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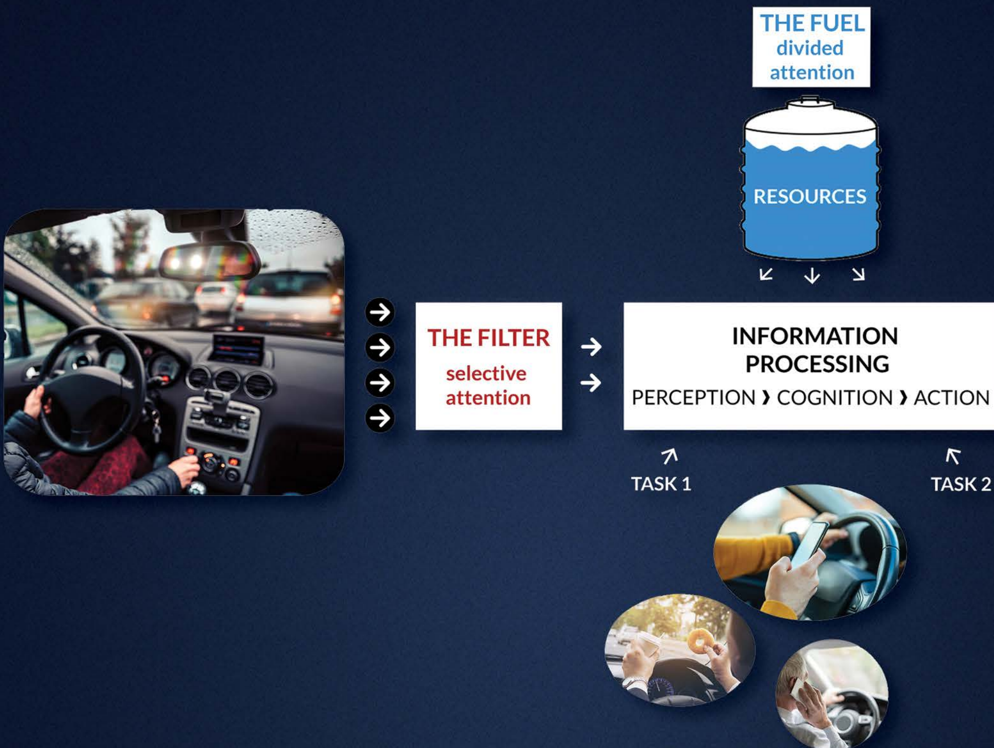

APPLIED ATTENTION THEORY

Christopher D. Wickens
Jason S. McCarley
Robert S. Gutzwiller

CRC Press
Taylor & Francis Group

Applied Attention Theory

Applied Attention Theory, Second Edition provides details concerning the relevance of all aspects of attention to the world beyond the laboratory. Topic application areas include the design of warning systems to capture attention; attention distractions in the workplace; failures of dividing attention while driving; and the measurement of mental workload while flying.

This new edition discusses the implications of virtual reality and augmented reality for human attention. It also covers the treatment of attention-based pedagogical methods used to enhance learning, and presents attentional issues in interacting with automation and AI. New chapters include applications of attention to healthcare, education pedagogy, highway safety, cybersecurity, and human interaction with autonomous vehicles and other AI systems.

The readership for this book is the professional, the researcher, and the student.

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Preface

We wrote this book in an effort to relink areas of study that arose at the same time and are of the same ancestry—the pioneering human performance research of Cherry, Fitts, Broadbent, and Mackworth—but that soon grew aloof from one another. One area was the basic study of attention, in which we saw sophisticated and exciting theories of how the senses gather and the brain processes multiple streams of information but reflected little concern for search, display processing mental workload, and multitasking in the complex world beyond the laboratory. Another area was the study of human behavior outside the laboratory, in which we found studies of complex displays, inattentive drivers, and overloaded pilots but too little consideration of the elegant theoretical work that might provide a basis for predicting the successes and failures of our real-world attentional endeavors. With this book, we have tried to reunite these two areas, identifying correspondences and complements, and we hope to stimulate other researchers to do the same.

The first edition was published in 2008, based primarily on research published prior to 2007. In the last 15 years, there has been a continued growth of attention research in both the theoretical and the applied domains, with important new developments that this second edition presents. In addition, certain domains, for example health care and highway safety, have embraced attention research as a venue for mitigating the unfortunate consequences of human error, and these too have gained added coverage.

One particularly important facet of this edition is that we have summarized attention applications to five specific disciplines—aviation, driving, education, health care, and cybersecurity—in a single chapter at the end of this book. A second addition to this edition is an entire chapter dedicated to the implications of attention theory to human interactions with an increasingly automated world.

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Christopher D. Wickens is an affiliate professor of psychology at Colorado State University. He received his BA in physical sciences from Harvard College in 1967 and his PhD in experimental psychology from University of Michigan in 1974. He served three years in the U.S. Navy. From 1984–2005, he was a professor of psychology at the University of Illinois. In 1984, he was also appointed in the Department of Industrial Engineering and at the Institute for Aviation, where he was head of the Aviation Research Laboratory and the Interdisciplinary Human Factors Division and also served as associate head of the Institute of Aviation.

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1 Introduction

The study of attention has importance that is at once historical, theoretical, and applied. From a historical perspective, more than a century ago, William James, the founder of American psychology, devoted a full chapter to the topic in his classic textbook, *The Principles of Psychology* (1950). Interest in attention as a field of psychological study waned during the behaviorist period in the first half of the century, when attention was (improperly) dismissed as a mediating mental variable that could not be directly measured and was therefore outside the bounds of scientific inquiry. Nevertheless, even during this time, a few classic studies such as Jersild's (1927) and Craik's (1947) work on attention switching were published. Following World War II, interest in attention blossomed, as will be discussed in the next chapter, and it remains a fundamental element of psychological research to this day.

The theoretical importance of attention can be seen at two different levels. First, as one of the three main limits on human information processing (along with memory and speed), attention is of interest in its own right: How many tasks can we do at once? How rapidly can we switch from task to task? How widely can we deploy attention across the visual field? Second, attention underlies many other psychological phenomena: it is necessary to hold information in working memory, and to efficiently move information to long-term memory. It is a vital component underlying decision-making and is integrally related to perception.

The applied importance of attention also manifests in several ways. Questions of memory, learning, and decision-making all scale up to real-world problems such as eye witness testimony, job training, consumer choice, and display design, and so the attentional components underlying these naturally scale up as well. But attentional challenges and issues also are directly relevant outside the laboratory: the dangers of distracted driving, the attentional overload of making sense of massive databases, the rapid attention switching required in the electronic workplace, the success or failure of unreliable alarms to capture attention, and the behavior of children with attention deficit disorder are all examples. Finally, in this age of expanding use of automation and artificial intelligence, there will be an enduring need for the human supervisor of automated systems to pay attention to what the algorithms are doing and not doing and to how well they are managing system performance.

1.1 VARIETIES OF ATTENTION

The word "attention" encompasses a broad array of phenomena. Another founder of American psychology, Titchener (Titchener, 1901, p. 108), noted in introducing his chapter on attention that, "The word 'attention' has been employed in the history of psychology to denote very different things" and then went on for a paragraph to list these different meanings. In this book we consider several varieties of attention (see also Parasuraman & Davies, 1984), which we can illustrate here within the context

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of highway driving. The driver will first want to maintain *focused attention* on the driving task in the face of many possible distractions, for example, competing tasks and nonrelevant events. Thus, focused attention can apply to a task or to a particular source of environmental information. Rarely, however, does the driver carry out only one task. Most often, she will have to choose between multiple options, for example, between lane-keeping and checking the GPS. Here, *selective attention* can be defined either at a gross level, as selecting to prioritize one task or another, or at a finer level, for example, scanning from one place to another. Intrinsic to the concept of selective attention is the notion of an attention switch, a transfer of focus from one task or channel to another.

In contrast to selective attention, *divided attention* entails the attempt to carry out two or more tasks (roughly) at once. This may be accomplished in two ways. In many cases, an operator divides attention over a coarse time scale, say, seconds or minutes, by switching focus between tasks or channels. This happens, for example, when a driver switches gaze between the road ahead, as needed to maintain lane position and scan for hazards, and to the roadside, as needed to look for signs. At other times there can be true parallel or concurrent processing, as when the driver steers while listening to a newscast on the radio or encodes the shape, color, and markings of a traffic sign simultaneously in a way that speeds recognition and compliance.

Finally, it is possible to speak of *sustained attention*, as mobilized in continuous mental activity. In some cases, this continuous activity may be of high complexity, for example, completing a 3-hour final exam. In other instances, it may be of low complexity, say, for example, maintaining an uneventful night watch. In either case, the effort to maintain vigilance over long periods of time will tax the human operator (Warm et al., 2008).

In addition to distinguishing these varieties of attention—focused, selective, divided, and sustained—we can conceptualize attention metaphorically in two different ways, as a mental filter or as mental fuel, both shown in Figure 1.1. The figure presents a conventional information processing model of human performance. The influence of selective attention on perception is represented by the front-end filter, selecting some stimuli or events to be processed and filtering others out as less relevant. Then, as information processing activities are carried out on the selected environmental information or on self-generated cognition, limits of the mental resources or fuel that supports such processing constrain the number of processes that can be carried out at once. This is true whether in the service of a single task (e.g., holding subsums while doing mental multiplication) or in the service of multitasking. Figure 1.1 presents a view of attention that is simplified but provides a heuristic foundation on which we will build throughout the chapters of the book

1.2 RELATION TO OTHER APPLIED DOMAINS

Attention links closely to at least four important domains of application, which we describe briefly here and will revisit later in the book.

First, in the study of *human error* (Hollnagel, 2007; Reason, 1990; Sharit, 2012), attentional errors such as *lapses* represent a major source of cognitive failure. Expanding on this notion, the emergent digital workplace, filled with a multitude of

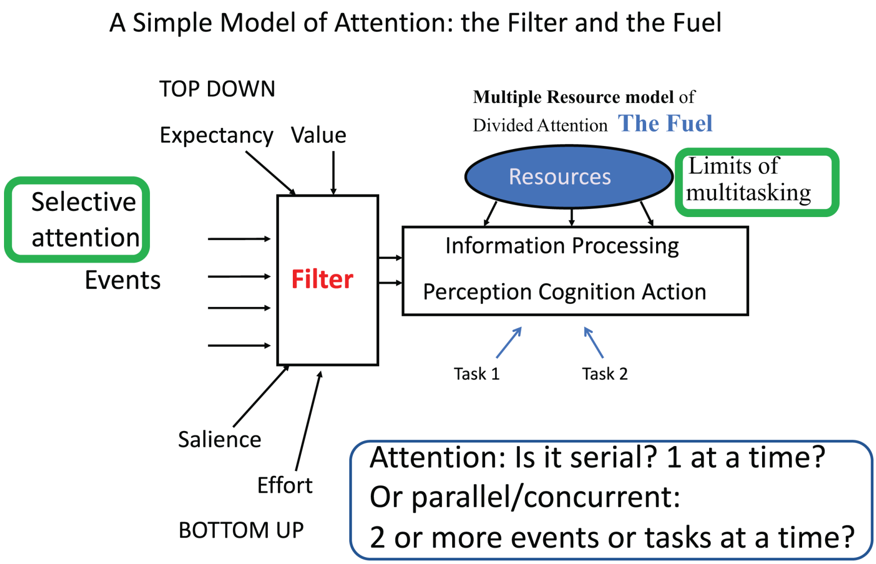

FIGURE 1.1 A simplified model of attention. The influences on the filter of selective attention are shown, as are the influences of limited resources on the information processing activities involved in divided attention and multitasking.

chat tools, social media services, websites, video conferences, and phone applications, is ripe to overwhelm and distract users, lowering their awareness of their work, each other, and the environment around them.

Second, lapses of attention are closely related to aspects of *situation awareness (SA)* (Durso & Sethumadhavan, 2008; Endsley, 1995, 2015, 2021; Tenney & Pew, 2006; Vidulich & Tsang, 2012), a concept that has gained great currency within the past three decades. SA can be characterized as "an internalized mental model of the current state of the operator's environment" (Endsley, 2021). It is conventional to break SA down into three ascending levels, (1) noticing events and information in the dynamic environment, (2) understanding the meaning of what you've noticed, and (3) predicting or projecting the implications for the future. Level 1, noticing, clearly depends on effective deployment of the attention filter. Levels 2 and particularly 3 are resource intensive, especially if the task is effortful or the operator is a novice. This can lead to error; an operator who fails to anticipate future events because of high concurrent task load will not succeed in dealing with those future events.

Third, the study of *mental workload* (Longo & Leva, 2019; Young et al., 2015) has been another popular area of applied interest within the past 40 years, as designers have endeavored to create systems that do not overtax operators' resources (Vidulich & Tsang, 2012), leaving mental fuel in the tank in order to handle unexpected emergencies. The study of mental workload calls for ways to measure the fuel expended and remaining and to reduce the demands imposed upon the operator in order to avoid the potential for overload (Grier et al., 2008). Measurement of workload has traditionally been a difficult problem, relying on subjective and objective measures, but it increasingly can be carried out in near real-time using physiological measures (e.g., Hughes et al., 2019).

Fourth, with the rapid development and deployment of artificial intelligence, computers, and automation, systems of vast complexity are being created, bringing with them complicated issues around human–automation interaction (Sawyer et al., 2021; Parasuraman & Wickens, 2008; Sheridan & Parasuraman, 2005). Two aspects of attention in human–automation interaction are also directly linked to situation awareness and workload, as described earlier.

1. A major impetus for introducing automation in the first place is the desire to reduce workload. At the individual human level, this may be to prevent operator overload, as when placing control of an aircraft on autopilot allows the pilot to concentrate on many other immediate responsibilities. At a level of “macroergonomics” and teaming, automation and workload are related by manpower concerns. If we automate the function of one member of a three-person crew, we have reduced personnel costs by 33%.
2. It is now well established that high levels of automation, designed to reduce workload, can also reduce operator awareness of the processes that are automated but over which the human may still have ultimate responsibility (Parasuraman & Riley, 1997). Such loss of situation awareness is often mediated directly by attention, as the human may cease paying much attention to the automated processes. This neglect can be catastrophic if the automation fails or if processes under control of the automation go wrong.

Attention also factors heavily into users needing to choose when and how closely to monitor increasingly automated systems, especially those that make decisions (Onnasch et al., 2014; Parasuraman & Manzey, 2010). Complacency and bias are both evident as people interact with automated components, and numerous “ironies of automation” (Bainbridge, 1983) continue to plague real-world implementation of the technology, and both the filter and fuel of attention are often involved (Strauch, 2018).

1.3 SCALING UP BASIC TO APPLIED RESEARCH

As we noted, the construct of attention spans the continuum from basic to applied issues. At one end of the continuum, we see elegant and well-controlled theoretical work, conducted with no specific application in mind and, because of high experimental control, often showing effect sizes that are statistically significant but no larger than a few tens of milliseconds in raw magnitude. At the other end, we see analyses of real-world accidents or incidents that are clearly related, in part, to attentional breakdowns (10%–50% of automobile accidents are related to distraction; Wiese & Lee, 2007). But because of the lack of control over the collection of such data, it is impossible to preclude other contributing causes or to draw strong causal inferences.

The challenge in engineering psychology, the domain that represents the spirit of this book, is to link the two endpoints. How do we identify which theory-based attentional phenomena scale up to account for real-world attentional failures and successes? How much variability do those controlled phenomena account for in the world outside the laboratory? Most critically, how well can they be manipulated by design and training interventions in the real world of human interaction with complex dynamic systems?

An issue that grows in importance as one moves from more basic to more applied research is the distinction alluded to between statistical significance, typically defined in terms of the *p*-level of a statistical test, and practical significance, defined by the size of an effect in raw units (Wilkinson & Task Force on Statistical Inference, 1999). A measure of statistical significance would tell us, for instance, whether we have reason to believe a 0.1-second reduction in braking time that occurred when drivers were tested with a new head-up display was anything more than statistical noise. An assessment of practical significance would tell us whether the effect, if it was real, was important enough to be relevant to vehicle design. Whereas basic research is typically most concerned with statistical significance, applied research must give equal concern to both types. After all, an intervention that only saves 1/100 of a second in drivers' braking response time (RT) will be of little practical benefit, even if it can be shown to produce a statistically significant effect at the conventional level of $p \leq .05$. On the other hand, a manipulation that offers a potential 1-second reduction in braking time may be of tremendous importance to applied researchers even if it has not quite reached the conventional ".05 level" cutoff for statistical significance (Wickens & McCarley, 2017). This is not to say that applied researchers can ignore statistical significance, only that they must temper their concern for it with an appreciation of practical significance.

Importantly, there are two phases to the process of scaling up findings from the laboratory to application. First is to demonstrate that laboratory-based phenomena in attention express themselves in real-world scenarios. Second, and equally important, is to devise attention-based solutions to enhance productivity and safety in these environments. In the following chapters, we try to show how this is done by integrating across the basic–applied continuum.

1.3.1 The Role of Models

An aspect of the efforts to transition from basic research to applications that has gained importance is the development of human performance and cognitive models (Byrne & Pew, 2009; Foyle & Hooey, 2008; Gray, 2007; Laughery et al., 2012; Palada et al., 2016; Salvucci & Taatgen, 2008; Steelman et al., 2011, 2017; Steelman et al., 2013; C. Wu & Liu, 2021). Such models can be of two general classes. Descriptive models, like the bottleneck model we will see in the next chapter, describe the mediating processing mechanisms of attention in a way that accounts for performance qualitatively. Computational models, elaborating on descriptive models, make quantitative predictions of actual performance measures such as attention switching time or probability of correct response. These are of great value because they may be able to predict safety measures like the one-second brake time savings discussed previously. Also analogous to the distinction between basic and applied attention research is a distinction between basic and applied computational models. Basic models tend to be more exacting, requiring a fairly high bar for validation. Applied models tend to be somewhat less precise but more encompassing of a wider range of conditions and environmental variables and have a fairly high bar for utility of real-world phenomena prediction.

The great value of applied computational models, once they are validated by human performance data, is that they can tell designers that a system is likely to be unsatisfactory to human operators before the system has been put into production or even “mocked up” for human testing. For example, a model might predict that drivers will need to bring their eyes off the roadway for at least 2 consecutive seconds to operate a particular piece of in-vehicle technology. Such a long visual neglect of potential roadway hazards might be considered unacceptable and force a redesign of the interface before it is introduced into the vehicle.

1.4 OUTLINE OF THE BOOK

The chapters of the book, in which we cover these varieties of attention from both a theoretical and applied perspective, are organized as follows:

Chapter 2

This chapter describes two of the most important historical concepts in attention and, as a consequence, provides some historical context, as well as defining two elements that underlie many of the concepts that follow.

Chapters 3, 4, 5, and 6

These four chapters consider auditory and tactile attention but focus on visual attention; visual processing has dominated attention research and theory over the past few decades, and has proven vitally important beyond the laboratory, where the visual world of displays and events is often of overwhelming complexity. Chapters 3 and 4 emphasize the attentional filter of Figure 1.1.

Chapters 7, 8, and 9

These three chapters address different issues of multiple task performance, moving beyond the visual perceptual world, and create the foundations of a general model of how tasks interfere or compete with each other when people must divide attention between them: interference caused by their difficulty and their similarity. These chapters thus address the attentional fuel of Figure 1.1. In addition, Chapter 7 also highlights the critical role of effort in single-task behavior, such as decision and choice, to the extent that humans tend to be effort conserving in their choice of activities. Chapter 9 examines how multiple tasks are managed in a discrete fashion.

Chapter 10

This chapter describes the role of attention and its application to the coming wave of high-tech influences on behavior including machine learning, artificial intelligence, robotic teammates, and automation.

Chapter 11

This chapter considers several real-world domains of practice in which attention research has been leveraged or is needed to improve safety, performance and awareness including in driving, aviation, health care, learning environments, and cybersecurity.

Within each chapter, we try to maintain a balance between theory and application, although occasionally, we may veer more one way than another. Our hope is that the book will continue to stimulate basic researchers to understand the importance of their work in the world beyond the laboratory and perhaps goad them into tackling some of the complex problems that exist there (research on driving and cell phone usage provides a terrific example of this endeavor). Equally, we hope that those involved in the applied human-factors area of design and measurement can appreciate the importance of attention and the value of good science underlying attentional phenomena in exercising their careers.

2 Single-Channel Theory and Automaticity

The concept of attention is often invoked colloquially to explain an inability to do more than "one thing at a time." This commonsense notion represents an intuitive description of the more formal psychological construct of *single-channel theory* (Broadbent, 1958; K. J. W. Craik, 1947; Welford, 1952, 1959, 1967, 1968), or single-channel behavior, an extremely constraining view of the capabilities of attention. Very simply, single-channel theory predicts that the time required to perform any two tasks together will be at least as great as the sum of the time required to carry out each in isolation.

At the other end of the spectrum of models is the possibility that attention can sometimes allow us to perform multiple tasks or process multiple channels of information simultaneously and without interference—that is, in *parallel* and with *unlimited capacity* (Townsend & Ashby, 1983; Townsend & Nozawa, 1995)—as if performance were automated, requiring little or no attention at all. While it is obvious that none of us can parallel process all possible task combinations, there are certain circumstances that do allow effective parallel processing, just as there are others that require nearly complete single-channel processing. The purpose of this chapter is to introduce the historical and theoretical foundations of each of these two diametrically opposed characterizations of attention support for human information processing, as their origins date to well before attention research became popular. Indeed, well over a century ago, William James (1950, p. 409) invoked the concepts of both single-channel theory and automaticity theory within one sentence: "If you ask how many ideas or things we can attend to at once, the answer is not very easily more than one, unless the processes are very habitual."

In considering these concepts, we will see how the extreme versions can be tempered to characterize real-world behavior that is neither completely serial nor completely parallel, and will invoke the construct of *mental effort* to span the range between these two endpoints. While both a fully serial and an unlimited-capacity parallel model can be rejected as general descriptions of human behavior and cognition, both are valuable (a) as anchors of a continuum against which other types of behaviors can be benchmarked and (b) as accurate characterizations of some forms of human behavior that system designers should either seek to avoid or attain. Our approach will focus on three historic paradigms of attention research: the *psychological refractory period (PRP)*, which was the foundation for single-channel theory; the *auditory shadowing* task, which helped pinpoint the single-channel bottleneck within the cognitive processing system and circumscribed single-channel theory's extreme rejection of human multitasking; and the paradigms underlying *automaticity theory.*

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2.1 SINGLE-CHANNEL THEORY AND THE PSYCHOLOGICAL REFRACTORY PERIOD

The historical roots of single-channel theory are planted within the paradigm of the PRP (Kantowitz, 1974; D. E. Meyer & Kieras, 1997a, 1997b; Pashler, 1994; Telford, 1931). In a PRP task, the subject is asked to make separate, speeded responses to a pair of stimulus events that are presented close together in time. As an example, imagine the driver who spills hot coffee on her lap at almost the same time the car in front of her slams on its brakes. Two reactions, to two different stimuli, are called for quickly.

The separation in time between the appearance of the two stimuli is called the *stimulus onset asynchrony*, or *SOA*. The general finding is that the response to the second stimulus is delayed by the processing of the first stimulus when the SOA is short. Suppose, for example, an observer is presented two stimuli, a tone (S_1) and then a light (S_2), separated by a variable SOA (the tone here is analogous to the hot coffee hitting the driver in our example, and the light is analogous to the onset of the leading car's brake lights). The observer has two tasks. In the laboratory simulation of this situation, the first ($Task_1$) is to respond by pressing a key (R_1) as soon as the tone is heard. The second ($Task_2$) is to respond by speaking a word (R_2) as soon as the light (S_2) is seen. If the SOA between the two stimuli is sufficiently short (less than the RT to the first stimulus), then response time to the light (RT_2) will be prolonged. RT to the tone (RT_1), in contrast, will generally be unaffected by the second task. The PRP delay in RT_2 is typically measured with respect to a single-task control condition in which the observer responds to S_2 while simply ignoring S_1.

The most widely accepted account of the PRP proposes that the human operator acts as a single-channel information processor. The single-channel theory of the PRP was originally proposed by Craik (1947) and has subsequently been expressed and elaborated on by Bertelson (1966), Davis (1965), Kantowitz (1974), Meyer and Kieras (1997a, 1997b), Pashler (1989, 1994), and Welford (1952, 1967). The single-channel model is also compatible with Broadbent's (1958) conception of attention as an information-processing bottleneck that can only operate on one stimulus or piece of information at a time. To explain the PRP, single-channel theory assumes that the processing of S_1 temporarily occupies the single-channel bottleneck of stimulus processing. Thus, until the single channel has finished processing S_1, the processor cannot begin to deal with S_2. The second stimulus S_2 must therefore wait at the gate of the bottleneck until it opens. This waiting time is what prolongs RT_2. The sooner S_2 arrives, the longer it must wait. According to this view, anything that prolongs the processing of S_1 at a point up to and including the bottleneck will delay RT_2 by the same amount of time. The PRP is longer if $Task_1$ requires a complex or unpracticed choice rather than a simpler or more familiar one (Pashler, 1994; Reynolds, 1966). This simple relationship between SOA and RT_2 is represented graphically in Figure 2.1, importantly indicating the one-for-one exchange between the two variables, or a slope of −1. That is, "the earlier you arrive, the longer you wait."

The information-processing bottleneck that causes the PRP does not appear to be located in peripheral sensory processing, where analysis is generally parallel and

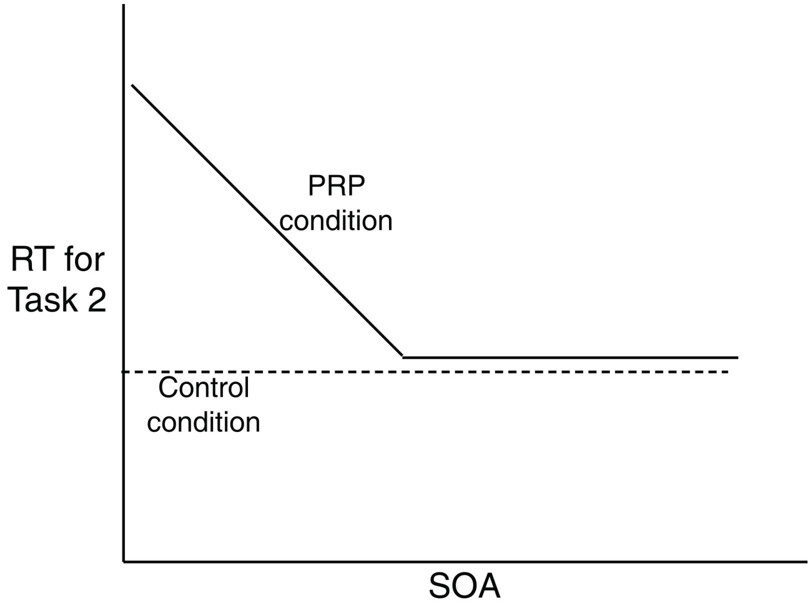

FIGURE 2.1 Graph of hypothetical RTs predicted by single-channel theory. RT_2 under a PRP paradigm, as the response to the second arriving stimulus, is graphed as a solid line and is a function of SOA. The control condition reaction time when RT_2 is performed alone is plotted as a dotted line for comparison. When SOA is short, S_2 must wait to be processed till R_1 is released. For every ms that SOA is lengthened, the wait time decreases by 1 ms, producing a slope of –1.0 early in the function. Eventually, the SOA becomes long enough that S_2 arrives well after completion of the R_1 bottleneck, at which point there is no delay in RT_2 relative to the dotted-line control condition shown by the short horizontal line on the Y axis.

relatively automatic (Pashler & Johnston, 1989; cf. Scharff et al., 2011). Nor does the bottleneck appear to reside in the literal physical act of carrying out a response (except in the obvious case in which two responses are physically incompatible, for example, because they require the same effector). The PRP thus appears to arise at one or more central stages of processing, in between sensory encoding and overt response execution. A great deal of research has attempted to identify the bottleneck stage(s) more specifically. The data suggest multiple possibilities.

