurable change.

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3 Integration of Artificial Intelligence (AI) into Sustainability Education and Research

Artificial Intelligence (AI) is increasingly embedded within education and research—and UNESCO underscores its potential to innovate learning and **accelerate progress toward Sustainable Development Goal 4 (quality education)**, while emphasising the importance of inclusive and equitable deployment (UNESCO 2024b). Further broad initiatives across UNESCO position AI as a crucial innovation to support broader sustainability goals such as climate action and lifelong learning. AI's potential is framed as transformative: adaptive learning

platforms personalize education by responding to learner needs, predictive analytics identify at-risk students or model environmental scenarios, and AI-driven simulations enable real-time engagement with complex systems such as ecosystems or climate models. Similarly, in research, AI supports data-driven discovery, hypothesis generation, and interdisciplinary collaboration. These applications are positioned as critical to building the next generation of sustainability leaders and researchers.

However, this perspective risks being overly optimistic if challenges are not critically acknowledged. The integration of AI raises questions of equity**:** in low-resource contexts, limited access to digital infrastructure, unstable internet connectivity, and teacher readiness may exacerbate rather than bridge the digital divide. While AI can personalize learning, it may also reproduce existing biases in data, embedding inequities into educational outcomes. For example, adaptive systems trained on data from privileged contexts may fail to serve marginalized learners effectively.

From an environmental perspective, AI also presents a sustainability paradox**.** Training large-scale AI models consumes significant energy and contributes to carbon emissions, raising doubts about whether its use in sustainability education is itself environmentally sustainable. If AI is to support sustainability goals, attention must be paid to "green AI" approaches that minimize energy consumption and prioritize responsible development.

Ethical issues further complicate AI's role in sustainability education. Data privacy, algorithmic transparency, and accountability remain significant concerns. Students' personal and learning data, if misused, can compromise trust and well-being. Moreover, overreliance on automated decision-making risks undermining critical socio-emotional and ethical dimensions of ESD, potentially reducing education to data optimization rather than a transformative social process. A more balanced analysis must therefore address both the opportunities and trade-offs of AI integration. While AI has the potential to strengthen personalisation, efficiency, and predictive

capacity, it also introduces new risks that require governance, ethical oversight, and contextual sensitivity. Without such considerations, there is a danger of positioning AI as a technological fix for deeply social and political sustainability challenges.

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4 Trends in AI-Driven Sustainability Education and Research

One of the most significant applications of Artificial Intelligence in education is the development of personalised learning systems. Unlike traditional approaches that apply uniform methods to all learners, AI-driven platforms adapt instruction to individual needs, abilities, and learning styles. By analysing real-time performance data, these systems can adjust content, pacing, and feedback to create customised learning pathways that enhance engagement, accessibility, and overall academic outcomes. Several emerging trends are shaping the future of AI in sustainability education and research.

4.1 AI-Powered Personalised Learning

There is a shift toward AI-powered personalised learning experiences, where adaptive platforms can tailor content to individual learners' needs, thereby improving engagement and comprehension. Adaptive learning systems use AI algorithms to tailor content, pacing, and feedback in real time based on student performance and preferences. These systems dynamically construct personalized learning trajectories, enabling data-driven interventions and real-time adjustments (Strielkowski et al. 2024).

Artificial Intelligence (AI) is revolutionising education by enabling personalised learning experiences catering to individual student needs, enhancing engagement and comprehension. Traditional one-size-fits-all teaching methods often fail to address students' diverse learning styles and paces. AI-powered adaptive learning platforms overcome this limitation by analysing learners' interactions, performance, and preferences to tailor educational content accordingly. For instance,

Halkiopoulos and Gkintoni (2024) conducted a systematic analysis highlighting how AI integration in e-learning facilitates personalised learning and adaptive assessment, improving student outcomes. Similarly, a study published in *Electronics* emphasises the role of AI in adjusting learning pathways in real-time, ensuring that students receive content that aligns with their current understanding and skill level. These adaptive systems not only identify knowledge gaps but also provide immediate feedback and resources to address them, fostering a more effective and engaging learning environment.

The impact of AI-driven personalised learning extends beyond individual academic performance to broader educational equity and accessibility. By customising learning experiences, AI helps bridge gaps for students who might struggle in conventional classroom settings due to various factors such as language barriers, learning disabilities, or socioeconomic challenges. Research by Al Nabhani et al., (2025) underscores the significance of AI in personalising educational content and enhancing the learning experience by providing real-time assistance based on student performance. Moreover, integrating AI in education supports educators by offering insights into student progress, allowing for more informed instructional decisions. As AI technologies evolve, their potential to democratise education and foster inclusive learning environments becomes increasingly evident. However, addressing ethical considerations, such as data privacy and algorithmic bias, is crucial to ensure that AI implementations in education are equitable and beneficial for all learners.

According to Sajja et al. (2024), proposed framework, "AIIA" (Artificial Intelligence Enabled Intelligent Assistant), integrating NLP to respond to student queries, generate quizzes, and chart personalized learning paths—demonstrated enhanced engagement and reduced cognitive load. A semester long case study in higher education was carried out by Baillifard et al. (2024) using a GPT powered personal tutor that automatically generated microlearning questions and modelled student understanding. They found that Students using this

AI tutor improved by about 15 percentile points compared to a control group.

Mejeh and Rehm (2024) show that the integration of Natural Language Processing (NLP) enhances adaptive learning platforms by capturing learner context and supporting self-regulated learning—indicating strong acceptance in co-designed school implementations. "Audemy," an adaptive, audio-based AI platform aimed at blind and visually impaired learners presented by Yang and Taele (2025) with over 2000 users, demonstrated that this system adapts pacing and content, enhancing accessibility and engagement—highlighting AI's potential to serve diverse learners.

Many learning institutions has integrated AI-powered adaptive learning systems into its sustainability curriculum, enabling students to engage with real-time climate data through interactive simulations (Leal Filho et al. 2025). By leveraging machine learning models, the platform customizes learning pathways based on student performance and interests, fostering deeper understanding of climate dynamics and policy implications. This approach has led to increased student engagement and improved retention of sustainability concepts.

The University of Edinburgh has developed AI-supported tools to assist researchers in navigating and synthesizing scientific literature. For instance, the ELM chatbot—based on large language models—helps users refine literature searches and access related works efficiently. Additionally, the University's Generative AI Laboratory (GAIL) consolidates NLP and machine-learning expertise to drive cross-sector innovation, including applications relevant to sustainability research (Floridi et al. 2018).

Despite there being many benefits that AI driven adaptive learning can substantially improve learner outcomes, engagement, accessibility, and personalization across education levels, widespread adoption hinges on addressing critical factors such as data privacy, algorithmic fairness, digital infrastructure, and educator support.

AR/VR for Immersive Learning

One of the most promising trends in AI-powered personalised learning is the integration of Augmented Reality (AR) and Virtual Reality (VR) to create immersive learning environments. These technologies offer learners the opportunity to engage with content in three-dimensional, interactive spaces that simulate real-world scenarios. When combined with AI, AR/VR systems can adapt simulations based on learners' actions, responses, and progress, creating hyper-personalized and emotionally engaging learning experiences (Xu et al. 2025). These tools can simulate complex environmental scenarios, providing students with interactive platforms to explore sustainability challenges first-hand. For example, AI-driven VR platforms such as Lobster and zSpace are now being used in schools and universities to provide virtual laboratory experiences where students can experiment safely with scientific concepts (Aljumaiah and Kotb 2021). These platforms allow the AI engine to track learner behaviour within the virtual environment and adjust difficulty levels or provide timely prompts (Gligorea et al. 2023).

AR applications in education, such as Google Expeditions and Merge EDU, offer location-based or object-triggered interactive learning experiences. AI further enhances these experiences by tailoring the pace and depth of information based on the learner's profile and real-time engagement metrics (Yaseen et al. 2025). According to researchers (Mallek et al. 2024), immersive learning environments improve knowledge retention, engagement, and conceptual understanding compared to traditional learning formats.

Immersive learning using AR and VR are becoming popular in education. When augmented with AI, they transcend static simulations by offering real-time adaptation, personalized feedback, and data-driven insights, making learning more effective and engaging (Marougkas et al. 2023). AR combined with AI offers contextual feedback using NLP, computer vision, and gesture recognition. This enables learning objects like 3D heart models or real-time translations overlayed in the environment, tailored to individual learners. AI-enhanced VR enables students to conduct virtual experiments and

explore abstract scientific concepts in ways not feasible with textbooks. STEM outcomes improve notably with these immersive simulations.

Challenges and Ethical Considerations in AI Powered AR/VR Learning

Although AR/VR tools promise immersive and engaging learning experiences, their adoption is often hindered by high costs. As noted by Samala (2025), schools and universities—especially those in under-resourced areas—face significant financial barriers due to the need for advanced headsets, high-end computing infrastructure, and specialised peripherals. In resource-limited settings, inadequate infrastructure and teacher preparation can further impede adoption (Mondal and Mondal 2025). Secondly, because AR/VR hardware evolves rapidly; schools may struggle to keep curricula and teacher training current as devices become outdated almost as soon as procured. Thirdly, extended use VR causes cybersickness (Lawson and Stanney 2021), frequently triggers symptoms such as nausea, headaches, dizziness, and eye strain. Fourthly Immersive environments may blur reality, potentially leading to disorientation, addiction, or diminished attention to real-world activities (Mimnaugh et al. 2023; Zhang et al. 2025).

Besides the challengers, AR/VR-based learning also comes with important privacy and ethical issues. These technologies collect sensitive biometric data like eye movements, gestures, and body responses, which raises concerns under laws like GDPR, COPPA, and HIPAA (David-John et al., 2021; Kröger et al., 2020; Hanisch et al., 2025). Regular text-based consent forms do not work well in immersive environments, leading to gaps in user understanding and legal protection (Calo 2023). Experts point out that laws and ethical rules have not kept up with the growth of AR/VR, and they urge the need for better transparency and responsibility (Hine 2024). AI-powered AR/VR systems can also show bias. If models are trained on unbalanced data, they may provide unfair experiences or even exclude marginalized learners, worsening educational inequalities (Boateng and Boateng 2025; Khan and Kaur 2023). To tackle these problems, we need clear

consent processes, transparency in how data is used, and fair design in algorithms. This will help ensure equal opportunities and build trust in AR/VR learning environments.

AI for Humanitarian and Environmental Challenges

AI is increasingly being leveraged to tackle humanitarian and environmental challenges such as the use of Google's Flood Hub, which forecasts floods in 80 countries, exemplify AI's potential in enhancing disaster preparedness and response.

Artificial Intelligence (AI) has emerged as a transformative force in addressing some of the world's most pressing humanitarian and environmental challenges. Among the most notable advancements is Google's Flood Hub, a platform that forecasts floods in over 80 countries, including vulnerable regions across South Asia, Africa, and Latin America (Matias 2024). By integrating machine learning, hydrological models, and satellite data, Flood Hub provides timely and highly localised alerts that allow authorities and communities to prepare for imminent flood events. This represents a significant shift from traditional early warning systems, which often suffer from delayed response times and imprecise forecasts. According to Google, its flood forecasting systems have already reached more than 460 million people globally and continue to expand (Google 2023). The application of AI in such contexts underscores how predictive analytics can mitigate the impacts of climate-induced disasters, saving lives, protecting infrastructure, and minimising displacement. A recent study published in *Nature* supports this, demonstrating that AI-based flood models can offer highly accurate forecasts even in data-scarce regions (Nearing et al. 2024). Flood Hub's predictive capabilities demonstrate how data-driven technologies can be used to monitor natural hazards and empower governments, NGOs, and at-risk populations to make informed decisions ahead of disasters. Beyond flood prediction, the use of AI in humanitarian and environmental domains extends to a broad array of applications, including wildfire detection, drought monitoring, epidemic outbreak prediction, and supply chain optimisation for

disaster relief. For instance, AI algorithms are being employed to detect early signs of wildfires using infrared imagery and sensor data, enabling emergency services to intervene more rapidly (UNESCO 2024c). Researchers, such as Yadav (2024), highlight the growing use of AI-powered tools, including predictive modelling and optimisation algorithms, to significantly improve logistics and resource allocation in disaster response efforts. These advancements promise to enhance overall efficiency and effectiveness in managing crises.

However, these AI systems rely on vast, real-time data sets and can identify trends and anomalies that would be imperceptible to humans. As the climate crisis intensifies, the ability of AI to process enormous volumes of complex data and generate actionable insights makes it an indispensable tool in anticipatory action and long-term resilience planning. Nevertheless, ethical considerations—such as data privacy, algorithmic transparency, and equitable access—must remain central to the deployment of AI to ensure it serves as a force for good in humanitarian and environmental governance (UNESCO 2024c).

Disaster Response Tools

In humanitarian crises, timely access to accurate information can mean the difference between life and death. Artificial Intelligence has begun to play a crucial role in enhancing disaster preparedness and response by equipping aid workers and affected communities with real-time, context-specific insights. AI-driven tools are increasingly designed to support decision-making, streamline communication, and deliver life-saving resources in challenging environments, thereby strengthening resilience and response capacity during emergencies.

- **Methods Matcher**

Humanitarian aid workers often operate under immense pressure with limited access to reliable, context-specific information. Business Insider (2025) describes how Mercy Corps has deployed **Methods Matcher**, a generative AI tool, to help field staff access timely, evidence-based information in real time. The **Methods Matcher** tool utilizes a large

language model (LLM)-based generative AI system trained on a curated database of humanitarian best practices. This database includes over 15 years of field-tested knowledge, covering topics such as food security, emergency shelter, disaster response, and water sanitation.

- **Signpost and AprendIA**

Signpost, developed by IRC's innovation lab Airbel, delivers vetted information to refugees via social media, while AprendIA offers personalised chatbot-based education for children in crisis zones—both examples of AI aiding humanitarian response (Miliband 2024). Another tool is **AprendIA**, supported by OpenAI, enables personalised educational content via messaging platforms in multiple local languages for crisis-affected learners (Miliband 2024; Reuters 2024b).

4.2 Challenges and Ethical Considerations

There are challenges and ethical issues concerned the use of AI for Humanitarian and Environmental Challenges. AI-intensive systems consume significant energy, raising sustainability and environmental cost concerns—especially in deploying large-scale forecasting systems. AI models may embed bias or breach community trust when trained on skewed datasets or deployed without transparency. Independent research underscores the importance of ethical safeguards to protect vulnerable groups. Humanitarian actors may mistrust "blackbox" AI models. Responsible innovation calls for explainability, robust oversight, and governance frameworks to ensure accountability and build user trust. AI tools may have Connectivity Issues although many organisations are working on making the tools usable offline, internet access remains a barrier in remote areas. Distributing live environmental and humanitarian data requires secure, ethical governance. Standards must safeguard against misuse while maximizing benefits.

Integration of Blockchain and AI to Enhance Data Security and Transparency in Research

Research is increasingly relying on large datasets and AI-driven analysis, raising concerns about data tampering, provenance, intellectual property management, and reproducibility. Traditional systems lack immutable auditing mechanisms. A recent proposal leverages blockchain to track dataset origins, transformations, and AI model outputs—thereby ensuring transparent, trustworthy research workflows (Marchioro et al. 2025).

Benefits of Blockchain for AI-Driven Research

The main benefits of applying blockchain in AI-driven research are: *Data Integrity and Provenance*—One of the core benefits of blockchain is its ability to provide a secure, immutable ledger of transactions. For AI-driven research, where model training and data analysis depend on the quality and integrity of input data, blockchain ensures traceability and prevents tampering. Each data entry or research activity recorded on a blockchain is timestamped and cryptographically linked, enabling researchers to verify the origin, modifications, and ownership of data (Sun et al. 2022).

This capability supports reproducibility and auditability in AI research, which are critical in scientific validation processes. According to (Khoi Tran et al. 2022), blockchain-based systems can document every stage of data preprocessing, model training, and result generation, thus facilitating trust and transparency across interdisciplinary research teams.

Enhanced Collaboration and Decentralized Data Sharing

AI-driven research often requires collaboration across institutions, countries, and sectors. Blockchain enables secure, decentralized data sharing without the need for centralized control or intermediaries. Through smart contracts and distributed storage protocols, blockchain allows researchers to share datasets and models with predefined access rights and conditions (Khoi Tran et al. 2022). This is particularly beneficial for collaborative projects involving sensitive health, environmental, or financial data. Researchers can access shared

resources transparently while maintaining data privacy and ownership through blockchain-enabled identity management systems (Khan et al. 2022).

Incentivizing Data and Model Sharing

Blockchain introduces novel mechanisms for incentivizing data and knowledge sharing among researchers. Token-based systems or micro-payments enabled by smart contracts can reward contributions such as annotated datasets, validated models, or peer reviews. This tokenization supports an open research culture and encourages community-driven innovation in AI (Barclay et al. 2022). These approaches help overcome one of the major barriers in AI research—access to high-quality training data—and foster equitable participation among researchers from low-resource environments.

Improved Ethical Compliance and Accountability

Ethical concerns in AI research—such as data bias, consent, and accountability—can be addressed through blockchain's traceability and governance features. For example, blockchain can store user consent records, data usage logs, and algorithmic decision trails, ensuring that AI systems are developed and deployed in compliance with ethical standards and regulatory requirements (Merlec et al. 2021). Blockchain also promotes accountability by linking each research action or dataset to a verifiable identity. This prevents data misuse, supports audit trails, and enhances confidence in AI outcomes, particularly in sensitive domains such as healthcare, climate policy, and national security (Sun et al. 2022).

Resilience Against Data Tampering and Cyber Threats

As AI systems become integral to critical decision-making, ensuring the cybersecurity of research infrastructure is essential. Blockchain's decentralized and consensus-driven architecture makes it highly resilient to cyberattacks, reducing single points of failure and unauthorized data manipulation (Rahim et al. 2025). By storing research logs, AI-generated insights, and sensitive metadata on

blockchain can protect against both internal and external threats, supporting long-term research integrity and knowledge preservation.

4.3 AI-Driven Predictive Models in Education and Research

The integration of Artificial Intelligence (AI) in education has ushered in a transformative shift, offering promising avenues to foster sustainable practices and long-term planning.

AI-Driven Predictive Models in Education

Predictive models powered by AI can analyse vast amounts of educational and environmental data to enhance resource allocation, optimize student outcomes, and support policymaking aligned with sustainability goals. AI-driven predictive models are increasingly being leveraged to forecast student performance, identify at-risk individuals, inform resource allocation, and personalise learning pathways—contributing to sustainable and equitable education ecosystems (Almalawi et al. 2024).

The integration of AI aligns with broader global efforts such as SDG 4, which aims to "ensure inclusive and equitable quality education and promote lifelong learning opportunities for all" (UNESCO 2023). Predictive modelling enhances decision-making capacity by providing data-driven insights that anticipate challenges and optimize solutions. Among the most impactful applications of AI are predictive models, which use historical and real-time data to forecast future events, such as student performance, dropout risks, or learning style preferences. These models enable proactive and personalized interventions that can help learners succeed and allow educators to make data-informed decisions. One of the most widely adopted applications of AI in education is the prediction of student academic performance and dropout risk. Models developed using logistic regression and ensemble methods—such as soft-voting combinations of logistic regression, Random Forest, and AdaBoost—have demonstrated effectiveness in predicting student attrition. Standalone logistic regression models have

also achieved high accuracy in anticipating dropout risk. These approaches enable universities to provide timely counselling and targeted academic support (Olive et al. 2025; Kok et al. 2024).

By analysing students' interactions with digital platforms, these models can predict knowledge gaps and recommend tailored learning pathways (Zawacki-Richter et al. 2022). AI systems are increasingly being utilised to provide personalised recommendations for courses, certifications, and career paths that align with learners' interests, strengths, and performance data. By employing predictive models—such as LSTM-based architectures and machine learning classifiers like Random Forests and SVMs—these systems analyse academic metrics, personal preferences, and labour market signals. This analysis supports informed educational and career decision-making (Trujillo et al. 2025; Bahalkar et al. 2024; Faruque et al. 2024). Furthermore, these advanced systems effectively connect academic trajectories with future employment opportunities by harnessing extensive educational datasets and advanced analytics.

Integrating learning analytics in educational settings has significantly enhanced the ability to identify at-risk students, enabling timely and targeted interventions to improve retention and success rates. By analysing data from various sources such as learning management systems (LMS), demographic information, and academic performance metrics, institutions can develop predictive models to flag students on the verge of academic failure or dropout. For instance, predictive models based on performance indicators—such as midterm exam grades, department, and faculty—have achieved 70–75% accuracy in identifying students at risk of academic failure (Yağcı 2022). Similarly, learning analytics systems using engagement-based alerts (e.g., detecting students who do not interact with learning platforms for extended periods) have proven more effective than demographic data in spotting at-risk students early, facilitating timely interventions, especially among disadvantaged cohorts (Foster and Siddle 2019). These findings underscore the value of data-driven

approaches in proactively supporting students and enhancing educational success.