- Conventionally, the central bottleneck has been argued to lie in *response selection*, the process of mapping a stimulus to the appropriate behavior (Pashler, 1994; Van Selst & Jolicoeur, 1997). Thus, manipulations of stimulus–response compatibility that delay the selection and execution of R_1 tend to delay R_2 by the same amount (McCann & Johnston, 1992; Pashler, 1994).
- The bottleneck can also encompass some perceptual-cognitive operations, such as mental rotation (Ruthruff et al., 1995) or classification judgments that do not involve well-learned stimuli (Johnston & McCann, 2006).

- Some findings have suggested the possibility of an additional or alternative bottleneck in motor response programming (Bratzke et al., 2008; Klapp et al., 2019).

In any case, a central locus for the bottleneck implies that the basic perceptual analysis of S_2 can begin even while the bottleneck is occupied by $Task_1$ and, conversely, that bottleneck processing of $Task_2$ can overlap with the execution of R_1 (Bratzke et al., 2009; Keele, 1973; Pashler, 1994; Pashler & Johnston, 1989). These relations are shown in Figure 2.2.

Imagine as an analogy two patients visiting the same physician for a checkup. The total time at the doctor's office for the first patient is the sum of the time it takes to fill out paperwork and be seen by the doctor. This time remains the same even if a second patient arrives soon after the first. The total time of the second patient's office visit, however, depends on how soon he arrives after the first patient. If the second patient arrives shortly after the first, then the two can fill out the paperwork concurrently. However, the second patient cannot see the doctor until the first patient's exam has been completed. After completing his paperwork, the second patient will therefore dawdle in the waiting room until the first patient has been discharged, and the length of his visit will be prolonged by exactly the length of the first patient's exam. On the other hand, if he arrives a little bit later, the second patient can fill out paperwork in parallel with the doctor's examination of the first patient. Some of his wait time will therefore be "absorbed" by the time needed to complete paperwork. Indeed, if the second patient's paperwork is completed at just the moment the first patient is discharged, or later, then the first patient's examination will cause no extra waiting time for patient 2. In this example, the doctor, who can examine only one patient at a

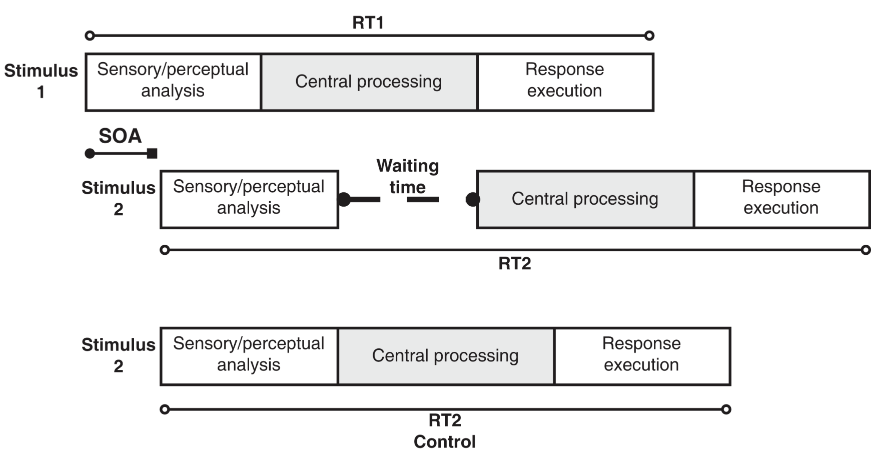

FIGURE 2.2 Single-channel theory explanation of the psychological refractory period. The figure shows the delay (waiting time; the dashed line) imposed on RT_2 by the processing involved in RT_1. This waiting time makes RT_2 take longer in the dual-task setting than in the single-task control.

time, is the single-channel bottleneck; the first- and second-arriving patients reflect S_1 and S_2, respectively; the difference in arrival time for the two patients is the SOA; the paperwork corresponds to the automatic perceptual processing, and the total visit times for each patient reflects RT_1 and RT_2.

Returning to the PRP, we see that the delay in RT_2 beyond its single-task baseline will increase linearly, on a one-to-one basis, with either a decrease in SOA or an increase in the time needed for $Task_1$'s pre-bottleneck and bottleneck processing, since both variables increase the time that $Task_2$ waits for bottleneck access. Assuming that the single-channel bottleneck is perfect (i.e., post-perceptual processing of S_2 will not start at all until R_1 is released), the relationship between SOA and RT_2 will look like that shown in Figure 2.1.

The central bottleneck model as shown in Figure 2.2 successfully describes a large amount of the PRP data (Bertelson, 1966; Kantowitz, 1974; D. E. Meyer & Kieras, 1997a, 1997b; Pashler, 1994; M. C. Smith, 1967). There are, however, three important qualifications to the general single-channel model as it has been presented so far.

1. On some trials, particularly when the SOA is very short, R_1 is delayed, and both responses are emitted at roughly the same time, or *grouped* (Borger, 1963; Kantowitz, 1974; J. Miller & Ulrich, 2008; Pashler & Johnston, 1989). An early interpretation of this effect was that S_1 and S_2 were perceptually integrated and analyzed as a single stimulus mapped to a pair of overt responses (Welford, 1952). An alternative and more widely accepted explanation proposes that observers strategically delay R_1 on some trials (Borger, 1963; Ulrich & Miller, 2008), perhaps to simplify motor control (J. Miller & Ulrich, 2008). Response grouping is also obtained when the observer is required to execute two different responses (e.g., a key press and a spoken word) to a single stimulus (Fagot & Pashler, 1992).
2. Sometimes RT_2 suffers a PRP delay even when S_2 arrives after R_1 has been completed, a loss termed a *residual PRP effect* (Jentzsch et al., 2007). The residual PRP effect appears to result when the observer monitors execution of R_1 before switching to the bottleneck processing of S_2 (Jentzsch et al., 2007; Welford, 1967).
3. The 1–1 trade-off between SOA and RT_2 is not always found (Kahneman, 1973), with a shallower slope suggesting some parallel processing between the two (Wickens, Dixon & Ambinder, 2006).

Finally, the nature of the PRP paradigm itself has been questioned. Navon and Miller (2002) argued that the paradigm itself, with its time pressure and instructions, doesn't just test the single-channel mechanism but creates it, which may explain point (3). Other researchers have suggested that with enough practice and appropriate cognitive control settings, an operator might be able to circumvent the PRP bottleneck stage (Maquestiaux et al., 2008; J. Miller et al., 2009; Schumacher et al., 2001) or reduce its completion time to a negligible duration (Ruthruff et al., 2003; Van Selst et al., 1999; see Chapter 9). In application, we must always determine whether and when single-channel theory is applicable to a task. We consider this next.

2.2 APPLICATIONS OF SINGLE-CHANNEL THEORY TO WORKLOAD PREDICTION

As noted, researchers have debated the precise locus of the PRP effect and have questioned whether the effect need always show up. We take the approach that applications are best realized by considering the task and environmental circumstances that are most likely to produce single-channel behavior. In the world beyond the laboratory, single-channel behavior is likely under three diverse sets of circumstances:

- When visually displayed sources of information requiring foveal vision are widely separated (Dixon et al., 2005; Liao & Moray, 1993). The single channel in this case is obviously peripheral, not the same central bottleneck that causes the PRP.
- When multiple tasks demand processing in rapid sequence. These are real-world analogies to the PRP paradigm, such as when a driver must respond to a sudden roadway hazard at the very instant that a passenger asks a question or that the coffee spills (Levy et al., 2006).
- When two tasks demand a high level of cognitive involvement, as when trying to listen to two engaging conversations at once or when thinking (problem solving) while reading an unrelated message.

These are obviously common and meaningful circumstances in many real-world contexts. The single-channel model has in fact found useful application in two important areas. One of these has been identifying the circumstances under which operators in safety critical tasks (e.g., driving, flying) tend to regress into some form of single-channel behavior akin to "attentional tunneling" or "cognitive lockout" (Wickens, 2005a; Wickens & Alexander, 2009). For example, fault management appears to induce such behavior (Moray & Rotenberg, 1989), as does the cognitive engagement fostered by certain tasks, like phone conversation (Horrey & Wickens, 2006; Strayer et al., 2003, 2011). We discuss these issues further in Chapter 9.

The second important application area of single-channel processing has been in workload modeling and prediction (Laughery et al. (2006), Hendy et al. (1997), Sarno and Wickens (1995); see also Chapter 7). Such modeling is designed to make both absolute and relative predictions of how successfully people will perform in multitask settings.

The goal of absolute predictions of task interference and workload calls to mind the kind of question asked by the Federal Aviation Administration before certifying new aircraft: are the demands imposed on the pilot excessive (Ruggiero & Fadden, 1987)? If excessive is to be defined relative to some absolute standard, such as "80% of maximal capacity," an absolute workload question is being asked. Practitioners speak of a "red line" above which workload should not be allowed to cross (see also Chapter 7). A common approach to absolute workload and performance prediction is *timeline analysis*, by which the system designer constructs a temporal profile of the workload that operators encounter during a typical mission, such as landing an aircraft, starting up a power-generating plant, or performing emergency CPR after a cardiac arrest (Kirwan & Ainsworth, 1992). In a simplified but readily usable version compatible with single-channel theory, this analysis assumes that workload is proportional to the ratio of the time occupied performing tasks to the total time available. If one is busy with one or more observable tasks for 100% of a given time interval, workload over that interval is 100%. Thus, the workload of a mission would be computed by drawing lines representing different activities, of length proportional to their duration. The total length of the lines within an interval would be summed and then divided by the interval time (Parks & Boucek, 1989), as shown in Figure 2.3. In this way, the workload levels experienced by different members of a team (e.g., pilot, copilot, or flight engineer) can be compared, and if necessary, tasks can be reallocated or automated. Furthermore, epochs of peak workload or work overload, in which load is calculated as greater than 100%, can be identified as potential single-channel bottlenecks. Finally, evidence suggests that errors are likely to appear when percent channel occupancy exceeds 80% (Parks & Boucek, 1989), thereby pointing to the 80% figure as a plausible "red line" of workload (Grier et al., 2008; Grier, 2015).

The straightforward assumptions that time is the key component for performance prediction and that only a single task can be performed at one time, consistent with single-channel theory, appear to be adequate in many cases (Hendy et al., 1997). But there are circumstances when these assumptions break down, and single-channel theory underestimates the capabilities of human multitasking (Dixon et al., 2005; Sarno & Wickens, 1995). Two of the most important causes for human performance to exceed single-channel predictions are automaticity and multiple resources. We

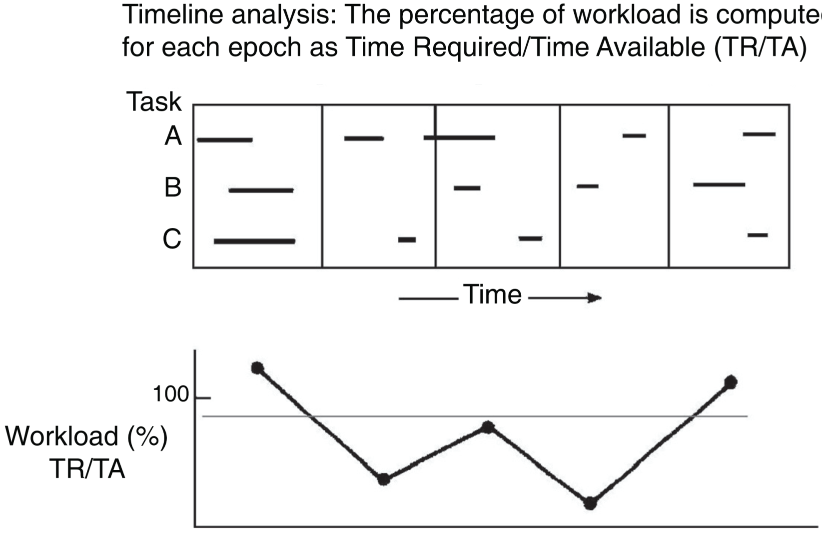

FIGURE 2.3 Timeline analysis of workload, based upon single-channel theory. The task timeline is shown at the top of the figure. Assuming that tasks are not rescheduled between intervals nor can be performed in parallel, the workload metric shown at the bottom can be thought of as the degree of overload or the likelihood that one task must be delayed or dropped.

discuss the first of these later in this chapter and again in Chapter 7, while deferring extensive treatment of multiple resources until Chapter 8. However, first, we consider another classic historical aspect of attention research closely related to the bottleneck of attention: work on the auditory shadowing task, and its relevance to early versus late selection theory.

2.3 DICHOTIC LISTENING: EARLY VERSUS LATE SELECTION

As discussed, a great deal of basic research has attempted to pin down the locus of the single-channel bottleneck in human information processing. The same issue has been addressed with a very different attention task, one that dominated attention research in the 1950s and 1960s: *dichotic listening* (Cherry, 1953; Cherry & Taylor, 1954; Moray, 1959; Treisman, 1964a, 1964b).

In dichotic listening, a task pioneered by Colin Cherry (1953), the experimenter presents a listener with two streams of information, typically both spoken messages, one to each ear. The listener's task is to *shadow* one of the messages, repeating it word for word as it is delivered, while ignoring the other message. Cherry found that listeners could shadow the relevant message easily and without interference from the irrelevant message, even when the messages were spoken in the same voice. (Notably, selective listening was more difficult and much less efficient when two streams of speech were spatially intermixed.)

Given that listeners can selectively shadow the relevant message so fluently, the question of interest becomes, How deeply is the irrelevant message processed? To answer this, experimenters can use either online (brain wave measurements or disruptions in shadowing, for example) or retrospective techniques (probes of the listener's memory for the irrelevant message, for instance). If data give no hint that the meaning of the irrelevant message has been processed, the bottleneck is presumed to be early in the information processing stream, prior to stimulus recognition and semantic processing (Broadbent, 1958). If there is evidence for semantic processing of the unattended message, then the bottleneck is presumed to occur after recognition (e.g., Deutsch & Deutsch, 1963; Keele, 1973), late in the information processing stream.

Cherry (1953) found evidence to suggest that only crude physical properties of the unattended message were processed. Shadowing a message in one ear, for instance, participants generally noticed if speech in the alternative ear changed from a man's voice to a woman's, but failed to encode the content of the irrelevant speech or even to notice if the language changed from English to German. These results led Broadbent (1958) to suggest that rudimentary physical properties of a message, such as location and pitch, could be processed in parallel, but that semantic analysis constituted an information processing bottleneck. The role of attention was to block irrelevant messages from reaching the bottleneck. By this account, then, selection was early in the information processing stream.

But contrary to Broadbent's filter model, a pair of classic studies in the 1960s provided strong evidence for some level of semantic processing in the irrelevant channel. First, Moray (1959) found that about one-third of listeners noticed their own name when it occurred in the irrelevant stream of speech. Later work replicated this finding quite closely (Wood & Cowan, 1995b). Second, Treisman (1960) found that if a meaningful passage "jumped" unexpectedly from the relevant to the irrelevant channel, attention would occasionally follow, causing the listener to briefly shadow the wrong channel before realizing their error and switching attention back to the correct one.

These findings indicated some level of semantic processing of a message that should have been, by instructions, filtered. This processing was shallower, though, than that of the message to which the listeners purposely attended. To explain these effects, Treisman (1964c) postulated an *attenuation model* of selective attention in place of a strict bottleneck model. Under Treisman's account, selection worked to attenuate or dampen unattended material rather than to block it fully. Semantic properties of attenuated messages generally failed to reach the listener's awareness but occasionally broke through, particularly when meaning was primed or personally relevant to the listener. Replications and extensions of Cherry and Moray's shadowing experiments gave further support for the attenuation model (Wood & Cowan, 1995a) but also demonstrated that listeners differed in their ability to effectively suppress the to-be-ignored message; listeners with high working memory capacity, a measure of attentional control skill (Engle, 2002, 2018), were less likely than others to notice their name in a to-be-ignored message (Conway et al., 2001). Some work also found evidence for an attenuation model in visual processing (Mack & Rock, 1998b), though other findings appeared to indicate that when visual attention was tightly focused, it operated as an early-selection bottleneck (Lachter et al., 2004). The latter results were taken as evidence that processing of irrelevant information results from attention "slippage" rather than "leakage."

But regardless of whether attentional filtering merely attenuates semantic processing or blocks it entirely, findings from dichotic listening are consistent with those from the psychological refractory paradigm in demonstrating that some sensory processing can occur without attention. Importantly, this early processing, whatever its extent and degree, by being "preattentive" can also be said to be automatic, occurring in the absence of the allocation of attention. Thus, we turn now to the concept of automaticity, examining in particular its status at the opposite end of the capabilities spectrum of human attention from the most severe bottlenecks of single-channel theory.

2.4 AUTOMATICITY

More than a century ago, William James pondered the "span of consciousness," wondering "how many entirely disconnected systems or processes can go on simultaneously" (1950). He concluded that "the answer is, *not easily more than one, unless the processes are very habitual*; [automatic] *but then, two, or even three*, without very much oscillation of the attention. Where, however, the processes are less automatic . . . there must be a rapid oscillation of the mind from one to the next, and no consequent gain of time" (p. 409, emphasis in original). More recently, investigators have documented improvements in time-sharing (divided attention) performance that occur as an operator practices a task or tasks (Bahrick & Shelly, 1958; Schneider & Shiffrin, 1977), and differences in time-sharing efficiency between task experts and novices (Damos, 1978). Such effects can be accounted for by a simple model that posits that (a) interference between tasks is a function of the demands of the task(s) for a limited supply of "mental resources" or mental effort (Kahneman, 1973) and (b) the resource demand of a given task diminishes with the operator's expertise until reaching a point of resource-free automaticity, at which the task can be time-shared without cost. Such is the status that is often attributed to well-learned skills, like walking.

In this regard, it should be noted that the term "automaticity" is a broad one that encompasses several aspects of performance (e.g., consistent, fast, error free), only one of which is perfect time-sharing (Logan, 1985, 1988). In particular, the term may also characterize a response that is automatically triggered, cannot be stopped, and therefore may in fact interfere with an ongoing activity (Schneider & Shiffrin, 1977). We consider this latter facet of automaticity in our discussion of focused attention in Chapter 6 and discussion of task switching and task management in Chapter 9. Here, we restrict ourselves to the time-sharing implications.

Within the last half century, research has addressed the properties of tasks and practice that can best produce automaticity that avails perfect time-sharing (Logan, 1988; Schneider & Shiffrin, 1977). The seminal work of Schneider, Shiffrin, and Fisk (Fisk et al., 1987; Schneider, 1985; Schneider & Fisk, 1982) has focused heavily on the essential role of stimulus–response *consistency* in producing automaticity. In a prototypical task, a small set of letters is designated as targets. The participant is then presented a visual display of one or more letters on each trial and asked to determine as fast as possible whether the display contains a target. When the mapping of stimuli to categories is consistent—that is, when the set of target letters is held constant for many trials (often in the thousands)—then automatic perceptual processing is achieved, such that the letter-detection task can be performed in parallel with other attention-demanding tasks (Schneider & Fisk, 1982) and is as fast with several targets as it is with one. In contrast, extensive practice on the same letter-categorization task but with the set of target letters varying from trial to trial produced far less improvement and fails to eliminate a decrement in dual-task performance. This is called *controlled* processing, in contrast to automatic processing. In other words, automaticity does not emerge from practice alone but only from practice with a consistent set of target stimuli.

Schneider and Fisk (1982) have generalized this phenomenon to circumstances in which it is the semantic target category that is consistent, not just a particular letter, indicating that automatic detection does not depend only on the consistency of the physical stimulus. Researchers have also demonstrated consistency-based automaticity with tasks using nonverbal stimuli, like the time-space trajectories of aircraft viewed by an air-traffic controller (Schneider, 1985; Vidulich et al., 1983), and have examined the automaticity of both postperceptual cognitive skills (Zbrodoff & Logan, 1986) and motor skills (Schmidt et al., 2019; Summers, 1989), the latter embodying the concept of a "motor program," such as that involved in signing one's name, skilled typing, or typing in a familiar password. The underlying theme in all these applications remains that consistency, coupled with practice, pushes performance toward automaticity.

The applied importance of automaticity theory is realized in at least two areas. The first of these is directly related to training attention skills, which we discuss in more detail in Chapter 11. Trainers can seek to automatize trainee skills (or their components) for two reasons. First, automatized skills, like steering a car or dribbling a basketball, leave resources available for performance of concurrent tasks that are not automatized, for example, noticing the appearance of a pedestrian in the roadway or the movement of a defender on the court. Second, skills that can be automatized, because of their consistency, make strong candidates to be isolated for part-task training (an example might be dribbling the basketball while running down the court). When they later are reintegrated into the full, complex task, they will not divert resources that can otherwise be allocated to the complex concurrent subtasks (Lintern & Wickens, 1991). This approach has also found its way into the development of training technology, which itself takes over parts of tasks while learners perform them early in training (Gutzwiller et al., 2013), in the hopes of creating such automaticity and simplifying complex environments for new learners. However, choosing a task amenable to the technique requires some thought; work that demands divided attention and coordination among multiple task components might benefit more from *varied priority training*, an approach that manipulates the effort dedicated to each task between blocks of training, than from true part-task training, which isolates task components completely (Gopher et al., 1989). Isolating concurrent task components for training can in fact lead to performance costs in the whole task (Wickens, Hutchins, et al., 2013). These considerations are discussed more in Chapter 11.

The second application of automaticity theory revisits the timeline modeling approach to workload prediction, discussed earlier and shown in Figure 2.3. While a true single-channel model predicts that tasks cannot overlap on the timeline, and therefore a workload (time-required/time-available ratio) of greater than 100% inevitably produces a loss in performance, a model that incorporates automaticity would enable some time-sharing or task overlap. Such assumptions have been embodied in approaches to workload prediction that recognize the low resource demands of automatized tasks (Aldrich et al., 1989; Laughery et al., 2006). This issue will be considered in more depth in Chapter 7. However, we note here that given the challenges of quantifying task demand, strict single-channel assumptions, even if they may not be fully accurate, are often adequate and preferred in application because time is easier to quantify and computationally model than is the degree of automaticity or the effort demanded by the task (Liao & Moray, 1993). Models that do not include effort as a parameter can often do an adequate job of predicting multiple task performance (Sarno & Wickens, 1995).

2.5 CONCLUSION

We have examined two concepts, single-channel processing and automaticity, that represent opposite extremes of human attentional capabilities, each evident in real-world tasks. In the following chapters, we will see each of these concepts reemerge in different forms, characterizing different aspects of attention. For example, in

Chapter 5 on visual search, we see contrasted clearly the single-channel assumptions of serial search with the automaticity concepts of parallel search. In Chapter 6, we discuss the automaticity with which different features of a single object are processed. In Chapter 7, we discuss in more detail the mediating concept of resource demand, which can create single-channel behavior when it is high, automatic behavior when it is low, and something in between when demands are moderate.

3 Attention Control

Many real-world tasks—driving, flying, process management, among others—require an operator to monitor multiple information sources over long periods of time. In such cases, as is discussed in Chapter 4, the operator learns to allocate focus adaptively, balancing attention between various channels with a frequency determined by their relative importance and bandwidth. Even when scanning is well tuned to the environment over the long run, though, it might still be useful to alert the operator to an unexpected or high-priority event, interrupting the normal path of scanning to ensure that important information is quickly encoded. Even an experienced and attentive driver, for example, might benefit from an alert that announces when the fuel gauge is approaching empty or from an alarm that signals an impending side collision. In other cases, designers might anticipate inexperienced operators, who bring little knowledge to bear on their interactions with a system. Effective design in those instances requires cues to guide attention in a stimulus-driven manner toward critical information. When designing instructional graphics or animations, for example, an educator may need to cue attention to important details that students, unfamiliar with the material, might otherwise overlook (Lowe, 2003).

In all of these cases, the system designer is faced with a challenge of *attention control*, catching the operator's attention and orienting it toward a timely piece of information. Although the job of drawing attention to an information channel seems straightforward, it can be difficult to create a cue that is noticeable but not disruptive. A visual cue that is easy to detect in a sparse or static display, for example, might be lost in a bank of blinking lights and spinning dials, particularly if it is in the visual periphery or the operator is busy with another task (Nikolic et al., 2004; Steelman et al., 2013). Conversely, a cue that is conspicuous enough to guarantee detection in a busy environment may be overly distracting and subjectively annoying (Bartram et al., 2003). Finally, in applied settings, even a cue that is not perceptually distracting can sometimes be misleading. An automated cue such as a hazard alert is based on an algorithm's inference that the cued object is important to attend to. Sometimes this inference is simple (e.g., a pedestrian in the path of a moving car is a hazard), but at other times, it may require sophisticated reasoning. For a host of reasons, this inference will occasionally be wrong, creating cues that are imperfectly reliable. The present chapter discusses several basic issues of attention capture and capture failures before turning to a discussion of the most important applications of attention control: the role of automation in directing attention via alarms and alerts.

3.1 INATTENTIONAL AND CHANGE BLINDNESS

The importance of attention control becomes obvious when environmental events fail to draw notice, as in the phenomena of *inattentional blindness* (Mack & Rock, 1998a) and *change blindness* (Jensen et al., 2011; Mack & Rock, 1998a; Rensink,

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2008; Simons & Ambinder, 2005; Simons & Levin, 1997). Inattentional blindness, sometimes described as the *looked-but-failed-to-see* effect (Hills, 1980), occurs when a lapse of attention causes an observer to overlook an object that is well above sensory threshold. Mack and Rock (1998a), for instance, found that when observers focused their attention intently on an object in their central vision, they often failed to detect an unexpected object in the visual periphery. More surprisingly, when attention was directed to an item in the visual periphery, many observers failed to notice an unexpected object in their central vision, directly where their eyes were fixated. These effects were not simply the result of poor stimulus visibility, as the probes were easily detected when the observers expected them.

Looked-but-failed-to-see errors are not fragile laboratory effects but are easy to produce and sometimes startling in their strength (see Simons & Chabris, 1999 for the seminal demonstration). They have been identified as a common cause of traffic crashes (Herslund & Jørgensen, 2003; Salmon et al., 2013; White & Caird, 2010) and implicated as a potential source of human error in other high-stakes contexts. In a study of simulated traffic stops, for example, 33% of the experienced police officers tested, and more than half of the trainees, failed to notice a pistol sitting in plain sight on the passenger's dashboard (Simons & Schlosser, 2017). In a simulated police foot chase, modeled after a real-life incident, almost 25% of participants pursuing a (pretend) criminal suspect ran past a (pretend) assault and battery without noticing, even under daylight conditions. Noticing rates dropped below 50% when participants performed a simultaneous attention-loading task and fell to 35% under nighttime conditions (Chabris et al., 2011).

Change blindness, another form of visual lapse, occurs when an observer fails to detect an event in their surroundings. Thus, whereas inattentional blindness is a failure to notice something here and now, change blindness is a failure to notice that something is different from what it was. For a computer user, this could be a failure to notice that a new message has arrived in a chat box; for a driver looking back to the road after a glance at the radio dial, it might be a failure to notice that a traffic light has changed (Beanland et al., 2017; Pringle et al., 2001); for a pilot contending with the demands of a busy cockpit, it may be a failure to notice that the light indicating a change of flight mode has turned on (Sarter et al., 2007). In a face-to-face conversation, more remarkably, it can even mean that a speaker fails to notice that the person to whom they were speaking has disappeared and been replaced by someone new. In a study by Simons and Levin (1998), an experimenter approached pedestrians on a college campus to ask for directions. As the experimenter and a pedestrian talked, their conversation was interrupted by a pair of workers (confederates of the experimenter, in actuality) who barged between them carrying a wooden door. As the workers tromped through, the original experimenter snuck away behind the door, and a new experimenter was left standing in his place. In most cases, the conversation carried on normally, with the pedestrians failing to notice that they were speaking to someone new.

How do such lapses occur? Very often, change blindness is a failure of attention. Data indicate that changes are likely to go unnoticed if they are not attended when they occur. Under most circumstances, a change in the visual environment produces a *transient*, a brief flutter of motion or flicker. These signals tend to attract attention and help ensure that the change is noticed. However, the change will often go undetected if it occurs while the observer (or camera) is looking away (Simons, 1996; Vachon et al., 2012) or if it happens to be masked by an occluding object (Levin et al., 2002; Simons & Levin, 1998), the flicker of a display (Rensink et al., 1997), egomotion (Wallis & Bulthoff, 2000), transients produced by concurrent events (O'Regan et al., 1999), a movie cut (Levin & Simons, 1997), or even just an eye movement (Grimes, 1996) or blink (O'Regan et al., 2000). In the terminology of Rensink (2002), a change in progress is usually easy to notice, but a completed change, one that occurred while attention was elsewhere or vision was obscured, is not (D. Davis et al., 2008).

It is easy to imagine real-world circumstances in which the difficulty of detecting changes might hinder task performance. Consider an operator monitoring a large dynamic display of air traffic. At any given time, most of the display will fall outside the momentary focus of attention, and a large number of changes will be likely to escape notice. Indeed, pilots monitoring a simulated airspace display detected fewer than half of all changes to air traffic flight paths or weather patterns, including changes that required updates to the monitors' own flight plan (Muthard & Wickens, 2002). When display monitoring was coupled with an attention-demanding flight control task, change detection rates dropped below 25% (Stelzer & Wickens, 2006). Research has also suggested that change blindness might produce identification errors in eyewitness testimony, causing the witness not to notice that an innocent bystander and a criminal suspect are different people (D. Davis et al., 2008). Changes that are meaningful or task relevant within their context are more likely to be spotted than changes that are of secondary importance (Rensink et al., 1997). For instance, safety-relevant changes within a construction (Solomon et al., 2021) or traffic scene (Beanland et al., 2017; Galpin et al., 2009; McCarley, Vais, et al., 2004; Pringle et al., 2001) are more likely to be spotted than are safety-irrelevant changes. An observer's expertise likewise seems to reduce the risk of overlooking a change in at least some contexts (Werner & Thies, 2000). In no case, though, does it seem that human operators are fully immune to the risk of change blindness.

Other examples of change blindness in tasks outside the laboratory are offered by Durlach (2004) and by Vachon, Vallieres, Jones and Tremblay, 2012 for complex dynamic system monitoring, and by Varakin et al. (index), for human-computer interaction.

Despite their remarkable insensitivity to completed changes, people assume that they will notice changes easily, a metacognitive error that has been termed *change blindness blindness* (Levin et al., 2000). Thus, not only are operators in a busy environment likely to overlook much of the activity going on around them, but they might also overestimate the degree to which their knowledge of the world is out-of-date or incomplete, a metacognitive error that could discourage them from seeking new information when appropriate. Theorists argue that the first step toward good situation awareness is to notice objects and events in the surrounding environment (Endsley, 1995). The phenomena of inattentional blindness and change blindness make clear that attention plays an indispensable role in this process (Wickens & Rose, 2001).

3.2 COVERT VERSUS OVERT ATTENTION

How is visual attention allocated? Helmholtz (1925), describing an experiment in which he tested his ability to see images briefly illuminated by a spark of light, noted that the direction of visual attention was not strictly locked to the direction of the eyes. Rather, it was possible to "keep our attention . . . turned to any particular portion that we please" of the visual field, "so as then, when the spark comes, to receive an impression only from such parts of the picture as lie in this region" (Helmholtz, 1925, p. 455), even while the eyes were fixed elsewhere. James (1950, p. 434) likewise noted a difference between "the accommodation or adjustment of the sensory organs" and "the anticipatory preparation from within of the ideational centres concerned with the object to which attention is paid."

Following Posner (Posner, 1980), this distinction that Helmholtz and James noted is now termed the difference between *overt* and *covert* orienting. An overt attention shift is one that involves a movement of the eyes, head, or body to orient the sensory surface toward the object of interest. In vision, this is most often a *saccade*, an abrupt, rapid movement with which the eyes dart from one point of fixation to another. A covert attention shift is a change of mental focus in the absence of any physical movements. Thus, a computer user can orient overtly by moving her eyes to look directly at a text message that has just popped up, or she can notice the message covertly in her peripheral vision without turning to look directly at it. Likewise, a person in a noisy room might turn his head and lean forward overtly when straining to hear a friend speak but focus attention covertly when trying to eavesdrop on someone else's conversation.

Research has found that in vision, overt and covert movements are subserved by many common neural mechanisms (Corbetta et al., 1998; Petersen & Posner, 2012) and are functionally linked, though in an asymmetrical manner; it is possible to shift attention covertly without moving the eyes, but a saccade cannot be executed until covert attention has shifted to the target location (Deubel & Schneider, 1996; Hoffman & Subramaniam, 1995; Kowler et al., 1995). Stimulus attributes that attract covert visual attention therefore tend to have similar, if less powerful, effects on saccades (Theeuwes et al., 1998). Basic attention researchers often try to isolate covert attention by asking observers to perform visual tasks while holding the eyes still, but in our naturalistic behavior, overt and covert attention typically work in concert. Operators performing real-world tasks rely heavily on overt scanning (Moray, 1993; Moray & Rotenberg, 1989), typically making two to three eye movements per second (Rayner, 2009). As the phenomenon of looked-but-failed-to-see errors demonstrates, however, an object that fails to engage covert attention can go unnoticed even if it's fixated.

3.3 THE SPOTLIGHT OF VISUAL ATTENTION

Covert visual attention is often described as analogous to a spotlight, enabling selective processing of the "illuminated" region of the visual field. Although the spotlight model, along with similar conceptualizations of attention as a mental zoom lens (Eriksen & St. James, 1986) or gradient of resources (Downing & Pinker, 1985;

LaBerge & Brown, 1989), carries some questionable implications (Bichot et al., 1999; Cave & Bichot, 1999; Duncan, 1984; A. F. Kramer & Hahn, 1995; Müller & Hübner, 2002; Yamani et al., 2013: in Chapter 6, we'll consider an alternative model) that remains popular and captures some important aspects of selective visual processing.

Evidence for the spotlight model originated in the work of C. W. Eriksen and colleagues (Eriksen & Hoffman, 1973, 1972) using what has become known as the *flanker paradigm*. In a typical flanker experiment, the observer's job is to identify a target letter at a prespecified location and to report their judgment with a keypress. The target is flanked by task-irrelevant letters that are mapped to either the same response as the target or an alternative keypress response. Although observers are instructed to ignore the flankers, the conventional finding is that RTs are longer when the flankers are response incompatible with the target than when they are response compatible. These effects are strongest when the separation between the target flankers is small, and they can disappear when the separation between target and flankers exceeds roughly 1 degree of visual angle (Eriksen & Hoffman, 1973; Yantis & Johnston, 1990). Thus, flankers very near the target item appear to be processed to the point of recognition even when the subject wishes to ignore them. Eriksen and Hoffman (1973) took such findings as evidence of an attentional spotlight with a minimum size of about 1 degree. As discussed more fully in Chapter 6, this conclusion implies that attentional selection will be difficult when items in a display or map are spaced too closely together.

3.4 POSNER'S CUING PARADIGM

Following on Eriksen's flanker task, an experimental procedure developed by Posner and colleagues provided a converging method for studying the spotlight of mental attention (Posner, 1980, 2016; Posner et al., 1980). In a typical version of Posner's cuing task, the observer is asked to keep her eyes on a central fixation mark and to make a speeded detection judgment of a signal that can appear in the visual periphery on either side. The observer's attention is manipulated by a cue that appears prior to signal onset. Figure 3.1 illustrates the events within a typical trial. Here, the cue is an arrow pointing toward one of the possible target locations. On *valid cue* trials, as seen in the left of the figure, the signal appears at the cued location. On *invalid cue* trials, as seen in the right of the figure, it appears at the uncued location. The signal appears and is gone in less than the time it takes to make a saccade. Generally, cue validity or cue reliability is above chance but below perfect, meaning that the target is more likely to appear at the cued than at the uncued location but is not guaranteed to do so. Some experiments also include a neutral cue condition, in which neither target location is cued. The effects of attention are measured by comparing RTs for valid, neutral, and invalid cue trials. Even for a task as simple as detecting the onset of an above-threshold spot of light, valid cues reduce RTs relative to neutral cues, and invalid cues increase them (Posner et al., 1980). Results are similar when a discrimination task is used instead of a detection task (Posner et al., 1980) or when judgment accuracy is used as the dependent variable (Z.-L. Lu & Dosher, 1998). The conventional interpretation of cuing effects is that cues allow observers to align the mental spotlight of attention with the expected target location (Posner et al., 1980).

3.5 CENTRAL VERSUS PERIPHERAL CUING

As might be expected, characteristics of the cue stimulus itself also influence attentional performance. This was first demonstrated by Jonides (1981), who compared the effects of central and peripheral cues. A *central*, or *endogenous*, cue specifies the location to be attended symbolically and is not actually located at the cued position. Most typically, it is presented at a fixation point in the center of the visual field. A central cue may be an arrow, as in Figure 3.1, a word, or any other kind of symbol, so long as it does not directly align with the location to which attention should be shifted. A *peripheral*, or *exogenous*, cue is a sensory signal that appears at the location to which attention is to be shifted. In Figure 3.1, for example, attention could have been exogenously cued to one location by blinking or briefly brightening one of the boxes. Jonides found that peripheral cues, unlike central cues, tend to draw attention even if they do not predict the target location with accuracy better than chance and tend to be effective even under relatively high levels of cognitive workload. For these reasons, peripheral cues are sometimes said to elicit attention shifts in *reflexive* or *bottom-up* manner, whereas central cues are said to require *voluntary* or *top-down* orienting, though, as discussed in what follows, this distinction is not always crisp.

Subsequent work found that exogenous and endogenous attention shifts differ in their time course and effects. Exogenous shifts are quick and powerful but transient, producing performance enhancements that peak within 100–200 ms of cue onset then disappear within the next 100 ms (Muller & Rabbitt, 1989; Nakayama & Mackeben, 1989) and may even reverse (Posner & Cohen, 1984). Endogenous shifts produce weaker effects and are executed more slowly, taking 200–300 ms to complete, but can be sustained longer (Cheal & Lyon, 1991; Muller & Rabbitt, 1989; Nakayama & Mackeben, 1989). Both exogenous and endogenous shifts appear to improve performance primarily by helping the observer filter distractors and other visual noise (Z. L. Lu & Dosher, 2000; Shiu & Pashler, 1995) but can also enhance perceptual quality (Barbot & Carrasco, 2017; S. Ling & Carrasco, 2006; T. Liu et al., 2009; Z.-L. Lu & Dosher, 2000). The speed and ease of exogenous attention movements mean that

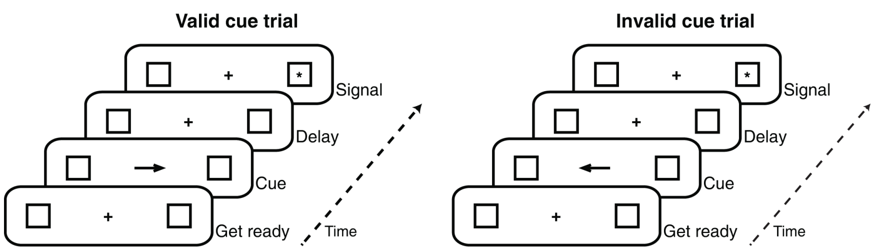

FIGURE 3.1 A sample trial from a Posner cuing task using a central cue. After a brief get-ready interval, a cue is presented to direct attention to one of two potential target locations. Here, the cue is an arrow that appears at the point of fixation. After a short delay, a target appears very briefly at one of the possible locations. On cue-valid trials, like that on the left, the target appears at the cued location. On cue-invalid trials, like that on the right, the target appears at the uncued location.

peripheral cues are likely to be more effective than central cues for alerting operators to critical information in their environment. A warning system that alerts drivers to roadway hazards using peripheral spatial cues, for example, is likely to produce faster and more accurate hazard detection than does a system using central cues presented on a dashboard display (Mahlke et al., 2007; Werneke & Vollrath, 2013). This is of course assuming that the peripheral cue is of sufficient salience to be noticed in peripheral vision, an issue addressed following, and in the next chapter.

Research since Jonides's early study has tried to determine exactly what combinations of stimulus properties and task constraints are needed to produce *attention capture*, an automatic shift of spatial attention to a given stimulus. The central question has been this: Is it ever possible for a visual stimulus to attract attention in a truly reflexive manner, independent of the observers' goals, strategies, and cognitive settings, or does the observer always exercise some control of spatial attention shifts? The debate has been drawn out and, thus far, inconclusive (Luck et al., 2021; Theeuwes, 2018), but it allows some simple generalizations to inform the design of visual alerts and alarms.

- First, and unsurprisingly, the more *salient* an object or event is, the more likely it is to grab attention. Here, salience refers to the visual distinctiveness of an object (Itti & Koch, 2000), or more colloquially, how strongly the item stands out amongst its surroundings (Nothdurft, 2006) based on its color, luminance, shape, and other visual properties. Critical visual signals should be made as salient as possible without obscuring other important information or causing unnecessary distraction or discomfort. Luminance changes caused by sudden motion (Abrams & Christ, 2003) or the abrupt appearance of an object out of nowhere (Hollingworth et al., 2010; Irwin et al., 2000; Yantis & Jonides, 1990) seem to be especially salient. Shape, or shape change conversely, is unlikely to be especially salient in the visual periphery given the poor level of resolution outside the central retina.
- Second, an object is more likely to draw attention if the operator is "tuned" to find it. An item that is not salient enough to attract notice quickly when the operator is not set for it might grab attention easily when the operator knows that it is task relevant (Folk et al., 1992; Yantis & Egeth, 1999).
- Third, even an object that is salient and known to be task relevant may fail to grab attention if the operator is already focused on or biased toward a different region of the display (Belopolsky & Theeuwes, 2010; Steelman et al., 2013; B. Wang & Theeuwes, 2018). Salience and attention set facilitate attention capture but don't guarantee it.

Evidence that the operator's state and control settings influence responses to exogenous cues blurs the line between voluntary and reflexive attention. Other findings likewise indicate that the boundary between voluntary and reflexive is fuzzy. For instance, familiar words such as "left" and "right," overlearned symbols such as arrows, and social cues such as a face in which the eyes are looking to one side have all been shown to prompt reflexive attentional orienting, even when they are presented as central cues (Gibson & Kingstone, 2006; Langton & Bruce, 1999; Ristic &

Kingstone, 2012). Moment-to-moment priming (Maljkovic & Nakayama, 1994) and other implicit motivation influences (Bourgeois et al., 2016) can also enhance the ability of a particular cue or cue feature to grab attention (Awh et al., 2012; Theeuwes, 2018).

3.6 AUDITORY AND CROSS-MODAL CUING

Although much research on attentional control has been conducted in the visual modality, researchers have adapted Posner's (1980, 2016) cuing task to explore auditory and tactile attentional processes. In a series of experiments by Spence and Driver (1994), for example, listeners were presented target sounds that could originate from either front or back, on either the left or right side. Their task was to judge as fast as possible whether the target came from the front or back. The target was preceded each trial by an auditory cue from either the left or right. In some experiments, the cue was unpredictive of the target location (i.e., the target was equally likely to appear on the cued and uncued sides), and in other cases, it predicted the target location with 75% validity. Front/back judgments were faster when the target came from the cued side than when it came from the uncued side, indicating that cues were useful for orienting auditory attention. Cuing effects were larger and longer lasting, moreover, when the cue was predictive. Thus, just as in vision, exogenous attentional cues were most effective when aided by endogenous processes. Interestingly, cues had no effect on the speed of auditory detection. The reason for this, the authors speculated, was that target detection did not require focused attention. This finding recommends auditory stimuli as alerts or alarms in applied settings, as we'll discuss more in what follows.

An additional characteristic that makes auditory alarms useful is that they summon not only auditory attention but also visual attention, that is, they are *cross-modal*. In fact, visual, auditory, and tactile attention are all spatially linked (Driver & Spence, 2004; Spence & Driver, 2004), allowing a cue in one modality to facilitate information processing for targets in a different modality. A sound that pulls auditory attention to a location will speed judgments of nearby visual targets (even without an eye movement), and a cue that directs visual attention to a given location will facilitate responses to nearby sounds (Spence & Driver, 1996). Spatial links are also seen between visual and tactile attention and between auditory and tactile attention (Lloyd et al., 2003; Spence, Pavani, et al., 2000). Bimodal cues, such as combined auditory/tactile alerts, appear to be uniquely effective at disengaging visual attention from ongoing processing. Multimodal cues are therefore likely to be especially useful for cuing visual attention under conditions of high visual workload (Santangelo et al., 2008; Santangelo & Spence, 2007; Spence & Santangelo, 2009). In flight tasks, for instance, responses to redundant auditory and visual displays are faster than either visual or auditory displays alone (S. A. Lu et al., 2012; S. L. Riggs et al., 2017).

Interestingly, cross-modal cuing effects do not always require that display channels in different modalities be physically coincident. What matters is the mental correspondence between locations. For example, an auditory or tactile cue from behind a driver speeds the detection of an impending rear collision more than a cue from the front, even if the only way for the driver to detect the collision is by checking the rearview mirror. This is true even if the attentional cues are purely exogenous. In other words, drivers' reflexive attention shifts recognize the spatial correspondence between the location of the nonvisual cue from behind and the visual information depicted in the rearview mirror (C. Ho et al., 2005; C. Ho & Spence, 2005).

Finally, although crossmodal attentional links can make alerts and alarms effective, they can also hinder human performance. Attentional foci in different modalities tend to hang together naturally, not just as a result of the observer's strategy. Thus, even when it might be beneficial to split auditory, visual, and tactile attention between spatially separated locations—either to monitor different multiple information channels (Driver et al., 1994) or to filter away an irrelevant stream in one modality (Spence, Ranson, et al., 2000; Spence & Walton, 2005)—people find it difficult to do so. For instance, drivers find it easier to shadow a stream of speech when it comes from a speaker directly in front of them, near the focus of visual attention, than when it comes from a speaker off to the side (Spence & Read, 2003).

Crossmodal attentional links carry implications for display design. When displays in different modalities present information that is to be compared or integrated—for example, when a speech stream provides directions to a driver whose vehicle is displayed on a dash-mounted electronic map or when an auditory alert is used to cue a pilot's visual attention to a display indicating a system error—display channels in the various modalities should be arranged near one another. Conversely, when an operator needs to focus on one channel while filtering away distracting information in another channel, the target channel should be spatially separated from the distractors channel even if the channels are all in different perceptual modalities. (These recommendations foreshadow another design guideline, the proximity compatibility principle, to be discussed in Chapter 6.)

Further implications of attentional control for display are discussed in the next section.

3.7 ALARMS AND ATTENTION GUIDANCE

Designers have used knowledge of attention control to create displays that capture and then direct attention in real-world systems. Of course, advertisers have long known about many of these strategies, taking advantage of them to draw attention toward products on shelves, billboards on roadsides, and pop-up ads on Web pages. The following sections discuss two sorts of applications: spatial cuing systems and alarms and alerts (Pritchett, 2017; Stanton, 1994; Wogalter et al., 2021). Both have the goal of capturing attention, often in a busy multitask environment, though they differ in that alarms and alerts tend to direct attention implicitly (e.g., the fire alarm will lead a person to attend to sounds or smells in the hallway), whereas spatial cuing systems, by definition, do so explicitly. Both are forms of automation in which a computer system decides that the human should be aware of something. As such, both have the potential to mislead the human operator if the inferences that the automated agent makes about what should be attended are wrong. In the language of signal detection theory, the errors may be of two different types: (1) false alarms, directing attention to a problem that does not exist (Breznitz, 1984) or (2) misses, failing to direct attention to a critical object or event.

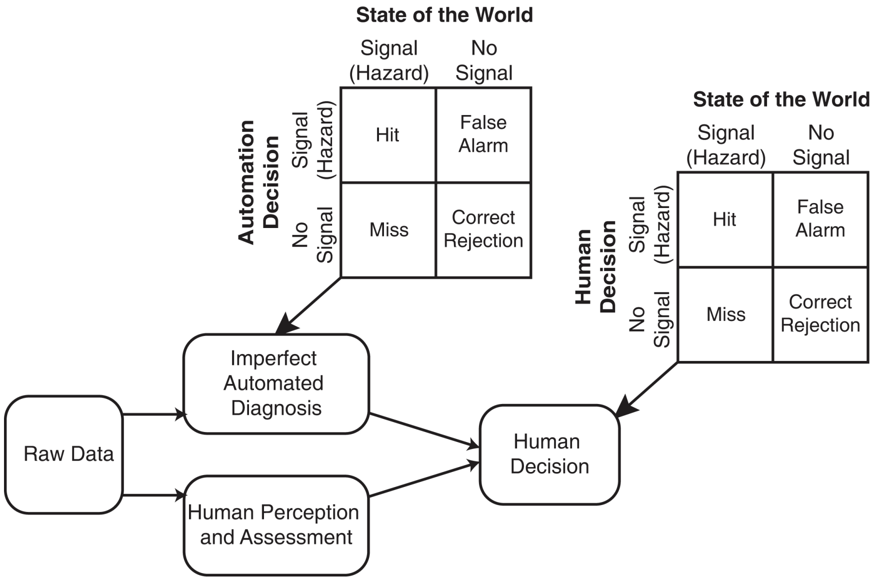

FIGURE 3.2 Parallel human and automation alerting system. The classic signal detection theory matrix is shown in the insets at the top, representing performance of the automated alert system alone and of the human relying on both the automated system and direct perception of the raw data.

Figure 3.2 provides a framework for understanding these systems. Here, the automated detector and the human operator both monitor raw data for events of interest, typically hazards (Getty et al., 1995; Parasuraman, 1987; Sorkin & Woods, 1985). Judgments from the automated detector are passed to the human, who can use them to improve his or her own decisions. Decisions can be represented within the 2×2 signal detection theory matrix, shown at the top of the figure. Along one axis, we represent the true state of the world, signal present or signal absent. Along the orthogonal axis, we represent the decision-maker's response, again, signal present or absent. Crossing the two potential states of the world with the two potential responses produces four possible outcomes of each decision: hit (true positive), miss (false negative), false alarm (false positive), and correct rejection (true negative). Over trials, the data in the matrix can be distilled to produce two different measures of detector performance: (1) sensitivity, commonly measured by the statistic *d'* (pronounced "d prime"), which represents how good the detector is at distinguishing signal from noise events and is closely related to overall accuracy rate, and (2) bias, commonly measured by the statistic *beta*, which reflects the decision-maker's tendency to err in the direction of false positive or false negative responses (Hautus et al., 2022; Wickens et al., 2022).

In the following, we discuss research bearing on five key factors that influence the effectiveness of such systems in appropriately capturing and guiding attention: (1) physical salience, (2) automation reliability, (3) detection task difficulty, (4) the nature of automation errors, and (5) base-rate effects. Although most of our discussion focuses on alarms or alerts, the general principles apply equally to other kinds of attention cuing systems.

3.8 ALERT SALIENCE

Consideration of the fundamental properties of the human senses (Proctor & Proctor, 2021) makes it apparent that auditory stimuli will be the most reliable attention grabbers for alarm systems. This is because the detection of auditory events is omnidirectional; a sound is about equally salient no matter how the head is oriented. This obviously is not the case with visual event detection, as visual stimulus perceptibility falls off rapidly with distance from the fovea, and visual events tend to be invisible at angles beyond around 90 degrees (Mckee & Nakayama, 1984; Wickens, Sebok, et al., 2016a, b). Tactile alerts also appear to grab attention efficiently (S. A. Lu et al., 2013; S. L. Riggs et al., 2017; Sarter, 2007; Sklar & Sarter, 1999; Van Erp, 2007).

The characteristics that make auditory stimuli effective in alerting can also make them intrusive, however. An unexpected auditory alert may well interrupt ongoing tasks that are of even higher priority (C. Ho et al., 2005; Wickens & Colcombe, 2007b), a phenomenon known as *auditory preemption* (see also Chapters 8 and 9). For this reason, designers often prefer visual to auditory alerts, particularly for events that are not safety critical (Latorella, 1996). With this in mind, aviation display designers have explicitly divided alerts into the three categories, warnings (most urgent), cautions (less urgent), and advisories (least urgent), and have stipulated that only warnings should have an auditory component (Wickens, Sebok, Walters et al., 2016b).