Beyond identification, learning analytics facilitate the customisation of interventions to address the specific needs of at-risk students, thereby fostering a more supportive and effective learning environment. Tailored interventions—including personalised tutoring, academic advising, or re-engagement initiatives—rely on explainable AI within learning analytics to reveal the key factors contributing to students' risk status, empowering educators to make informed intervention decisions (Ifenthaler and Yau 2020). Moreover, implementing early warning systems—as explored by Jayaprakash et al. (2014)—has significantly improved student retention by alerting instructors to declining performance or engagement in real time, enabling timely interventions. These systems empower educators to act swiftly, offering support responsive to each student's unique challenges. Collectively, these approaches highlight the transformative potential of learning analytics in creating adaptive educational environments that prioritise student retention and success.

Emerging AI systems are increasingly recommending courses, certifications, and career paths aligned with learners' interests and the labour market. For example, new course recommender platforms integrate job-market skill demands into learner suggestions using LLMs and reinforcement learning (Frej et al. 2024). Similarly, SkillRec employs neural network–based predictive models to recommend relevant job skills based on role titles (Ong and Lim 2023). These examples show how predictive analytics is being harnessed to better align academic choices with future opportunities.

Predictive modelling—through analysis of past expenditures and forecasting of future financial needs—enables educational institutions to make data-informed decisions regarding staffing, facilities, and program offerings. These approaches help optimise budget allocation and long-term planning (Mohzana and Al Pasori 2025). Through demand forecasting, universities can avoid resource wastage while ensuring adequate support for high-demand programs. AI models also

foster social equity by identifying students who may benefit from additional academic or emotional support, especially those from marginalized backgrounds. Predictive analytics enables the early detection of inequality patterns, helping institutions deploy targeted inclusivity initiatives (Holmes et al. 2021). In turn, this contributes to sustainable educational outcomes for diverse learners.

Benefits of Predictive Models in Education

There are several benefits of predictive models in education. Firstly, AI-driven predictive models enable educators and administrators to make proactive decisions, where early alerts about students' academic struggles allow for timely interventions that improve retention and success rates (Papamitsiou and Economides 2014). Secondly, Predictive models that utilise demographic and behavioural data are increasingly being used to uncover systemic patterns of disadvantage—allowing educators to identify underserved student groups and allocate resources more equitably (Almalawi et al. 2024; Jiang and Pardos 2021). Thirdly, unlike traditional assessments, predictive models can continuously and automatically analyse data from thousands of students. This allows institutions to scale personalized learning and performance monitoring without increasing staff workload.

Despite the Benefits, AI-Driven Predictive Models in Education also Present Several Challenges:

- Data Privacy and Consent: The use of personal data in educational predictive analytics raises serious privacy concerns—students need transparency and informed consent regarding data collection and usage. Robust ethical guidelines and clear institutional policies are essential to ensure privacy protections are upheld (Francis et al. 2023; Hoel and Chen 2016).
- Bias and Fairness: Predictive models can reflect existing biases in their training data—leading to unfair outcomes that disadvantage particular groups. Addressing fairness and ensuring explainability in these systems is an active and growing area of research (Chinta et al. 2024; Kizilcec and Lee 2020).

- Overreliance on Automation: There is a risk that educators may overly depend on AI tools without critical human judgment. Predictive insights must be interpreted carefully and used to complement—not replace—teacher expertise.

Also AI's ability to process large, complex datasets is revolutionising sustainability research.

AI-Driven Predictive Models in Research

Predictive models powered by AI are enabling researchers to uncover patterns, simulate future scenarios, and inform proactive decision-making in fields such as agriculture, energy, urban planning, and climate science. Machine learning models are being used to analyse climate data, predict biodiversity loss, and optimize renewable energy systems (Reichstein et al., 2019). Natural Language Processing (NLP) tools help researchers conduct large-scale literature reviews and trend analyses across environmental science publications (Khosravi et al. 2023). AI-driven predictive models help researchers simulate the outcomes of various sustainability policy scenarios (Leal Filho et al. 2023). Furthermore, AI tools are increasingly used in monitoring and evaluation frameworks for sustainability projects, allowing real-time impact assessments (UNESCO 2024c).

The integration of AI with Internet of Things (IoT) technologies is giving rise to "digital twins"—virtual replicas of real-world systems such as forests, buildings, or cities. These AI-powered models—such as **digital twins** used in urban resilience and climate monitoring—simulate and optimise environmental, social, and economic systems in real time, enabling proactive planning and operational decision-making (Reuters 2024c; ITPro 2024). In urban sustainability research, digital twins enable researchers and planners to simulate climate policies, energy systems, and traffic flows—often in real-time—before their actual implementation. For example, Sydney's urban digital twin utilises integrated environmental and traffic data to forecast outcomes such as crash risks, while peer cities employ digital twins to model resilience to flooding and pollution. These tools enable identification of

sustainable development strategies with minimised environmental cost (Sohail et al. 2024; Abouelrous et al. 2023; Reuters 2024c). As computing power increases, the use of digital twins is expected to expand across agriculture, water management, and industrial ecosystems.

To maintain Sustainability requires interdisciplinary collaboration across ecological, economic, and social systems. AI supports integration by synthesising data from multiple sources—combining mathematical models, simulations, and real-time data into 'data-to-knowledge' pipelines that deliver actionable insights via pattern recognition and system modelling (Behery et al. 2023; Yelne et al. 2023). According to Alonge and Isreal (2025), Hybrid AI systems—which integrate data-driven models with structured domain knowledge—offer enhanced research accuracy and more reliable decision support compared to purely data-driven approaches. Future sustainability research will increasingly involve AI tools that support transdisciplinary collaboration, allowing experts from ecology, economics, data science, and engineering to co-create solutions.

AI is emerging as a key driver of circular economy research. By analysing consumption patterns and supply chain data, AI helps identify inefficiencies and enhance resource recovery across circular supply chains (Farshadfar et al. 2024). AI-enabled tools can simulate product lifecycles, evaluate environmental footprints, and inform sustainable product design (Shah et al. 2025). This aligns with global efforts toward decarbonization and responsible production through AI-supported policy and business model optimisation (Danish and Senjyu 2023).

AI is revolutionising climate modelling by improving the resolution and speed of simulations. Traditional climate models are often computationally expensive and slow. AI surrogate models—for instance, using transformer-based architectures—can generate comparable results in a fraction of the time without sacrificing accuracy (Xu et al. 2024). AI is also being applied to carbon tracking and management. By integrating satellite data with machine learning,

researchers now estimate CO_2 emissions in near-real time, facilitating informed net-zero strategies (Halff & McCormick 2024; Couture et al. 2024).

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5 Methodology

This chapter employs a structured literature review methodology to synthesise current perspectives on Artificial Intelligence (AI) in sustainability education and research. The review followed established guidelines for systematic literature reviews in educational technology and computer science (Kitchenham 2004; Webster and Watson 2002). Relevant literature was identified through searches in major academic databases, including Scopus, Web of Science, IEEE Xplore, and Google Scholar. Keywords such as *"Artificial Intelligence," "Sustainability Education," "Sustainability Research," "AI for SDGs," "Personalised Learning," and "Predictive Modelling"* were used to ensure comprehensive coverage of the topic.

The inclusion criteria focused on peer-reviewed journal articles, conference proceedings, and institutional reports published between 2015 and 2025, prioritising studies that addressed the intersection of AI, sustainability, and education or research. Exclusion criteria eliminated opinion pieces, grey literature without academic rigour, and sources lacking empirical or conceptual depth. The selected studies were analysed using a thematic synthesis approach (Thomas and Harden 2008), which enabled the identification of key themes related to AI applications, opportunities, challenges, and ethical considerations.

Exclusion criteria eliminated opinion pieces, grey literature without academic rigour, and sources lacking empirical or conceptual depth. The selected studies were analysed using a thematic synthesis approach (Thomas and Harden 2008), which enabled the identification of key themes related to AI applications, opportunities, challenges, and ethical considerations.

By adopting this structured review process, the chapter ensures transparency, reproducibility, and a critical appraisal of existing

knowledge, while also identifying gaps that warrant further investigation in future research. Figure 2 shows the flowchart of the literature review methodology.



Fig. 2 The flowchart of the literature review methodology

6 Challenges and Ethical Considerations: Implication for Theory and Policy

The integration of Artificial Intelligence (AI) and blockchain technologies in education and research offers significant potential for enhancing sustainability, transparency, and efficiency. However, these advancements bring with them a range of technical, ethical, and societal challenges that must be critically addressed if they are to contribute meaningfully to sustainable development.

From a technical standpoint, blockchain systems face well-documented barriers to scalability and performance. Public blockchains such as Ethereum struggle with transaction throughput, latency, and storage capacity. At the same time, consensus mechanisms like Proof-of-Work (PoW) and Proof-of-Stake (PoS) introduce additional computational overhead (Akther et al. 2025). AI-driven

learning and research systems necessitate substantial computational power, raising valid concerns about their ecological footprint. For instance, powerful generative AI models require considerable electricity and water resources (Li et al. 2025). Studies also confirm that AI's rapid energy demand is increasing environmental strain—from training and inference—to a point where AI may consume a growing share of global energy supply, threatening sustainability objectives (Durmus Senyapar and Bavinder 2025; de Vries 2023).

Integration complexity further compounds these issues. Effective deployment requires interdisciplinary expertise across cryptography, distributed ledger systems, cloud infrastructure, and AI governance—skills that many institutions currently lack (Rahim et al. 2025). Without sufficient capacity, blockchain-AI systems risk superficial or ineffective adoption. Usability remains a key challenge: for AI-powered tools to be impactful in educational and research settings, they must integrate smoothly with researchers' existing workflows—rather than disrupt them. Platforms like **cnvrg.io**, which support seamless connections to tools like **Jupyter Notebooks**, **TensorFlow**, and **RStudio**, exemplify this approach (cnvrg.io 2025). Similarly, **JELAI** demonstrates how AI-based learning analytics can be directly embedded into Jupyter environments, preserving methodological continuity while enhancing analytical capabilities (Valle Torre et al. 2025).

Beyond technical issues, ethical considerations remain critical. AI systems are shaped by the datasets used to train them, which often embed bias and inequity. AI systems in education and research often inherit biases embedded in their training data or design processes, critically reinforcing social inequalities in academic and research contexts. Binns (2018) underscores how algorithmic fairness is deeply rooted in data and philosophical underpinnings, while a recent review highlights the structural bias challenges across educational AI systems, including data, algorithm, and interaction-level sources. Moreover, in education, AI-driven grading or feedback risks overlooking cultural context or nuance, while in research, biased datasets compromise validity and erode trust (Leal Filho et al. 2023). Blockchain, although

often praised for transparency, introduces dilemmas around data privacy, ownership, and jurisdictional regulation (Taherdoost 2022; Zhuk 2025).

Equity and access represent another significant challenge. AI-enabled personalised learning presupposes reliable digital infrastructure, skilled educators, and access to devices—resources that remain unevenly distributed (Vesna et al. 2024). The widening digital divide threatens to exacerbate educational inequalities and undercut the inclusive goals of Education for Sustainable Development, particularly SDG 4 (Velmurugan et al. 2025; Rydzewski 2025; Goal 4 2025). Scholars stress the need for deliberate policy interventions and participatory design to ensure equitable adoption (Parthasarathy et al. 2024).

Looking ahead, future directions must focus on embedding Fairness, Accountability, Transparency, and Ethics (FATE) principles into AI and blockchain frameworks (Memarian and Doleck 2023). The adoption of Explainable AI (XAI) will also be essential for building trust by making decision-making processes interpretable to educators, researchers, and learners (Durán and Pozzi 2025). Regulatory clarity is crucial for addressing challenges related to intellectual property, cross-border data sharing, and accountability in AI governance. For example, the EU's regulatory framework—particularly the AI Act—must navigate IP, privacy, and cybersecurity concerns in generative AI systems (Novelli et al. 2024); cross-border AI deployments raise jurisdictional and accountability conflicts requiring more explicit legal guidance (Covenant 2025); and AI's complex relationship with IP, especially around data scraping and ownership, underscores the urgency for clarified regulatory approaches (OECD 2025). Finally, investment in "green AI" and sustainable blockchain is necessary to minimise energy demands and align technological innovation with ecological imperatives (Strubell et al. 2019; Vinuesa and Sirmacek. 2021).

In summary, while blockchain and AI integration hold significant promise, their success depends on addressing scalability, ethics, and equity. Future work must prioritise green computing, inclusive access,

interdisciplinary training, and transparent governance to ensure that these technologies serve as enablers of sustainability rather than contributors to its erosion.

6.1 Future Trends and Directions in AI-Driven Sustainability Research: Theoretical and Practical Insights

The rapid integration of Artificial Intelligence (AI) into education and research is unlocking new pathways for advancing sustainability, shaping a future filled with potential. Among the emerging trends, Explainable Artificial Intelligence (XAI) stands out as a beacon for transparency in decision-making processes, addressing one of the most pressing challenges in AI adoption. In educational settings, particularly within sustainability-focused curricula, XAI not only fosters trust but also promotes ethical engagement and equips learners with vital critical thinking skills. Beyond the classroom, AI ignites innovation in sustainability research, driving transitions to a circular economy and enhancing environmental modelling and predictive analytics. Together, these developments reflect the transformation of AI from a mere predictive tool into a collaborative partner, inspiring us all to pursue sustainable solutions. Explainable Artificial Intelligence (XAI) plays a pivotal role in enhancing transparency and trust in AI systems, especially in educational contexts where understanding decision-making processes is essential for fostering critical thinking and ethical engagement. In sustainability education—where interdisciplinary reasoning, value-based decision-making, and long-term impacts are core—XAI offers a unique opportunity to bridge the gap between AI outputs and human understanding, making AI not just a tool for prediction, but a partner in learning. For students, XAI can demystify how AI systems arrive at conclusions, enabling them to critically evaluate, question, and interact with these systems. This supports deeper learning and encourages responsible engagement with technology (Guidotti et al. 2018; Arrieta et al. 2020). For instance, in environmental modelling and climate education, students engage with system models and simulations—such as those depicting temporal

climate dynamics or policy scenarios—to develop systems thinking. These approaches enable learners to comprehend complex interdependencies, evaluate trade-offs, and reflect on the influence of data and reasoning pathways (Frey 2025; Alibeyoglu et al. 2024; Dela Calzada et al. 2025).

Explainable AI (XAI) offers educators insight into AI-driven learning analytics—such as feature importance in student success models (Swamy et al. 2022)—which enables them to interpret AI-generated feedback and adjust pedagogical strategies, thereby reducing "black-box" anxiety (European Digital Education Hub 2024; Feldman-Maggor et al. 2025). Moreover, interpretability is essential in sustainability-focused education: educators who understand AI decision logic are better positioned to mentor students in ethical reasoning and interdisciplinary integration—key competencies in Education for Sustainable Development (Vinuesa and Sirmacek 2021; Sinakou et al. 2019).

By increasing transparency, XAI builds trust, making educators and students more likely to adopt AI systems as partners in learning. This is particularly important in sustainability education, where critical engagement with data, inclusivity of diverse knowledge systems, and long-term thinking are crucial. Trust in AI's processes and outcomes ensures that the use of AI aligns with the values of sustainability and education (Gunning and Aha 2019). As AI becomes increasingly embedded in digital education platforms, its **explainability** will be pivotal in shaping how it supports **educator decision-making**, **co-creative pedagogy**, and **personalised learning**—particularly within sustainability-focused curricula (Chaudhry et al. 2022; Khosravi et al. 2022; Leal Filho et al. 2025).

One emerging trend is the application of AI in circular economy research. For instance, AI enhances waste reduction and material efficiency by optimising recycling, resource recovery, product design, and supply chain processes (Sikander 2024; Ellen MacArthur Foundation 2019; Reuters 2024a). Moreover, AI significantly advances interdisciplinary sustainability research by integrating data and

insights across fields such as environmental science, economics, and social sciences to support holistic, systemic solutions (Valencia-Arias et al. 2025; Ragland 2025).

AI enhances sustainability research by enabling the processing of large and complex environmental datasets. Machine learning, particularly deep learning, has become a central component in environmental monitoring. It enables the analysis of satellite imagery for real-time detection of deforestation and burned areas using multimodal image data (Janga et al. 2023; Fodor and Conde 2023). AI-driven models also enhance predictive climate modelling, capturing complex weather and environmental patterns (Hamdan et al. 2025). These capabilities support evidence-based policymaking and early warning systems that can mitigate environmental risks. Convolutional neural networks (CNNs) have been increasingly applied in remote sensing to monitor environmental infractions such as illegal mining and forest encroachment. Lightweight CNN models have been developed to detect unauthorised open-pit coal mining (Liu and Zhang 2023), while fully convolutional networks have been used to identify unregistered mines and tailings dams in Brazil (Balaniuk et al. 2020). More recently, dual-mode frameworks leveraging CNNs have been applied to detect both illegal mining and illicit harvesting in the Brazilian Amazon (Rodrigues et al. 2024).AI systems can also fuse data from different sources—such as climate models, weather stations, and sensors—to improve forecasting accuracy.

AI-powered predictive models are increasingly being used to simulate future environmental scenarios—including climate patterns, sea-level rise, and extreme events—by integrating large, complex datasets and recognising non-linear trends (Hamdan et al. 2025). Similarly, AI tools applied to satellite and Earth observation data enable the near-real-time estimation of carbon emissions and ecosystem changes, aiding in the development of effective net-zero policies (Deloitte/WEF 2024). Reinforcement learning has been applied to optimise water management strategies and energy consumption in smart cities. For example, deep RL models—such as LSTM-based agents

—help manage smart water distribution networks more efficiently (Zaman et al. 2023). RL can also simulate complex watershed control scenarios, learning adaptive strategies in real time (Ortega et al. 2024). Such dynamic modelling approaches may potentially support circular economy transitions by identifying efficient resource recovery and waste reduction strategies.

Sustainability research is inherently interdisciplinary, involving the integration of diverse fields like ecology, economics, and sociology. AI dramatically accelerates knowledge synthesis by automatically analysing and integrating scientific literature, datasets, and policy documents—often in support of evidence-based decision-making. For instance, AI-driven tools can reduce human screening workloads by over 78% in evidence synthesis tasks (Edwards et al. 2023), turn vast bodies of research into structured, queryable datasets using LLMs (Wang et al. 2024), and streamline living systematic reviews in observational research through NLP automation (Manion et al. 2024). Natural Language Processing (NLP) tools like BERT or GPT-based models can conduct automated literature reviews, identify research gaps, and summarize findings across disciplines. These tools support systematic reviews and meta-analyses in environmental and climate science, enhancing the efficiency and quality of research outputs.

Figure 3 shows the challenges and ethical considerations in AI and Blockchain for sustainability. We can refer to the color coded as; Blue (Technical): Scalability, performance, energy-intensive AI models, and usability issues; Red (Ethical): Bias, data privacy, and ownership concerns; Orange (Equity): Digital divide and unequal access to AI-driven learning; Gold (Future Directions): FATE principles, Explainable AI, regulatory clarity, and green AI; Green (Outcome): Trust, transparency, and sustainability in education and research. This shows how current challenges feed into future directions, ultimately shaping sustainable and equitable AI integration.

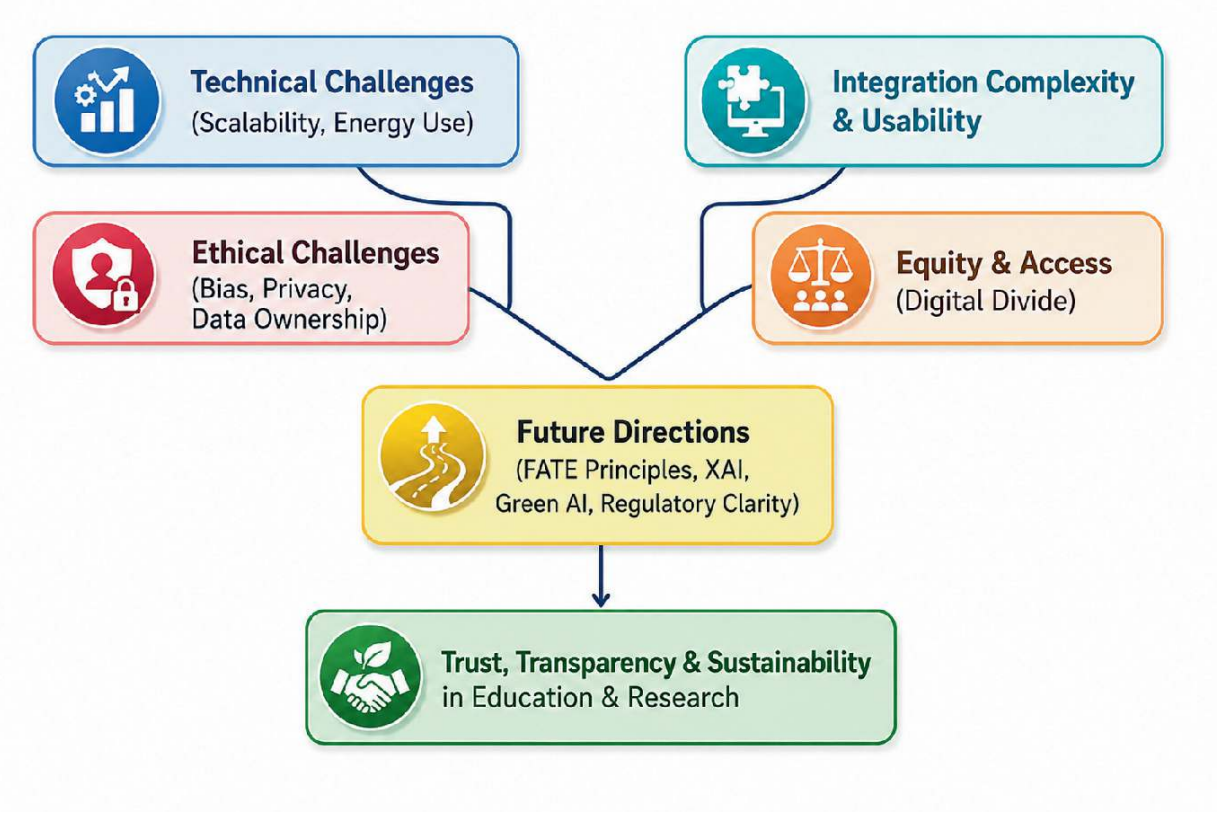


Fig. 3 Challenges and ethical consideration in AI and Blockchain for sustainability

The identified challenges and ethical considerations directly relate to the research questions outlined in this study. For the first question—on how AI-driven adaptive learning and predictive models can enhance sustainability education—the findings highlight both the opportunities of personalisation and the risks of bias and inequity, underscoring the need for responsible design and implementation. For the second question—concerning the potential of immersive and innovative technologies—the discussion of technical barriers such as scalability, energy use, and usability illustrates the limitations that must be overcome for AR/VR and AI systems to support sustainability-focused learning meaningfully. Finally, for the third question—on ethical, equity, and governance issues—the analysis of data privacy, digital divide, and the importance of FATE principles and Explainable AI (XAI) provides clear evidence of the governance frameworks required to ensure trustworthy adoption. Thus, the challenges and future directions identified are not separate from the research aims, but rather reinforce

and contextualise them, offering a critical bridge between the literature review and the study's research questions.

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7 Recommendations for Future Sustainability Education and Research: Policy and Practice Perspectives

Building on the findings and challenges identified, several future recommendations are necessary to strengthen the integration of sustainability in education and research:

Invest in Ethical and Sustainable AI Technologies

As AI becomes more embedded in education, adopting sustainable or "green AI" principles—particularly those that reduce environmental impact—will be essential. At the same time, ensuring equitable access and investing in educator professional development in ethical and effective AI use are key to preventing the widening of educational inequalities (Verdecchia et al. 2023; OECD 2024).

Promote Interdisciplinary and Transdisciplinary Approaches

To effectively address complex sustainability challenges, educational institutions should foster collaboration across disciplines and between academia, industry, and communities. This will enhance holistic understanding and real-world impact (Galloway et al., 2025). AI experts should work alongside education and research professionals to develop context-sensitive AI tools (Galloway et al., 2025).

Implement Robust Policy Frameworks

Governments and institutions should develop policies that incentivize sustainability integration in education and research, including funding for interdisciplinary projects, open access initiatives, and inclusion strategies to ensure marginalized groups benefit equitably (UNESCO 2024a). Institutions must implement policies addressing data ethics,

algorithmic transparency, and responsible AI use in academic settings (UNESCO 2024a).

Enhance Capacity Building and Faculty Development

Training educators and researchers in sustainability concepts and AI literacy is critical. Institutions should provide ongoing professional development to equip staff with the skills needed to design and deliver sustainability-focused curricula effectively (Leal Filho et al. 2023). It requires institutional commitment, curriculum redesign, capacity building, and the adoption of innovative pedagogies and methodologies that emphasize experiential learning, critical reflection, and transdisciplinary approaches (Leal Filho et al. 2023). Additionally, sustainable practices within academic institutions themselves—ranging from energy-efficient operations to responsible resource use—model the principles they aim to teach and research (Galloway et al., 2025).

Foster Learner-Cantered and Participatory Pedagogies

Sustainability education should emphasize active learner engagement, critical thinking, and problem-solving through project-based and experiential learning, which can be enhanced by AI-powered adaptive platforms (Galloway et al., 2025; Zawacki-Richter et al. 2022).

Prioritize Equity and Inclusion

Future efforts must focus on making sustainability education accessible to diverse populations, addressing systemic barriers, and integrating social justice perspectives into curricula and research agendas (Galloway et al., 2025).

Although significant progress has been made, gaps remain in the empirical evaluation of AI's long-term impact on education and research quality. There is a need for more longitudinal studies to assess the effectiveness and risks of AI adoption across different academic disciplines (Zawacki-Richter et al. 2022). Future research should also explore how AI literacy training for educators and researchers can mitigate ethical risks while maximizing AI's benefits (Ng et al. 2021).

Despite growing awareness, embedding sustainability comprehensively into education and research remains a complex challenge. It requires institutional commitment, curriculum redesign, capacity building, and the adoption of innovative pedagogies and methodologies that emphasize experiential learning, critical reflection, and transdisciplinary approaches (Leal Filho et al. 2023). Additionally, sustainable practices within academic institutions themselves—ranging from energy-efficient operations to responsible resource use—model the principles they aim to teach and research (Galloway et al., 2025).

Developing responsible future Trends In AI-Driven Sustainability Education and Research requires that technological advancements benefit all stakeholders without causing harm. Institutions must implement frameworks that promote transparency, accountability, and fairness in AI applications, fostering trust and social acceptance. Therefore, incorporating sustainability into AI-driven education equips students with the knowledge and skills necessary to address future environmental challenges.

Developing responsible future Trends In AI-Driven Sustainability Education and Research requires that technological advancements benefit all stakeholders without causing harm. Institutions must implement frameworks that promote transparency, accountability, and fairness in AI applications, fostering trust and social acceptance.

Integrating Artificial Intelligence (AI) into educational settings necessitates the establishment of frameworks that emphasise transparency, accountability, and fairness to foster trust and social acceptance. The rapid adoption of AI technologies in education has raised concerns about ethical implications, particularly regarding decision-making processes that affect learners' outcomes. Memarian and Doleck (2023) highlights the importance of Fairness, Accountability, Transparency, and Ethics (FATE) in AI applications within higher education, emphasising the need for clear guidelines to ensure ethical AI deployment.

Building trust in AI systems also involves addressing the challenges of explainability and user understanding. The concept of Explainable AI (XAI) has emerged as a critical component in making AI decisions more transparent and comprehensible to users, thereby enhancing trust. A study by Durán and Pozzi (2025) discusses the role of transparency and trustworthiness in AI education, suggesting that incorporating XAI principles can lead to more ethical and accepted AI applications in educational contexts. By implementing frameworks prioritising these ethical considerations, educational institutions can ensure that AI technologies are used responsibly, promoting equitable learning environments and maintaining public confidence in technological advancements.

7.1 Incorporating Sustainability into AI-Driven Education: Implications for Practice

Incorporating sustainability into AI-driven education is essential for equipping learners with the competencies to navigate and resolve future environmental challenges. AI technologies enhance educational experiences by delivering personalised learning environments integrating sustainability-focused content, such as climate change, circular economy, biodiversity, and renewable energy. Through adaptive learning algorithms, students can engage in real-time simulations, project-based learning, and interdisciplinary activities that contextualise sustainability within their personal and professional futures. According to Zawacki-Richter et al. (2019), integrating AI in education facilitates greater learner autonomy and relevance by tailoring content to individual contexts. This flexibility can be directed to embed sustainability themes meaningfully. Furthermore, AI-based systems can expose students to predictive environmental modelling, data interpretation, and scenario analysis, which are invaluable in fostering critical thinking and responsible citizenship. By embedding sustainability principles into AI-driven educational platforms, institutions can cultivate digital literacy and environmental consciousness among future leaders.

Nevertheless, while AI can support sustainability education, it is also vital to address the environmental costs of AI itself. The carbon footprint of training large-scale AI models and operating data-intensive platforms has raised concerns about energy efficiency and long-term ecological impact. As highlighted by Strubell et al. (2019), the environmental cost of developing sophisticated AI models can be significant necessitating a parallel commitment to green computing and ethical AI development. Sustainable AI in education must, therefore, encompass what is taught and how it is taught. This includes promoting transparency in data usage, minimising energy-intensive processing, and leveraging cloud-based infrastructures powered by renewable energy. Research by Vinuesa et al. (2020) further supports this dual approach, emphasising that AI should be developed and deployed in ways that align with the United Nations Sustainable Development Goals (SDGs). By adopting sustainability-centric AI frameworks in both content and computation, educational systems can ensure that the technological tools used to advance environmental education do not inadvertently undermine ecological goals.

AI-driven sustainability education offers immense potential to transform how students engage with and understand complex global issues. However, successful integration requires addressing challenges related to ethics, access, and pedagogical alignment. As the field evolves, collaboration between educators, technologists, and policymakers will be crucial to ensure that AI serves as a force for equitable and meaningful education for sustainability.

Co creation of value serves as a solution to this. Integration of AI in sustainability education not only enhances pedagogical tools but also necessitates the co-creation of value among stakeholders to ensure ethical, equitable, and effective implementation. Co-creation of value refers to a collaborative process where multiple stakeholders actively participate in designing, developing, and evaluating educational practices and technologies (Prahalad and Ramaswamy 2004; Vargo and Lusch 2016). In the context of AI-driven sustainability education, co-creation enables educators, students, parents, technologists, and

policymakers to align AI tools with local needs, ethical standards, and pedagogical goals, ensuring broader acceptance and impact.

By engaging in co-creation, stakeholders can collaboratively identify and address key challenges such as ethical use, data privacy, access disparities, and curriculum relevance. For example, involving students and teachers in the design of AI-supported learning environments ensures that the tools developed are contextually appropriate and support active learning around sustainability topics (Luckin et al. 2016). Parents and community members can contribute perspectives on equity, cultural relevance, and digital literacy, which are critical to bridging the digital divide and ensuring fair access (Seldon and Abidoye 2018).

Furthermore, technologists and policymakers play vital roles in aligning AI development with educational standards and societal values. Multi-stakeholder governance frameworks, as highlighted by Holmes et al. (2019), foster shared accountability for data privacy, responsible AI use, and evolving policy needs. Such frameworks not only enhance trust but also offer agility in responding to the rapid pace of AI innovation.

Co-creation also supports the development of dynamic feedback loops, where AI tools continuously learn from stakeholder input, improving over time to meet educational objectives more effectively (Zawacki-Richter et al. 2022). This approach transforms stakeholders from passive recipients into active partners, enriching the design of sustainability curricula with diverse insights and promoting long-term engagement.

Co-creation of value offers a pathway to design inclusive, ethical, and adaptive AI frameworks for sustainability education. It ensures that all voices are heard, responsibilities are shared, and technological advances are grounded in human-centric values, ultimately enhancing the transformative potential of AI in education.

Sustainability in education and research transcends knowledge transmission; it is a transformative process that shapes attitudes, behaviours, and institutional cultures. This holistic approach is

essential to empower individuals and communities to respond effectively to planetary crises and build a resilient, equitable future (UNESCO 2024c). As the role of education and research continues to evolve, embedding sustainability at their core remains crucial for fostering innovation, responsibility, and long-term societal well-being.

Figure 4 shows the illustration that highlights how multiple strategic recommendations collectively strengthen sustainability education and research in an AI-driven era. Ethical AI practices, interdisciplinary collaboration, robust policy frameworks, capacity building, learner-centered pedagogies, and equity-focused initiatives all converge toward incorporating sustainability within AI education. This integration, supported by co-creation among stakeholders, ultimately drives the development of resilient and equitable futures for both education and society. With colour coded, here's the final color-coded illustration; Red (Ethics): Invest in ethical and sustainable AI; Blue (Collaboration): Promote interdisciplinary approaches; Yellow (Policy): Implement robust policy frameworks; Purple (Capacity): Enhance capacity building; Green (Pedagogy): Foster learner-cantered pedagogies; Orange (Equity): Prioritize equity and inclusion; Khaki (Integration): Incorporate sustainability in AI education → Co-creation of value; and Dark Green (Future): Resilient and equitable future.

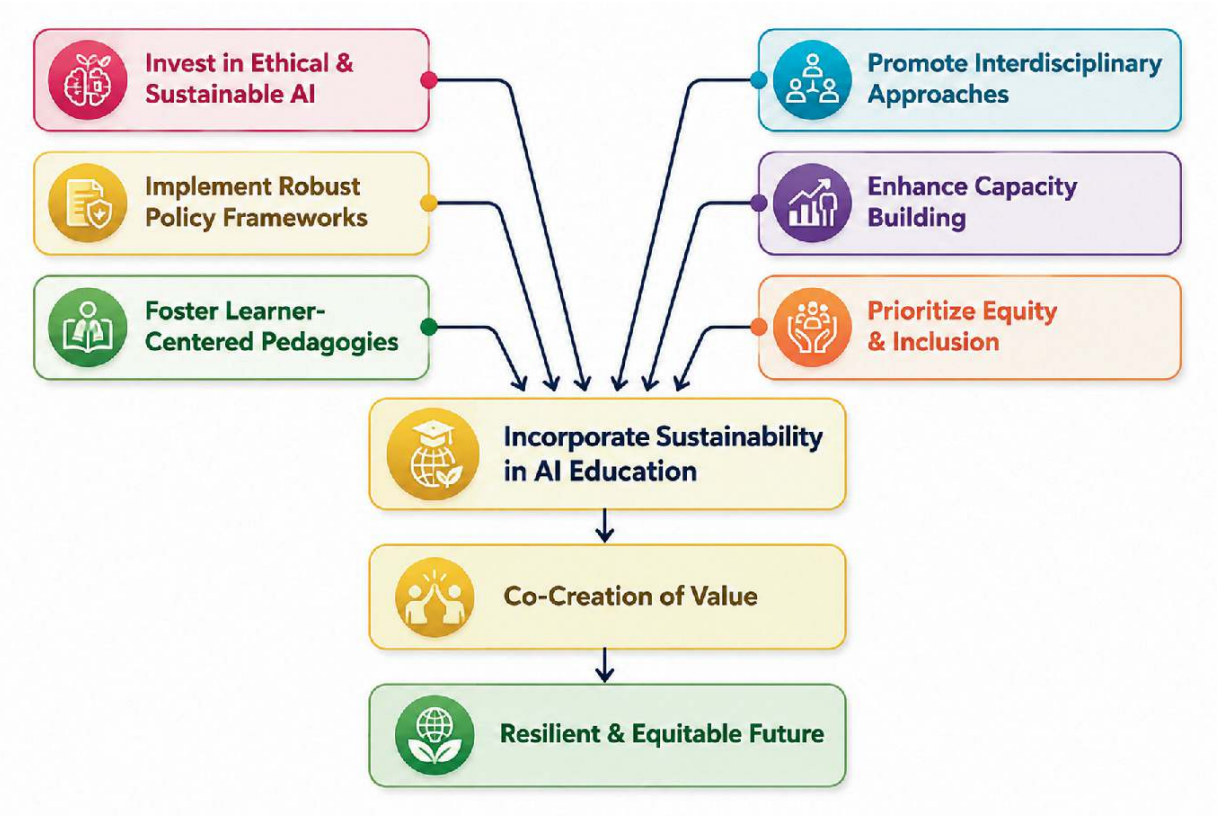


Fig. 4 Illustration that maps out the recommendations for future sustainability education and research

The recommendations presented in this section directly address the three guiding research questions of the study. For the first research question—how AI-driven adaptive learning and predictive models can enhance student engagement, comprehension, and decision-making in sustainability education—the recommendations on fostering learner-centred pedagogies, prioritising equity and inclusion, and embedding sustainability content into AI-driven platforms provide practical pathways for translating technological potential into meaningful educational outcomes. The second research question—what is the potential of AI-enhanced immersive and innovative technologies in fostering a deeper understanding of complex sustainability challenges—is addressed by promoting interdisciplinary and transdisciplinary approaches and enhancing faculty capacity building. These strategies ensure that educators and researchers are well-prepared to integrate AI, AR/VR, and predictive modelling tools into curricula, thereby

supporting systems thinking and problem-based learning on sustainability issues. The third research question—what ethical, equity, and governance issues must be addressed to ensure the responsible integration of AI and blockchain in sustainability education and research—is directly linked to recommendations for investing in ethical and sustainable AI technologies, implementing robust policy frameworks, and co-creating value through multi-stakeholder engagement. These recommendations highlight the importance of frameworks such as Fairness, Accountability, Transparency, and Ethics (FATE) and the role of Explainable AI (XAI) in building trust and ensuring responsible adoption.

Together, these recommendations not only reinforce the study's findings but also provide actionable strategies to align technological innovation with sustainability goals, thereby ensuring that AI in education and research contributes to resilient, equitable, and future-ready societies (Table 1).

Table 1 How the research questions link to the theory, policy and practice mapping table

8 Conclusion: Contributions to Theory, Policy, and Practice

The integration of Artificial Intelligence (AI) into sustainability education and research presents transformative opportunities to address some of the most urgent global challenges. From personalised learning and immersive technologies to predictive modelling and blockchain-enhanced research, AI offers powerful tools to improve access, efficiency, and innovation. At the same time, critical issues around equity, ethics, transparency, and environmental costs must be carefully managed to ensure that these technologies contribute positively to sustainable development. The findings of this study contribute at three interconnected levels. **For theory**, they extend existing frameworks in education for sustainable development (ESD), ethics, and learning sciences by embedding AI-driven adaptivity,

immersive simulations, and explainable AI into sustainability contexts. **For policy**, they highlight the urgent need for robust frameworks that promote green AI, interdisciplinary collaboration, and equitable access to digital innovations. **For practice**, they provide actionable strategies for educators and institutions, including learner-centred pedagogies, co-creation with stakeholders, and the adoption of responsible AI and blockchain systems. By aligning theoretical innovation with policy frameworks and practical applications, AI-driven sustainability education and research can cultivate future-ready citizens and generate solutions that advance both human and planetary well-being.



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The Symbiotic Equation: Artificial Intelligence as a Catalyst for Sustainability Education and Research

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Abstract

The intersection of Artificial Intelligence and Sustainability offers a revolution in the way we address environmental emergencies and teach our children and grandchildren to tackle them. This final chapter details with the key relationship between the disciplines and suggests that AI is used to analyse complex data and model ecological systems, which is essential to solve problems such as climate change and resource depletion. The discussion is organised into three main points. The first is a discussion about the growing significance of AI as a tool for decoding the complexity of "wicked" environmental problems. Second, it highlights the top trends in the future such as AI-driven predictive modeling for climate tipping points, lifecycle assessments for circular economies and the emerging role of generative AI to redefine

sustainability pedagogy and communication. Third, it emphasises some of the pressing research needs, including reducing AI's own environmental impact, combating algorithmic bias to enable equitable solutions and designing effective pedagogies to use. In times of mounting pressure to meet climate objectives, this interconnectedness will emerge as a hallmark, and become the backbone, of a human intelligence-as-machine relationship, facilitated through precision education and cultivation, to build an equitable and regenerative future.

Keywords Artificial intelligence – Sustainability – Trends – Machine relationships – Research

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1 Introduction

At the dawn of the twenty-first century mankind is confronted with a paradox: we have a significant—and unmatched—computer capacity but are at the same time facing existential environmental crises in the form of climate change, biodiversity loss, and resource depletion. These "wicked problems" have become so complex that they have transcended simple analytic processes. Artificial Intelligence (AI) and sustainability combine two "mega themes" into one when they converge. AI allows us to process vast and disparate data sets, enables pattern recognition unseen by human eyes and can develop massive systems to achieve levels of accuracy not attained before (Barata and Kayser 2024). But the key leverage point is sustainability and its education dimension.

The efficient implementation of this vision necessitates cultivating future thinkers who are fluent not only in the language of algorithms but also in the ethics of care (Chigbu and Makapela 2025). The prospects for a sustainable future will be shaped by our success in preparing students to harness AI for constructive purposes, rather than for extraction (Mbah et al. 2025). This critical interdisciplinary linkage is emerging as a paramount concern, one that is increasingly essential for long-term human and planetary well-being (Mbah et al. 2025).

There are various means via which AI can be incorporated in support of sustainability teaching and research with the possibility of a golden ticket, one that needs to be pursued at every opportunity (Low et al. 2025). The traditional paradigm appears to remain insufficient for addressing the scale and interdependence of the real-life environmental threats (Mbah et al. 2025). From climate systems, biodiversity networks, and global supply chains, data seeps in at levels that old-style statistical analysis tools find difficult to process (Chigbu and Makapela 2025). Table 1 provides an overview of the synergies between AI and sustainable development.

Table 1 Some synergies between AI and sustainable development

Also in research, AI—and its extensions via machine learning and predictive analytics in particular—allows scientists to detect subtle relationships and early warning signs that would otherwise fly under the radar. AI models can now predict crop failures, for example, months in advance by putting satellite imagery, weather patterns, and soil data together (Barata and Kayser 2024). This foresight enables proactive interventions that may protect livelihoods and reduce food waste, allowing an edge in terms of early addressing food security issues.