A lesson derived from basic research on attention capture is that onsets tend to capture attention. Hence, flashing or blinking signals will generally make effective visual alarms, because the flashing entails repeated onsets, any of which may eventually be noticed as the eyes are busy scanning the environment (Wickens & Rose, 2001). A second generalization is that unique colors can be effective as alarms and alerts (e.g., a red light in a swarm of green). However, the ability of a color change to capture attention might be reduced if nearby stimuli are also color-coded. As discussed in Chapter 5, the salience of a colored item is decreased by background stimuli of mixed colors.

The most severe limitation on generalizability of the conclusions from basic attention capture research is the fact that in most operational environments, the visual space that the operator is required to monitor is much bigger than the typical computer screen used by the basic attention researcher—where, for example, onsets are sometimes taken to capture attention almost without fail (Yantis, 1993). Within a large visual workspace, onsets won't always capture attention. An example here is the failure of the onset of a green box in an automated aircraft to make the pilot aware of a change in automation mode (Nikolic et al., 2004; Sarter et al., 2007).

Because important alerts are typically auditory, effort has been made to determine the parameters of sound that convey different levels of urgency (Edworthy et al., 1991; D. C. Marshall et al., 2007; Wickens, Sebok et al., 2016b). However, caution must be taken, because increasing urgency may also lead to increasing listener annoyance—a real problem if false alarms are common, as is discussed in the following sections.

One final concern when designing visual alerts for attention guidance or spatial cuing is the possibility that highly salient exogenous cues may mask the raw data beneath them. For example, consider the soldier whose attention is cued by the onset of a box surrounding the location of a potential enemy target (Maltz & Shinar, 2003; Neyedli et al., 2011; Yeh et al., 2003, 1999). If the raw stimulus information (i.e., the image of the enemy target) is faint or noisy, the soldier may not be able to easily discern whether an object is actually present behind the visual cue or, worse yet, whether the cued object is actually an enemy. If the automation is always correct in designating location and identity of bad guys, then this perceptual challenge will be irrelevant. But if the automation is less than perfectly reliable in its classification, the consequences of degrading the view of the raw data image because of a cuing overlay can be severe (see also Chapter 6). The concern of masking can be addressed by using an arrow adjacent to and pointing toward the target rather than a shape surrounding the target object, in other words, taking advantage of endogenous orienting (Wickens & Rose, 2001). This leads to the second important feature of attention-guiding automation: its reliability or accuracy.

3.9 ALERT RELIABILITY

When alert systems are asked to detect or predict dangerous events (e.g., midair collisions, hurricane tracks intersecting a city) in a world that is inherently probabilistic, they will sometimes be wrong, driving their reliability below 100%. In particular, with predictive alert systems, the longer the look-ahead time or span of prediction, the lower the system's predictive reliability will be (Thomas & Rantanen, 2006). Automation reliability, mimicking the concept of cue validity discussed already (Posner et al., 1980), will affect overall system performance along with two related but distinct attributes of user cognition and behavior: trust and dependence (Hoff & Bashir, 2015; Lee & Moray, 1994; Lee & See, 2004; Parasuraman & Riley, 1997). Trust is the subjective belief that automation will perform as expected. Dependence, correlated with trust, is the actual behavioral tendency of the human to do what automation prescribes (e.g., look where the automation says to look or evacuate the building when the fire alarm says to). Generally, both of these measures drop as automation reliability declines. However, it is easy to envision systems in which trust is low (i.e., the human expects automation to make errors) but dependence remains high, either because (1) the automation, though imperfect, is adequate, or (2) the human operator's workload is high, and attentional resources are needed for nonautomated tasks. Attentional implications from imperfect automation are multifaceted (Parasuraman & Manzey, 2010), but here we focus mainly on the influence on behavioral dependence, rather than trust.

Figure 3.2 presented a schematic depiction of the human–automation "team" (Getty et al., 1995; Parasuraman, 1987). Within the bottom half of the figure, we can consider the detection performance of the team as a function of the reliability of the automation. Not surprisingly, overall team sensitivity improves when the automation is more reliable. This improvement reflects both the fact that the aid is making more correct decisions and the fact that because the aid is more reliable, the user is more willing to depend on it (Bartlett & McCarley, 2020). However, human automation team performance is rarely optimal and is often poorer than the automation could achieve by itself (Bartlett & McCarley, 2020, 2017; Boskemper et al., 2021; Huegli et al., 2020; Xu et al., 2007).

In a meta-analysis of such studies of parallel automation and human judgments, Wickens and Dixon (2007) found that when automation reliability is above around 80%, the human–automation team tends to perform better than the human alone, a finding replicated in a second meta-analysis by Rein et al. (2013). However, when automation reliability drops below around 70%, the human can continue to depend on it even when his or her own unaided performance is superior. Wickens and Dixon analogized automation in such circumstances to a "concrete life preserver": the human would be better off letting go of the automation rather than clinging to it and sinking with it. For example, researchers have found that physicians depending on automated devices to detect tumors on mammograms do no better—and in some respects worse—than physicians without such aids (Alberdi et al., 2004; Fenton et al., 2007) (though see Bartlett & McCarley, 2020, for evidence that users do not always continue to depend on unreliable aids). In their meta-analysis, Wickens and Dixon (2007) also observed that automation dependence, no matter the aid's reliability, is greater under dual-task than under single-task conditions, indicating a rational strategy of the operators to offload some of the monitoring responsibility to the automated agent when concurrent tasks are demanding, or of high priority.

3.10 LEVEL OF UNAIDED HUMAN PERFORMANCE: DISCRIMINATION DIFFICULTY

Performance of the human–automation team also depends to some extent upon the level of unaided human performance. We might envision that as the task becomes easy, human operators become more confident in their own ability and therefore more likely to reject an aid's advice, even when it might be useful. More formally, the mathematics of signal detection theory stipulate that to reach optimal performance, the operator should rely on the aid more when the task is difficult than when it is easy (Boskemper et al., 2021; Lynn & Barrett, 2014; Sorkin & Dai, 1994).

Empirical data present a mixed picture, however. An experiment (Tikhomirov et al., in preparation) comparing automation use in easy and difficult signal detection tasks found that participants depended more heavily on the aid's judgments in the difficult task, as expected. Relative to optimal levels, however, automation dependence was lower in the difficult task than in the easy task. In other words, when the unaided task was difficult, participants undershot the optimal dependence level by a larger amount. This effect is consistent with the more general *sluggish beta effect* (Healy & Kubovy, 1978; Wickens, Helton, et al., 2022), the tendency for decision-makers in a signal detection task to adopt a response bias that is less extreme than optimal.

Figure 3.3 presents an integration of the joint effects of aid and human sensitivity on human–automation team efficiency (Tanner & Birdsall, 1958) in a signal detection task, gathered from a series of experiments by Bartlett and colleagues (Bartlett & McCarley, 2020, 2017; Boskemper et al., 2021; Tikhomirov et al., in

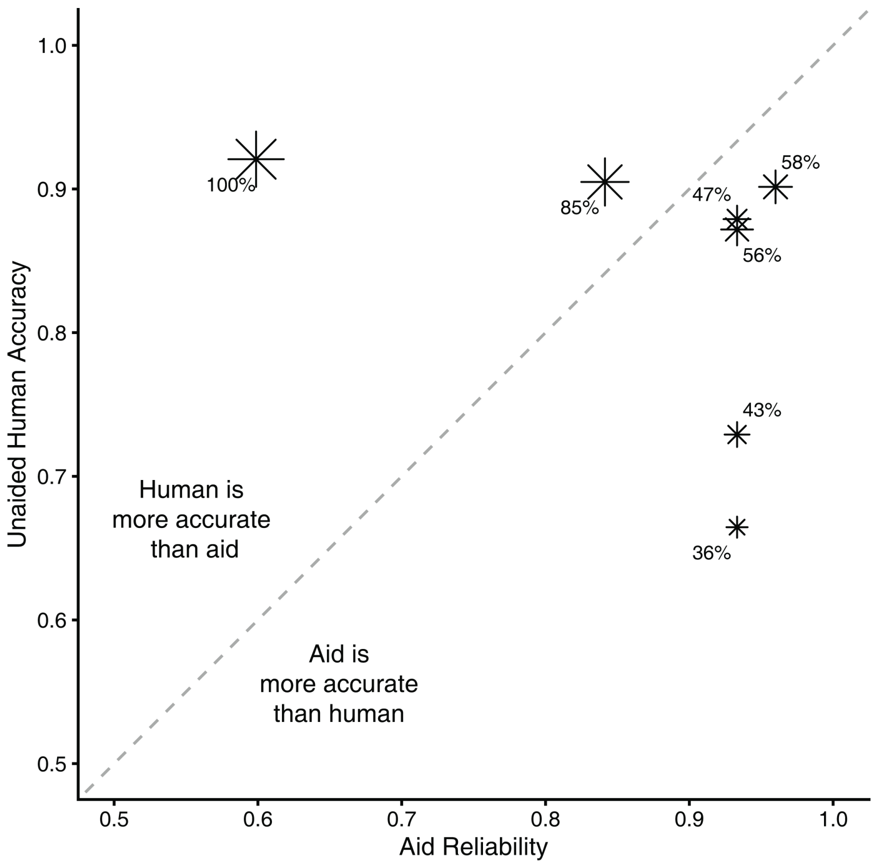

FIGURE 3.3 The performance of human–automation teams in signal detection tasks plotted as a function of the aid's reliability and the unaided human operator's accuracy. The dependent measure, encoded in the size of each data point and by the attached text labels, is efficiency (Tanner & Birdsall, 1958). Efficiency less than 1 indicates suboptimal human–automation team performance. Data suggest that as unaided performance becomes more difficult or the aid becomes more reliable, aided performance falls farther from best-possible levels (Bartlett & McCarley, 2020, 2017; Boskemper et al., 2021; Tikhomirov et al., in preparation).

preparation). Here, efficiency is a measure of observed team sensitivity relative to the optimal level. An efficiency score of 1 indicates that the human–automation team has achieved statistically optimal performance. Values less than 1 indicate that the human–automation team is performing below best-possible levels. Data are presented as a function of the aid's reliability and the unaided human's accuracy, both ranging from chance-level performance (0.5) to perfect (1.0). The data show that efficiency is highest when the aid is least reliable, that is, when the operator's ideal strategy is to not depend much on the aid. Conversely, efficiency is lowest when the unaided task is most difficult. Both of these effects imply a tendency toward automation disuse (Parasuraman & Riley, 1997). While the data plotted are for detection tasks, this representation could be extended to automation-assisted recognition tasks and diagnosis as well.

3.11 THE NATURE OF AUTOMATION ERRORS: MISSES VERSUS FALSE ALERTS

As the SDT matrix in Figure 3.2 makes clear, and as we discussed briefly, two different forms of errors are possible in a detection task: misses and false alarms. In designing and implementing alerting systems, the designer can influence the relative frequency of the two types of automation errors by adjusting the alert threshold. This allows a range of system behaviors from false alarm–prone to miss-prone (Dixon & Wickens, 2006). Observations by Bliss (2003) confirm that both types of errors exist in aviation alerting systems, although false alerts are somewhat more prevalent.

Although both categories of errors are undesirable, there is evidence that the two forms of "error-proneness" induce qualitatively different forms of behavior from the human in the human-automation team (Dixon & Wickens, 2006; J. Meyer, 2004; J. Meyer & Lee, 2013; Parasuraman & Wickens, 2008). Miss-prone alerting systems require the human to more carefully monitor the raw data that automation is processing, without relying as heavily on the automation to detect critical events. As a consequence, less attention is available to perform concurrent tasks (Dixon et al., 2007; Dixon & Wickens, 2006; Wickens et al., 2010). In contrast, FA-prone automation has two linked negative influences. First, false alarms will induce frequent and unnecessary interruptions to the operator's concurrent tasks (see Chapter 9). Second, as false alarms become more annoying, the human may begin to ignore all alarms—the so-called "cry-wolf effect" (Sorkin, 1988)—or even disable the alerting device entirely, to the obvious detriment of safety.

Since the designer has some discretion in setting the alert threshold and thereby the bias of the system toward either misses or false alarms, the question has arisen as to which type of error is worse. The answer is not clear-cut, as it obviously depends, in part, on the consequences of a total system miss, in which both the human and automation fail to detect an event in time to avoid some disastrous consequence. However, there is some evidence that, all things being equal, a false-alarm prone system may have more consequential effects (Dixon et al., 2007; Rice & McCarley, 2011; but see Bartlett & McCarley, 2018). This is in part because FAs will eventually produce a cry-wolf syndrome, and in part because frequent FAs, in the time before the operator has come to ignore them, will divert attention from concurrent tasks.

But it is important also to consider some circumstances in which false alarms can be beneficial. In air traffic control, the conflict alerting system commits a relatively large number of false alerts (between 15% and 40% depending on the airport ATC facility: Wickens, Rice, et al., 2009), meaning that the controller is often alerted to a pending loss of separation between a pair of aircraft that will resolve itself even with no intervention from the controller. The prevalence of such false alerts does not appear to contribute to a cry-wolf effect but instead tends to provide feedback to the controller's own perception that the aircraft in question merit careful monitoring. Such feedback can be viewed positively as a reinforcement of the controller's own judgment.

3.12 BASE-RATE EFFECTS

The frequency of alert false alarms, and therefore the choice of the designer's threshold setting, depends in large part on the base-rate or frequency of the dangerous events to be detected (Parasuraman et al., 1997). As an example, in air traffic control, the base rate of two planes on a direct collision course is much lower than that of two planes approaching a less severe conflict (e.g., predicted to pass within 2 miles of each other). As another example, the base rate of tumors to be detected in radiology for a young healthy individual is likely to be far less than that of a patient who has been referred on the basis of other symptoms and a family history. When the base rate is low, and the designer also needs to keep the miss rate low (i.e., when the cost of a miss, like letting a weapon slip through the TSA inspection station, is severe), it becomes necessary for the designer to set a low alert threshold, creating a false alarm–prone system. Indeed, the nature of this FA-proneness can be graphically expressed by another parameter coming out of the SDT matrix, the *positive predictive value (PPV)* (Ferreira et al., 2020; Getty et al., 1995; Sanquist et al., 2008). This is the probability that an alert, when triggered, is actually a hit and not a false alarm, i.e.,

$$PPV = \frac{\text{Number of true alerts}}{\text{Number of true alerts} + \text{number of false alerts}}.$$

When true signal events are infrequent and the alert threshold is low, the PPV can be extremely low (Getty et al., 1995; e.g., Parasuraman et al., 1997; Sanquist et al., 2008), meaning that the vast majority of alerts are false. For example, some tornado warning systems have been observed to have false alarm rates of more than 75%.

It should be noted in closing that our focus has been mostly on attention alerting—that is, simply notifying the operator that something is wrong—more than on spatial attention cuing, that is, telling the operator where to look. Many of the same findings on human and system reliability appear to apply in both cases. However, they differ in one key respect: attention cuing systems can actually produce two different kinds of "misses": failing to direct attention at all and directing attention to the wrong location. Though an accurate spatial cue directing attention to a critical signal is more helpful than a general, non-spatial alert (Wiegmann et al., 2006), an inaccurate spatial cue may be particularly pernicious, as it can direct attention away from a true target (Yeh et al., 2003).

3.13 SOLUTIONS

The most obvious solution to the human performance costs of imperfect alerting automation is to increase the automation's reliability. Though this often entails a purely engineering solution (i.e., designing better sensors and algorithms), one human-factors approach that can sometimes be taken is to reduce the look-ahead time of predictive automation such as that used to forecast events or collision warnings. Of course, the look-ahead time should be no shorter than the time necessary for the human to respond appropriately to the alerted state. For example, it would be pointless to adopt a look-ahead time of 5 seconds for a pilot collision warning. The automation's judgments would be highly reliable but would leave far too little time for the pilot to avoid the impending collision (Thomas & Rantanen, 2006).

A second potential solution is to adopt *likelihood alarms*, alerting systems that report their own degree of uncertainty in classifying events as signal or noise (Sorkin & Woods, 1985; Xu et al., 2007). However, the operational success of this approach in a dual-task context remains ambiguous (Sorkin et al., 1988; St. John & Manes, 2002; Wickens & Colcombe, 2007a; Wickens & Colcombe, 2007b; Zirk et al., 2019). A third approach is based on the concept of *preattentive referencing* (Woods, 1995). Here, the human is given access to continuous information about the evolving state of the alert domain (e.g., the raw data), often in non-focal sensory channels such as peripheral visual displays or ambient sonification, which might be used, for example, to display the continuous sound of a heartbeat in an intensive-care monitoring workstation (M. Watson & Sanderson, 2004). Finally, solutions in training can be suggested, typically in training attention allocation to be calibrated with actual system reliability. This would also include training the alarm users to understand the inevitable trade-off between misses and false alarms, helping them to better tolerate the high false alarm rate that must be expected when low-base-rate events are coupled with imperfect diagnostic automation.

3.14 CONCLUSION

This chapter has discussed properties of events that capture or grab attention, in laboratory-based tasks and in the real world, where alarms were the most important application. However, other forms of cuing devices, such as highlighting, can be equally relevant to basic research on cuing. In both the theoretical and applied environments, the reliability with which the cue alerts the operator to a meaningful target or event proves to be a critical concept.

We also discussed the characteristics of events and observers that portend failures to capture attention. In both successes and failures of attention capture, this chapter's focus was on environmental properties and hence on factors that guide attention in a so-called bottom-up, event-driven fashion. Yet we know also that we can exert choice over where to attend and often can override the bottom-up effects of salience using top-down or knowledge-driven processes. The next chapter integrates various factors responsible for guiding our selection, whether bottom-up or top-down, and emphasizes the very prominent role of visual scanning in selective attention.

4 Visual Attention, Scanning, and Information Sampling

The previous chapter, drawing in part from basic laboratory research, explained that attention is controlled by a combination of top-down and bottom-up processes. The current chapter focuses nearly exclusively on visual attention, and more specifically, on overt visual attention, i.e., eye movements. In real-world environments, how does the human operator decide where to sample for visual information? In thinking about movements of overt visual attention around the environment, we first analogize the traveling focus of attention to our own travel around a geographical environment, then describe eye movement measures, and then introduce a computational model of visual scanning. We conclude by briefly describing applications to predicting noticing and to expertise.

4.1 SOURCES OF ATTENTION MOTIVATION

Thinking about why we might decide to travel somewhere—whether meandering about the rooms in our home, driving around town, taking a vacation, or visiting a website—a number of potential influences on our choice of a destination come to mind.

1. We might go someplace out of habit (e.g., wandering into the kitchen every morning when you get up).
2. We might go someplace because something there grabbed our attention (e.g., checking in on the room next door because you heard a loud noise from there).
3. We might go someplace because a lot generally happens there and we therefore expect to get new information upon our visit (e.g., visiting a local hangout because we know other people convene there frequently to share gossip).
4. We might go someplace because we need to retrieve something relevant to a task we are working on (e.g., logging into the university library to download an article we need to read).
5. We might go someplace simply because it has intrinsic value to us (e.g., visiting the mountains to clear our head).
6. As we move from place to place, finally, we might plan our path of travel by considering efficiency and economy, grouping errands by location so we can avoid unnecessary multiple trips from home—later in the chapter, this

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is referred to as the *in-the-neighborhood* effect. This tendency to avoid the costs of long travel will probably be amplified to the extent that the travel is difficult or costly (e.g., because our car does not run well, traffic is heavy, gas is expensive, or, if we are on foot, because we are carrying a heavy load).

As this list suggests, we can think of an individual traveling somewhere as guided by multiple influences that combine in ways we might not fully understand. A corresponding analysis can be made of the forces that direct movements of visual attention as an operator tries to maintain awareness within a dynamic, evolving environment (Wickens, McCarley et al., 2008). Here, we can parse the influence of the various factors listed in Table 4.1 on eye and head movements in a way that corresponds to the analysis of the aforementioned factors' influence on physical travel.

Although it is sometimes important in theoretical research to isolate covert from overt attention, basic and applied researchers agree that eye movements generally provide a reliable indicator of attention allocation (Just & Carpenter, 1984; Moray, 1993). The correlation between where an operator has looked and what the operator has noticed is imperfect, as demonstrated, for example, by the phenomenon of inattentional blindness, discussed in the last chapter. But in contexts such as the airplane cockpit (Fitts et al., 1950), the driver's seat (Horrey et al., 2006; Mourant & Rockwell, 1972), the computer workstation (Fleetwood & Byrne, 2006), and the kitchen (Land et al., 1999; Land & Hayhoe, 2001), the operator's oculomotor scan path is a pretty good record of what has been attended when.

We also note that eye movements in the service of information sampling are often coupled with or assisted by other motor activities. For attention shifts that travel longer than roughly 20 degrees of visual angle, eye movements are coupled with head movements (Kim et al., 2010; Murata & Kohno, 2018). For even longer shifts, body movements might be necessary to access a critical information source, as when we walk across the room to pull a book from the shelf. With computer interfaces, we often use manual interactions such as mouse movements or keystrokes to reveal hidden information. We can characterize the actions needed to access visual information based on the physical effort they require, with eye movements being the easiest and fastest to execute and large-scale body movements requiring the most effort.

TABLE 4.1
Sources of Influence on Visual Information Sampling.

Source
(1) Habit (procedural scanning)
(2) Attention capture by salience
(3) Information content: Event rate or bandwidth
(4) Information content: Contextual relevance
(5) Information value
(6) Effort conservation

4.2 EYE MOVEMENT MEASURES

Oculomotor behavior in an operational environment can be characterized by a variety of measures. Some of the most common and important are as follows.

An *area of interest (AOI)* is simply an area of the scene within which all individual fixations are considered by the analyst to be functionally equivalent. In applied contexts, an AOI might be a particular display channel (e.g., the speedometer or an electronic dashboard map), a collection of channels (e.g., the entire dashboard), or potentially a large region of space (e.g., the outside world viewed through the windshield). Decisions about how to define AOIs depend on the precision required for the analyst's purposes.

A single pause of the eye, usually lasting about 1/5 to 1/3 of a second (Rayner, 2009), constitutes a fixation. A *dwell*, *glance*, or *gaze* is a series of one or more consecutive fixations within the same AOI. The *dwell* or *gaze duration* is the total consecutive time that the eyes remain within the AOI before moving to the next one. The *mean dwell duration* is the dwell time averaged over multiple visits to the AOI. *Percentage dwell time (PDT)* in an AOI is the total time that the eyes spend within the AOI, summed over multiple gazes, divided by the total time in all AOIs. PDT in a given AOI can be thought of as a measure of the overall degree of attentional interest in that AOI over some task-defined period of time (e.g., while passing another vehicle).

Event fixation latency is the latency between the occurrence of a discrete event and the first fixation into the AOI where the event occurred. For example, event fixation latency might be the time between the occurrence of an out-of-tolerance reading on an instrument and the operator's next fixation on the instrument. It may be thought of as a measure of noticing time. The probability of noticing an event is expressed as the ratio of event-driven glances to a given AOI to the total number of such events occurring within the AOI. For instance, if half of the events within an AOI are followed within a criterion amount of time by a fixation in the AOI, then the probability of noticing the events is estimated to be 50%. Such a calculation assumes, of course, that a fixation results in actual noticing, and hence does not account for inattentional blindness, discussed in the previous chapter.

Given a set of N AOIs, an $N \times N$ *transition matrix* reports the probabilities of the eyes moving between particular pairs of AOIs. Figure 4.1 gives an example for an environment with three AOIs. Here, the cell in row i, column j contains the conditional probability of the operator's fixation moving to AOI j given that fixation is currently in AOI i. The transition matrix thus encodes a first-order Markov process. Variations in probability from the top to the bottom of a column indicate *sequential dependencies* in the operator's scan pattern, in other words, they signal that choices about which AOI to fixate next depend on the location of the current fixation. An entry along the negative diagonal represents the probability of consecutive fixations within the same AOI. Repeated fixations within an AOI yield a long dwell. The sum of probabilities within each column can provide a general measure of attentional attractiveness within each AOI. In Figure 4.1, AOI C is least attractive.

The *mean first passage time (MFPT)* is the average length of time that the eye stays away from a given AOI before it returns (Moray, 1986). Thus, it can be used to characterize a period of visual *attentional neglect* during which time the operator

Transition to AOI:

Transition from AOI:	A	B	C
A	0.20	0.40	0.40
B	0.67	0.33	0.00
C	0.33	0.33	0.33

FIGURE 4.1 A transition matrix of hypothetical data showing sequential dependencies in scanning.

will be vulnerable to missing critical events that occur within the AOI in question; consider, for example, how the MFPT for roadway scanning can determine the hazard risk of collisions in driving (Horrey & Wickens, 2007; Wickens & Horrey, 2009).

4.3 LIMITS OF VISUAL SCANNING AS A MEASURE OF ATTENTION

Of course, the visual scanning measures noted have some limitations in their ability to index the allocation of central attention.

1. They do not reveal changes in attention allocation within an AOI, nor do they detect digressions of covert attentional focus from the point of oculomotor regard. Similarly, they do not reveal which attribute of a fixated object the observer is processing (e.g., the color versus shape of a map symbol, the bank versus pitch of an aircraft attitude indicator, or the emotional tone versus the identity of a face).
2. They cannot easily discriminate between the allocation of attention to a visual source versus a nonvisual (e.g., auditory, tactile, or cognitive) source unless the eyes are closed. If the eyes are open, they must be fixated somewhere within the visual environment, even if attention is disengaged from the incoming visual information. A fixation might reflect a blank stare, with no comprehension of the visual environment.
3. They cannot gauge the processing of peripheral visual information. This issue is particularly important in ground or air vehicle control, given the large amount of relevant information that can be extracted from peripheral motion fields (Horrey et al., 2006) or other global characteristics such as the attitude of the true horizon while flying in an aircraft.
4. Long values of gaze or dwell duration are inherently ambiguous. They could signal the high difficulty of extracting data from a given AOI (e.g., a blurred word or small text), or they could signal extracting a lot of information from an information-rich source (e.g., looking at a clear but detailed section of satellite imagery).

In spite of these limitations, there are environments in which eye movement data can provide detailed insights into the operator's selective attention and information seeking. These are environments that are heavily visual, within which AOIs are well-defined and can be considered sources of dynamic information. Environments that can be characterized this way include, for example, the airplane cockpit and the unmanned vehicle control station.

4.4 INFLUENCES ON VISUAL INFORMATION ACCESS

We turn now to a description of each of the six sources of influence on visual information sampling identified in Table 4.1, describing each in isolation before discussing efforts to model their combined influences.