In respect of AI systems for sustainability in education, complex topics such as carbon cycles, ocean acidification, or urban heat islands, can become tangible and real by means of AI-powered simulations and digital twins (Hagedorn et al. 2023). Manipulating variables in real time allows students to see how policy decisions connect and impact systems in complex ways—an epistemology that inspires a systems mindset and builds student understanding (Hajj-Hassan et al. 2024). AI can also provide suggestions for personalised learning pathways—adjusting content based on individual students, making complex material accessible to those who need it (Hagedor et al. 2023).

And more importantly, AI equips the next generation of learners with the analytical firepower needed in making sustainability choices. Is a forest saved for carbon sequestration or to be reclaimed and

produced as renewable inputs? AI-based multi-criteria optimisation models help facilitate solving such complexities as students or researchers in integrating environmental, social, and economic impacts into broader models (Low et al. 2025). Incorporating such tools into curricula equips graduates to understand sustainability challenges, but also to plan and develop evidence-driven solutions (Chigbu and Makapela 2025). In a world where environmental change accelerates faster than human intuition, AI is a critical cognitive ally that augments our common capacity to envision and fashion a regenerative future.

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2 Some Future Trends

There are, at the moment, three key trends contributing to the rapidly evolving integration of AI into sustainability teaching and research.

First, we have predictive modeling and climate tipping points (OECD 2022). Researchers are shifting away from descriptive analytics and toward prescriptive and predictive modeling. AI uses especially deep learning and neural networks in analysing climate patterns, predicts more accurately extreme weather events, and models the multiple potential cascading elements of crossing different ecological tipping points (Supto 2025). In the classroom, the effect is seen in real-time simulations by students, displaying how policy decisions determine global warming, thereby bridging data abstraction to practical interactive learning experiences (Low et al. 2025).

Second, we have AI-driven lifecycle assessment and circular economy. AI tools such as Machine learning (ML) algorithms are changing the domain of LCA in academia (Strielkowski et al. 2024). Rather than doing manual, lengthy audits, AI can now evaluate supply chains in real-time. It finds weak spots and provides suggestions for material substitutions that decrease the carbon footprints. In education, this can mean providing students with the opportunity to study manufacturing processes via the “digital twins” of manufacturing process redesign, which is a circular system (Nishant et al. 2020). This is where waste is cut down and resources are continually reused.

Third, we have generative AI for sustainability communication and curriculum design. Large language models (LLMs), for instance, now change the way teachers teach and conduct coursework (Agostini and Picasso 2024).

In recent years, with generative AI, educators have been designing adaptive learning modules to suit students based on their stage of development, mapping complex science concepts into more digestible narratives (Hagedor et al. 2023). Additionally, students are being trained to utilise these tools to compile information from large volumes of sustainability studies, drafting policy papers and creating engaging visual narratives to disseminate climate science to the public (Low et al. 2025). This may foster a better understanding of how scientists can use what they know to improve societal practice.

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3 Urgent Research Needs

Integrating artificial intelligence with sustainability science and education has huge potential, but there is a need to address some important research gaps. The lack of a critical inquiry into some key matters may risk the introduction of AI tools which are environmentally costly, socially biased, and pedagogically ineffective (Mbah et al. 2025).

A fundamental challenge in research is that it must address the environmental paradox of AI. Training large language models and complex neural networks consumes staggering amounts of electricity and water, and leaves a massive carbon footprint. More research is thus necessary on "Green AI"—building energy-efficient algorithms, optimising hardware architectures, designing data centers powered by renewable energy (Bolón-Canedo et al. 2024).

Also, there is a need to set common standards and guidelines for reporting the environmental cost of AI models and letting researchers and educators make intelligent decisions about what tools they use (OECD 2022). Without this groundwork, AI sustainability efforts could inadvertently deepen the very issues that they are meant to address

(OECD 2022). Just as urgent is research into algorithmic bias and environmental justice (Anand and Coeckelberg 2026). In this process, AI trained on past data would exacerbate, or even replicate, the already existing inequalities (Anand and Coeckelberg 2026). In the case of a model which fine-tunes urban green space allocation optimisation to be best suited for urban regions—for instance-, the research may miss vulnerable neighborhoods if such under-investment can be reflected in training data (Anand and Coeckelberg 2026).

Further research also is required on how to create fair frameworks that incorporate due consideration to structural factors such as social contexts, to guarantee the application of AI-based sustainability options in an equitable way, and to guarantee that AI-based sustainability solutions address all communities fairly (Anand and Coeckelberg 2026). This entails developing diverse, representative databases and algorithms that emphasise justice as well as efficiency.

Another major research needs revolving around global, inter-disciplinary methods and interoperability of data. Sustainability issues include climate science, economics, sociology, ecology, and each one of these disciplines has a different data standard or analytic tradition. Research is urgently needed on robust ways to incorporate and integrate these various datasets and to link disciplinary language, creating the means of synthesis from which AI can draw wisdom from all domains (Nishant et al. 2020). We should also create shared ontologies, opening open-access repositories that promote the co-creation of knowledge between computer scientists and domain experts (Henriksen et al. 2024).

Finally, extensive research is required about the pedagogical framework for AI literacy in sustainability education. What is the best way to train pupils and students to be critical users as well as ethical architects of AI tools? Educators need evidence-based curriculum models to teach technical skills combined with ethical reasoning, so that graduates may understand the capabilities and limitations of AI (Mbah et al. 2025). In this context, studies about how generative AI can facilitate individualised learning styles while preserving academia's

integrity and how simulation-based tools can develop systems thinking about complex environmental challenges need to be considered.

Tackling these research needs is not merely an academic exercise; it is an essential condition for AI to serve as an ally in building a sustainable and just future, rather than becoming an additional layer of complexity that shrouds the road ahead.

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4 Conclusions

As this chapter has shown, there is a potential for a symbiotic relationship between AI and sustainability education and research. But this symbiotic equation is more than a simple marriage; it represents a critical shift in our ability to care for the planet. Just as a catalyst minimises the activation energy required for a chemical reaction, AI is uniquely poised to accelerate our transition from inertia to action on sustainability education and research in the face of environmental collapse. It condenses decades of data analysis into days, reveals trends in ecological decline that are invisible to the naked eye, and models the long-term consequences of our choices with unprecedented precision. But symbiosis is about mutual benefit and interdependence.

AI is not a silver bullet to be implemented in support of sustainability education and research alone, nor an oracle to worship without scrutiny. Its algorithms need an ethical compass, nuanced contexts, and intergenerational perspectives, which only human educators and researchers can supply it. In this collaboration, the computational complexity is dealt with by AI and the human custodianship of values, justice, and purpose is kept intact. The classroom is the operations theater in which this symbiosis is forged, where students learn to work not just with their hands to command AI tools but also question those AI tools, recognise their biases, and deploy their power for more regenerative purposes.

Stretching across the threshold of technological revolution and ecological crisis, this symbiotic equation can provide us with some

guidance heading forward. It is a reminder that intelligence—whether artificial or human—has its highest task not to control but to serve life.

As part of future efforts, we need more works on the environmental costs of AI Itself. Training large scale models requires huge carbon and water consumption. We need vigorous research on "Green AI": producing more energy-efficient algorithms, hardware and data center practices. Also, we need to bear in mind that historical data-based AI models may risk reproducing existing disparities. For example, a resource allocation algorithm used to optimise allocation of resources could ignore marginalised groups if data from that group has been neglected. It is important to research fairness-aware frameworks to guarantee that AI sustainability solutions are fair and inclusive.

Finally, we need more works on the pedagogical effectiveness of AI on a sustainability context. What is the best way to teach sustainability students about AI literacy? What are some ethical frameworks we need to incorporate into the curriculum? We need validated teaching models that guarantee that not only do students know how to use AI tools, but also know what the philosophical and ethical implications are of delegating some tasks to machines.

As the world moves towards the 2030 and 2050 climate goals, the challenge of using AI in support of sustainability will be massive. AI will no doubt fuel innovation, but we need a workforce that is educated to harness it wisely. We have transitioned from a time of information scarcity to a time of information overload; AI will help remove the noise, but human insight, developed through education, must determine the action taken.

With due care, educators and researchers may use AI as a tool in making their way through the most important technological shift of our time, in service of the most important cause of our time: the survival and flourishing of our planet.



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Crime Prevention Through Artificial Intelligence—Challenges and Potential for Sustainable University Teaching

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Abstract

The 11th of the Sustainable Development Goals (SDG) explicitly addresses 'sustainable cities and communities' and calls for more inclusive, safe and resilient cities (UN 2024). Nevertheless, safety and a feeling of security are often neglected in urban development, with the design and functional aspects more frequently in focus. At the same time, crime in general, as well as crime that occurs in public spaces, is constantly on the rise (Vykopalová 2021). In this context, this paper examines whether and how artificial intelligence (AI) in university planning education can contribute to making public spaces safer. The

challenges and potential of artificial intelligence in university teaching are discussed through a case study of the Raschplatz, a semi-public space at the central train station in Hanover (Lower Saxony). Over the course of a project from 2023 to 2025, students from the Faculty of Architecture and Landscape Sciences at Gottfried Wilhelm Leibniz University Hanover photographed situations at the Raschplatz where they felt safe or unsafe and conducted a brief survey among the users of the area. The survey asked 270 users how often they visited the Raschplatz and why, how long they typically stayed in the area, and how safe they felt there, among other things. The students used these results to create visualisations of crime prevention measures with and without the Dall-E 2 AI text-to-image model. The study examines the extent to which spatial planning and AI can contribute to the development of measures that enhance the feeling of safety in public spaces, and demonstrates how and where planning and AI can benefit from each other. Through the case study of the Raschplatz, the paper critically reflects on how AI (tools) can help enhance sustainable and innovative teaching. It demonstrates that AI-generated visualisations can effectively illustrate potential measures; however, it also highlights the apparent limitations of using AI to prevent crime through urban or environmental planning. For example, AI's visualisation of those measures is often technically accurate, but not well suited to the existing spatial structures. AI can help increase students' interest in task processing and prompt reflection, and contribute to controversial debates in university teaching.

Keywords SDG – Visualisation – Safety – Public spaces – CPTED

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1 Introduction: Crime Prevention and Artificial Intelligence in Urban Development

The 11th Sustainable Development Goal (SDG) on 'Sustainable cities and communities' aims to 'Make cities and human settlements inclusive, safe, resilient and sustainable' (UN 2024). This goal was formulated in 2015, yet actual safety and the feeling of safety are often

still neglected in urban development in many places (UN 2024). However, it can be observed that crime in general, as well as crime occurring in public spaces worldwide, is steadily increasing (Vykopalová 2021). The concept of criminal law, or formal crime, encompasses activities that are considered criminal and which result in legal consequences. Other socially harmful or disruptive actions can also trigger a police operation and be judged as criminal (see Mihalic 2018). According to the crime statistics of the German police, crime rates have risen in recent years, particularly in cities such as Hanover (PD Hannover 2023). However, these statistics often do not accurately reflect the realities of people's lived experiences in these areas, as the definitions of different crimes are limited, and the spatial context in which they occur is often not differentiated (Groß 2021). The impact of such statistics, such as the correlation between media reports and the increase in crime reports, particularly in the wake of the coronavirus pandemic, is often discussed in this context (e.g. Massenkoff and Chalfin 2022).

The spatial planning literature discusses measures which can make public places safer (e.g. Jeffery 1971; Newman 1972; Wickert 2023). However, these have not (yet) been implemented or tested in many places. The connection between spatial development and the fear of crime has been analysed in the research on fear (Wickert 2023). A starting point was provided by the architect and urban planner Oscar Newman in the 1970s with 'Defensible Spaces' and 'Crime Prevention Through Urban Design' (Newman 1972). Newman developed five principles for increasing the 'defensibility' of space, which deal with the territoriality of space in the sense of 'my home is my castle', with natural surveillance through the design of space, the image of squares, the milieu and neighbourhood meeting points (Newman 1972). Newman's concept has been further developed many times, e.g. into Crime Prevention Through Environmental Design (CPTED). CPTED offers numerous examples of urban crime prevention, including enhanced visibility, landscaping, lighting, cleanliness and social control (Jeffery 1971).

Neighbourhood relationships and activities, as well as social cohesion, and their influence on the feeling of safety, are also discussed in this context (Katzidis 2021). In urban development (e.g. in the context of smart city concepts), research to date has primarily focused on the design of public spaces and crime, as well as the feeling of safety (Schröder 2021). Furthermore, in the context of neoliberal urban development, urban research has examined the privatisation of formerly public spaces, such as train stations. In addition to CCTV and company rules, security personnel are also used to enhance security, or at least create a feeling of security.

At the same time, the use of AI and AI-generated images are becoming increasingly popular (e.g. Lee et al. 2024), not only in everyday life, but also in spatial development, in the education of planners and in university teaching in general. For example, UNESCO (2023) has already published a quick-start guide on how to use AI in higher education, including challenges and recommendations for its ethical use, such as academic integrity, the lack of regulation, privacy concerns, cognitive bias, gender and diversity, accessibility and commercialisation. Nowadays, universities have to prepare their students for the latest technology and relevant learning tools (Bearman et al. 2023) while also taking the ethical aspects into account (Kelly et al. 2023: 12). They have the responsibility of training their students for the labour market and thus also for AI (Bearman et al. 2023). 'By educating students on AI, universities can help prepare them to be active participants in the development and implementation of AI technology, ensuring that it benefits society as a whole' (Chan 2023: 3). Using AI in education and pedagogy has become a trend (Liu et al. 2022: 2) and it is hard to imagine life without it. This paper thus addresses the research problem on how AI tools can help enhance sustainable and innovative teaching on spatial planning courses by critically merging questions about crime prevention, AI and university teaching. Using the example of the Raschplatz in Hanover, the focus is not only on the benefits but also on the limitations and risks of applying artificial intelligence. In the Raschplatz project (see Sect. 3), students

took photographs and edited them using AI software to identify ways in which the public space could be perceived as safer by the public. They also conducted short surveys of people using the space to determine which aspects (surroundings, people, design, facilities, etc.) could contribute to a greater sense of safety.

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2 Background: AI and University Teaching—A Promising Combination?

Digitisation, understood as the conversion of analogue information into digital form, is progressing continuously and has become indispensable in many spheres of life, in both in rural and urban areas. More interesting than digitisation is digitalisation, i.e. the digital transformation and the processes it initiates and shapes in society. Although AI is only one aspect of digitalisation, it can be deployed and used in very different areas. In addition to high-performance digital infrastructures and a functioning municipal data management system, whether AI can be used effectively and constructively depends on the type of city in question (Güles and Schweitzer 2021: 16). AI is increasingly used every day, in our use of the internet, smartphone features, apps, public transport or household appliances (Popenici and Kerr 2017: 5).

Apart from discussions around smart city concepts, AI has been used less in urban development compared to other areas, such as medicine, robotics or computer science. Nevertheless, AI can already contribute to improving the quality of life, strengthening participation and making municipal administrations more efficient, e.g. in the context of mobility platforms or the further development of autonomous driving (see Güles and Schweitzer 2021). However, the use of AI also harbours potential risks that cannot (yet) be assessed in many areas. These include issues relating to copyright and fraud as well as other fundamental questions about whether or where AI might replace democratically elected individuals or bodies. As there is currently no comprehensive overview of the potentials and risks of AI in urban

development, and it is unclear how and where AI can or should be used in municipalities, numerous models and research projects have sprung up (see Difu 2024).

In university teaching, AI is becoming increasingly important and is already influencing academia, with its influence expected to grow even more in the future (Jochim and Lenz-Kesekamp 2025: 151; Hossain et al. 2024: 9174). The connection between teaching and AI are not new, but can be traced back to the 1970s (Tsz Kit Ng et al. 2023: 8446; Crawford et al. 2023: 3). AI has 'the immediate potential to change the way we learn, memorize, access, and create information' (Popenici and Kerr 2017: 6); it can have a huge impact on teachers and on teaching itself (Liu and Xiao 2025: 487) and can improve the quality of both teaching and learning (Liu et al. 2022: 1). While traditional teaching was mainly teacher-centric rather than focused on engaging students, teaching with AI is more learner-oriented and can help to boost students' enthusiasm (Liu et al. 2022: 2; Wang et al. 2023: 5634). Higher education institutions in particular feel under pressure to adapt to these new technologies (Jochim and Lenz-Kesekamp 2025: 150) and to monitor their power in relation to issues like hidden algorithms or monopolisation (Popenici and Kerr 2017: 4). Higher education cannot ignore the serious discussions on the future of teaching and learning in times of AI (Popenici and Kerr 2017: 10). Especially in the education sector, but also in industry and other sectors, educators need to keep on top of the theory, pedagogy and practical applications of AI (Lee et al. 2024: 9; Tsz Kit Ng et al. 2023: 8446). Institutional responses to AI range from welcoming it to banning it (Kelly et al. 2023: 1), with many beginning to formulate guidelines or recommendations for its (Spivakovsky et al. 2023: 182).

Several studies have already discussed the advantages and disadvantages of AI tools. Depending on who uses it and what it is used for, AI can support major transformation processes in university teaching (Jochim and Lenz-Kesekamp 2025: 149; Yan et al. 2024)—but also major disruptions (Eager and Brunton 2023; Kelly et al. 2023: 12). It may also change the roles schools, teachers and learners played in

the past (Rabah Al Mukhallafi 2020: 4; Fahimirad 2018: 110). For example, students can use chatbots to draft individual sentences or entire texts (Jochim and Lenz-Kesekamp 2025: 149; Walker et al. 2007; Ge and Hu 2020: 2; Sullivan et al. 2023). Studies show that AI is improving every day. For example, ChatGPT exhibits good language competencies, precision rates and creativity, but lacks adequate argumentation and references, and can return irrelevant or inappropriate responses (Farazouli et al. 2024: 371). Additionally, users' language skills can be enhanced through chatting or conversing with AI applications (Lotze 2016; Sullivan et al. 2023). Chatbots can take over roles like 'Socratic opponent', 'collaborative coach', 'guide on the side', 'personal tutor', 'study buddy' and others (UNESCO 2023: 9). AI can provide flexible learning settings enabling students to study at their own pace and convenience (Hossain et al. 2024: 9175; Crawford et al. 2023: 9). Educators can determine their ability, learners can adapt their needs according to their preferences as well as the progress can be monitored (Rabah Al Mukhallafi 2020: 43; Ge and Hu 2020: 4). In addition, translation accuracy can be improved with AI (Rabah Al Mukhallafi 2020: 43). Cheating and plagiarism by students using AI is also a widely discussed problem in the university landscape (Jochim and Lenz-Kesekamp 2025: 150; Chan 2023: 1; An et al. 2025: 3; Crawford et al. 2023: 7). As AI is not good at detecting irony, sarcasm or humour (Popenici and Kerr 2017: 2), its use can lead to misinterpretation.

Chatbots can provide teaching materials (Kiryakova and Angelova 2023; Eager and Brunton 2023; Spivakovsky et al. 2023: 184) or help teachers to adapt their material to the needs of students (Kohnke et al. 2023; Liu et al. 2022: 11). AI can also design teaching activities or assessments (Liu and Xiao 2025: 500; Ge and Hu 2020: 2; Spivakovsky et al. 2023: 184). For example, in university education, AI can adapt learning platforms as it can function as an interactive smart tutor embedded in digital textbooks (Hossain et al. 2024: 9180) or as a discussion partner for students (Rabah Al Mukhallafi 2020: 42). Furthermore, in classroom management, AI can track attendance and

marks or help to facilitate communication by using virtual applications (Hossain et al. 2024: 9180; Rabah Al Mukhallafi 2020: 44; Liu et al. 2022: 11; Ge and Hu 2020: 2; Fahimirad 2018: 110). In addition, AI can enhance accessibility and inclusivity by supporting students with disabilities, for example through text-to-speech or speech-to-text applications (Hossain et al. 2024: 9180–9181; Rabah Al Mukhallafi 2020: 42–43; Kelly et al. 2023: 3; Ofosu-Ampong 2024: 2).

Rybinski and Kopciuszewska (2021: 1130) have observed 'that machine learning models can replicate human decision processes with a high degree of accuracy. […] The cost of machine reading in time and money is much lower than the cost of human text processing, and the accuracy is high, so machine learning and especially deep learning models may soon become a popular tool […] and be adopted by quality assurance departments in higher education institutions.' However, there is also the risk of manipulation through AI which universities need to confront, while acknowledging that the production of free knowledge should not be limited by AI (Popenici and Kerr 2017: 4). Furthermore, AI has the potential to reduce the administrative burdens on universities (Popenici and Kerr 2017: 2; Hossain et al. 2024: 9183) by taking over certain time-consuming processes. Eager and Brunton (2023: 2) assume that AI will become more important in content creation, as well as in management tasks.

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3 Methods

The paper explores the challenges and potentials of AI in university teaching within the scope of a charette, a one-day exercise that students completed independently focusing on the Raschplatz, a semi-public space at the central train station in Hanover, Germany (Lower Saxony), has been selected (see Fig. 1). The Raschplatz is a transit location characterised by high frequency, multifunctional use by a varied demographic. It serves as a hub for local and long-distance train, bus and tram services. It is also home to numerous retail stores and shops serving everyday needs. The surrounding area also has various

entertainment facilities, including a casino and a cinema, in addition to accommodation for people with special needs. In local media, the Raschplatz is frequently cast in a negative light as a ‘problematic site’ (NDR 2025) with frequent reports of addicts and crime. An attempt was made to counteract the negative image by temporarily introducing new uses in the early and summer months of 2023 and 2024, which included setting up a volleyball court and holding events. Since 2024, the city of Hanover has been developing a master plan for the northern part of the train station, including the Raschplatz, as part of its inner-city strategy. A redesign of the area is intended to address its challenges (LHH 2024).

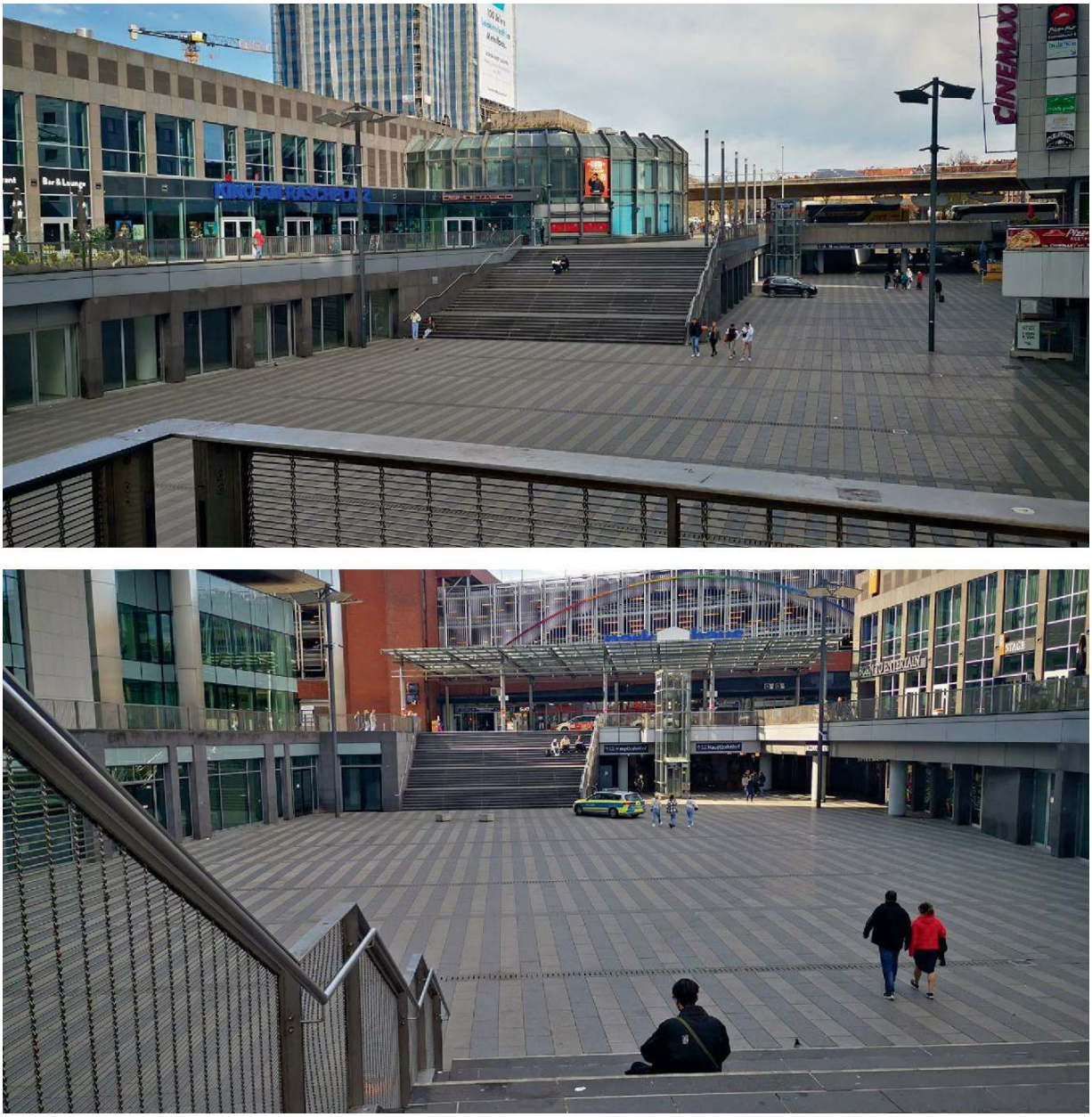


Fig. 1 The Raschplatz in Hanover as a transit point. *Source* Lina Schumann

Over the course of a project carried out between 2023 and 2025, students of the Faculty of Architecture and Landscape Sciences at Gottfried Wilhelm Leibniz University Hanover each took five photographs of situations at the Raschplatz in which they felt safe or unsafe and conducted a short survey of users of the area (in this study the term ‘users’ refers to people who the students encountered at the Raschplatz who were there for a variety of reasons or who just pass

through it). The two pictures Fig. 1 belong to the category of safe space. The photos are taken from above, providing an overview of the area. For the survey, 270 users were asked about how frequently they use the Raschplatz and why, how long they spend there and how safe they feel there, among other things. The students used the results of the survey and of their observations to create visualisations of crime prevention measures with and without the Dall-E 2 AI tool. The aim was to be able to compare artificial and human designs and ideas. At the time of the project, the students were at very different levels when it came to using image-generating AI. For some, this was their first time using such AI, which was also evident in the prompts they entered and, consequently, in the varied results. Dall-E 2 is a paid-for AI image generator from OpenAI that creates realistic and artistic images based on voice inputs, which either uses the user's own images or creates new ones. The study addresses the extent to which spatial planning and AI can support the development of measures to enhance a feeling of safety, as well as the question of whether and how these two approaches can be integrated. Furthermore, the example clearly illustrates the limitations and drawbacks of using AI, and how implausible and ill-suited ideas and suggestions can be to the real world. Nevertheless, limitations of this study cannot be ignored: One aspect is that the case study is limited to Raschplatz in Hanover. This place refers as an example for high frequented and multifunctional areas very well, but it is important to take other places in other countries into account as well to evaluate similarities and differences. Another aspect is the Dall-E 2 AI tool, which was used for this analysis. In the meantime, there are a lot of changes and upgrades in AI tools. If the study would be rearranged these days, the results would may differ as the "knowledge" of the AI tools is much bigger now. All in all, the results can be interpreted as a starting point of how to deal with AI in sustainable University Teaching.

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4 Results and Discussion: Challenges and Potentials of AI in University Teaching

In this section, we critically reflect on how AI tools can enhance sustainable, innovative teaching, using the example of an urban planning issue. The paper demonstrates that AI-created visualisations can be used to vividly illustrate possibilities, but it also highlights the apparent limitations of using AI for crime prevention measures through urban or environmental planning.

In total, 270 participants took part in the survey: 50% are female and 41% are male; 9% did not declare their gender (see Fig. 2).

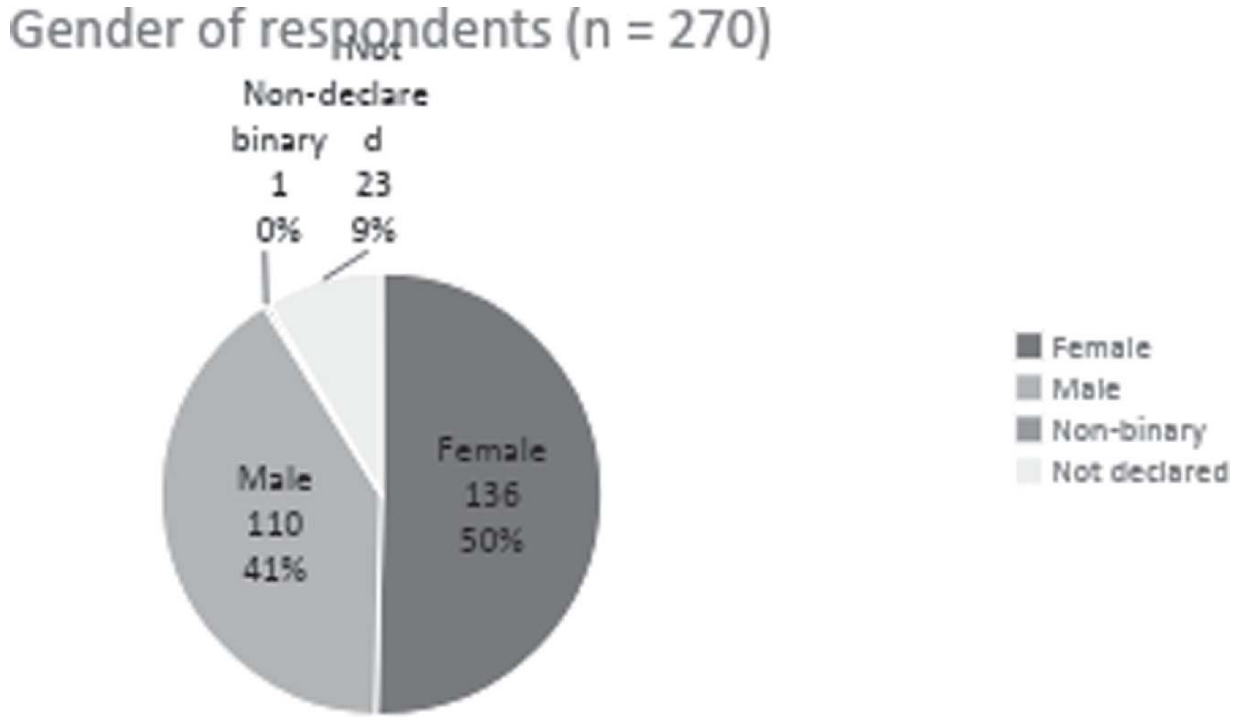


Fig. 2 Gender of the respondents (n = 270). *Source* The authors

The results of the survey show that many of the people surveyed do not feel safe at the Raschplatz (Fig. 3): 90 people reported a feeling of safety ranging from 1 (absolutely not safe) to 4 (somewhat safe), while 123 people rated their sense of safety as between 6 and 10 (rather safe to absolutely safe) and 48 people assessed their feeling of safety as 5, which represents a vague feeling of not being entirely safe, but also not unsafe. The results show that a third of those surveyed do not feel safe at the Raschplatz, indicating a need for urban development measures to

counteract this perception and improve the image of this heavily frequented area.

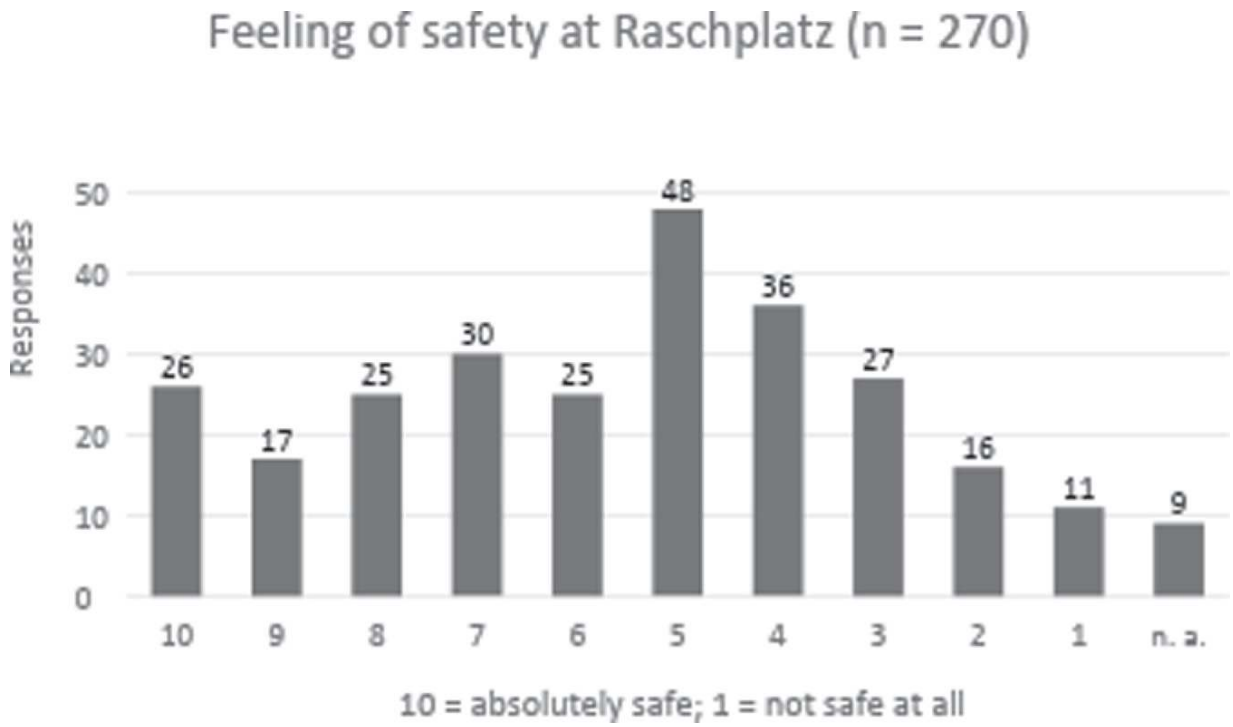


Fig. 3 Feeling of safety at Raschplatz (n = 270). *Source* The authors

When asked what positively influences their feeling of safety, the presence of other people was mentioned 201 times (multiple responses possible), equating to 59% (see Fig. 4). Seventy-eight respondents (23%) stated that the environment or surroundings increase their feeling of safety. Animals (nearly 6%) and other aspects (7%) were mentioned only a few times; 19 people (6%) did not answer. These results demonstrate the connection between spatial development measures and the fear of crime, showing that the design of an area can significantly influence how safe people feel. The presence of other people in particular increases the feeling of safety.

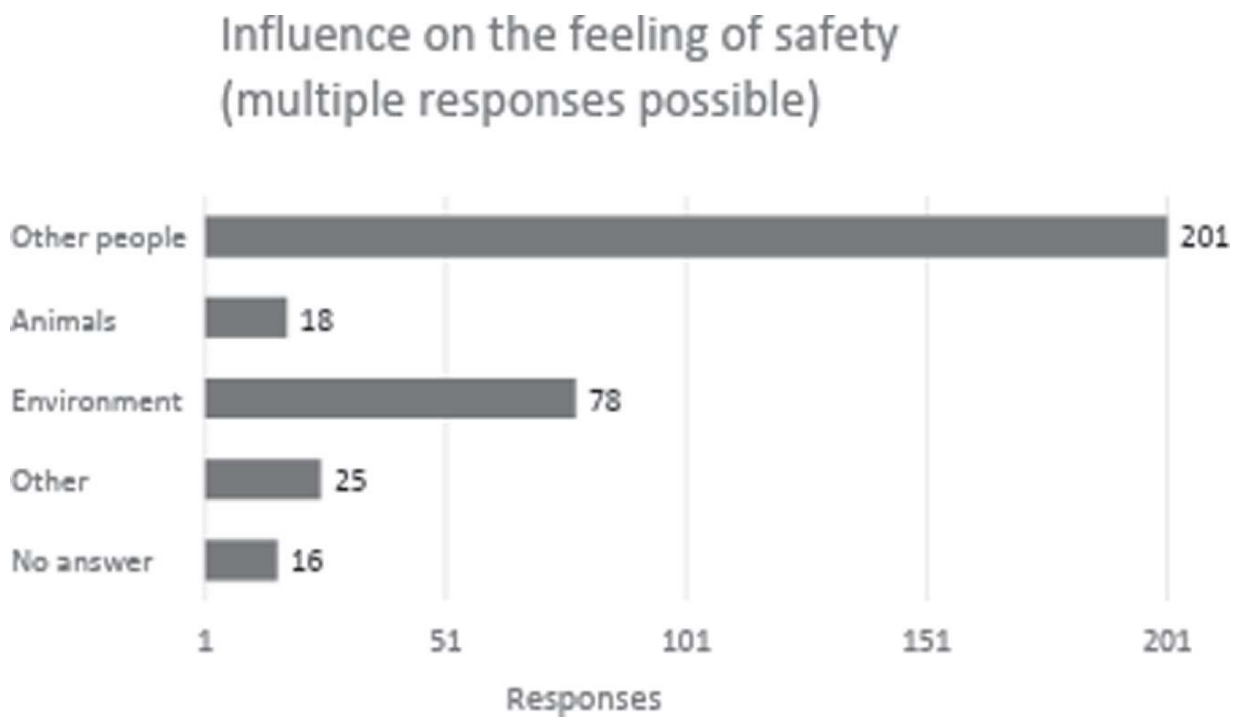


Fig. 4 Influence on the feeling of safety (multiple responses possible). *Source* The authors

The data collected through face-to-face surveys enables an empirical-based dataset, which will be used in the next step to discuss the application of AI in university teaching. Depending on the type and use, AI can take on different functions in teaching and learning (Girgensohn et al. 2023: 12ff.; see Sect. 3). Chatterjee and Dethlefs (2023) state '[the] AI model can be your friend, philosopher, and guide … and even your worst enemy'. For example, it can be used for inspiration, to concretise a research question, or to structure texts, as well as for literature research (Girgensohn et al. 2023: 12ff.). How lecturers design their lectures can stimulate and engage students, as well as enhance learning and academic performance (Vercellotti 2018), and is crucial in determining the quality of teaching (Ge and Hu 2020: 4). AI can be used in various ways to stimulate critical reflection among students on safety and crime prevention, particularly in specific urban areas. In the context of the charette, the AI-generated images stirred controversial debates and lively discussions in class. The AI-generated images were critically compared to those created by the students themselves.

The analyses show that AI's visualisations of measures are often technically accurate, but are usually not well suited to the specific spatial structures in question (see Greinke et al. 2024). For example, an image of a 'dark corner' at the Raschplatz, taken under an underpass, was enhanced by AI with more lighting and greenery. This prompt was tested in line with Jeffery's CPTED principles, focusing on sufficient lighting and abundant greenery to enhance the feeling of safety. The AI model then added lamps and enlarged a staircase. However, it is not structurally possible to enlarge the staircase because the space above it is occupied by buildings and a pedestrian walkway. This shows that while the AI model can implement the desired prompts accurately, it cannot integrate them properly into the spatial context. The prompts 'viewability' and 'social control' (based on Jeffery's CPTED) were interpreted by simply adding CCTV to the visualisations (Fig. 5), suggesting that the AI model relates social control directly to CCTV monitoring.



Fig. 5 Original image (left, © Johanna Weißflog) and image modified using AI (right, © modified with Dall-E 2) to show randomly installed cameras to improve social control

AI has improved rapidly in recent times and now delivers better results for the prompts entered. For example, the AI model creates manageable spaces with green areas in many images, but the plantings are often very large and may impair visibility, which in turn can create potential spaces of fear. Although this has improved considerably, there

are still some questionable suggestions (Fig. 6). These sometimes rather inappropriate results have encouraged reflection on the part of students. For example, the AI model almost completely disregards social aspects (see Greinke et al. 2024). However, the students' designs explicitly include seating options and (groups of) people, as this is how social interactions typically arise in such a space (e.g. Kessl and Reutlinger 2007; Löw 2018), and these can reinforce or inhibit a feeling of security. The students' designs often incorporate more CPTEDs, which are also tailored to the specific nature of the space. The AI model, on the other hand, uses its knowledge of CPTEDs but is unable to integrate them effectively into the space to enhance the feeling of safety. Inappropriate AI results are thus not entirely detrimental for university teaching, because they can promote students' learning by encouraging them to discuss the results critically and reflect on their ideas more actively.



Fig. 6 Original image (top, ©Amelie Streit and Marlene Reinmüller) and image modified using AI (bottom, © modified in Canva) to show randomly installed planting

One challenge is the rapid progress of AI technology in relation to university teaching. Teachers are typically trained in their subject area but often lack training in the technical implementation of AI, which is

why they are often hesitant to integrate it into their teaching (Chiu and Chai 2020). For example, a survey at a leading Australian university showed that lecturers often do not feel sufficiently supported and trained by their institution, while also being critical of the slowness with which the university adopts new technologies and methods (Lee et al. 2024: 9). Typically, lecturers are slow to adapt to new technologies (McGrath et al. 2023) and build specific skills on their own; they need to learn how to integrate AI or the output of chatbots into their teaching (Liu and Xiao 2025: 503). Some report that AI is changing so fast that they do not feel confident—not least because 'they lack access to relevant technological pedagogical content knowledge' (Tsz Kit Ng et al. 2023: 8463). Teachers must therefore expend considerable effort to keep up to date.