4.4.1 Habit

Certain aspects of visual scanning behavior are controlled by what appears to be habit. Thus, the tendency in most Western cultures to visually search fields from top to bottom and left to right appears to relate to reading habits. For a pilot, the standard hub-and-spoke pattern of instrument scanning is taught and practiced, and, hence, becomes a form of habitual information acquisition (Bellenkes et al., 1997).

4.4.2 Salience

As discussed in Chapter 3, attention capture has been the focus of much basic research. In operational settings and applied research, the concern is on understanding the characteristics that might be manipulated to override the other five influences on sampling behavior presented in Table 4.1. Note that event fixation latency is a good way of quantifying attention capture in an operational environment.

Chapter 3 briefly discussed a real-world study that illustrated the failures of relatively salient events to capture attention. The experiment was carried out in the glass cockpit of a Boeing 747–400 simulator, using 17 highly trained commercial pilots (Sarter et al., 2007). The goal was to understand how these scanning strategies differed from those in the conventional cockpit and, in particular, to gain insight into the symptoms of the mode awareness problem in the glass cockpit, whereby pilots are often surprised by or unaware of changes in the mode of operation of the flight management system (FMS). Figure 4.2 presents a schematic FMS. Changes in the current mode of operation are indicated by the onset of a green box surrounding the critical flight mode annunciator on the instrument panel. Analysis found that the latency between onset of the green box and next fixation on the relevant flight mode annunciator was long, measuring several seconds, and that 40% of the time, the operator failed to look at the annunciator at all. This finding demonstrates insensitivity toward a stimulus that might otherwise have been predicted, from extrapolating basic research, to capture attention quickly (Yantis, 1993).

4.4.3 Information Content: Bandwidth

If a channel, operationally defined here as an AOI, has a high event rate, the operator will tend to sample it more frequently than if its event rate is lower (Carbonell et al.,

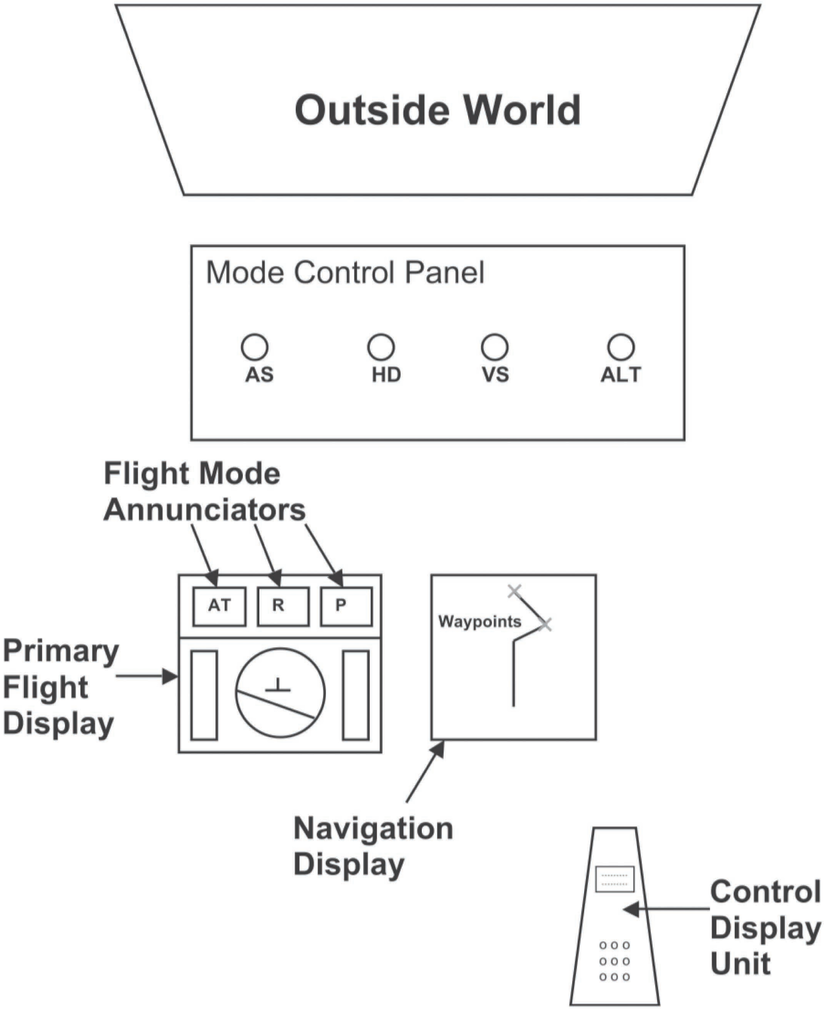

FIGURE 4.2 Schematic illustration of a flight management system. The flight mode annunciators are small green boxes located on the left panel.

1968). If the amount of information at an AOI can be specified in the language of information theory (i.e., in bits), then the bandwidth of the AOI is

$$(bits / event) \times (events / second) = bandwidth(bits / second).$$

In practice, if informative events occur frequently on an AOI, the bandwidth will often be simply expressed as events per second. In a driving scenario, for instance, the bandwidth for the AOI defined by the tail end of the car in front of the operator might be the average number of times per second that the brake lights illuminate (Horrey & Wickens, 2007).

In a series of classic studies, Senders (Carbonell et al., 1968; Senders, 1964, 1983) asked participants to monitor banks of display channels with moving pointers, watching for occasional readings outside of a nominal range. Pointer movements differed in bandwidth across channels. Data revealed that channels were sampled with a frequency proportional to their bandwidth (see Eisma et al., 2020, for a large-scale replication and extension). Thus, AOIs with a high rate of information flow were sampled proportionately more than those with a low rate of information flow. This general finding has been replicated in tasks demanding manual information access, such as opening windows on a computer desktop (Bitan & Meyer, 2007; Wickens & Seidler, 1997). Examination of pilot instrument scanning reveals that the attitude indicator, which shows the pitch and roll of the aircraft, is the instrument that changes most frequently given the dynamics of the aircraft and is also the instrument scanned most frequently (Bellenkes et al., 1997).

Ideally, the operator's sampling behavior will reflect accurate estimates of AOI bandwidths. As discussed in what follows, however, operators' subjective estimates of signal probability across AOIs often differ from objective AOI bandwidths, leading to sampling failures.

4.4.4 Information Content: Context

As just described, operators will tend to sample high-bandwidth channels more often than low-bandwidth channels. However, the probability of sampling a low-bandwidth channel may increase if contextual cues suggest that information is now available there. This purpose is often served by auditory alarms. For example, the sound of a pulse oxygen alarm in the surgical theater will likely direct the anesthesiologist's visual attention to the pulse-oxygen meter; an engine warning alarm in the cockpit will likely lead the pilot's visual attention to the engine instruments; and the ping of a text message arrival is likely to divert the computer user's visual attention to the chat box. Contextual information that momentarily prioritizes an AOI can also come from a prior visual dwell on another AOI. For example, an indication of an oncoming aircraft on a cockpit traffic display should direct the pilot's visual attention to the outside world (Helleberg & Wickens, 2003; Wickens, Goh, et al., 2003). Such contextual dependence will lead to transient sequential dependencies in the statistical analysis of eye movements as represented in Figure 4.1 (Ellis & Stark, 1986).

Both bandwidth and context, influences 3 and 4 from Table 4.1, can then be grouped under the higher-level category of expectancy, since both describe the operator's expectation of obtaining information from a channel. Bandwidth determines the overall frequency of sampling a single AOI based on its information throughput rate, whereas contextual relevance influences the probability of transitioning between two particular AOIs within a given time window, either because one AOI establishes context that makes the other one momentarily relevant or because both AOIs are temporarily related to the same task.

4.4.5 Information Value

The expected value of sampling an AOI is the product of the probability of finding information there and the value of the information to be found. As we might therefore expect, an information channel that conveys important or useful information will tend to be sampled more frequently than a channel that conveys less valuable information, even if the bandwidth of the two AOIs is the same. Here, value can be conceptualized in two different but related ways, (1) as the formal value of information, measured in bits or (2) as the subjective value, or *utility*, of the information. We use the latter meaning. In a multitasking scenario, the value of an AOI can be estimated as the perceived relevance of the AOI to a given task times the perceived importance of the task, summed across tasks (Wickens, Goh et al., 2003).

To provide an example of the critical distinction between value and bandwidth, for the motorist driving at night, the roadsides in the forward view may be of low bandwidth—visibility is poor, and roadside hazards are rare in any case. However, the negative value of failing to notice the rare hazard event, when it does occur, should keep the frequency of roadside scanning high.

Though Senders (1964) did not directly look at value in his early scanning experiments, Sheridan (1970) and Carbonell et al. (1968) incorporated both expectancy/information bandwidth and information value or utility into normative models of how often a supervisor should sample. Combining expectancy and value in this manner produces behavior driven by expected value, consistent with classic models of decision-making (Wickens, Goh, et al., 2003; Wickens, McCarley et al., 2008). Several investigators have examined divergences between actual and ideal mental models as reflected in information sampling patterns (e.g., Bellenkes et al., 1997; Fisher & Pollatsek, 2007; Pollatsek, Fisher, et al., 2006). Studies of driver attention, for instance, have found that drivers often fail to notice hazards such as pedestrians or bicyclists—high-value events—when they appear in unexpected locations (Theeuwes, 1996; Theeuwes & Hagenzieker, 1993). We'll return to the topic of scanning in driving in Chapter 11.

4.4.6 Information Access Effort

The physical design of the operator's visual environment can shape the operator's scanning. Characteristics that influence sampling efficiency include the visual angle separating information channels, the depth separation between the channels, the density of clutter embedding task-relevant information (Wickens, 1993), and the complexity of manual or vocal interactivity needed to access a channel (i.e., keyboarding or voice control in a menu driven display system).

Figure 4.3 presents a model of the presumed effort of moving attention across different distances (Martin-Emerson & Wickens, 1992; Sanders & Houtmans, 1985; Schons & Wickens, 1993; Wickens, Dixon, & Seppelt, 2005; Wickens, 1993; Wickens, Dixon, & Seppelt, 2002). At very small angles, no eye movement is required at all—only a refocus of internal attention—hence, the cost of shifting between channels is low. At angles greater than around 2 to 4 degrees, an eye movement is required to shift attention between channels. Effort does not increase much with slightly larger

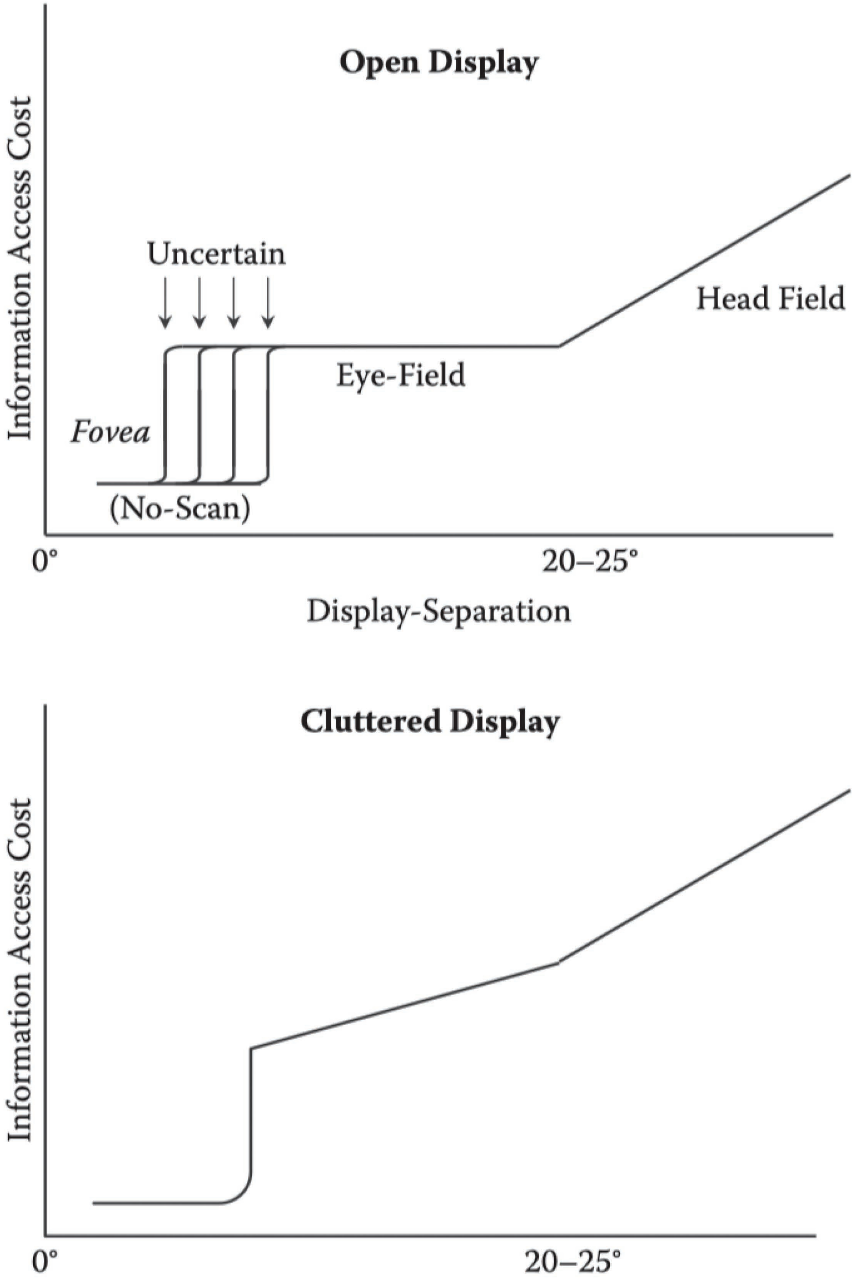

FIGURE 4.3 A model of information access effort in uncluttered (top) and cluttered (bottom) displays.

angles of movement, though, because the eye movement is essentially ballistic. The major cost is simply in planning and initiating the movement, although there may be a slightly greater effort cost for vertical scans than for lateral ones (Wickens, Dixon, & Seppelt, 2002, 2005). At visual angles of source separation beyond perhaps 20 to 30 degrees, a visual attention shift requires a head turn, a nonballistic activity the cost of which, in time and effort, increases with length of movement (Kim et al., 2010; Wickens, Dixon, & Seppelt, 2002). This head turn is typically coupled with a saccade (Kim et al., 2010). Costs increase further as visual angles are reached where body rotation begins to be required. This trichotomization of the visual field was characterized by Sanders and Houtmans (1985) in terms of a no-scan region, an eye field, and a larger head field.

Access to information within the head field can be further encumbered by additional factors. Pilots wearing heavy helmets or a head-mounted displays may scan more narrowly than is ideal because the weight of their gear makes it difficult to execute head movements (Seagull & Gopher, 1997). And an aircraft or spacecraft pilot who moves the head about one axis, while executing a turn about another axis, can experience a disorienting effect known as the Coriolis illusion (Previc & Ercoline, 2004). Other influences on information access effort include:

- changes in visual accommodation when shifting attention between depth planes (Edgar, 2007);
- the time needed to search through a cluttered work environment for a target whose location is *a priori* unknown, as discussed in Chapter 5 and reflected in the steeper slope for the cluttered display at the bottom of Figure 4.3 versus the uncluttered display at the top;
- the time cost of access to information within a computer menu, as determined by the response selection (Hick, 1952; Hyman, 1953; Yeh & Wickens, 2001) and execution time (Fitts, 1954; Wickens et al., 2000);
- the effort demanded by concurrent nonvisual tasks, for example, cell phone conversation behind the wheel (Recarte & Nunes, 2000). This can be predicted from limited resource models discussed in Chapter 7.

The obvious effect of access costs will be to suppress effort-demanding sampling behaviors in favor of easier ones. The in-the-neighborhood heuristic mentioned at the start of the chapter is an example. This heuristic suggests that when information channels are grouped within a display, attention shifts will be more common within groups than between groups. In other words, attention will tend to dwell within a cluster for a while before moving on to another cluster. A pilot who glances at the general instrument panel in the cockpit will tend to sample several instruments before looking back at the outside world rather than making more frequent attention shifts between the panel and the outside world to sample one instrument at a time (Helleberg & Wickens, 2003). Access costs can also discourage scanning movements toward the periphery of a display in a way that can be counterproductive. Operators will tend to undersample channels more when they are in the periphery of the display than when they are centrally located (Eisma et al., 2018), a phenomenon known as the "edge effect" (Stelzer & Wickens, 2006). This effect can extend to the sampling of side mirrors in the automobile (Large et al., 2016; Murata & Kohno, 2018), since they are outside the eye field and within the head field. Information access costs will further inhibit checking of the blind spot with a full torso rotation.

It should be noted that the effort trades off with some of the other five factors listed in Table 4.1. As one example, we can treat effort as a form of subjective cost that offsets the expected utility of gaining information from a source. This integration has been employed in models of information seeking in decision-making (Gigerenzer et al., 1999; Gray & Fu, 2004; MacGregor et al., 1987; Seagull et al., 2004; Wickens & Seidler, 1997), as described more fully in Chapter 7, where we describe the combined effects of salience and effort on cues use for decision and diagnosis.

As a second example of an interaction between effort and other factors, we can consider the case in which contextual task demands require the operator to compare readings on two or more channels, for example, to check the actual value of some system parameter against the commanded value. Here, the cognitive effort required to retain information in working memory will add to the effort of moving attention, and the cost will be greater for long than for short movements (Schons & Wickens, 1993; Sweller, 1994; Vincow & Wickens, 1993; Wickens & Seidler, 1997). The interaction of scanning effort with cognitive load helps motivate the display design principles of functional relatedness (Andre & Wickens, 1992; Eisma et al., 2018; Lee et al., 2017; Wickens et al., 1997) and proximity compatibility (Wickens & Carswell, 1995), the latter of which is discussed more fully in Chapter 6.

4.5 THE SEEV TRADEOFF MODEL

The applied researcher and practitioner can benefit from an understanding of how the collective influences on visual sampling will operate together. With this objective in mind, we describe a model called *salience-effort-expectancy-value*, or *SEEV*, which incorporates the primary forces that move attention of the skilled operator to sample various sources of information (Wickens, Goh et al., 2003; Wickens, McCarley et al., 2008; Wickens, 2015).

Within SEEV, expectancy and value are classed as top-down forces, encoding the operator's mental model of the system. Salience and information access effort are classed as bottom-up forces, the former attention drawing and the latter attention inhibiting. Together, these forces determine the probability that a source will be attended. The model does not treat habit as a separate factor because it assumes that this influence is subsumed under the operator's mental model.

The model further assumes that an operator may place different weightings or *pertinence values* (Bundesen, 1990) on each of the four different sources of attention guidance. These values implement the operator's attentional strategy by weighting the influence of attentional guidance sources. An operator who knows that critical channels are clustered near the center of the display, for instance, might prioritize effort by assigning it a high pertinence. Doing so would discourage long saccades toward the peripheral (and less useful) channels. An operator who knows that peripheral channels have the same expected value as central channels might assign effort a low pertinence, prioritizing channel bandwidth and value instead. In effect, differential weighting of guidance sources reflects a higher-order form of expectancy, specifically, expectancy about which information sources are most useful in the operator's task.

If we imagine an environment of *N* AOIs, we can use a simple computational form of the SEEV model to predict the operator's steady-state distribution of attention across AOIs and from this, the expected average time to notice critical events (Wickens, Goh, et al., 2003; Wickens, McCarley et al., 2008). First, we calculate an attentional weight for each AOI, using the formula (Bundesen, 1998; Luce, 1959; Senders, 1983)

$$A_i = sS_i - efEF_i + \left(exEX_i \times vV_i\right).$$

Here, *i* indexes the AOIs, 1 to *N*; uppercase letters refer to characteristics of the AOI—its salience, bandwidth, etc.; and lowercase letters reflect the operator's pertinence values (as a default, these may all be considered = 1). *S/s* refer to salience, *EF/ef* to effort, *EX/ex* to expectancy, and *V/v* to information value. Since effort is defined as the distance between AOIs, the effort of a single AOI can be approximated by the distance of that AOI from the centroid of all AOIs. AOI characteristic values and source pertinence values are assigned *a priori* on the basis of a task analysis. Multiplying the parameters for expectancy and value reflects the fact that if an AOI has either bandwidth of 0 or a value of 0, then it should receive no top-down prioritization. A simple heuristic for assigning characteristic values is to rank AOIs from low to high on each characteristic (e.g., by salience, by bandwidth) and treat the rankings as the model's parameters. Once weights have been calculated, the relative steady-state frequency of attention shifts to AOI_i is predicted to be

$$f_i = \frac{A_i}{\Sigma A}.$$

This version of the SEEV model (or slight variations on it) has been validated in multiple contexts, including simulated flight (Steelman et al., 2011, 2013; Wickens, Goh, et al., 2003; Wickens et al., 2008), simulated driving (Horrey et al., 2006), and in medical procedures including caesarian-section surgery (Koh et al., 2011) and the induction of general anesthesia (Grundgeiger, Hohm, et al., 2021; Grundgeiger, Wurmb, et al., 2020). In several cases, skilled operators' steady-state scanning has been predicted well based on the expectancy and value parameters alone (Grundgeiger, Wurmb, et al., 2020; Horrey et al., 2006; Koh et al., 2011), suggesting that operators downweighted salience and effort and prioritized expected value, behaving in a way that was roughly optimal. Results from other studies have indicated, though, that effort sometimes inhibits scanning even when it should not, as operators tend to scan peripheral channels less than is optimal, focusing attention more heavily on central channels (Eisma et al., 2018; Steelman et al., 2011).

4.5.1 Applications of the SEEV Model

We can envision at least four human-factors applications of a model of scanning such as SEEV.

1. The model can be used to generate scan patterns driven only by expectancy and value, simulating the behavior of an optimal or expert observer. These

scan patterns can be used either as a guide for operator training or a benchmark for assessing operator performance. The match between the operators' scanning behavior and the predictions of the expected-value SEEV model has in fact been shown to predict the quality of pilot performance in a simulated flight environment (Wickens, McCarley et al., 2008).
2. The model can be used to predict the effects of design manipulations, and in particular, to predict interactions of display characteristics. For example, Steelman et al. (2013) found that the influence of expectancy on PDT was larger for channels near the center of the display, which had low information access costs, than that for channels in the periphery, an interaction that was accounted for by the model.
3. The model can further aid design by providing a predicted metric of display optimality. More specifically, the total scanning distance predicted by the expected value model, taken over a given number of attention shifts, can be treated as an inverse metric of scanning efficiency; holding channel bandwidths and values fixed, a larger total scanning distance indicates a less efficient display layout (Wickens et al., 1997). In general, a strategy of designing displays to minimize total scanning distance will reward layouts that place frequently used displays close together and impose lower workload (Eisma et al., 2018). Display design tools can be created that continuously calculate this distance as display elements are moved around (Sebok et al., 2012). The importance of efficient channel layout will be amplified when peripheral displays move beyond the eye-field into the head-field and to the extent that the display space is cluttered.
4. Because it predicts the time between attentional visits to an AOI via the mean first passage time, the model can be used to anticipate the risk of attentional neglect of highly valued channels. For instance, it can be used to predict a driver's relative vulnerability to missing a roadway hazard while scanning downward to interact with different forms of in-vehicle technology (Horrey & Wickens, 2007; Wickens, Goh, et al., 2003; Wickens & Horrey, 2009).

4.6 ADAPTING SEEV TO PREDICT NOTICING

SEEV has also been adapted to predict the probability of attention capture or noticing an event in time (as opposed to just the probability of looking at a place in space, which SEEV predicts) (Steelman et al., 2017; Steelman et al., 2013; Wickens, Hooey, et al., 2009; Wickens, 2015). In this model, called *NSEEV* (for noticing-SEEV), visual attention is again driven by salience, effort, bandwidth, and expectancy as in SEEV. However, NSEEV incorporates four added features of the specific visual event whose noticing time is to be predicted: its expectancy, its salience, ongoing cognitive load (Vachon et al., 2012) and the distance from the operator's current point of fixation or retinal eccentricity at the instance the event occurs (Wickens, 2015). The noticeability of an event in any given AOI will therefore fluctuate over time as the operator's gaze changes. The steady-state distribution of AOI fixation locations is, of course, predicted by SEEV.

The time required to detect a critical event is estimated in NSEEV by multiplying an estimated average fixation duration by the mean number of attention shifts that take place between signal onset and the model's next fixation on the signal. If the expected fixation duration is 300 ms, for instance, and an average of 4.5 fixations is required to fixate the critical AOI following signal onset, then average detection time would be estimated as 1,350 ms. The frequency of missed signals can be estimated as the proportion of instances in which the model fails to fixate the critical AOI within a criterion amount of time following signal onset, for example, how often a driver fails to notice a roadway hazard within 1.5 seconds

As expected, the model predicts longer detection times and lower detection rates for events that occur in the visual periphery. And whereas analysis of steady-state attentional distribution using SEEV has found good fits based on expectancy and value alone, without need for salience or effort parameters (Grundgeiger, Beckh, et al., 2020; Grundgeiger, Wurmb, et al., 2020; Horrey et al., 2006; Koh et al., 2011), analysis using NSEEV has found that salience emerges as a stronger influence in modeled behavior when critical signals are themselves salient (Steelman et al., 2011). In other words, the modeling suggests that operators use salience adaptively, ignoring it (pertinence weighting = 0) when it is uncorrelated with value but relying on it to guide their scanning when it predicts the occurrence of a signal.

4.7 NOVICE–EXPERT DIFFERENCES IN SCANNING

Differences between novices and experts in a variety of skills can be characterized by where they attend and when (Brams et al., 2019; Wickens & Dehais, 2019; Ziv, 2016). Indeed, given that the SEEV model reflects scanning behavior as driven by the operator's mental model and that the mental model is a critical component of expertise (based on, e.g., the calibration between expectancy and objective bandwidth), the relation between scanning and expertise in the model is self-evident. A study of pilots' scanning behavior illustrates.

Bellenkes et al. (1997) compared the behavior of novice and experienced pilots in flight scenarios involving a series of climbing, turning, and accelerating maneuvers. Consistent with other findings, the data indicated that the attitude indicator was by far the most frequently fixated instrument on the panel, a result driven by at least three factors:

1. it contains two dynamic attributes, pitch and bank;
2. related to the first point, it has the highest bandwidth amongst the cockpit instruments;
3. it is the primary instrument to support the pilot's most important task of aviating, or preventing stall, and it therefore has a high information value.

Novices' mean dwell duration on the attitude indicator was about 1.5 times longer (1 s) than that of the experienced pilots' (600 ms). The novices also fixated on the instrument more frequently than did the experts. The combined effect of long dwells and frequent fixations was that the attitude indicator acted as an attention sink for the novices, leaving little reserve attention for other instruments, even those that were predictive of the future state (i.e., the vertical speed indicator). This meant that the novice pilots were poor at anticipating changes in aircraft state, and their flight performance suffered accordingly.