Studies have already shown that lecturers are more open to incorporating AI into their teaching and could envision integrating it into their curricula and instructional methods (Jochim and Lenz-Kesekamp 2025: 155). Students' views, on the other hand, vary considerably: a few want a ban on AI, some seek blanket permission to use it, while others would prefer a more limited permission to use it on an ancillary basis as a study aid (Jochim and Lenz-Kesekamp 2025: 155). Jochim and Lenz-Kesekamp (2025: 157) discuss how teachers need to be up to date on the latest developments and adequately prepared to avoid feelings of being overwhelmed. Nevertheless, both students and lecturers agree that AI will inevitably be very present in the future (Jochim and Lenz-Kesekamp 2025: 163). If teaching staff are to support students in understanding and working with AI, then the staff themselves will need to have a sound understanding of how to best harness its advantages and manage its dangers and limitations (Spivakovsky et al. 2023: 19; Tsz Kit Ng et al. 2023: 8465). Against the backdrop of rapidly advancing digitisation, the functions of AI are constantly changing, such that lecturers can hardly keep up, particularly if their previous training did not prepare them for AI. The risk of errors in using and managing AI in courses is thus high. Some

studies have already recommended training for university teachers to avoid these problems (Jochim and Lenz-Kesekamp 2025: 163).

In addition to the challenge of rapid technological development, university teachers must harness AI effectively. Nowadays, teachers are no longer merely expected to convey content, but also to enhance learning processes, for example by connecting real-world problems with technical solutions in an interactive technical environment (Tsz Kit Ng et al. 2023: 8463). Growing up in an environment saturated with technology or with online learning does not automatically mean that students are prepared to use technologies, including AI, effectively (Kelly et al. 2023: 3). Their knowledge, experience and confidence in using AI is relatively low (Kelly et al. 2023: 9), although this varies between disciplines, with students in science and engineering fields more aware than students in healthcare (Kelly et al. 2023: 10). Hence the gradual integration of AI into specific coursework tasks and learning goals to avoid misunderstandings and disorientation is important (Eager and Brunton 2023: 16). AI can help to strengthen the quality of teaching (Ge and Hu 2020: 4), but to achieve this educators need flexible, continuous and expert support and guidance. Institutions need to ensure that the use of AI aligns with their regulations and values and that students clearly understand how they are allowed to use it (Eager and Brunton 2023: 16). Students' privacy needs to be safeguarded and they need to understand the ethics around its use (Ma and Lei 2024: 108). Institutions should thus include these aspects of AI in curricula and ensure that its integration is based on the needs of each discipline (Kelly et al. 2023: 12; Tsz Kit Ng et al. 2023: 8465; Chan 2023: 17; An et al. 2025: 10). Furthermore, institutional infrastructure and teaching equipment will need to be updated (Tsz Kit Ng et al. 2023: 8465). Teachers will need to update their syllabi, develop new forms of assessment and monitoring, and include critical analysis in their teaching (Spivakovsky et al. 2023: 198). Chan (2023: 14) suggests that universities take responsibility and be transparent in data collection, feedback and criticism. She puts forward six fundamental aspects for managing AI in teaching and for supporting teachers, students and

other staff: (1) training, (2) ethical use and risk management, (3) incorporating AI without replacing humans, (4) enhancing holistic competencies, (5) fostering a transparent AI environment, and (6) data privacy and security (ibid.: 12–15). To these aspects, Ma and Lei (2024: 108) add establishing 'professional smart education teams on campus', which possess expertise on how to integrate AI technology into teaching. Wang et al. (2023: 5642) also demand support from the government, with supportive policies aimed at integrating new technologies into education.

The technical progress and rapid development of AI also present unique opportunities for university teaching. For example, this case study of the Raschplatz has made clear how important the sound formulation of prompts and the consequences of errors in such inputs actually is. An AI tool can only generate what it is told to generate: imprecise prompts produce imprecise results. The language of the prompts should also be considered, as the model generated different designs when the prompts were given in English. Some students recognised this themselves and incorporated it into their work, but others did not. All of these aspects should be discussed on university courses. Moreover, fears that students' writing and critical thinking skills will decline as a consequence of their use of AI (Chan 2023: 2) can be mitigated through such class discussions. In this case study, these issues prompted students to question their actions with AI even more critically than before (see also Greinke 2024). Additionally, students were encouraged to document their approach to AI and record individual steps, including the prompts they used. This enabled them to understand the details of what happened and why, and to discuss this intensively with their fellow students (see also Kasneci et al. 2023). For teachers, it is essential to consistently reflect on the risks and limitations with students to train them to adopt a critical stance and to keep them on their toes (Liu and Xiao 2025: 501). Using AI effectively requires strong critical thinking skills as well as digital literacy (Kelly et al. 2023: 3). It is essential for teachers and students to interact with each other, as most of the AI applications used on university courses

rely on self-learning or self-use. However, to learn effectively, it is important to interact and reflect (Liu et al. 2022: 9). Most students learn better by combining human/computer interaction and group discussions in class (Liu et al. 2022: 10).

Another aspect that should not be neglected is the changing relationship between educators and learners. Due to the widespread use of AI, it can sometimes be challenging to determine who has produced which results, and what learners have actually done or achieved themselves. The question 'Who has written this?' arises, thereby questioning students' authorship (Farazouli et al. 2024: 372). This disrupts assessment practices, as well as the educator-learner relationship (ibid.).

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5 Conclusion and Outlook

Since 2015, the 11th SDG aims to 'Make cities and human settlements inclusive, safe, resilient and sustainable' (UN 2024). However, it can be observed that crime in general, as well as crime occurring in public spaces worldwide, is steadily increasing (Vykopalová 2021). Since the 1970s, the spatial planning literature discusses measures which can make public places safer (e.g. Jeffery 1971; Newman 1972; Wickert 2023). However, these have not (yet) been implemented or tested in many places. At the same time, the use of AI and AI-generated images are becoming increasingly popular (e.g. Lee et al. 2024), not only in everyday life, but also in spatial development, in the education of planners and in university teaching in general. Therefore, this paper contextualizes crime prevention and artificial intelligence in urban development and in university teaching by addressing the research problem on how AI tools can help enhance sustainable and innovative teaching on spatial planning courses.

The study show that integrative spatial and urban development is important for the safe, socially and environmentally compatible transformation of towns and cities. To achieve this, planning skills which bring together societal, environmental and conservation

considerations in an interdisciplinary and transdisciplinary manner are needed to develop resilient strategies and solutions. Planning is *per se* transformative and future-oriented. AI-gerated images as a tool for young planners, which facilitates the development of imaginaries and visualisation, can be helpful, especially when it comes to communicating possible futures, a key task of planning, with the general public, for instance. Working with AI-generated images can be a starting point for discussions and exchange.

By using the example of the Raschplatz in Hanover, the study analyse the benefits as well as the limitations and risks of applying artificial intelligence. In the frame of a charette, students took photographs and edited them using AI software to identify ways the public space could be perceived as safer. The results vary depending on the accuracy and level of detail of the prompts students enter. They also conducted short surveys of people using the space to determine which aspects (surroundings, people, design, facilities, etc.) could contribute to a greater sense of safety. The students combined survey results and their observations to create visualisations of crime-prevention measures, with and without AI, to compare artificial and human designs and ideas. Especially, the survey provided insight into the daily use of the space and how users actually perceive it. According to the survey, the main factor in increasing feelings of safety is the presence of "other people". In contrast, the AI-images translated "social control" directly to CCTV monitoring instead of enhancing places for social encounter.

The use of AI in educating planners and in developing and implementing urban development strategies can be constructive especially in regard to communication, but it also entails risks. For example, planners can use AI for modelling, but they should always critically question the model's outputs and to what extent they can actually be implemented in practice. The sometimes comical or even absurd outputs make clear that their source is not a thinking human being but a trained machine or algorithm—after all, AI remains a language model and not a professional spatial planner (see also

Shanahan 2024). AI can be very helpful for university teaching in stimulating active critical reflection among students, who tend to be receptive to it given their affinity for new technology. Furthermore, the fast development of AI makes it necessary to continuously work and adapt the research design. For instance, the AI-generated imaginaries of a safe Raschplatz could be used as a starting point for another user survey, and the created images could be used to spark conversation. This would enable and ensure a feedback loop among students, AI, and the users of the Raschplatz, bringing AI-generated imaginaries back into reality. As long as the use of AI continues to be critically evaluated, innovatively and continuously further developed, it can undoubtedly become a valuable tool in classes.

The use of AI university teaching needs to be tackled head on starting now—all the more so given that its status and impact remain uncertain (Spivakovsky et al. 2023: 184). The new technology should therefore be actively integrated into research and teaching and not swept under the carpet. To achieve this successfully, it is essential that teaching staff receive regular training (Eager and Brunton 2023) and that students are sensitised to its use at an early stage. The opportunities and risks should be identified and assessed to ensure its successful integration into university teaching and spatial planning practice, as its utility for the latter may well grow. Nevertheless, if AI is properly utilised, it can extend and complement human capabilities in teaching, learning and research, functioning as a partner but never replacing people completely (Popenici and Kerr 2017: 3; Kasneci et al. 2023; Spivakovsky et al. 2023: 191). This requires seeing AI as a tool and a means to an end, rather than as a final solution or an end in itself (Eager and Brunton 2023: 16). To achieve SDG 11 on 'Sustainable cities and communities', young urban and environmental planning professionals should consider how it can best be harnessed. However, one aspect that should not be neglected is the huge amount of energy and water consumption required for its use. From a sustainable development perspective, this begs the question of how essential the

use of AI actually is, which sustainable university teaching must also take into account.



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Table 5 Selected hyperparameter values for the RF model

n_estimators	min_samples_split	min_samples_leaf	max_samples	max_features	max_depth
500	50	10	0.4	8	70

Table 5 In what ways do traditional values shape your overall attitude toward AI's role in fostering both technical skills and moral/intercultural upbringing in higher education?

Group	Belarus	China	Uzbekistan
International Students	65% stress positive shaping via AI's flexibility in blending patriotism with skills, fostering moral growth in diverse settings	80% note harmony's role in AI decisions for ethical upbringing alongside technical proficiency	72% highlight hospitality influencing engagement for inclusive intercultural dialogue
Local Students	78% focus on resilience values shaping AI attitudes toward diligent skills and collective moral development	85% emphasize authority respect guiding positive AI use for balanced training and awareness	78% advocate for family values in AI to enhance communal upbringing and decision-making

Source Developed by the authors using the results of query

Table 1 Main seven main themes and keywords for *Kankyo* Cafés (adapted from Tada 2018a, page 210)

No.	Theme	Keywords
1	The future of our planet– "Thinking about the environment"	Nature/society/culture, subject/connection (relationship), human, "science-based civilization"
2	"Environmental issues are human issues" towards the solution	Pollution and global environmental problems, problem grouping and uncertainty, chemical substances, science and technology level, society level, human level, ethical issues
3	"Thinking about harmonious coexistence with nature" –our relationship with biodiversity	Nature, symbiosis, biodiversity, ecosystem services
4	*The sense of wonder* by Rachel Carson	*The sense of wonder* (Rachel Carson), sensibility, aesthetics, environmental thought
5	Ethics of "life and the environment"	*Silent spring* (Rachel Carson), bioethics, human ethics, environmental ethics
6	Relationship between the environment and SDGs	Sustainability, biosphere/ society/economy
7	Environmental studies – relationship between life, nature, and society	Life/nature/society, symbiosis, circulation, diversity, science/literature/education

Table 1 AQI significance in terms of health

AQI ($\mu g/m^3$)	Air quality conditions for health
0–50	Good
51–100	Moderate
101–150	Unhealthy for sensitive groups
151–200	Unhealthy
201–300	Very unhealthy
301–500	Hazardous

Source https://www.airnow.gov/aqi/aqi-basics/

Table 3 Impact of lag features on AQI prediction

Feature window (h)	**RMSE**	**R^2 score**
3	10.36	0.97
6	7.48	0.98
12	12.87	0.96

Table 3 The table outlines how Europe and India approach sustainability and AI education within distinct policy and developmental contexts

Dimension	Europe	India
Key education policy	Digital Education Action Plan; GreenComp	National Education Policy 2020
AI in school education	Emerging national curricula, pilots	CBSE AI elective, AI for Youth
Sustainability focus	Climate ethics, Green Deal alignment	Environmental awareness, development, and balance
Key challenges	Disciplinary silos	Infrastructure and equity gaps

Table 13 Educators' views on AI, gig economies, and NEET mitigation

Theme	Belarus	China	Uzbekistan
Familiarity and AI Preparation for Gig Work	"AI trains for gig flexibility but must uphold diligence to avoid NEET." (80% mention)	"Harmonious AI prepares for gig careers with ethical awareness." (85% mention)	"Communal AI mitigates NEET by aligning gig skills with family values." (65% mention)
NEET Awareness and Value Conflicts	"NEET clashes with resilience; AI can reinforce stable work ethics." (75% mention)	"AI addresses NEET by balancing innovation with authority respect." (70% mention)	"Hospitality helps AI prevent disengagement in gig contexts." (65% mention)
Mitigation Strategies via AI	"Use AI simulations for value-aligned gig training." (80% mention)	"Integrate ethics modules to harmonize gig with upbringing." (80% mention)	"Foster communal AI tools to counter NEET risks." (80% mention)

Source Developed by the authors using the results of educators' interviews

Table 1 Actions to determine sustainability of AI literacy

Action	Intended outcome
HEI commit to one AI tool and demonstrate limitations	Addresses any digital inequality amongst students and reduces reliance on AI tools as the only source for learning
Upskill staff in the use of AI tools ethically and sustainably	Staff prepare students for future work with AI involved and aid critical thinking amongst the academic community
Engage students in projects that assess the environmental lifecycle of AI tools or digital infrastructure used in the classroom	Students become responsible GAI users and learners
Use real-world case studies (e.g., Microsoft's water usage for AI, Google's carbon goals) to ground learning in current debates	Students understand ethical and environmental concerns via company policy
Embed AI use within the context of the UN SDGs, especially SDG 4 (quality education), SDG 9 (industry, Innovation and Infrastructure), and SDG 13 (climate action) and with a uniform way of SDG reporting in HE	Provides a clear picture of the landscape and spotlights the implications of AI use on sustainability

Table 8 Educators' insights on AI-facilitated intercultural collaboration

Theme	Belarus	China	Uzbekistan
Engagement in AI-Supported Dialogue	"AI platforms facilitate team innovation with respect for collective resilience." (80% mention)	"Harmonious AI tools enhance mutual respect in cross-cultural projects." (85% mention)	"Hospitality values boost participation in AI-driven inclusive collaborations." (70% mention)
Balance Between Skills and Upbringing	"AI bridges innovation skills with upbringing harmony in diverse peers." (75% mention)	"Ethical oversight in AI ensures upbringing alongside technical teamwork." (70% mention)	"Communal AI fosters personal growth and intercultural skills." (70% mention)
Challenges and Improvements	"Address AI biases to better support post-Soviet collective dialogue." (65% mention)	"Customize for authority to avoid conflicts in harmonious exchanges." (75% mention)	"Enhance for family-like interactions to prevent isolation." (65% mention)

Source Developed by the authors using the results of educators' interviews

Table 1 Research directions linking AI with educational skill teaching and upbringing

Directions/scientific schools/approaches	Description	Key researchers	References
AI Literacy and Ethical Education	This approach emphasizes integrating AI literacy into curricula to teach technical understanding of AI alongside ethical considerations, such as bias, privacy, and societal impacts, fostering both computational skills and moral reasoning in students	Irene Lee, Cynthia Breazeal, Wayne Holmes	Lee et al. (2011), Miao and Holmes (2021), Picard et al. (2004)
Human-AI Collaboration (Hybrid Learning Systems)	Focuses on hybrid models where AI supports adaptive skills training (e.g., intelligent tutoring for problem-solving) while human teachers provide ethical oversight and personal development, ensuring balanced upbringing	Ole Molenaar, Vincent Aleven, Beverly Woolf	Molenaar (2022), Aleven et al. (2009), Woolf et al. (2013)
Ethical AI Design and Equity Frameworks	Involves developing AI systems that mitigate biases and promote equity in education, connecting technical efficiency in skills training with ethical principles like fairness and inclusivity to support cultural and moral upbringing	Mutlu Cukurova, Rose Luckin, Neil Selwyn	Holmes et al. (2022), Luckin (2017), Selwyn (2022)
Adaptive Personalized Learning with Value Integration	Utilizes AI-driven adaptive systems for individualized skills acquisition (e.g., in STEM) while embedding values such as ethical decision-making and intercultural awareness to enhance holistic upbringing	Kurt VanLehn, Philip Winne, Valerie Shute	VanLehn (2011), Alexander and Winne (2012), Shute et al. (2017)
Teacher-AI Partnership Models	Approaches that position AI as a tool to augment teachers' roles in delivering skills training and facilitating ethical discussions, promoting collaborative environments for both technical proficiency and personal growth	Jeremy Roschelle, K. R. Koedinger	Roschelle et al. (2025), Koedinger (2024)

Source Developed by the authors

Table 1 Student rankings for skills and their importance for animal surveys, with 1 = most important and 10 = least important, in both field and virtual reality (VR) conditions. Colours indicate direction of change in ranking with green representing a positive change, red is a negative change, and blue is neutral

Skill	Field rank (average)	VR rank (average)	Change
Ability to identify species	1.8	1.0	● ▲ 0.8
Data recording	3.4	3.4	▬ 0.0
Ability to navigate a map	4.0	8.6	● ▼ 4.6
Knowledge of habitat	4.4	6.4	● ▼ 2.0
Time management	5.6	6.8	● ▼ 1.2
Knowledge of bird ecology	6.0	5.0	● ▲ 1.0
Ability to use species ID books	6.2	4.4	● ▲ 1.8
Ability to use AI apps	7.0	5.5	● ▲ 1.5
Independence	7.8	6.8	● ▲ 1.0
Communication	8.8	8.4	● ▲ 0.4

Table 1 Hyperparameters of the RF algorithm considered in the tuning process

Name	Description	Tested values
n_estimators	The number of trees in the forest	10; 50; 100; 250; 500; 750; 1000; 1250; 1500; 2000; 2500; 3000; 4000; 5000
max_depth	The maximum depth of the tree	None; 2; 6; 10; 15; 20; 30; 40; 50; 60; 70; 80; 90; 100; 125; 150
min_samples_split	The minimum number of samples required to split an internal node	2; 4; 8; 10; 25; 50; 75; 100; 500; 1000; 5000; 10,000
min_samples_leaf	The minimum number of samples required to be at a leaf node	2; 4; 8; 10; 25; 50; 75; 100; 500; 1000; 5000; 10,000
max_features	The number of features to consider when looking for the best split	1; 2; 3; 4; 5; 6; 7; 8; 9; 10; 11; 12; 13
max_samples	If the bootstrap parameter is set to True, this hyperparameter indicates the number of samples to draw from X to train each base estimator	0.1; 0.2; 0.3; 0.4; 0.5; 0.6; 0.7; 0.8; 0.9; None

Table 7 In what ways has AI-facilitated intercultural dialogue influenced your personal growth and collaborative abilities in a multicultural higher education environment?

Group	Belarus	China	Uzbekistan
International Students	68% emphasize AI's positive influence on growth via diverse dialogues fostering innovation and respect	82% note harmony in AI platforms boosting mutual understanding and team skills	74% highlight hospitality-enhanced collaborations for personal and intercultural development
Local Students	70% focus on structured AI aiding collective respect and skills in multicultural settings	85% stress balanced upbringing through harmonious group interactions	78% advocate for communal values in AI-driven dialogue promoting inclusive growth

Table 1 Competencies in ecological versus algorithmic literacy across cognitive (knowledge), ethical (values), and systems (holistic) dimensions

Dimension	**Ecological literacy competencies (sustainability context)**	**Algorithmic literacy competencies (AI/digital context)**
Cognitive **(knowledge and thinking)**	Understanding core ecological principles (e.g. biodiversity, ecosystems, natural cycles) and human–environment interactions. Critical thinking to analyse environmental problems and solutions. Systems thinking about ecological networks and sustainability cause-and-effect relationships	Understanding how algorithms and AI systems function (data, logic, machine learning). Awareness of algorithmic presence in society (e.g. social media feeds). Computational thinking and problem-solving using data. Critical evaluation of algorithmic outputs (e.g. spotting biases or errors)
Ethical **(values and bias)**	Cultivating environmental ethics and empathy for nature (stewardship, conservation values). Commitment to sustainability, intergenerational equity, and justice for impacted communities/species. Personal responsibility for one's ecological footprint	Recognising ethical issues in AI: bias, fairness, privacy, transparency, accountability. Adhering to principles of responsible tech use (non-maleficence, avoiding harm). Developing a critical stance toward algorithmic decisions (e.g. questioning unjust outcomes). Commitment to using AI for social good while respecting human rights
Systems **(holistic and societal)**	Seeing the environment as an interconnected system, understanding feedback loops in climate, water, and biodiversity systems. Ability to connect local actions to global environmental impacts (systems thinking in sustainability). Participating in collective action and policy advocacy for systemic change	Understanding complex socio-technical systems shaped by algorithms (e.g. how AI affects economies, communication, and daily life), Navigating the "ecosystem" of data, platforms, and stakeholders. Ability to influence or at least respond to algorithmic systems (e.g. adjusting privacy settings, engaging in civic debate on AI governance). Seeing AI's role in larger systems (education, health, smart cities) and its potential to drive systemic change or risks

Table 2 Axial coding

Axial code	Related open codes	Articles
Enhancing managerial efficiency & decision-making	- Enhancing teacher productivity- Reducing time spent on administrative tasks - Automating curriculum planning	Mehta et al. (2021), Xie et al. (2024), Zaugg (2024), Rosi (2024), Siminto et al. (2023)
Strengthening data-driven decision-making	- Data-driven decision-making enhancement - Predictive analysis of student performance - AI algorithm integration in decision processes	Mehta et al. (2021), Hutson et al. (2022), Suryanarayana et al. (2024), Dwivedi et al. (2024), Xu (2025), Siminto et al. (2023)
Enhancing organisational interaction	- Improving communication between administrators ↔ teachers - Reducing organisational conflicts - Strengthening intra-organisational communication	Lowa (2023), Cao and Jian (2024), Suryanarayana et al. (2024), Zaugg (2024), Rosi (2024)
Personalising learning	- Supporting personalised learning - Tailoring curriculum to individual students - Providing adaptive learning recommendations	Mehta et al. (2021), Hutson et al. (2022), Suryanarayana et al. (2024), Lowa (2023), Cao and Jian (2024), Zafari et al. (2022), Jia and Tu (2024), Alam and Windiarti (2025), Kashive et al. (2020), Djouiba (2024)

Axial code	Related open codes	Articles
Resource optimisation	- Reducing school operational costs- Improving human resource management - Minimising resource waste	Mehta et al. (2021), Cao and Jian (2024), Hutson et al. (2022), Zhang and Leong (2024), Ayoubi et al. (2023)
Security & data protection	- Enhancing school data security - Monitoring student safety	Mehta et al. (2021), Cao and Jian (2024), Hutson et al. (2022), Suryanarayana et al. (2024), Irfan (2023), Nouri (2024)
Monitoring & evaluation	- Improving staff performance assessments- Tracking teacher effectiveness - Developing AI-driven student evaluation systems	Mehta et al. (2021), Xie et al. (2024), Hutson et al. (2022), Suryanarayana et al. (2024), Zaugg (2024), Rosi (2024)
Facilitating teaching–learning processes	- Streamlining access to educational data - Simplifying the monitoring of teaching –learning processes- Analysing parental feedback	Lowa (2023), Hutson et al. (2022), Xie et al. (2024), Mehta et al. (2021), Cao and Jian (2024), Suryanarayana et al. (2024)
Enhancing student learning experience	- Promoting game-based learning- Fostering creativity in learning environments - Creating diverse learning in sustainable education	Mehta et al. (2021), Hutson et al. (2022), Cao and Jian (2024), Zhang and Leong (2024), Wu (2023), Jia and Tu (2024), Zafari et al. (2022)

Axial code	Related open codes	Articles
Transparency & reporting	- Increasing financial transparency in schools - Improving reporting processes - Delivering analysed reports to administrators	Lowa (2023), Cao and Jian (2024), Hutson et al. (2022), Mehta et al. (2021), Suryanarayana et al. (2024)
Predictive data analysis	- Forecasting student educational needs - Predicting learning behaviours - Leveraging AI for learning analytics	Suryanarayana et al. (2024), Mehta et al. (2021), Dwivedi et al. (2024), Zhang and Leong (2024)
Accelerating managerial processes	- Reducing delays in educational program implementation - Streamlining school hiring processes	Lowa (2023), Hutson et al. (2022), Suryanarayana et al. (2024), Zaugg (2024)
Improving educational planning	- Optimising class scheduling - Supporting budget planning	Mehta et al. (2021), Cao and Jian (2024), Xie et al. (2024), Suryanarayana et al. (2024)
Strengthening parent–school communication	- Increasing transparency in parent –school interactions - Analysing parental feedback	Mehta et al. (2021), Cao and Jian (2024), Pimentel (2024)
Supporting strategic decision-making	- Providing intelligent student feedback- Aiding administrators in strategic planning - Embedding sustainable education within the curriculum	Lowa (2023), Cao and Jian (2024), Suryanarayana et al. (2024), Dai (2024), Roberts (2024)

Table 10 Error metrics obtained after hyperparameter tuning of the ANN model

Error metric	Training	Validation
MAE [kW]	24.42	37.46
MSE [kW^2]	1079.3	2524.5
RMSE [kW]	32.81	50.16
MAPE [%]	8.27	12.57

* Training time [s]: 200.06
** Training prediction time [s]: 1.00

Table 10 To what extent are you familiar with gig economics, and how does AI in education prepare you for it through skills training (e.g., flexible digital tools) while aligning with upbringing values like diligence?

Group	Belarus	China	Uzbekistan
International Students	65	85	72
Local Students	60	80	68

Table 3 Hyperparameters of the ANN algorithm considered in the tuning process

Method	Name	Description	Tested values
Random search	*solver*	The solver to be used in the optimization of the weights	*sgd; adam*
	hidden_layer_sizes	Number of hidden layers and neurons in each layer	148 combinations
	activation	Activation function for the hidden layers	*logistic; tanh; ReLU; identity*
	learning_rate	Learning rate for weight update	*constant; invscaling; adaptive*
Grid search	*learning_rate_init*	The initial learning rate used	1; 0.1; 0.01; 0.001; 0.0001; 0.00001; 0.000001
	alpha	Regularisation term	1; 0.1; 0.01; 0.001; 0.0001; 0.00001; 0.000001; 0.0000001

Table 8 Error metrics obtained after hyperparameter tuning of the MARS model

Error metric	Training	Validation
MAE [kW]	35.45	36.37
MSE [kW^2]	2343.9	2507.1
RMSE [kW]	48.35	50.05
MAPE [%]	12.06	12.35

* Training time [s]: 995.84
** Training prediction time [s]: 0.22

Table 4 Educators' perspectives on AI Integration

Theme	Belarus	China	Uzbekistan
AI Enhancing Traditional Values in Skills Training	"AI platforms can embed patriotic narratives in STEM simulations, building diligence alongside technical skills." (80% mention)	"Harmonious AI tools support respect for authority in personalized learning, balancing proficiency with moral growth." (85% mention)	"Hospitality values can be integrated into collaborative AI apps, fostering family-like team skills." (60% mention)
Conflicts with Cultural Preservation in Upbringing	"Western AI risks diluting community solidarity; we need local adaptations for ethical reasoning." (70% mention)	"AI must align with Confucian ethics to prevent erosion of harmony in upbringing." (65% mention)	"Gig-like flexibility in AI may clash with family responsibility; customization is key." (45% mention)
Recommendations for Harmonization	"Develop AI modules with national history for balanced training and values." (90% mention)	"Incorporate group-based AI ethics training to reinforce cultural preservation." (80% mention)	"Use AI for communal projects that uphold hospitality in personal development." (85% mention)

Source Developed by the authors using the results of educators' interviews

Table 12 Error metrics obtained after hyperparameter tuning of the *LinearSVR* model

Error metric	Training	Validation
MAE [kW]	40.23	40.50
MSE [kW^2]	3248.0	3278.0
RMSE [kW]	56.99	57.23
MAPE [%]	13.41	13.50

* Training time [s]: 2859.22
** Training prediction time [s]: 0.11

Table 12 In what ways can AI in higher education address conflicts between gig/NEET paradigms and traditional upbringing values to foster innovative, value-aligned training?

Group	Belarus	China	Uzbekistan
International Students	70% emphasize AI's role in mitigating gig/NEET conflicts via flexible skills aligned with patriotism	80% highlight diligence-integrated AI for value-aligned career paths reducing disengagement	73% note hospitality in AI training fostering communal innovation against NEET
Local Students	65% focus on resolving stability conflicts through AI-upheld diligence and collective values	82% stress harmonious AI solutions balancing gig viability with ethical upbringing	72% advocate for family-oriented AI to counter NEET via culturally sensitive training

Table 1 Application of AI technologies in different sectors of the economy

S/N	Sector	Technology	Application examples	Reference
1	Medicine	Machine learning; deep learning; natural language processing; robotics	Unsupervised protein-protein interaction algorithm, leading to therapeutic discoveries; decision-making using electronic records; softbots used as psychotherapeutic avatars; carebots that deliver care to elders or those with limited mobility	(Hamet and Tremblay 2017)
2	Education	Machine learning; deep learning; computer vision	Assessment of students and schools using analytics; grading and evaluation of papers and exams; personalized intelligent teaching; online and mobile remote education using virtual assistants	(Chen et al. 2020)
3	Manufacturing	Machine learning; deep learning; computer vision; robotics	Generating designs using detailed briefs from engineers and designers; digital twins for remote work with equipment; production fault detection and quality control; predictive maintenance for machinery	(Buchmeister et al. 2019)
4	Finance	Machine learning; deep learning; natural language processing	Credit risk modeling and analysis; financial fraud detection; forecasting for high-frequency trading; financial literacy advisory services	(Goodell et al. 2021)
5	Agriculture	Machine learning; deep learning; computer vision	Detection and classification of diseases on plants; precise soil management; crop yield prediction and management	(Sharma 2021)
6	Transportation	Machine learning; deep learning	Detection of road anomalies; accident detection and prevention; traffic flow detection and control smart parking management; autonomous driving vehicles	(Gangwani and Gangwani 2021)

S/N	Sector	Technology	Application examples	Reference
7	Business	Machine learning; natural language processing; automation	Automated budgeting and planning; predictions and management of sales; email processing automation and management; chatbots as customer service representatives	(Enholm et al. 2022; Madanaguli et al. 2024)
8	Environmental management	Machine learning; deep learning	Wastewater treatment processes; water quality assessment; identification of flood susceptible areas; pollutant concentration forecast in the atmosphere; solid waste forecasts and management	(Ye et al. 2020)
9	Art and creative industries	Machine learning; deep learning; generative AI; computer vision	Generative art creation; sustainable supply chain optimization; eco-design and material recycling in artistic production; training for circular practices	(Núñez-Cacho et al. 2024)
10	Energy management	Machine learning; deep learning; generative AI; computer vision	Predictive demand forecasting; load balancing via smart meters; energy audits for waste-to-energy recovery; modular infrastructure for renewable integration	(Novikau and Musallam 2025)

Table 1 Some synergies between AI and sustainable development

Parameter	Characteristics
Individualised learning to foster sustainability competencies	AI personalises educational material according to students' learning needs, interests and pace, creating unique learning journeys and real-time feedback to deepen environmental critical knowledge. Recent empirical research demonstrates a strong connection between the use of generative AI tools and the development of perceived sustainable competency among students, mediated by knowledge-sharing practices
AI aid in curriculum development and policy analysis	AI helps the developers of curriculum and educators analyse large datasets from different sources for trends, gaps, and emerging topics in sustainability. Programmes such as SDGPolicyGPT leverage LLMs for examining policy documents which allow governments to monitor adherence to SDGs, spot issues in their planning (blind spots), and inform policymaking on evidence-based grounds
Student-led AI of social good projects	Hands-on AI lessons can be taught through experiential learning programmes, where students are asked how to deploy the chatbots to solve current or future pressing sustainability challenges in their locality, and where technical education directly connects with the UN SDGs. Similar course redesigns embed AI across software development phases along with sustainability principles based on the SDGs, so students can contrast traditional approaches to the application with AI-inspired ones
Advanced data analysis for sustainability studies	AI solutions aid students and researchers to retrieve and examine huge datasets pertinent to sustainability, so that research projects and solutions associated with SDGs can be pursued. AI finds active use across eight relevant research clusters (health care, water management, clean energy, vegetation, etc), where deep learning and neural networks may tune systems and extract insights based on satellite images
Gamified learning and engagement	AI is harnessed in designing education games or gamified learning experiences that simulate actual sustainability problems to enable students to play and learn about solutions and navigate the complexity associated with environmental problems to gain a sense of fun
Scalable and accessible scalable	Sustainability education with AI-driven platforms may provide open, scalable MOOCs and online tools that engage global audiences beyond the four walls and address global inequalities with sustainability education beyond them and help underrepresented students with limited technical skills

Table 6 Error metrics obtained after hyperparameter tuning of the RF model

Error metric	Training	Validation
MAE [kW]	25.58	33.54
MSE [kW^2]	1179.4	1982.9
RMSE [kW]	34.31	44.46
MAPE [%]	8.68	11.37

* Training time [s]: 212.29
** Training prediction time [s]: 6.07

Table 1 Open coding extracted from articles

Open code	Related articles
Improving teacher productivity **Increasing interaction between managers and teachers**	Lowa (2023), Cao and Jian (2024), Suryanarayana et al. (2024), Zaugg (2024)
Predictive analysis of student performance **Automated curriculum planning management** **Reduction of time spent on administrative tasks**	Mehta et al. (2021), Mehta et al. (2021), Hutson et al. (2022), Suryanarayana et al. (2024)
Providing intelligent feedback to students **Strengthening data-driven decision-making**	Mehta et al. (2021), Lowa (2023), Cao and Jian (2024), Dwivedi et al (2024)
Transparency in school financial management **Enhancing the quality of staff performance evaluation**	Lowa (2023), Cao and Jian (2024), Hutson et al. (2022), Suryanarayana et al. (2024)
Supporting personalised learning **Increasing speed and accuracy in information processing** **Developing intelligent systems for student assessment**	Mehta et al. (2021), Hutson et al. (2022), Dwivedi (2024), Zhang and Leong (2024), Suryanarayana et al. (2024)
Facilitating supervision of the teaching–learning process	Lowa (2023), Hutson et al. (2022)
Strengthening school information security	Mehta et al. (2021), Cao and Jian (2024), Hutson et al. (2022), Suryanarayana et al. (2024)
Increasing meaningfulness in the decision-making process **Reducing human errors in school management** **Improving internal communication**	Mehta et al. (2021), Lowa (2023), Cao and Jian (2024), Suryanarayana et al. (2024)
Developing intelligent educational tools	Mehta et al. (2021), Lowa (2023), Cao and Jian (2024)

Open code	Related articles
Reducing school operational costs **Reducing managerial workload** **Better management of human and sustainable resources** **Using AI for learning data analysis** **Using robots in education**	Mehta et al. (2021), Cao and Jian (2024), Hutson et al. (2022), Zhang and Leong (2024), Suryanarayana et al. (2024)
Increasing transparency in parent-school communication	Cao and Jian (2024), Hutson et al. (2022)
Personalising curricula **Predicting students' educational needs** **Predicting student learning behaviours**	Mehta et al. (2021), Lowa (2023), Cao and Jian (2024), Suryanarayana et al. (2024)
Monitoring teacher performance	Mehta et al. (2021), Hutson et al. (2022), Zaugg (2024)
Facilitating game-based learning	Mehta et al. (2021), Hutson et al. (2022)
Enhancing creativity in the learning environment	Cao and Jian (2024), Hutson et al. (2022), Suryanarayana et al. (2024)
Facilitating access to educational data	Zhang and Leong (2024), Suryanarayana et al. (2024)
Identifying students needing additional support	Lowa (2023), Cao and Jian (2024), Dwivedi et al (2024), Zhang and Leong (2024)
Assisting in educational budget planning	Mehta et al. (2021), Cao and Jian (2024), Zhang and Leong (2024)
Accelerating the hiring process in schools	Lowa (2023), Hutson et al. (2022), Zaugg (2024), Rosi (2024)
Providing learning suggestions to students **Reducing internal conflicts** **Monitoring student safety**	Mehta et al. (2021), Hutson et al. (2022), Zhang and Leong (2024)
Increasing flexibility in school management	Lowa (2023), Cao and Jian (2024), Suryanarayana et al. (2024)
Identifying group learning opportunities	Zhang and Leong (2024)

Open code	Related articles
Optimising class scheduling **Reducing delays in implementing educational programs** **Using AI algorithms in decision-making**	Mehta et al. (2021), Mehta et al. (2021), Cao and Jian (2024), Suryanarayana et al. (2024)
Improving access to sustainable educational resources	Lowa (2023), Hutson et al. (2022), Zhang and Leong (2024)
Creating a diverse learning environment	Lowa (2023), Cao and Jian (2024), Suryanarayana et al. (2024)
Analysing parent feedback	Mehta et al. (2021), Cao and Jian (2024)
Improving the reporting process in schools	Mehta et al. (2021), Lowa (2023), Hutson et al. (2022), Dwivedi et al (2024)
Reducing resource consumption in schools, promoting sustainability	Zhang and Leong (2024), Suryanarayana et al. (2024)
Providing analysed reports to managers	Mehta et al. (2021), Mehta et al. (2021), Hutson et al. (2022)
Supporting strategic decision-making for managers **Identifying high-performing teachers**	Mehta et al. (2021), Lowa (2023), Cao and Jian (2024)
Optimising the student performance evaluation process	Dwivedi et al. (2024), Suryanarayana et al. (2024)

Table 14 In what specific ways could AI in higher education bridge gaps between traditional values and modern gig/NEET paradigms to promote value-aligned personal and career development?

Group	Belarus	China	Uzbekistan
International Students	70% emphasize AI bridging via gig skills aligned with patriotism for career development	80% highlight harmonious AI resolutions balancing NEET prevention with ethical upbringing	74% note family-oriented AI fostering communal gig viability without disengagement
Local Students	68% focus on AI reinforcing stability against gig/NEET clashes through diligent training	82% stress value-aligned AI for harmonious career paths mitigating ideological shifts	76% advocate for hospitality-integrated AI to bridge communal norms and modern paradigms

Table 1 Two main categories when discussing AI in sustainability education

Benefits	**Limitations**
Help in research and teaching	Bias
Help in programming	Hallucination
Explanation	Inconsistencies
Real-life cases and examples	Costs
Generating ideas/brainstorming	Making students lazy
Translation, correction	Dependence
Writing, copy-editing	Unreliability

Source Authors

Table 9 Educators' perspectives on AI and SDGs

Theme	Belarus	China	Uzbekistan
AI's Alignment with SDG-Relevant Skills	"AI in management enhances SDG 9 innovation with diligent training." (85% mention)	"Harmonious AI supports SDG 17 partnerships in technical fields." (80% mention)	"Communal AI aids SDG 4 inclusivity in economics disciplines." (80% mention)
Upbringing Integration for SDG Equity	"Embed patriotism in AI for SDG 10 reduced inequalities." (70% mention)	"Ethical AI fosters moral development aligned with SDG 4." (80% mention)	"Hospitality values in AI promote SDG 10 fairness." (75% mention)
Gaps and Recommendations	"Customize AI to avoid Western biases in SDG curricula." (75% mention)	"Integrate Confucian ethics for better SDG synergy." (65% mention)	"Tailor for Central Asian norms to enhance SDG relevance." (70% mention)

Source Developed by the authors using the results of educators' interviews

Table 2 Responses (keywords and category names) of participants in the 10th *Kankyo* Café and responses of AI. N, Nature; S, Society; L, Life. INC-5, fifth session of the intergovernmental negotiating committee under the United Nations environment programme

keyword	Type name
INC-5	NSL
Citizens' coalition	N.S.
Development of new plastics technology	SL
Words to inform the younger generation	S
Effective ways to communicate information about regulations	S
(AI) Behavioral change	NSL
(AI) sustainability	NSL
(AI) next generation	NSL

Table 2 How selected policy frameworks advance dual literacy goals in sustainability (ecological literacy) and digital technology (algorithmic literacy)

Policy document	**Support for ecological/sustainability literacy**	**Support for algorithmic/digital literacy**
India NEP 2020 **(National Education Policy 2020)**	Emphasises environmental awareness and sustainable development across the curriculum. Introduces *Environmental Education* as a subject and promotes the values of conservation and global citizenship. Calls for project-based learning on climate change, waste management, etc., aligning education with the SDGs	Prioritises twenty-first-century digital skills. Introduces contemporary subjects like *Artificial Intelligence* and *Design Thinking* in schools. Stresses mathematical and computational thinking from early grades, with coding introduced by middle school. Aims for a "technology-enabled" education ecosystem, bridging the digital divide while instilling digital literacy
UNESCO 2021 **("Reimagining Our Futures Together" Report)**	Frames sustainability as a core transformative pillar of education. Advocates "learning to live in harmony with the planet," calling for curricula that foster ecological literacy, climate action, and "green skills" for a carbon–neutral future. Urges education systems worldwide to re-balance human–nature relationships and integrate Education for Sustainable Development (ESD) at all levels	Highlights the significance of pupils having proficiency in AI and digital technologies. One way to steer the digital shift towards a more human-centred approach is to teach students to think critically about digital technologies. It is crucial for educators to emphasise the importance of pupils developing digital competence and understanding the political and ethical consequences of technology. The author argues that we should not rush into adopting technology but should instead work towards a more inclusive and fair usage of Artificial Intelligence

Policy document	Support for ecological/sustainability literacy	Support for algorithmic/digital literacy
***OECD* 2019 (OECD Learning Compass 2030 and related frameworks)**	Aligns future education goals with sustainability competencies. OECD's 2030 framework calls for knowledge of environmental science and climate change, and "attitudes and values" like empathy for the environment. Promotes "green" skills and systems thinking as essential for students to thrive in a climate-challenged world	Also highlights the need of having AI abilities and being literate in digital media for success in the modern age. Recognises digital cognition, data literacy, and fluency with information and communication technologies as essential abilities alongside critical thinking and creativity. The Organisation for Economic Cooperation and Development (OECD) recommends that member nations train their youth to tackle the "twin transitions" of decarbonisation and digitisation head-on. To make sure no one falls behind in the digital revolution, policies state that educational innovation should use AI
***EU Digital Education Action Plan 2020* (European Commission, for 2021–27)**	(Primarily a digital policy but supports sustainability indirectly.) Stipulates that digital education should be inclusive and help close skill gaps, which aligns with broader sustainability (equity) goals. The EU's parallel Green Deal and education initiatives (notably the separate GreenComp framework in 2022) complement the Action Plan by encouraging environmental sustainability content in curricula. For example, schools are encouraged to use digital tools to teach climate science and connect students internationally on sustainability projects	Strong focus on digital literacy: aims to ensure all learners and teachers gain digital competencies. Invests in infrastructure and training so that by 2030, 80% of youth and adults have basic digital skills. Promotes understanding of AI in education, including developing AI curricula and ethical guidelines. One Action Plan goal is to "*raise awareness on the opportunities and challenges of AI*" via education. Emphasises tackling the digital divide as a matter of social justice, so that algorithmic literacy isn't limited to the privileged

Table 1 Chatbot availability in Italy. *Source* ChatGPT (July 31st, 2025. Prompt: "ChatGPT, when did you become available in Italy? And what about the other chatbots?")