Based on these findings of novice–expert differences, Bellenkes et al. (1997) developed and tested three different techniques for training novice pilots' attention. In one technique, salience cues were used to drive the novices' scanning, guiding attention around the instrument panel in a way that mimicked the typical scan pattern of an expert (Rosch & Vogel-Walcott, 2013). This passive training did not prove effective. In the second technique, novices were provided with part-task training in how to extract information from the attitude indicator, with the aim of reducing dwell times on that most critical instrument and freeing up attention for other instruments. This intervention had limited success. The third training intervention simply provided novices with a more elaborate narrative description of the flight dynamics underlying the changes on the instrument panel. This technique proved to be the most successful. These results confirm that scanning strategies are largely knowledge driven and that aiding the pilot to develop an accurate mental model of flight dynamics (top down processing) is probably a more secure way to enable effective scanning than is the use of passive cuing. This conclusion echoes the findings from studies of drivers' hazard anticipation, discussed earlier (Pollatsek, Narayanaan, et al., 2006; Pradhan et al., 2009; Yamani, Bıçaksız, Palmer, et al., 2018).

Notably, modeling of expert and novice differences in scanning also points to ways in which the SEEV model might fail to capture aspects of performance. An empirical comparison found that an expectancy-value version of the SEEV model predicted scanning behavior equally well for junior and senior anesthesiologists during simulated induction of anesthesia (see Chapter 11). During real procedures, however, the senior anesthesiologists conformed less closely to the model's predictions than did the junior ones. Authors of the study suggested that senior anesthesiologists might have adapted their behavior more than the junior anesthesiologists in response to interruptions or unexpected events in the real procedure, thereby diverging from the model's predictions (Grundgeiger, Wurmb, et al., 2020). This finding demonstrates the value of the model in identifying sources of attentional guidance in applied environments and simultaneously underscores the importance of the modeler's role in assigning parameter values to events and AOIs when the model is used predictively to anticipate the effects of display manipulations or retroactively to identify causes of performance failure.

4.8 CONCLUSION

We have described factors that should and do influence information sampling in operational environments. Models that incorporate these factors in an optimal fashion can be used to identify inefficiencies and errors in operators' real scanning behavior and to provide a standard of ideal behavior for training operators. Models that emulate the inefficiencies of real human scanning can be used to assess the quality of a display layout and to predict the risk of an operator overlooking a critical event in an operational setting. Similar factors can be presumed to influence nonvisual attention as well, although how to identify the moment-to-moment focus of selection within other perceptual modalities remains a challenge.

5 Visual Search

Visual search is one of our most common attentional behaviors. It pervades everyday behavior and is an important skill in many professional tasks. Accordingly, human factors researchers have studied search across a variety of domains, including driving (e.g., G. Ho et al., 2001; Mourant & Rockwell, 1972); map reading (e.g., Yeh et al., 1999); medical image interpretation (e.g., Nodine & Kundel, 1987; C.-C. Wu & Wolfe, 2019); baggage x-ray screening (e.g., Enright & McCarley, 2019; McCarley, Kramer, et al., 2004); human–computer interaction (e.g., Fisher et al., 1989; Fleetwood & Byrne, 2006; Hornof, 2004; J. Ling & van Schaik, 2006, 2004); industrial inspection (e.g., Drury, 1975; Gramopadhye et al., 2002); photo interpretation (Leachtenauer, 1978); and airborne rescue (Stager & Angus, 1978). At the same time, basic scientists have used search tasks to study visual information processing and perceptual representation (Neisser, 1963; Treisman & Gelade, 1980; Wolfe & Bennett, 1997). These various efforts have built a body of applied knowledge on a deep theoretical foundation.

By definition, a visual search task asks the observer to either detect, localize, or identify (Carrasco et al., 2004) a target whose position in the search field is unknown *a priori*. Beyond this, search tasks differ widely in their characteristics. A few aspects are of particular interest. First, search varies in the degree to which the operator knows precisely what to look for. In some cases, no single target object is specified, and the searcher's task is simply to spot objects of potential interest. Drivers are expected to notice a detour sign, for example, even if they are not anticipating or searching specifically for it. Similarly, a proofreader is required to look for misspellings without knowing which words will have errors. In other cases, the target is a known item with well-specified properties. This occurs, for instance, when a driver actively searches for a specific exit sign or when a manuscript reader searches for a particular name. Target foreknowledge enables top-down or knowledge-driven search processes, helping direct attention toward likely target stimuli. In the absence of target foreknowledge, search and detection depend more heavily on bottom-up processes.

Engineering psychologists have used the term *search conspicuity* to describe the ability of an item to attract notice when the observer is searching for it and *attention* or *object conspicuity* to describe the ability with which it attracts notice otherwise (Martens, 2000), as determined by its physical properties and location (B. L. Cole & Hughes, 1984). Not surprisingly, search conspicuity is typically higher than object conspicuity; we are more likely to notice something if we are looking for it than if we aren't (Charlton, 2006; B. L. Cole & Hughes, 1984). Clearly, though, there are many cases in which the operator is not forewarned to search for a specific and potentially important target. Examples might include a warning label on a product or a detour sign at the side of the road. In creating task-critical signage, labels, or symbology, the designer should therefore strive to maximize bottom-up, object conspicuity.

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Search tasks can also be characterized by the spatial and temporal structure of the stimulus field. Spatially, search tasks vary from structured to free field. In the former, the search field is well organized. In the latter, it is open or haphazard. Items in a computer pull-down menu, for example, are neatly arranged. In contrast, an x-ray of a traveler's backpack is likely to be disorganized, and a piece of glass to be inspected for defects provides a fully open, unstructured field of search. Search tasks also vary in the degree to which the arrangement of the stimulus field is predictable. The anatomical structures within a chest x-ray, for example, may differ in their exact dimensions from patient to patient but will be highly similar in their general form and arrangement. On the other hand, the layout of objects in a baggage x-ray is likely to differ arbitrarily from traveler to traveler. Spatiotemporal structure is useful in that it not only enables more systematic search patterns but can also make the target's position more predictable. Thus, like target foreknowledge, a stimulus field that is structured over space and time can help enable efficient search through top-down processing.

5.1 A MODEL OF APPLIED VISUAL SEARCH

Research in industrial inspection (Drury, 1975), medical image reading (Nodine & Kundel, 1987; Swensson, 1980), and baggage x-ray screening (Gale et al., 2000) has converged on a model of applied visual search as a series of perceptual, attentional, and decisional processes. Qualitatively, the model helps researchers and practitioners understand the ways that visual search might fail and to identify cognitive sub-processes that might be targeted for improvement. Formalized, it allows quantitative performance predictions. When the searcher's goal is to minimize the possibility of missed targets—for instance, the risk of an overlooked defect on a circuit board or an undetected malignancy in a mammogram—the model can provide an estimate of the search time necessary to achieve an acceptable level of performance accuracy. When the goal is to minimize search time—for example, the time needed to divert the eyes from the road to a dashboard map—it can allow predictions as to whether and when search times will exceed acceptable limits. Because it posits processing stages analogous to those of the more basic theories of visual search discussed next (Itti & Koch, 2000; W. Schwarz & Miller, 2016; Treisman & Sato, 1990; Wolfe, 2021), the model also provides a framework for relating real-world search to the perceptual and cognitive mechanisms identified by laboratory research.

Within the model, search begins with *orienting*. Here, the observer assesses the general layout and contents of the search field and identifies potential target items for closer inspection (Kundel et al., 2008; Kundel & Nodine, 1975; Swensson, 1980). Orienting occurs simultaneously across the search field and can usually be completed within a single glance. It is sometimes characterized as *preattentive*, implying that it happens automatically and without capacity limits (Neisser, 1967; Treisman, 1985).

If the target is conspicuous, it will be detected during orienting, an effect sometimes called *pop-out*. Otherwise, the observer is required to *scan* the image. Although it is possible (Woodman & Luck, 2003; Yamani et al., 2013) and sometimes even beneficial (Boot et al., 2006) to scan covertly, holding the eyes fixed while shifting the mental spotlight of attention, scanning is usually overt, with the searcher executing a series of saccades (see Chapter 4) to fixate and scrutinize various regions of interest. The goal of scanning is to bring the target within the searcher's *functional visual field* (FVF) (Nelson & Loftus, 1980; Sanders, 1970), the region around the point of regard within which the target can be acquired. Once this occurs, a successful target-present judgment requires accurate *decision-making*, by which the observer matches a pattern extracted from the search field to a stored mental representation of the target and reaches a yes/no judgment by comparing the strength of the match to a response criterion (D. M. Green & Swets, 1966). Following each decision, positive or negative, the observer can either continue scanning for further targets or can terminate search. The process of scanning and making decisions continues until the searcher concludes that the expected value of finding a target is outweighed by the cost and effort of further search (Drury & Chi, 1995; Hong, 2005).

A target can be missed either because the searcher fails to scan the image adequately or because the searcher fails to recognize the target after bringing it within the FVF. Data suggest that the processes of scanning and target recognition are functionally independent and that task manipulations that improve one process may not affect the other (Koller et al., 2009; McCarley, Kramer, et al., 2004). Efforts to improve search can therefore be targeted at either of the two processes (e.g., Gramopadhye et al., 2002; M.-J. J. Wang et al., 1997).

Although the model as described is qualitative, versions of it appropriate to single- and multiple-target search tasks have been described mathematically (Baveja et al., 1996; Drury, 1975; Spitz & Drury, 1978). With estimates of parameter values, researchers and practitioners can use these formal models to derive quantitative performance predictions. Figure 5.1 shows predicted probability of detection curves as a function of search time, based on formulas from Morawski et al. (1980). Subprocesses of the general model have also been implemented as computational cognitive models (Adeli et al., 2017; Elazary & Itti, 2010; Fleetwood & Byrne, 2006). Given a visual stimulus (sometimes very simplified) as input, these models generally predict the search scan path, enabling predictions about the probability and speed of target detection.

5.2 THE STANDARD SEARCH MODELS

In laboratory search tasks—that is, tasks designed to study cognitive processes without closely emulating a naturalistic or applied search task—the target and distractors are usually discrete objects, such as nonoverlapping shapes or alphanumeric characters. Most often, the search display remains visible until the observer's response is made, and the target and distractors are chosen to be easily discriminable in free viewing. This means that with effort, the observer can in theory achieve near-perfect response accuracy. The main dependent measure of interest is therefore RT. Observers are generally instructed to respond as quickly as possible while aiming for accuracy that is high but not perfect.

A goal of many laboratory search studies has been to distinguish between parallel and serial processing (Sternberg, 1966). In parallel search, all items within the stimulus field are processed simultaneously. In serial search, items are processed in sequence. Search can also be classified as either self-terminating or exhaustive

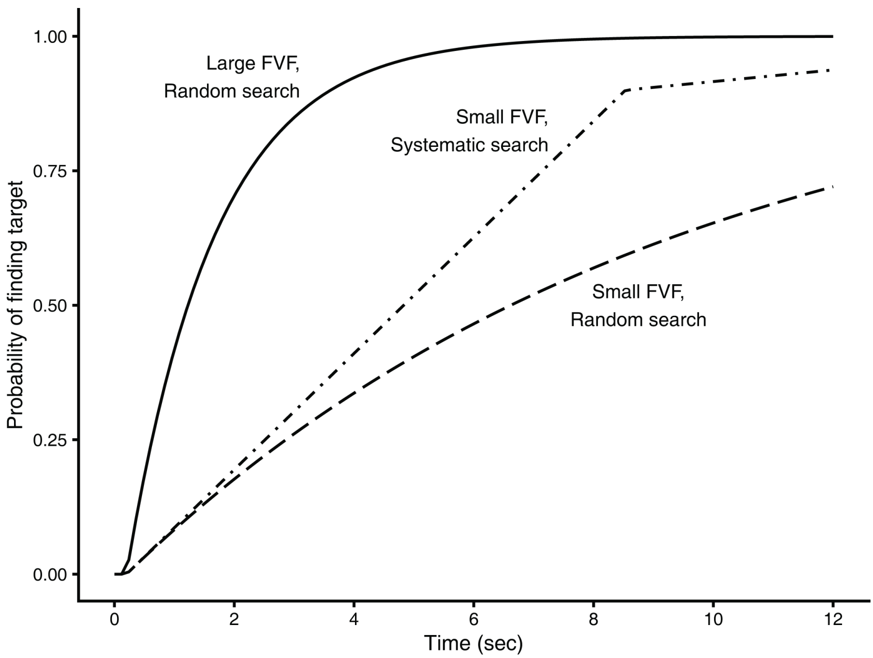

FIGURE 5.1 Predicted probability of detection curves for three search tasks, based on models from Morawski et al. (1980).

(Sternberg, 1966). In a self-terminating model, search ends as soon as a target is discovered. In an exhaustive model, search continues through the full field even if a target is discovered early. Baggage x-ray screening provides a real-world example of self-terminating search; as soon as any threat object is detected in a passenger's bag, the passenger is pulled aside. Mammography provides an example of exhaustive search; since the course of treatment depends on knowing how many lesions are present, search of the mammogram has to continue even after a first lesion is discovered.

The standard form of the parallel model assumes that the time needed to process any given item in the search field is the same regardless of how many other items are present, a characteristic known as *unlimited capacity*. The standard form of the serial model assumes that items are processed one at a time, in single-channel manner, and that the average processing time is the same for all items (Townsend & Nozawa, 1995). Search on target-present trials can be either self-terminating or exhaustive, regardless of whether processing is parallel or serial, but the standard parallel and the serial models both assume that exhaustive processing is required to determine that a target is absent. That is, all items must be processed to the point of identification for the searcher to know that none of them matches the target. Given these assumptions, the conventional method of attempting to distinguish between serial versus parallel and self-terminating versus exhaustive models is to manipulate the number of items in the search field, or set size, and examine the effect on RTs for "yes" (target-present) and "no" (target-absent) judgments (Sternberg, 1966). Set size is manipulated by keeping the number of targets in each display at zero or one while varying the number of nontargets (different predictions arise when more than one target is present).

Figure 5.2 shows the RT patterns predicted by the standard parallel and serial models. In the standard parallel model (left plot), the target and distractors are processed simultaneously, and the rate of target processing is the same regardless of how many distractors are present. The model therefore predicts that when search is self-terminating, RTs for target-present trials will be independent of the number of distractors. In other words, the RT × set size function will be flat; this is the pop-out effect mentioned earlier. A flat RT function for target detection is considered a key diagnostic of parallel, unlimited-capacity search.

In contrast, when search is exhaustive, either by default or because a target is absent, the standard parallel model predicts that RTs will increase as a concave function of set size. This increase arises because the RT for exhaustive search is determined by the finishing time of the slowest item in the search field. Because of stochastic variation in the processing times for individual items, the chance of one or more slow finishing times increases as items are added to the field. Thus, for purely

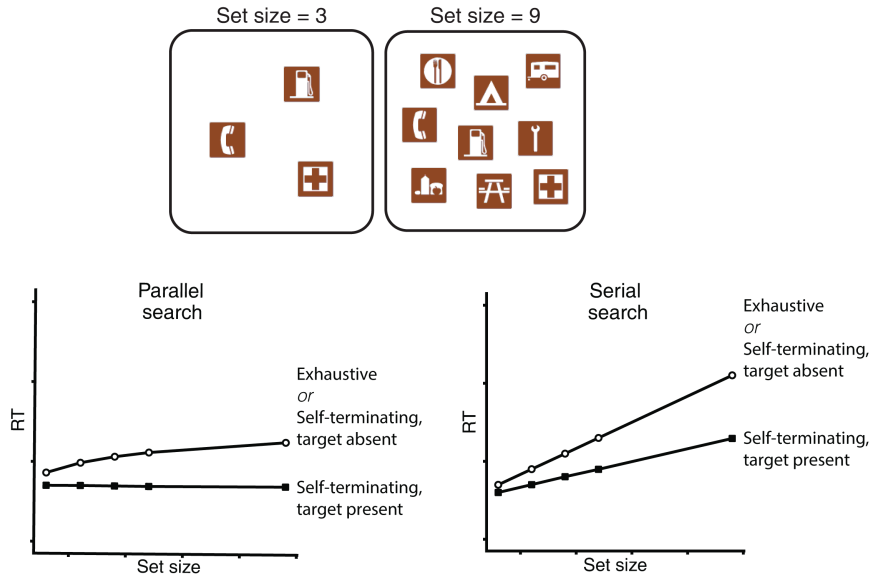

FIGURE 5.2 At the top are displays of two set sizes in a visual search task using traffic icons as stimuli. The observer's task is to determine whether a designated target icon (e.g., a first-aid symbol) is present among varying numbers of distractor icons. At the bottom are RT patterns predicted by the standard parallel and serial search models. The standard parallel model predicts that RTs for self-terminating target-present trials will be unaffected by set size—a flat search function—whereas RTs for target-absent will increase as a concave downward function of set size. The standard serial model predicts that RTs will increase as a linear function of set size. If search is self-terminating, the search function will be twice as steep for target-absent trials as for target-present trials. If search is exhaustive, target-present and target-absent functions will have the same slope.

statistical reasons, RTs for exhaustive search increase modestly with set size even in the parallel unlimited-capacity model.

The standard serial model (right plot in Figure 5.2) predicts a linear increase in RT as a function of set size, since adding distractors increases the average number of items that have to be inspected in each trial. The self-terminating form of the model predicts further that the slope of the RT × set size function will be twice as large for target-absent as for target-present trials, since when a target is present, the searcher will on average need to inspect only half of the items before making a response. Properties of the serial self-terminating search model described allow us to approximate response time as

$$RT = base^{+} + processing \times N \div 2,$$

for target-present responses, and

$$RT = base^{-} + processing \times N,$$

for target-absent responses. Here, N is the set size and *processing* is the average time needed to inspect an item. $base^{+}$ and $base^{-}$, respectively, are the base times for target-present and target-absent trials. These reflect the time needed for early perceptual processes, and for decision and response processes at the end of search. $base+$ and $base^{-}$ might be equivalent but can differ if, for example, the time needed to manually execute a response is longer for one type of decision than the other. When the positions in a display are consistently searched in the same order—for example, when a searcher scans for typos line by line from top to bottom of a page, or when a caller listens to options in an auditory menu—the self-terminating serial model also predicts order effects, with detection times being shorter for targets in early positions than for those in later positions (Neisser & Lazar, 1964). The exhaustive serial model predicts that RT slopes will be equivalent for target-absent and target-present trials and will be the same regardless of target position.

Unfortunately, the problem of characterizing visual search is often more difficult than the standard parallel/serial and self-terminating/exhaustive taxonomy suggests (Townsend, 1990). The prediction of flat RT functions from parallel search, for example, is based on the assumption of unlimited processing capacity. If processing rates for individual items become slower when set size increases, then adding nontargets to a display will increase target-present RTs even if search is parallel and self-terminating. Under certain conditions, in fact, a limited-capacity parallel model can perfectly mimic the mean RT predictions of a serial model (Townsend, 1971).

And even an unlimited-capacity parallel model can produce positive RT slopes. The predictions of the standard parallel model shown in Figure 5.2 presume negligible error rates. When each distractor has a nonnegligible chance of being misidentified, however, then increasing the number of distractors increases the probability of one or more false-positive detections. To control the error rate, the observer must increase processing time, leading to slower responses for larger set sizes. While flat search functions are therefore good evidence of parallel, unlimited-capacity processing, positive search functions are not strong evidence for serial processing or even for limited capacity.

The dichotomous classification of search as either self-terminating or exhaustive is also oversimplified, ignoring the possibility that an observer might end search early with an informed guess or might search beyond exhaustively, either by double-checking some items or locations before concluding that a target is absent (Chun & Wolfe, 1996; Shiffrin & Cousineau, 2004) or simply by forgetting which items have already been inspected (Horowitz & Wolfe, 1998; McCarley et al., 2003). Finally, as discussed in what follows, empirical findings and theoretical advances have shown that search tasks simply don't fall neatly into parallel versus serial categories. Real search behavior involves interleaved, interacting, parallel, and serial processes.

Nonetheless, the parallel/serial and self-terminating/exhaustive distinctions are useful. The flat search slopes of the standard parallel model are a performance benchmark for the design of visual symbology, and the predictions of the standard serial model do a reasonable job describing search times in some applied tasks. The time needed for a controller to detect an air traffic conflict, for instance, increases as an approximately linear function of the number of aircraft within the display (Remington et al., 2000), and the time necessary to locate an item on a digital map increases as a near-linear function of the number of onscreen markings (Yeh & Wickens, 2001). The parallel/serial dichotomy has also provided the context for much of the work that cognitive psychologists have done on visual search and provides a useful point of entry to current search theory.

5.3 PREATTENTIVE AND ATTENTIVE PROCESSING

The parallel/serial distinction is often mapped to a distinction between preattentive and attentive processes in vision. Preattentive processes are presumed to operate automatically, in parallel, and without capacity limits. Attentive processes are limited in capacity, selective, and may have to be deployed in serial.

An influential theory of preattentive vs. attentive visual processing came in Treisman's *Feature Integration Theory (FIT)* (Treisman & Gelade, 1980). FIT proposed two stages of visual processing. In the first stage, the visual scene was encoded within a set of rudimentary *feature maps*. Each map registered a specific, simple visual property: red, blue, vertical, tilted, straight, curved, etc. Features were encoded preattentively, and a unique feature could therefore "pop out" from a display. But because the maps were independent of one another, multiple features of a single object were not bound to one another by default. Binding occurred in the second stage, when focused attention moved from location to location in the visual field, tying together spatially aligned features. Outside of focused attention, object properties could be jumbled or even miscombined (Treisman & Schmidt, 1982). FIT assumed that the focal attention shifts used to combine features were covert mental operations, not directly tied to eye movements, but allowed that eye movements might be necessary to overcome sensory limits on visual acuity (Treisman & Gelade, 1980). The need for the two-stage preattentive versus attentive architecture in FIT and similar models was presumed to arise from limits on neural capacity. "To deal with the whole visual input at once, and make discriminations based on any combinations of features in the field," Neisser (1967, p. 87) wrote, "would require too large a brain . . . to be plausible." Formal computational analyses have confirmed that intuition (Tsotsos, 1990).

Support for FIT seemed to come from the finding that RT functions were nearly flat for feature targets but were linear and positive for feature conjunction targets (Treisman & Gelade, 1980). In Figure 5.3, for example, a curved letter pops out from among straight segments (left panel) and a light letter pops out from among dark letters (middle panel), but a light curved letter among dark curved and light straight letters (right panel) is not immediately obvious. Effects like this matched the prediction that detection of rudimentary visual features would be parallel and unlimited capacity, but detection of feature conjunctions would require serial scanning with focused attention. Data also revealed unexpected search asymmetries (Treisman & Gormican, 1988; Wolfe, 2001) between stimuli. As seen in the left panel of Figure 5.4, for instance, a gapped circle pops out from among complete circles, but a complete

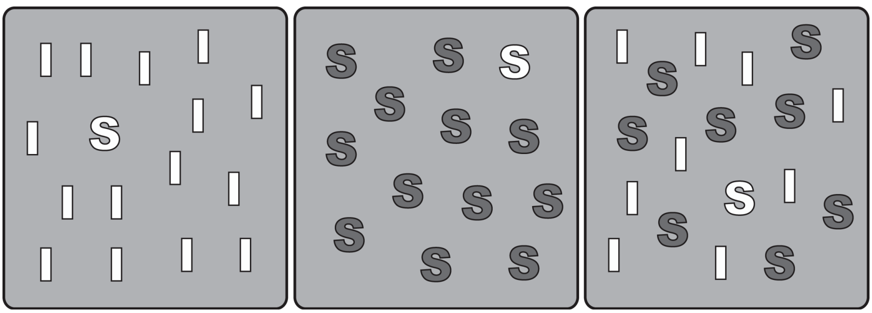

FIGURE 5.3 In the left and middle panels, targets are distinguished by the basic features of curvature and lightness, respectively. In the right panel, the target, a white S, is distinguished by the conjunction of curvature and lightness.

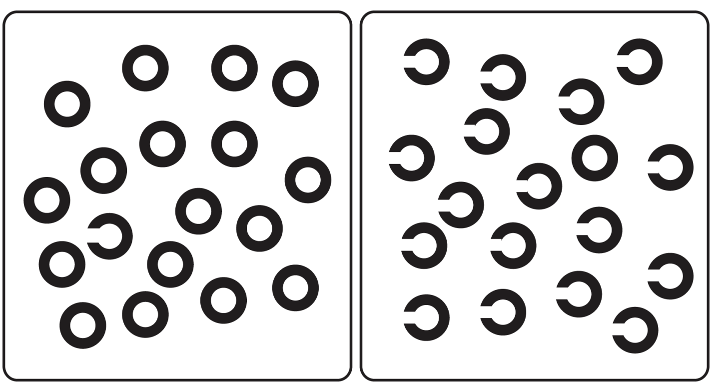

FIGURE 5.4 An example of a search asymmetry. Left panel: A gapped circle target among complete distractors. Right panel: A complete circle target among gapped distractors.

circle is difficult to find among gapped circles. This effect was interpreted as a sign that the property favored by the asymmetry constituted a basic visual feature. For example, the asymmetry in favor of gapped circles suggests that line terminators are basic features (Treisman & Gormican, 1988). Properties that appeared to meet the criteria for basic features included color, brightness, motion, depth, curvature, line terminators, and size/spatial frequency (Wolfe, 1998b).

Since its introduction several decades ago, FIT has been critiqued and qualified in many ways. Nonetheless, the preattentive/attentive dichotomy that Treisman proposed retains heuristic value for engineering psychologists. The difference in search slopes for features and feature conjunctions implies a rule for the design of symbology: critical information should be represented by simple, distinctive visual features, not combinations of features. The finding of search asymmetries dictates further that a critical symbol should be distinguished by the *presence* of a feature, not the absence. Consider, for instance, command and control map symbology that uses green, cyan, and red symbols, respectively, to represent friendly, neutral, and hostile actors, and uses a small but easy-to-notice shape feature to "tag" a classification as uncertain (Fletcher et al., 2011). Preattentive feature detectors for the color red would let the operator easily detect the presence of hostile actors. To know whether a hostile classification had been made with high confidence, though, the operator would need focused attention to conjoin the relevant symbol's color and shape. Moreover, because certainty is denoted by the absence of a shape feature, the operator would be slower to notice hostile actors identified with high confidence than those identified with less confidence. An improved design might symbolize high confidence by the presence of a unique feature tag rather than its absence (Fletcher et al., 2011; Yamani & McCarley, 2011, 2010). Alternatively, to make a high-confidence hostile symbol as easy to detect as possible, the new design might assign that symbol an entirely unique color or shape, bypassing the need for focused attention to conjoin color and shape.

5.4 SEARCH GUIDANCE

The original FIT proposed a separation between preattentive feature detection and serial focused scanning, with no communication between the two processing stages (Wolfe et al., 1989). Data since have updated our ideas about the relationship between preattentive and attentive processes. As discussed more in Section 5.5, it is now clear that attention shifts in visual search are accomplished primarily through eye movements and that the window of attention within a fixation can cover more than one object at a time (Findlay & Gilchrist, 2003; Hulleman & Olivers, 2017; Zelinsky & Sheinberg, 1997).

It is also evident that preattentive output is more sophisticated than just the detection of basic features and that the preattentive and attentive stages are linked. Preattentive processes identify regions of interest across the search field then guide focused attention toward locations where a target is most likely to be found (Treisman & Sato, 1990; Wolfe et al., 1989). As a result, RT slopes do not form bimodal distributions, as might be expected if search tasks fell into discrete categories of fast and parallel versus slow and serial (Wolfe, 1998a). Convention is therefore to describe search as being more or less efficient rather than as parallel or serial (Wolfe, 1998b).

Computational models implement search guidance through a *priority map* (Wolfe, 2021; Zelinsky & Bisley, 2015), a dynamic representation that encodes the estimated importance of the information at each point in the visual field. Activation in the priority map does not specify the content of any given point but indicates how urgently that point should be visited by focused attention. Search is efficient when the target creates an activation spike that attracts attention quickly. Search is inefficient when the target fails to generate strong activation.

The priority map assesses the importance of each point by preattentively integrating bottom-up and top-down signals (Wolfe, 2021). Three sources of input are most relevant to applied search: visual salience, feature activation, and contextual constraints.

5.4.1 Bottom-Up Guidance: Visual Salience

As noted in Chapter 3, vision scientists use the term “salience” to describe the physical distinctiveness of an object in the visual field, independent of the operator’s goals or attentional set (Itti & Koch, 2000; Nothdurft, 2006; Theeuwes, 2010; Zhang et al., 2012). A target that is highly salient will generally be found more quickly than a target that is less salient, and salience is therefore a major component of object conspicuity. Figure 5.5 shows the distribution of salience across a traffic scene, as calculated by the model of Itti & Koch (2000).

Salience is determined by feature contrast—differences in luminance, color, orientation, spatial frequency, and motion between an object and its surroundings (Itti & Koch, 2000; Nothdurft, 1992, 1993), as can be detected by center-surround visual filters (Gao et al., 2008). The link between feature contrast and visual salience leads to guidelines for predicting and manipulating target salience. First, target salience will increase when the feature differences between the target and its surroundings increase, and a target that differs from surrounding objects in multiple features (e.g.,

FIGURE 5.5 The distribution of salience in a traffic scene as estimated by the model of Itti and Koch (2000). Dark regions in the right panel indicate points of high salience in the left panel. In this case, salience peaks occur at the location of the foreground traffic signs and, to a lesser degree, the treetops poking above the horizon on the left—objects that are high in contrast with their backgrounds.

both color and orientation) will tend to stand out more than a target that differs in just one feature (either color or orientation alone) (Nothdurft, 2000b). Second, a target will be less salient when the distractors that surround it are heterogeneous, since feature variation amongst the distractors will tend to mask the target–distractor contrast. Conversely, similarity between distractors allows them to be perceptually grouped and filtered easily (Duncan & Humphreys, 1989; Humphreys et al., 1989). For similar reasons, dense spacing of homogeneous distractors allows a dissimilar target to stand out more easily (Maljkovic & Nakayama, 1994; Nothdurft, 2000a).

Some computational models of salience also use feature contrast to detect and isolate conspicuous objects within naturalistic scenes (Borji et al., 2015). The result is a salience map that represents objects rather than just feature-contrast hot spots. These salience-based object maps, at least in some cases, predict human search patterns better than simpler feature-based salience maps (Stoll et al., 2015). A bias toward attending to objects can in fact cause observers to fixate discrete foreground objects even when searching for a target they know is camouflaged in the scene background (Boot et al., 2009; Neider & Zelinsky, 2006).

A study of visual search within aeronautical charts illustrates the value of target salience (Beck et al., 2010). Observers searched for a designated target symbol in charts that contained regions of low and high clutter. On some trials, the target was salient, and on others, it was not, as determined by color contrast between the target and the chart background. Salient targets were found quickly and with parallel search, even when they were embedded in heavy clutter. Nonsalient targets required careful scanning. In the most difficult condition, mean RT was nearly an order of magnitude shorter for salient targets (roughly 4 seconds) than for nonsalient targets (approaching 40 seconds).

When a target object is known to be salient, as in the high-salience condition of the experiment just described, observers have an incentive to use salience as a search cue. More generally, salient regions within natural scenes tend to be information dense (Elazary & Itti, 2008; Henderson & Hayes, 2017; Masciocchi et al., 2009; McCarley et al., 2014), and in the absence of other attention-guiding cues, a strategy of prioritizing the salient parts of the search field can be reasonable. Operators might not rely on salience by default, however (Foulsham et al., 2014; Peacock et al., 2019), and can override salience-driven scanning entirely when other information is available to guide search (Einhäuser et al., 2008; Foulsham & Underwood, 2007). Even when targets are salient, therefore, top-down guidance can improve search efficiency.

5.4.2 Top-Down Guidance: Feature Activation

An early study of visual search (B. F. Green & Anderson, 1956) asked participants to scan through matrices of colored two-digit numbers looking for a designated target number. RTs depended on whether the searchers knew what color the target would be. When searchers were not told what color the target would be, RTs were determined by the total number of items within the display. When searchers were told the target's color, however, nontargets of a different color had very little effect on RT. The searchers seemed to quickly filter away items of other colors and limit their scanning to the items that remained. Subsequent research has replicated this effect and confirmed that attention guidance is also possible on the basis of features beyond color (Egeth et al., 1984; Treisman & Sato, 1990; Wolfe et al., 1989). Other features known to guide search effectively include luminance contrast and polarity (lighter vs. darker than background) (Pashler et al., 2004; Theeuwes & Kooi, 1994), movement (McLeod et al., 1988), depth (Nakayama & Silverman, 1986), orientation (Wolfe et al., 1989; Wolfe et al., 1992), size (Wolfe et al., 1989), and aspects of shape including curvature and line termination (Treisman & Gormican, 1988; see Wolfe & Horowitz, 2004 for review).

Computational models implement feature guidance by weighting signals from visual feature maps to the priority map (Navalpakkam & Itti, 2005; Treisman & Sato, 1990; Wolfe, 1994), increasing relative activation at locations in the visual field that contain known target features (Hopf, 2004; Saenz et al., 2002). Feature guidance is driven by a *target template* (Duncan & Humphreys, 1989), a mental representation of the target, held in working memory, that determines which visual features should be prioritized. Guidance is most effective when the template is specified precisely; scanning is more efficient when the searcher is provided a picture of the target rather than a verbal description (Malcolm & Henderson, 2009) and is best if the cue picture matches the target exactly, including in size and orientation (Hout & Goldinger, 2015; Vickery et al., 2005). Unfortunately, this level of target specificity is impractical in most naturalistic search tasks. A baggage x-ray screener, for instance, can't know exactly what the threat hidden in a particular bag might look like. Guidance for broad categories of targets is possible, however, particularly for highly typical category members (Hout et al., 2017; Yu et al., 2016). In the example of baggage x-ray screening, an operator might search for categories such as firearms, blades, or explosives. To develop target templates for categorical search, operators should be trained using diverse target exemplars (Bravo & Farid, 2012; Gonzalez & Madhavan, 2011; McCarley, Kramer, et al., 2004).

Feature guidance is especially difficult when an operator searches for multiple, visually dissimilar targets at the same time, for example, when a transportation security screener is expected to search for multiple categories of threat object—firearms, blades, explosives—in every bag. Search for multiple dissimilar targets is slower and more error-prone than search for a single target, and these effects persist even after extensive training (Menneer et al., 2007, 2009, 2012). Menneer et al. (2007) recommend that to minimize the costs of multiple-target search, targets be grouped into categories based on similarity of color and a separate searcher assigned to each color category. In baggage screening, for example, one operator might be assigned to search for metal objects, which are visualized as blue, and another assigned to search for explosives made from organic materials, which are visualized as orange. This would allow each searcher to look for multiple types of targets simultaneously while still taking advantage of color guidance (Menneer et al., 2009).

Display designers can take advantage of feature guidance to reduce the costs of visual clutter. Consider a study of air traffic displays (Remington et al., 2000). Controllers monitored for conflicts in displays of 12 to 20 aircraft. A conflict existed anytime two aircraft were on converging flight paths at the same altitude. In a control condition, typical of current ATC displays, altitude was coded by a text block attached to each aircraft's icon. In a color-coded condition, aircraft at different altitudes were

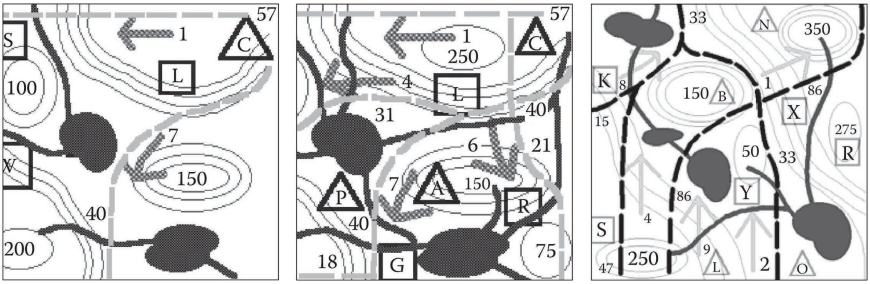

FIGURE 5.6 The left and center panels, respectively, present examples of low-clutter and high-clutter maps from a study by Yeh and Wickens (2001). RTs for visual search through these maps increased as a function of clutter. The right panel presents a cluttered map with low-priority information lowlighted and high-priority information displayed in high contrast. In this case, visual search through high-priority objects was unaffected by clutter from lowlighted objects.

drawn in different hues, allowing the controllers to easily identify and focus attention on aircraft in the same altitude range. Conflict detection was several seconds faster in the color-coded display, an effect that was statistically and practically significant. Other research has found similarly that color-coding of object classes in a digital map allows for efficient visual search within a given object class (Yeh & Wickens, 2001).

An alternative to color-coding, suitable for use in monochromatic displays and for observers whose color vision is deficient (4%–8% of males, depending on the population: Birch, 2012), is *intensity coding*, the rendering of different information classes at different levels of luminance contrast. This can involve either highlighting of high-priority information or *lowlighting* of low-priority information (Fisher et al., 1989; Kroft & Wickens, 2003; Wickens, Alexander et al., 2004). Color and intensity coding both allow operators to search without interference from background information but keep the background information visible in the event that it's needed. Figure 5.6 presents examples of displays with and without lowlighting of background information. Of course, the usefulness of such coding depends on the reliability of the algorithms that decide which information to foreground, as discussed in Chapter 3.

5.4.3 Top-Down Guidance: Context

Applied search often takes place through structured, meaningful scenes, where predictable objects appear in predictable locations. These contextual constraints guide search in at least two ways. The first is by activating semantic knowledge (C.-C. Wu et al., 2014). A classic experiment by Potter (1975) found that observers could recognize and categorize scenes with high accuracy from exposures of 125 ms or less, and work from Biederman and colleagues (1974) found that violations of familiar spatial arrangements could influence scene recognition in even briefer exposures. Findings like these confirm that spatial and semantic expectations are triggered during orienting, making them available quickly to guide search. Accordingly, visual search of natural scenes is knowledge driven, focusing on meaningful regions and likely target locations even when they are not salient (Henderson et al., 2009; Henderson & Hayes, 2017; Peacock et al., 2019).

The second route by which context guides search is through learned statistical regularities, independent of semantic knowledge. In studies of an effect called *contextual cuing* (Chun & Jiang, 1998), observers performed conventional laboratory search tasks with letters and simple shapes as stimuli. Characters appeared in random spatial patterns, but across blocks of trials, some patterns were repeated, with the target in the same place. Over blocks of trials, searchers learned to recognize repeated patterns and quickly direct attention to the predictable target locations (Chun & Jiang, 1998; Chun & Nakayama, 2000). This implies that simple associative learning can help searchers know where targets are most likely to appear within a structure search field, even without any semantic understanding of the scene or display.

The ability to use context to guide attention—in short, knowing where to look—is an element of skilled search. Examining a chest x-ray, expert radiologists show efficient and directed eye scan patterns, whereas novice viewers scan haphazardly (Kundel & La Follette, 1972). Similarly, medical technologists but not laypeople use the predictable features of a micrograph within a specific diagnostic category to help them find a sample of bacteria morphology (Hoyer & Ingolfsdottir, 2003). The distinction between semantic attentional guidance and contextual cuing suggests converging approaches to training skilled visual search. Semantic guidance can be taught through direct instruction and exercises that improve understanding. For example, interventions using diagrams, photographs, and video to teach novice drivers how to anticipate traffic hazards have been shown to improve search behind the wheel, producing benefits that generalize beyond the specific training scenarios and persist over time (Chapman et al., 2002; Pollatsek, Fisher, et al., 2006; Pradhan et al., 2009). Contextual cuing will require repeated exposure to task-relevant stimulus scenes. Nodine et al. (1996), for instance, found that radiology residents who had received mammography training but were inexperienced reading images were slower and less accurate at finding low-contrast masses than were readers with thousands of trials of experience.

5.5 THE FUNCTIONAL VISUAL FIELD (FVF) AND OCULOMOTOR SCAN PATTERNS

Although observers can encode the gist of a scene and sometimes detect a target at a glance, naturalistic visual search typically involves eye movements (Findlay & Gilchrist, 2003). The purpose, obviously, is to bring the point of regard close to the target, wherever it is in the search field. More precisely, the aim is to bring the target within the FVF, "the area of the visual field around fixation from which a signal can be expected to be detected given sensory and attentional constraints" (Hulleman & Olivers, 2017, p. 7).

The FVF—sometimes called the visual lobe (Chan & Courtney, 1996), useful field of view (Ball et al., 1988), or functional field of view (Pringle et al., 2001)—is measured by presenting a target at varying distances from the point of fixation, with the eyes held fixed, and determining the distance at which some measure of psychophysical performance falls below a criterion level. Because performance falls off gradually, the FVF is not a crisply-bounded window of visibility but a gradient, and an estimate of FVF size should be regarded as simply a convenient summary of how steeply performance declines. The FVF is not to be confused with the angle of foveal vision and is often larger than the 4-degree angle usually associated with the fovea. As might be expected, the exact size of the FVF varies with stimulus characteristics and task demands. In general, the FVF is smaller when the target is embedded among distractors (Jacobs, 1986; e.g., Mackworth, 1965) and when target–distractor discriminability is low (Jacobs, 1986; Young & Hulleman, 2013). The FVF also tends to be smaller in older than in younger adults (Scialfa et al., 1987; Sekuler & Ball, 1986; Yamani, McCarley, et al., 2015), and shrinks when the observer is placed under acute stress (Bursill, 1958; Weltman et al., 1971) or when foveal processing load is high (Ikeda & Takeuchi, 1975; Schwartz et al., 2005; Williams, 1982). Interestingly, nonvisual cognitive load appears to degrade visual processing equally across the visual field, without constricting the FVF (Gaspar et al., 2016; Ringer et al., 2016).

The size of the FVF determines how carefully the observer must scrutinize the search field to detect a target. A large FVF enables the observer to cover a bigger part of the image with each gaze, meaning that fewer eye movements are required to blanket the field (Kraiss & Knäueuper, 1982). Accordingly, FVF size is correlated with search efficiency. Among photointerpreters, for example, FVF size strongly predicts search speed and detection rate for targets hidden in aerial imagery (Leachtenauer, 1978). Likewise, searchers with a large FVF tend to show shorter target detection times in industrial inspection tasks (Gramopadhye et al., 2002) and are faster to notice events within cluttered real-world scenes (Pringle et al., 2001). Among older adults, a narrow FVF is associated with poorer driving performance (Clay et al., 2005; J. M. Wood et al., 2012).

The relationship between FVF measurements and search performance suggests that it might be possible to improve search efficiency through training to expand the FVF, though it is likely that benefits will be specific to the target stimuli used in training. A training protocol to increase FVF size, for example, produced faster detection of faults in a mock industrial inspection task, but the benefits were largest for the specific fault type (rivet or area) that had been used as targets in the training program (Gramopadhye et al., 2002). Some data have suggested that action video games might expand the FVF (Feng et al., 2007; C. S. Green & Bavelier, 2003), but these effects do not seem to be robust (Boot et al., 2008; Sala et al., 2018).

Another strategy for improving search, complementary to expanding the FVF, might be to structure the observer's oculomotor scan path to ensure that the full search field is covered by attention. This approach is probably plausible in tasks that require controlled, effortful shifts of attention (Ruddle & Lessels, 2006), for example, when scanning requires the observers to make body movements or to pan a camera's field of view. In experiments that asked them to search for coins in a large patch of grass, observers tended to walk the search area in a regular, back-and-forth pattern even without instruction (C. A. Riggs et al., 2017). Searchers may also show orderly tendencies in free eye movements, for instance, by preferring horizontal scanning over vertical scanning (Gilchrist & Harvey, 2006). But in general, efforts to explicitly train systematic eye scanning patterns have not produced convincing improvements to search performance, perhaps because the cognitive effort required to remember and follow a rigid scan path diverts attention from target encoding and recognition (M. R. Kramer et al., 2019). A more useful method to improve scanning is probably to train observers in the semantics and statistical regularities of the search scene, as discussed earlier.

5.6 STOPPING POLICY AND MISSED TARGETS

In the standard self-terminating model, the search field contains at most one target, and the operator can therefore end search immediately when a target is found. Generalizing the model to tasks in which multiple targets might be present, an operator can end search confidently any time that all targets are known to have been discovered or the potential remaining targets are unimportant. A search-and-rescue operator looking for a pair of lost hikers in aerial imagery can end search safely as soon as both hikers have been spotted. Alternatively, an industrial inspector can reject a sheet of glass as flawed as soon as any imperfection is detected, whether or not the sheet contains any additional imperfections.

But when the searcher is not certain that all targets have been discovered, the decision to end search is likely to be determined by strategic factors. The standard self-terminating model (and the standard exhaustive model, by definition) assumes that if no target is found, search continues just until the entire search field has been examined. Cost–benefit analyses and empirical data both argue against this presumption. Dependent on the payoff attached to target detections and misses, the cost attached to search time, and the searcher's scanning strategy, an optimal economic model can lead to scanning that is more or less than exhaustive (Drury & Chi, 1995). Empirically, at least some false negative responses in naturalistic search tasks seem to result from a failure to fixate on or near a hidden target (McCarley, Kramer, et al., 2004; Nodine et al., 2002), confirming that negative responses do not always follow an exhaustive scan.

For shorthand, we will use the term "target-absent response" to denote any decision to end search that is not triggered by the discovery of a target, although in tasks in which multiple targets are possible on a given trial, the response might come after some targets have already been found. A target-absent response results when the operator has reached their stopping threshold, a criterion level of confidence that there are no targets remaining (Wolfe, 2021). The stopping threshold is higher when search is difficult or when misses are costly, as expected, but it is not calibrated to these factors optimally (Drury & Chi, 1995). Threshold setting can also vary from trial to trial, with the operator becoming quicker to end search after a series of correct target-absent responses and more reluctant to end search after missing a target (Wolfe, 2021). More surprisingly, the stopping threshold appears to drop when the display contains a highly salient nontarget, suggesting that a compelling distractor can effectively trick an operator into quitting search early, at the risk of missing a target (Moher, 2020).

Two additional factors further influence the risk of missed targets: the *target prevalence effect* and *satisfaction of search*.

5.6.1 The Target Prevalence Effect

In laboratory search tasks, a target is typically present on half of all trials. In naturalistic search tasks such as baggage x-ray screening, however, targets can be exceedingly rare. Low prevalence rates increase the risk that a target, when it is present, will go undetected. In a study by Wolfe et al. (2005) and colleagues, miss rates increased from about 7% to about 30% when target prevalence rate decreased from 50% to 1%. The prevalence effect obtains whether target–distractor discriminability is low or high (Rich et al., 2008) and affects skilled searchers in naturalistic domains (K. K. Evans et al., 2013; Wolfe et al., 2013) as well as novices performing laboratory tasks.

At least three mechanisms contribute to the target prevalence effect. First, searchers making long runs of target-absent responses can get into a rhythm that leads to motor errors on the occasional trial when a target is present. These errors are usually recognizable and can be easily corrected (Fleck & Mitroff, 2007). Second, searchers who have established the expectation that targets are rare may set a low quitting threshold, producing a trade-off in which target-absent responses are made quickly but often before the searcher has scanned the field carefully (Rich et al., 2008). Finally, searchers adjust their response criterion for classifying individual items within the search field, adopting a bias toward categorizing objects as distractors (Wolfe & Van Wert, 2010).

The prevalence effect is not overcome by financial incentives to searchers (Pedersini et al., 2010) or by messages that warn searchers when their responses were too quick (Wolfe et al., 2007). However, it was nearly eliminated when searchers performing a low-prevalence task were exposed to occasional retraining blocks of high-prevalence trials with feedback (Wolfe et al., 2007).

5.6.2 Satisfaction of Search

A satisfaction-of-search error occurs when the detection of one target interferes with detection of other targets in the search field. After finding one abnormality in an image, for instance, a radiologist becomes less likely to notice a second abnormality that would have otherwise been detectable (Ashman et al., 2000; Berbaum et al., 1990). As the term "satisfaction of search" implies, errors of this type were originally presumed to result when detection of a target led the operator to quit search without checking carefully for further targets (Tuddenham, 1962). However, further investigation showed that searchers generally do not stop scanning early after finding an initial target, and in fact, they often fixate the second target after detecting the first one (Berbaum et al., 1998, 1991; Cain et al., 2013). Satisfaction-of-search errors (the term remains in common use) instead seem to result from a combination of two other mechanisms. First, after detecting an initial target, the searcher becomes poorer at encoding and recognizing subsequent targets. This loss of processing quality manifests as a drop in signal detection measures of sensitivity (Berbaum et al., 1990) and might be caused by the working memory load that results from holding the first target in mind after it has been detected (Cain et al., 2013). Second, after finding the first target, the operator adopts a more conservative response criterion for further target detection (Berbaum et al., 2015; Krupinski et al., 2017).

5.7 COLLABORATIVE SEARCH

Some tasks allow multiple observers to search collaboratively. As expected, collaboration tends to improve performance, though the size of the improvement varies between tasks. A complication that arises when measuring the benefits of collaboration is that group and individual performance can differ for purely statistical reasons. Consider a case in which two or more observers search in parallel, viewing the same stimuli and searching for the same targets but without interacting or influencing each other in any way, and assume that RT for a given trial is determined by the first person to respond. This arrangement constitutes a *horse race model* of speeded judgments. Mean RT for searchers in a horse race arrangement will tend to be shorter than the mean of the individuals' RTs simply because RT for the group is determined by whichever searcher happens to be fastest in every trial, an effect called *statistical facilitation* (Raab, 1962). In unspeeded signal detection tasks, an effect called *probability summation* can improve or harm sensitivity in a way analogous to statistical facilitation/debilitation (Jones, 2016). Performance better than expected from statistical effects, in either speeded or unspeeded tasks, implies that searchers are interacting in a productive way (Eidels et al., 2011; Jones, 2016; Townsend & Wenger, 2004). Performance worse than expected implies interference between the searchers.

How well do groups perform relative to statistical expectations? In speeded search, collaborators can outperform statistical facilitation but frequently don't. Collaborative search is most efficient when searchers use a division-of-labor strategy, with each group member covering a different subset of the search field or looking for a different target (Brennan et al., 2008; X. Chen, 2007; Niehorster et al., 2019). Surprisingly, target acquisition is slower when collaborators are allowed to talk with one another while they search than when they are not (X. Chen, 2007; Neider et al., 2010). This effect might reflect cognitive load imposed by language production and comprehension. Alternatively, it might indicate a tendency for communicating searchers to look in the same direction, causing more overlap in their scan paths and less efficient coverage of the search field (McCarley et al., 2020). In either case, the implication is that collaborators should plan their division of labor before beginning their task, then minimize unnecessary communication as they search. Some results have suggested that gaze-linked displays, visualizations that allow each searcher to know where the others are looking, can encourage more efficient collaboration (Brennan et al., 2008), but this effect has not generalized well (McCarley et al., 2020; Messmer et al., 2017; Neider et al., 2010).

The benefits of collaboration are more pronounced when target detectability is low. Signal detection analyses find that collaborative searchers achieve sensitivity substantially higher than expected from probability summation (Malcolmson et al., 2007). These effects hold whether collaborators are co-located or remote, communicating by voice (Enright & McCarley, 2019), and they persist even under conditions of high target uncertainty (Enright et al., 2020).

5.8 SUMMARY: ENABLING BETTER SEARCH

How can the human-factors practitioner make search easier and more effective?

- Code critical symbols with simple, unique visual features that contrast with their surroundings. Use color- or luminance-coded displays to reduce clutter, and make sure critical symbols are distinguished by the presence of a unique feature not the absence.
- Even when symbols are designed to be salient, try to make sure the searcher knows what to look for.
- To allow better guidance, let searchers focus their attention on a small, homogenous category of target objects, rather than trying to search for many different, dissimilar targets at once.
- Train searchers using targets, distractors, and backgrounds as similar as possible to those of the criterion search task. Train them with instructions and exercises to improve their semantic understanding of the search scenes, and expose them to repeated examples of stimuli to help them learn predictable target locations and features.
- When search requires deliberate, effortful head or body movements, searchers can probably be trained to follow systematic scan patterns. When search covers a smaller area and relies primarily on eye movements, training to follow a systematic scan path might be less successful.
- Be aware that miss rates increase when targets are rare and when there is more than one target to find in the search field. Use occasional sessions of high-prevalence retraining to boost searchers' performance in tasks of low target prevalence.
- In speeded tasks with targets that are not hard to recognize (after they have been fixated), be sure that searchers working collaboratively use a division-of-labor strategy, for example, by scanning different regions of the display. Alternatively, allow multiple searchers to work in parallel but independently. Without coordinating their behaviors, multiple searchers working together are often slower than expected from statistical facilitation.
- In unspeeded tasks with hard-to-detect targets, allow multiple searchers to communicate as they work. Collaborators working together in difficult detection tasks achieve sensitivity higher than expected from probability summation.

5.9 CONCLUSION

Applied visual search is a multistep process that involves orienting, scanning, and decision-making. Formal models of search can allow system designers to anticipate the effects of changes to task demands or procedures and can provide performance benchmarks for assessing operators' search speed and effectiveness. Guidelines derived from attention theory, then, can enable the design of displays, training, and operations to improve each stage of search performance.