Chatbot/AI	Availability in Italy	Key notes
ChatGPT	Yes, since April 2023	Restored after regulatory approval
Google Bard → Gemini	Yes, since July 2023	Now rebranded as Gemini, integrated with Google services
Bing AI/Copilot	Limited access	Available to European users via invite or waitlist
Claude, Grok, others	Available online	International versions, no regional restrictions
Replika	No (banned and fined)	Removed due to privacy concerns
Velvet AI	Yes, since January 2025	Italian open-source project
Minerva, Vitruvian-1	Emerging phase	Promising local models
Fauno	Italian open-source	Academic model designed specifically for the Italian language

Table 2 Descriptive statistics of the pollutants and AQI

Descriptive statistics						
	Temp	**RH**	**WD**	**WS**	**PM_{10}**	**AQI**
Valid	7456	7456	7456	7456	7456	7456
Missing	0	0	0	0	0	0
Mean	27.919	51.728	204.007	1.516	99.962	74.098
Std. deviation	7.800	22.566	118.722	1.081	87.381	60.052
Minimum	0.000	0.000	0.000	0.000	10.640	10.000
Maximum	45.930	98.000	360.000	6.880	599.480	495.000

Table 13 Table comparing the forecasting performance of four machine learning models (RF, MARS, ANN, and LSVR) across different academic day types: class days, Saturdays, Sundays and holidays, exam periods, Christmas holidays, Easter holidays, summer vacation, and other interruptions. Performance is evaluated using MAE, MSE, RMSE, and MAPE. The table also identifies the best-performing result and model for each period and metric

Model	Error Metric	Day Type								
		1	2	3	4	5	6	7	8	1-8
		Class Days	Saturdays	Sundays and Holidays	Exam Periods	Christmas Holidays	Easter Holidays	Summer Vacation	Other Interruptions	All Periods
Total days		140	52	65	59	8	4	34	4	366
RF	MAE [kW]	31.13	27.53	27.32	31.66	39.53	41.93	33.60	24.11	30.48
	MSE [kW²]	1646.2	1280.9	1253.5	1875.9	3195.0	2355.3	1734.4	908.4	1603.3
	RMSE [kW]	40.57	35.79	35.40	43.31	56.52	48.53	41.65	30.14	40.04
	MAPE [%]	8.92	12.58	14.18	8.92	18.23	17.19	13.02	9.08	11.05
MARS	MAE [kW]	32.97	28.71	35.61	31.50	70.15	55.62	32.29	42.56	33.70
	MSE [kW²]	1843.2	1411.8	2719.1	1854.4	9132.8	4008.6	1716.7	2575.9	2118.6
	RMSE [kW]	42.93	37.57	52.14	43.06	95.57	63.31	41.43	50.75	46.03
	MAPE [%]	9.57	12.54	18.70	8.85	31.20	22.36	12.10	15.73	12.41
ANN	MAE [kW]	32.04	27.21	26.62	29.93	47.48	40.79	34.04	28.97	30.64
	MSE [kW²]	1717.5	1218.5	1142.9	1628.1	4997.1	2228.4	1769.7	1386.8	1608.8
	RMSE [kW]	41.44	34.91	33.81	40.35	70.69	47.21	42.07	37.24	40.11
	MAPE [%]	9.23	12.45	13.89	8.81	21.63	16.36	13.26	10.79	11.19
LSVR	MAE [kW]	37.42	28.04	42.77	37.73	70.50	60.91	35.45	24.69	37.75
	MSE [kW²]	2571.7	1323.7	5042.0	2616.2	9594.5	5309.6	2098.0	913.8	2961.6
	RMSE [kW]	50.71	36.38	71.01	51.15	97.95	72.87	45.80	30.23	54.42
	MAPE [%]	10.43	12.68	21.90	10.46	31.44	23.58	13.19	9.14	13.64
Best Result	MAE [kW]	31.13	27.21	26.62	29.93	39.53	40.79	32.29	24.11	30.48
	MSE [kW²]	1646.16	1218.47	1142.94	1628.13	3195.01	2228.45	1716.68	908.37	1603.30
	RMSE [kW]	40.57	34.91	33.81	40.35	56.52	47.21	41.43	30.14	40.04
	MAPE [%]	8.92	12.45	13.89	8.81	18.23	16.36	12.10	9.08	11.05
Best Model	MAE [kW]	RF	ANN	ANN	ANN	RF	ANN	MARS	RF	RF
	MSE [kW²]	RF	ANN	ANN	ANN	RF	ANN	MARS	RF	RF
	RMSE [kW]	RF	ANN	ANN	ANN	RF	ANN	MARS	RF	RF
	MAPE [%]	RF	ANN	ANN	ANN	RF	ANN	MARS	RF	RF

Table 4 Hyperparameters of the SVM algorithm considered during the tuning process

Name	Description	Tested values
C	Epsilon parameter in the epsilon-insensitive loss function (errors smaller than epsilon are ignored)	1; 5; 30; 50; 100; 150; 200; 250; 300; 350; 400; 450; 500; 1000… 15,000
Epsilon	Regularisation parameter	10^x, for x = [−3; − 2.5; − 2; − 1.5; − 1.0; − 0.5]

Table 3 Selective coding of AI applications in school management

Selective concept	Related axial codes
Enhancing Managerial Efficiency in Schools	- Improving management efficiency -Accelerating managerial processes - Enhancing educational planning for sustainable education
Intelligent and Strategic Decision-Making	- Strengthening sustainable decision-making -Supporting strategic decision-making - Predictive data analysis
Facilitating Educational Processes	- Streamlining teaching–learning processes -Elevating student learning experiences - Personalising learning on sustainability
Resource Optimisation and Security	- Optimising sustainable resources - Ensuring security and data protection
Transparency and Enhanced Communication	-Promoting transparency and reporting - Strengthening parent-school communication
Comprehensive Monitoring and Evaluation	-Systematic monitoring and evaluation -Developing intelligent tools for student and teacher performance tracking

Table 7 Selected hyperparameter values for the MARS model

max_terms	max_degree	penalty
40	7	2.5

Table 2 Knowledge domains of survey and interviews

Domain	Focus	Description
Views on Traditional Values in AI-Integrated Cultures	Integration of traditional values with AI functions	This domain explores students' perceptions of traditional values (family, respect for authority, diligence) within local cultures and how they can be harmonized with AI's roles in education, such as enhancing skills training through adaptive tools while supporting upbringing elements like ethical reasoning and cultural preservation
Cultural Attitudes Towards AI in Education	Impact of traditional values on AI-influenced learning styles and decisions	This focuses on how cultural frameworks shape attitudes toward AI's dual functions – promoting technical proficiency in skills training and fostering upbringing through moral development and intercultural awareness – while examining traditional values' influence on educational choices and engagement
Participation in AI-Facilitated Intercultural Dialogue and Collaboration	AI's Role in Cross-cultural educational interactions	Evaluates involvement in intercultural initiatives supported by AI: collaborative platforms that bring together a diverse array of peers, highlighting how AI links skills development (team-oriented innovation) with upbringing (promoting harmony and mutual respect) in international higher education contexts
Significance of SDGs in AI-Enhanced Academic Disciplines	Alignment of AI functions with SDG-relevant fields	Analyzes the importance of SDGs concerning academic fields. Also emphasizing how AI integrates skills development (SDG 8) with upbringing values like equity and sustainability (SDG 4 and 10) within cross-cultural educational settings
Perceptions of Gig Economies and NEET Awareness in AI Contexts	AI'S influence on modern work paradigms and youth disengagement	Investigates awareness of gig economy trends and NEET perspectives. The idea is to connect them to the educational functions of AI by exploring how AI prepares students for flexible career trajectories (skills development aspect) while addressing potential conflicts with upbringing values such as diligence. It may help mitigate NEET risks through innovative, value-driven training
Perceived Conflicts Between Traditional Values and NEET/Gig Concepts	Tensions in AI-supported upbringing amid ideological shifts	Assesses the conflicts between traditional values (like hard work and community solidarity) and NEET/gig economy ideologies, evaluating how AI in education can bridge these gaps by aligning skills training for gig economy sustainability with upbringing to reinforce cultural norms and prevent disengagement in non-Western contexts

Source Developed by the authors

Table 2 Hyperparameters of the MARS algorithm considered in the tuning process

Name	Description	Tested values
max_terms	The maximum number of terms generated by the forward pass	10; 25; 27.5; 30; 32.5; 35; 37.5; 40; 42.5; 45; 47.5; 50; 75; 100; 150; 200; 250; 300; 350; 400; 450; 500; 750; 1000
max_degree	The maximum degree of terms generated by the forward pass	1;2;3;4;5;6;7;8
penalty	A smoothing parameter used during the pruning pass and for determining whether to add a hinge or linear basis function during the forward pass	2;2.5;3;3.5;4

Table 4 Performance of ML models with enhanced features

Model	**RMSE**	**R^2 score**
LR	9.02	0.98
RF	10.36	0.97
XGBoost	7.51	0.98
SVR	25.80	0.81

Table 6 Cultural reflections on AI in education

Theme	Belarus	China	Uzbekistan
Positive Impact on Skills Training	"AI boosts diligence in learning styles, aiding post-Soviet resilience in technical fields." (85% mention)	"Respect for authority shapes AI preferences for structured, proficient training." (90% mention)	"Communal values guide engagement with AI for inclusive skill decisions." (65% mention)
Challenges to Upbringing Elements	"Cultural frameworks demand AI adaptations to maintain collective moral awareness." (70% mention)	"Harmony requires AI to foster ethical decisions, not just efficiency." (60% mention)	"Hospitality influences attitudes; AI must avoid isolating intercultural growth." (65% mention)
Influence on Educational Choices	"Traditional values drive selective AI use for balanced proficiency and ethics." (75% mention)	"Authority respect leads to AI choices emphasizing moral over pure technical gains." (70% mention)	"Family-oriented attitudes prioritize AI that supports communal engagement." (65% mention)

Source Developed by the authors using the results of educators' interviews

Table 1 Sample presentation evaluation rubric

Criterion	Excellent	Good	Needs improvement	Insufficient
Problem Definition	Problem clear, data strong, context well explained	Problem understandable, data sufficient	Problem partially clear	Problem unclear
Data Analysis	Data accurate, graphs effective, interpretation scientific	Data understandable	Data limited	Data incorrect/incomplete
Use of AI	AI outputs accurate, creative and applicable	Recommendations obtained from AI	AI used limitedly	AI not used at all
Sustainability Approach	Ecological-social-economic integration strong	Largely applicable	Partial sustainability	Not sustainable
Community Participation	Various stakeholders included, realistic plan	Stakeholders identified	Participation weak	No participation
Presentation Skill	Clear, fluent, good time management	Understandable	Disorganised	Insufficient
Use of Visual Material	Effective, readable and aesthetic	Sufficient	Limited	Incorrect/inappropriate

Table 15 Educators' reflections on AI as a mediator between gig/NEET paradigms and cultural values

Theme	Belarus	China	Uzbekistan
Identified Conflicts with Traditional Values	"Gig/NEET undermines patriotism; AI must reinforce diligence." (90% mention)	"Conflicts with harmony; AI can resolve through ethical shifts." (85% mention)	"Clashes with solidarity; AI bridges via communal norms." (80% mention)
AI's Role in Resolution	"AI training balances skills with cultural stability." (75% mention)	"Harmonious AI mitigates ideological tensions in upbringing." (80% mention)	"Value-aligned AI prevents disengagement in gig paradigms." (80% mention)
Ideological Shifts and Recommendations	"Adapt AI to post-Soviet values for positive development." (70% mention)	"Embed Confucian principles in AI for balanced paradigms." (75% mention)	"Customize for Central Asian hospitality to foster alignment." (70% mention)

Source Developed by the authors using the results of educators' interviews

Table 3 The results of answers on the questions "In what ways can AI in higher education harmonize traditional values such as patriotism/national pride and hospitality with modern skills training and personal growth?"

Group	Belarus	China	Uzbekistan
International Students	70% emphasize AI's potential to promote patriotism via national history modules in skills training, balancing with personal growth	82% highlight harmony through AI-facilitated group projects that preserve respect while fostering innovation	76% see hospitality integrated via collaborative AI tools for intercultural exchanges, supporting cultural preservation
Local Students	78% focus on reinforcing national pride through AI-customized curricula that embed diligence in ethical upbringing	88% stress Confucian values in AI systems for authority-respecting personalized learning paths	82% advocate for family/hospitality in AI platforms that enhance community-based skills and moral development

Source Developed by the authors using the results of query

Table 11 Selected hyperparameter values for the *LinearSVR* model

C	Epsilon
450	0.031623

Table 9 Selected hyperparameter values defined for the ANN model

solver	hidden_layer_sizes	activation	learning_rate	learning_rate_init	alpha
adam	(200, 200, 50)	logistic	adaptive	0.01	0.01

Table 1 How the research questions link to the theory, policy and practice mapping table

Research question	Implications for theory	Implications for policy	Implications for practice
RQ1. How can AI-driven adaptive learning and predictive models enhance student engagement, comprehension, and decision-making in sustainability education?	Extends learning theories by integrating adaptive, data-driven personalization into education for sustainable development (ESD)	Encourages policies promoting AI-supported personalized curricula to align with SDG 4 (quality education)	Guides educators in implementing AI-driven platforms to improve student engagement, equity, and retention
RQ2. What is the potential of AI-enhanced immersive technologies (AR/VR) in fostering a deeper understanding of complex sustainability challenges?	Contributes to experiential and constructivist learning theories by embedding immersive, real-world simulations	Informs policies supporting investment in immersive infrastructure and interdisciplinary sustainability programs	Provides practical tools (AR/VR + AI) for educators to design engaging, scenario-based sustainability learning
RQ3. What ethical, equity, and governance issues must be addressed to ensure the responsible integration of AI and blockchain in sustainability education and research?	Advances theoretical frameworks on AI ethics, fairness, accountability, transparency, and sustainability paradoxes	Urges policymakers to adopt FATE principles, data privacy laws, and green AI standards in education and research	Supports institutions and teachers in applying explainable AI (XAI), co-creation, and inclusive strategies in classrooms and research labs

Table 1 Relationship between AI applications in higher education and SDG 4 targets

Application area in higher education	Purpose and use in educational practice	Related SDG 4 targets
Intelligent tutoring and adaptive learning systems	Support students by adjusting learning content and pace according to individual needs and academic progress	SDG 4.1 (Improved learning outcomes), SDG 4.3 (Equitable access to tertiary education)
Learning analytics and early-warning systems	Use student data to identify learning difficulties, risk of dropout, and the need for academic support	SDG 4.4 (Relevant skills development), SDG 4.5 (Reduction of educational inequalities)
Automated assessment and feedback tools	Provide timely and consistent feedback while reducing instructional workload	SDG 4.1 (Quality education), SDG 4.c (Effective teaching capacity)
Virtual academic support and advising systems	Assist students with academic guidance, course information, and access to learning resources	SDG 4.3 (Access to higher education), SDG 4. a (Inclusive learning environments)
Accessibility and assistive learning technologies	Enable participation of students with disabilities through speech recognition, translation, and adaptive interfaces	SDG 4.5 (Equity and inclusion), SDG 4. 4. 4.4.a (Inclusive education facilities)
Data-driven institutional decision systems	Support planning, resource allocation, and student retention strategies within institutions	SDG 4.b (Efficient education systems), SDG 4.c (Institutional capacity building)

Source Created by Authors

Table 11 How do NEET attitudes among peers influence your views on AI's role in mitigating youth disengagement, balancing career preparation (skills training) with cultural values (upbringing)?

Group	Belarus	China	Uzbekistan
International Students	68	82	75
Local Students	62	85	70

Table 1 A snippet of studies discussing EIAIISHETP

Author(s)	Title	Methodology	Findings	Inferences drawn in relationship with EIAIISHETP
Shwedeh et al. (2024)	AI adoption and educational sustainability in higher education in the UAE. In artificial intelligence in education: The power and dangers of ChatGPT in the classroom	5 point Likert scale survey through various assertions (proxies)	Data privacy, trust, security concerns	The uncontrolled and open nature of AI now opens the potential for unauthorised access to personal or institutional data stored in online database
Lawal (2025)	Artificial intelligence in higher education	Critical review	Rising case of data privacy issues	
Chivose (2023)	The adoption and usage patterns of ChatGPT among students and faculty members in higher education	Survey, interview, and focus group discussion	Privacy concerns	
Nwozor (2025)	Artificial intelligence (AI) and academic honesty-dishonesty nexus: Trends and preventive measures	Review of literature	Rising cases of academic dishonesty as a result of advanced use of AI	Induced AI products such as data leakages impact sustainable higher education. These products test the reliability and confidence imposed on reports and knowledge produced, integrally questioning academic integrity of knowledge produced in higher education
Mangundu (2025)	Navigating artificial intelligence governance: Insights from south African higher education IT decision-makers	Exploratory investigation	Lack of preparedness to use AI and acknowledgement	

Author(s)	Title	Methodology	Findings	Inferences drawn
Farangi et al. (2024)	Use of generative AI in research: Ethical considerations and emotional experiences	Narrative frames and follow-up interviews	Plagiarism	AI's relationship with EAP is complex, with opinions about its application to sustainable higher education as it continuously promotes dishonesty in academic writing and decreases reading culture among students and educators
Onifade and Alex-Nmecha (2023)	Tackling plagiarism challenges in the age of information overload by LIS professionals in Nigerian academic institutions	A phenomenological research design using semi-structured interview		
Kostopolus, (2025)	Student use of generative AI as a composing process supplement: Concerns for intellectual property and academic honesty	Examination of hypothetical scenarios		
Theodorio et al. (2024)	Demystifying Rwandan, Lesotho, and Nigerian educators' viewpoints on STAI in higher education	Semi-structured questionnaire		
Anis and Khalid (2024).	Perception of the effects of using ChatGPT, Grammarly, and Quillbot on writing skills	Questionnaire	Over reliance on AI	Overly dependent on open AI tools could knowingly or unknowingly lead to a reduction in sustainable, critical thinking and writing skills
Fitria (2021)	QuillBot as an online tool: Students' alternative in paraphrasing and rewriting English writing	Document analysis	Overly reliance gaslights ethical issues, including ethical quandaries and the validity of information sourced and used by AI	

Author(s)	Title	Methodology	Findings	Inferences drawn in relationship with EIAIISHETP
Chivose (2023)	The adoption and usage patterns of ChatGPT among students and faculty members in higher education	Surveys, interviews, and focus group discussions	Overreliance on AI and machine learning model	
Nishant et al. (2020)	Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda	Review of literature	Difficulties in critical intervention strategies Solving immediate solution while also introducing long term threats	
Okolo et al. (2022)	Making AI explainable in the global south: A systematic review	Systemic review of literature	Explainable AI systems need to be modelled and deployed to suit global south workplace context	For sustainable sub-Saharan higher education, Africanised AI-modelled teaching and learning solutions are needed to fill the perpetuated gap between discrimination that exists between AI modelled from global north and south
Nasila (2024)	African artificial intelligence: Discovering Africa's AI identity	A comprehensive book relaying viewpoints of established authors	The necessity for establishing Africanised identities in AI models was argued for reasoning and possible implementation	
Shwedeh et al. (2024)	AI adoption and educational sustainability in higher education in the UAE. In artificial intelligence in education: The power and dangers of ChatGPT in the classroom	5 point Likert scale survey through various assertions (proxies)	Compliance with policies and regulations	Unequal access to AI and noncompliance with laws and rules governing its use in education may encourage corruption and unethical behaviour, obstructing efforts to provide sustainable higher education

Author(s)	Title	Methodology	Findings	Inferences drawn in relationship with EIAIISHETP
Jin et al. (2025)	Generative AI in higher education: A global perspective of institutional adoption policies and guidelines	Case study	Gaps policy frameworks, and unequitable access to GAI tools	