In the next chapter, we'll consider the implications of attention research for information display in nonsearch tasks.

6 Spatial Attention and Displays

In serial visual search, as discussed in Chapter 5, a cognitive priority map guides attention from one location to another across the visual field. Although objects might be perceived as particularly salient (Stoll et al., 2015), attentional selection operates by shifting from location to location, much like a spotlight (Posner et al., 1980). This mode of selection is often described as *space based* (Duncan, 1984). An alternative and more flexible form of attentional processing, *object-based attention*, is also possible, though. Next, we contrast space- and object-based mechanisms of attention, then consider their implications for display design.

6.1 SPACE-BASED ATTENTION THEORY

As just noted, we can adopt the metaphor of the spotlight or flashlight to characterize space-based attention (LaBerge & Brown, 1989; Posner et al., 1980; Wachtel, 1967). According to this analogy, the focus of attention moves across the environment to highlight things in different locations. However, as the spotlight illuminates an object of interest, its beam can only narrow so much as it zooms in to inspect (Eriksen & St. James, 1986). Hence all visual information remaining within the beam, even if it is unwanted, will get processed, diverting resources from processing the wanted information. That is, such information causes a disruption of focused attention on the wanted or relevant information. These characterize the problems of trying to drive while looking through a scratched or dirty windshield or examining a cluttered map to try to read detailed information.

The findings of focused-attention disruption are well captured by the so-called flanker paradigm developed by Eriksen and Hoffman (1973), as discussed in Chapter 3, in which the response time to classify a central target letter is increased by response-incompatible letters near the target. But this disruption is diminished as the flankers are moved outward away from the target, defining an area of the spotlight for mandatory processing, which Broadbent (1982) estimated to be approximately 1 degree of visual angle. However, disruption of focused attention can occur across a wider range of space. For example, open windows in the background of a computer desktop can distract attention from the active window, even over angles much larger than 1 degree (Mori & Hayashi, 1995).

Our examples stressed the unwanted processing of response-incompatible information, in part because the degrading effects of these are starkly revealed in performance (RT delays). However, it should be noted that nearly any stimulus items within a small region around a target item can produce interference. This is the real-world problem of visual clutter.

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Just as spatial proximity between multiple stimuli makes it difficult to focus attention on a single item, so, intuitively, does spatial separation make it difficult to divide attention between two visual channels (Wickens, Dixon, & Seppelt, 2002, 2005; Wickens, 1993). The divided-attention cost of greater spatial separation does not appear to be linear but is a compound of different components, as was shown in Figure 4.3. (We will make several references to that figure in this chapter: the reader might want to bookmark it.) When two items or sources of information are close together, there may be no cost to divided attention. Once they are separated by a few degrees of visual angle, however, both are no longer within the FVF (defined in Chapter 5), and eye movements therefore become necessary to look back and forth from one item to the other. At this point, the two channels are said to be in the eye field. As the separation between them grows larger, the channels encroach on the "head field" (Sanders, 1970), at which point neck rotation is needed to shift gaze between them (Kim et al., 2010), an abrupt increase in the cost of switching attention. As a result of the transition from the FVF to the eye field to the head field, the performance costs imposed by spatial separation between channels may often follow a function corresponding to that shown in Figure 4.3 (Wickens, Dixon, & Seppelt, 2002, 2005).

6.2 OBJECT-BASED ATTENTION THEORY

Under a strictly space-based model of attention, the difficulty of allocating attention between two display channels would depend strictly on the distance between them: a small spatial separation would make divided attention easy and focused attention difficult, and a large spatial separation would have the opposite effect. But data reveal that this model is too simplistic, as the difficulty of focusing or dividing attention between two elements also depends on whether an element B belongs to the same object as an attended element A. If B is task irrelevant but belongs to the same object, processing of A will be hurt compared to the case when B belongs to a separate object. If, in contrast, B is also supposed to be processed (divided attention between A and B), its belongingness to the same object will help. Two examples of "belonging to the same object" are the gender and expression of emotion of a face, and the location and size (representing population) of a circle representing a town on a map. (In fact, there are actually three dimensions represented in the map example, since the location will represent both the X and Y coordinates.)

An experiment by Duncan (1984) illustrates the benefits of belonging to the same object for divided attention. Stimuli, two examples of which are shown in Figure 6.1, were boxes with lines through them. The boxes could be either small or large and could be gapped on either the left or right side. The lines could be either solid or dashed and could be tilted either left or right. Stimuli were flashed onscreen very briefly each trial and then masked, and the observers' task was to report two predesignated stimulus properties. Duncan found that judgments were easiest when both target properties belonged to the same object (e.g., box size and gap side) than when one belonged to each object (e.g., box size and line orientation). In fact, participants found it just as easy to report two properties of the same objects as to report a single property, suggesting that attentional selection encompassed multiple features of a

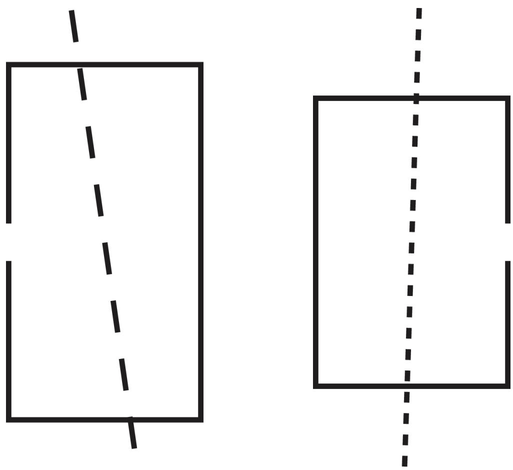

FIGURE 6.1 Examples of stimuli, each comprising a box and a slanted line, like those used by Duncan (1984).

single object effortlessly. Importantly, because the two objects were superimposed on one another, the costs of dividing attention between the box and the tilted line could not be attributed to spatial scanning. In a similar experiment, Lappin (1967) found that observers could report the size, shape, and color of one object just as well as they could report a single attribute of the object and far better than they could report either a single attribute of three objects (i.e., the shape of the three) or a different attribute on each of the three objects. Again, this suggests highly efficient parallel processing of the features of a single object.

In contrast to how a single object helps divided attention, some of the most compelling evidence for the cost of focusing attention on one feature of an object comes from the Stroop task (MacLeod, 1992; Stroop, 1935). Look at the set of words in Figure 6.2 and try to read, as fast as possible, the color of ink of the word (e.g., "white, grey, white, black . . ."), not the name of the word. Do this with the list on the left. Then do the same task with the symbols on the right and notice how much more fluent is your reporting on the right. The difference is simply that each item in the list on the left is an object with two attributes that map onto your response options, the word name and the color ink. When the name and ink map to incompatible options, your response is slowed in exactly the same fashion that resulted with the Eriksen flanker task. Kahneman et al. (1992) integrated such evidence as we have discussed previously to propose their object file theory of attention, postulating that perceptual processing is parallel within the features of a single object but serial across different objects. Thus, when the ink color and semantic properties are processed in parallel, and they offer incompatible color responses, there is interference. Kahneman's research has shown that Stroop interference is greatly diluted or eliminated altogether when the ink color to be named and the conflicting semantic information are separated rather than being part of the same object.

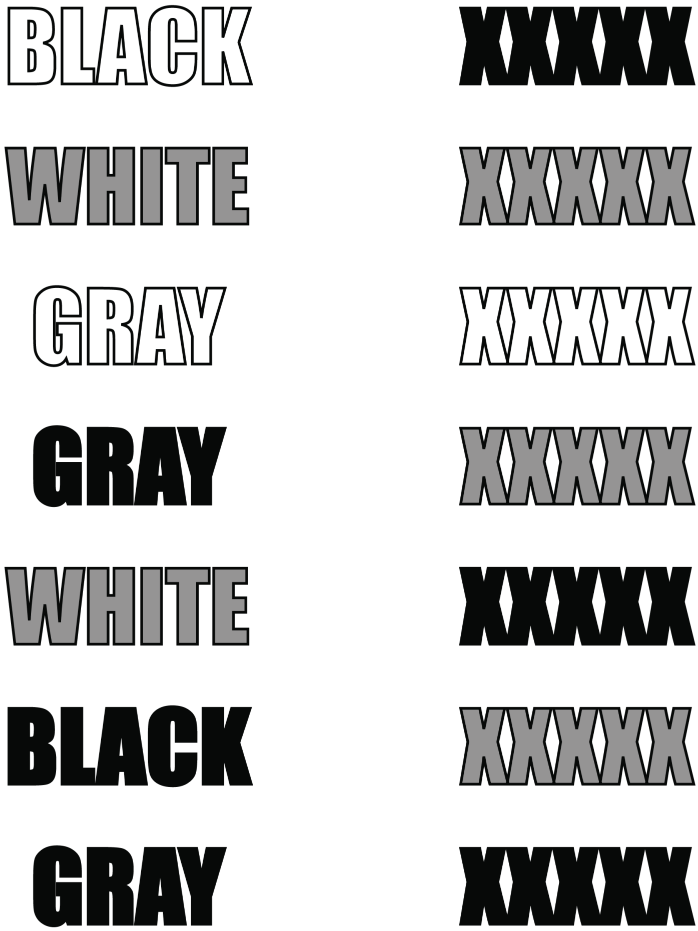

FIGURE 6.2 The Stroop task, usually performed with different colors (hues) but here rendered in black, gray, and white. Going down the columns, report the color ink of each string, first on the left then on the right.

6.3 THE PROXIMITY COMPATIBILITY PRINCIPLE

At this point, we can summarize the collective results of what we have discussed, as shown in Figure 6.3. On the left, two or more elements on a display (or in the natural environment) can be close to or distant from one another, where closeness in psychological terms can be defined either by spatial proximity or by belonging to the same object. On the right, tasks can require either that attention be divided between elements or focused on individual elements. We speak of divided-attention tasks as having "high task proximity," since both display elements require processing, and of focused-attention tasks as having "low task proximity," since processing of the task-relevant channel should be isolated from processing of the other. There is then a

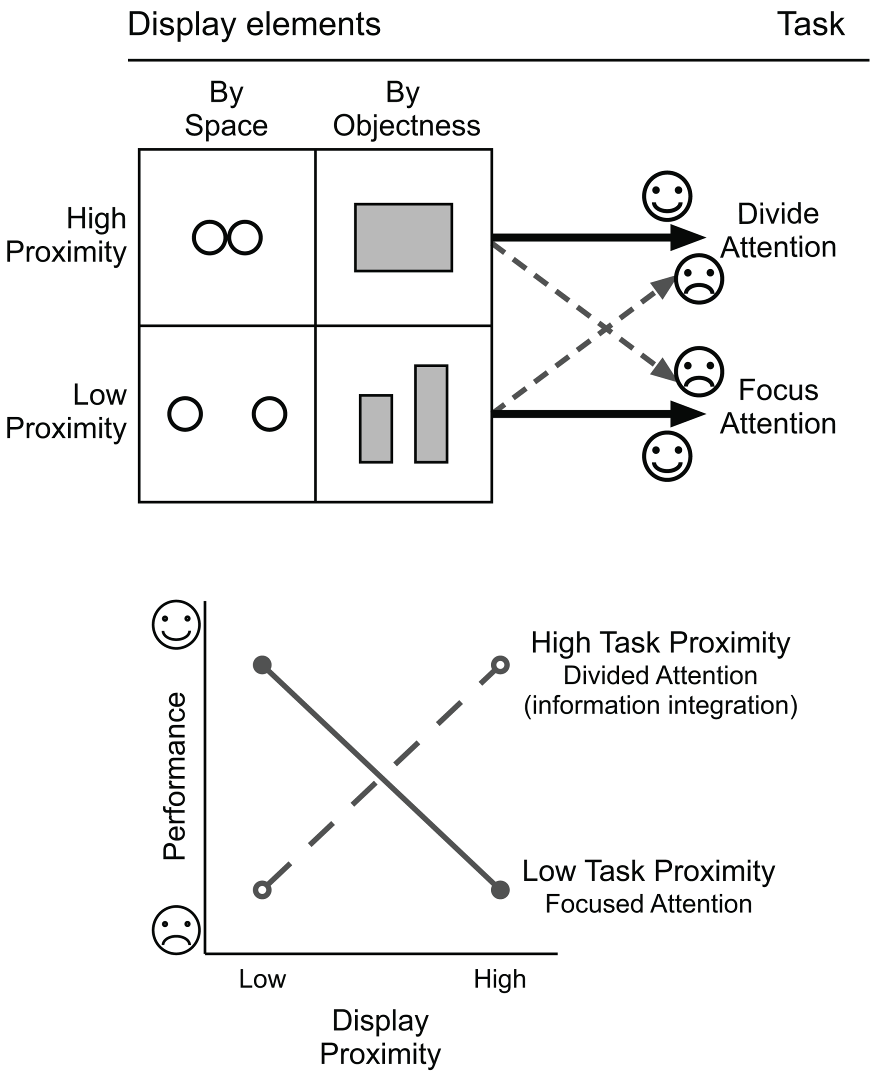

FIGURE 6.3 Conceptual representation of the PCP. At the top, different display proximities (left side) created by space or objectness are either compatibly (solid arrows) or incompatibly (dashed arrows) mapped to different attention tasks (right side). High (close) = divided attention for information integration; low (distant) = focused attention. Below is shown a graphical depiction of the statistical interaction expressed by the PCP, with better performance represented by higher values on the Y axis. Note: sometimes the term "task proximity" can be replaced with "mental proximity," and "display proximity" can be interchanged with "perceptual proximity."

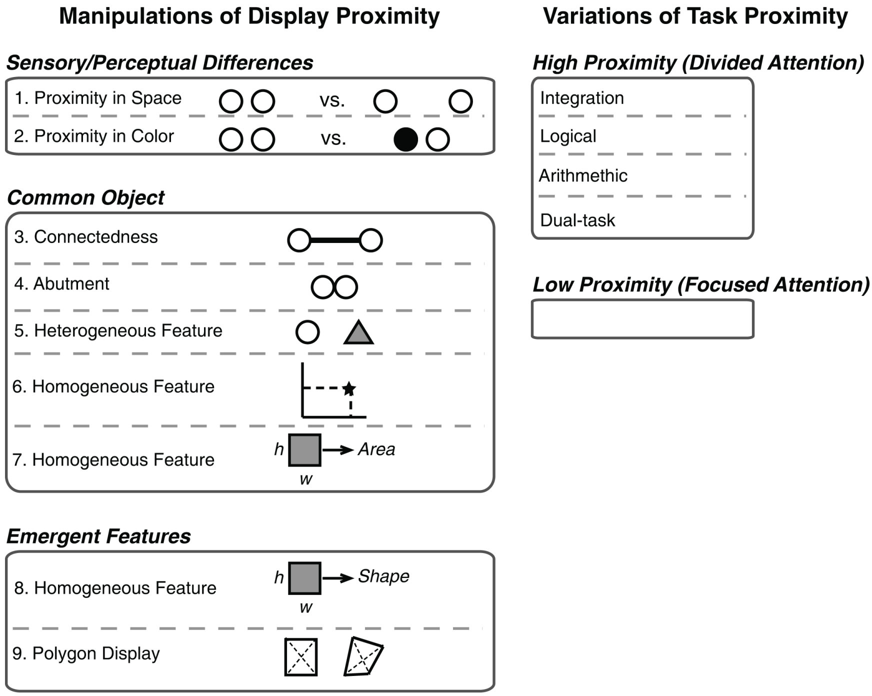

FIGURE 6.4 The dimensions of display proximity (left side) and task proximity (right side) as defined in the text. Most examples on the left side are of high display proximity, so, in the framework of Figure 6.3, they would be compatibly mapped to the integration tasks on the right. The different rows are described in the text.

compatible mapping between the display format on the left and the task requirement on the right as shown by the heavy arrows: high display proximity supports high task proximity, while low display proximity supports low task proximity. The dotted arrows show low compatibility mappings. This relationship is rendered graphically by the interaction at the bottom of the figure. The relatively simple mapping, defining *the proximity compatibility principle* (PCP) (Wickens & Carswell, 1995), can be elaborated on considerably on both the display-proximity and the task-proximity end, as shown in Figure 6.4, and as we describe in the following pages in which we illustrate this elaboration with real-world examples.

6.4 TASK PROXIMITY

In elaborating on the "attention task" at the right side of Figure 6.3, it is important to distinguish focused-attention tasks from two different types of divided-attention tasks. The first type is a dual task, in which each display element is associated with a separate response and goal, for example as when a driver reads a map while trying to steer. The task in Duncan's (1984) experiment was of this form. The second type is an integration task, in which attention is divided between the two elements, but information from both is mapped onto a single goal and response, demanding mental combination. Such mental integration tasks are common in the real world, for example, in comparing one's selected answer with the correct answer on a key on a test question or in mentally linking symbols on a figure to keys in the graph legend. Sometimes this integration is logical or Boolean, such as identifying all aircraft heading east above a certain altitude. Sometimes it is arithmetic, such as multiplying the speed and time an aircraft has traveled to determine the distance. Our discussion contrasts focused-attention with divided-attention integration tasks, since dual-task situations, while having commonality with integration tasks, also share some features with focused attention (Carswell & Wickens, 1996). Divided attention in dual tasking will be discussed extensively in the next two chapters.

6.4.1 Display Proximity

Turning to the left side of Figures 6.3 and 6.4, display or "perceptual" proximity can be defined in several ways that extend the two primary categories of space- and object-based attention. Each of these ways are represented by different rows in Figure 6.4.

6.4.1.1 *Sensory/Perceptual Similarities*

As we have discussed, spatial proximity modulates the effort required to move attention from one location to another (Figure 4.5 of Chapter 4 and Row 1 of Figure 6.4). A classic example is the book designer's goal to keep the figure on the same page as the text that discusses that figure rather than require a page turn to go from the figure to the text. Such an information-access task (page turning and text search) competes for cognitive resources with the retention of information relevant to one source (figure or text) while accessing the second as required in cognitive integration (Y. Liu & Wickens, 1992a). Dupont and Bestgen (2006) have applied this design guideline of proximity to embedding icons within the text, directly next to the text description. Such embedding yields close proximity between icons and text and was found to help users more effectively program a display that also contains the icons. See also Lohrenz et al. (2004).

It is important to realize that spatial nearness is only one way to create a perceptual experience of proximity between two elements (Garner, 1974). Manipulations of color (Yeh & Wickens, 2001), including both hue and intensity (Wickens, Alexander, et al., 2004), can achieve the same ends, as shown in Row 2 of Figure 6.4. Color similarity, like spatial proximity, will also make it easier for people to divide attention between channels in an otherwise cluttered visual field. Such a finding relates back to material on visual search discussed in Chapter 5; when two target elements share a common preattentively processed feature (such as color), both will "pop out" from the background and therefore be more easily related or compared (i.e., integrated).

As a concrete example, and as discussed in Chapter 5, the use of color has been suggested as an aid to air traffic controllers trying to identify aircraft on a collision course. Recognizing that aircraft are at a risk of collision requires the controller to mentally integrate the crafts' trajectories and altitudes. Two same-color techniques can be employed to help such mental integration. First, all aircraft flying at a given

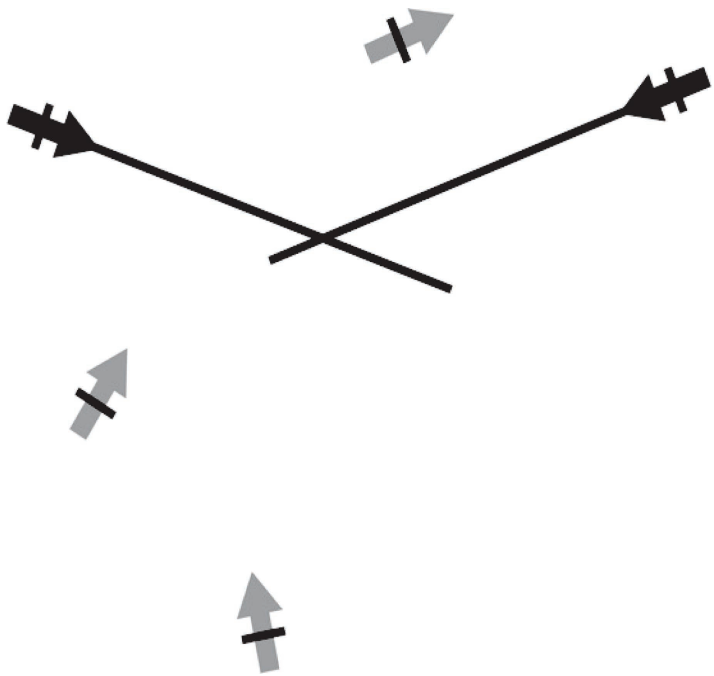

FIGURE 6.5 A schematic example of the User Request Evaluation Tool designed to help the air traffic controller understand the joint conflict trajectories (an integration task) of two aircraft that may be on a collision course. Note that the two conflicting aircraft are both joined by lines (linking) and are represented in a common color (highlighting).

altitude can appear in the same color (Remington et al., 2000), making it easier to isolate and divide attention only between those that represent potential collision threats. Second, a particular aircraft pair on a conflict trajectory could be colored red, thus making it easier for the controller to both notice them and understand their joint trajectory, the latter being an integration task. Such a concept has been employed in an air traffic control system called the *User Request Evaluation Tool* (Wickens, Mavor et al., 1998), explained schematically in Figure 6.5). Note that from a designer's standpoint, close display proximity can be created by using the common color when it is otherwise impossible to relate the two aircraft by moving them nearer one another in space (Row 1, Figure 6.4) since their position in space is determined by what the aircraft are doing, not by what the designer or user wants. In fact, this constraint is common to all maps; the designer simply can't "move things around" on a map to make it easier for the user to relate them.

6.4.1.2 *Object Integration*

As we move down to Rows 3 through 7 on the left side of Figure 6.4, we see that objectness can be defined in several ways. First, larger objects can be created by connecting smaller objects with a link. (Row 3, the two circles on the barbell) or by making them abut one another (Row 4). Second, objects can be defined by the separate attributes of a single "blob" such as the color, brightness, and size of a geometric shape (Row 5), the X-Y position of a point in a graph (Row 6), or the height and width of a rectangle (Row 7). We now elaborate each of these aspects of object-based proximity in turn.

6.4.1.2.1 Connections and Abutment

Just as spatially separated objects can be grouped by color, so too can they be grouped by a line or link that joins them (Row 3) (S. E. Palmer & Rock, 1994), as attention appears to be automatically drawn along connecting-line features (Jolicoeur & Ingleton, 1991). In the URET display of Figure 6.5, for instance, the two airplanes in conflict are not only like-colored but also joined by a line. As another example, in presenting complex device instructions that combine pictures of the device components with sentences describing what to do (e.g., "turn the knob to the left"), large gains in usability are achieved when the printed instruction sentence is linked to the pictorial rendering of the actual knob by a dashed line (Tindall-Ford et al., 1997). While such links can create clutter in a display (as we shall see, possibly disrupting focused attention), this clutter can be minimized by keeping the intensity of the linking lines relatively low. It is possible to set contrast high enough so the links can be perceived but not so high as to disrupt focused attention on the connected elements (Wickens, Alexander, et al., 2004).

6.4.1.2.2 Heterogeneous versus Homogeneous Featured Objects

Row 5 of Figure 6.4 shows two objects created by three heterogeneous features: size, brightness, and shape. Such features are described as heterogeneous because they are found to be processed by different perceptual analyzers (Treisman, 1985). This is typical of the symbols in many graphs (e.g., black square, white square, black circle, white circle), of the representation of towns on a demographic map (e.g., population, political leaning, mean income represented by size, color, and shape, respectively). The reader will recognize that the stimuli used in the Stroop task shown in Figure 6.2 are heterogeneous objects, with a semantic and a color dimension. Rows 6 and 7 show two *homogeneous* featured objects, each defined by its height and width. These are said to be homogeneous because a single perceptual feature—length—defines both. A display designer, confronted with the question of how to represent two aspects of a single entity, may be challenged as to whether to use heterogeneous or homogeneous features. The answer appears to lie in both the kind and degree of integration or task proximity that is required (Carswell & Wickens, 1996; Wickens & Carswell, 1995).

- If the integration goal is simply for the user to consider both aspects of the entity at once in a Boolean logical operation (for example, is a given city both large and conservative in population?), then heterogeneous featured objects are the ideal choice of representation, because they best allow parallel processing of the two dimensions (Lappin, 1967). In particular, heterogeneous object features are an economical way of presenting lots of information in a space containing several objects (e.g., map with several cities), because all attributes of a single object can be processed in parallel, the processing being divided between the different analyzers. Heterogenous symbols are thus good clutter reducers. Heterogeneous feature objects also effectively produce *redundancy gains* (J. Miller, 1982; Morey et al., 2018), where all features lead to the common response: consider the stop sign with color (red), shape (octagon), and text (STOP) being the prototype of a redundant, heterogeneous-featured object display.

- If the integration goal is an arithmetic or comparative one, however, heterogeneous features no longer provide the same benefit, since each feature is expressed on its own different scale or "perceptual currency," which cannot easily be compared. For example, an aircraft pilot who wants to compare actual speed with target speed does not want one to be expressed as length and the other as color. Instead, it is better for both to be spatial, perhaps as the height of two abutted bar graphs (Row 4). Many integration tasks involve mental multiplication in which the rate of some operation (e.g., rate of travel or rate of spending) is to be multiplied by the time of operation to produce a total quantity measure (e.g., distance traveled or total amount spent). Heterogeneous features serve this task poorly, but homogeneous features do so better. A particularly useful form of representation is to code one variable as the height of a rectangle and the other variable as the width (Row 7), making the area of the rectangle equal to the product of the two variables (Barnett & Wickens, 1988). This coding maps the value of interest directly to a visual feature of the display, replacing a cognitive operation (multiplication) with a perceptual judgment (area estimation). Since perception often proceeds more automatically than cognition, this replacement is a desirable human-factors goal and is one basic underpinning to the design of *ecological displays*, which we discuss in what follows (Bennett & Flach, 2019; Vicente, 2002; Vicente & Rasmussen, 1992). The user does not have to multiply numbers in their head but simply and directly can perceive the size of the rectangle.

6.4.1.3 *Close Proximity by Emergent Features*

An *emergent feature* of a display is a perceptual property that results in an unexpected way from an arrangement or configuration of more elemental features. It is not simply a difference in sensory magnitude but a salient and surprising percept "that make[s] the whole *qualitatively* different from the sum of its parts" (Pomerantz & Cragin, 2014, p. 88, emphasis in original). We have just seen an example of an emergent feature in terms of the height and width of a rectangle interacting to yield a directly perceived feature, the area (Row 7). Correspondingly, the difference between height and width in this display produces a second emergent feature of shape, as also shown in Row 7. A tall, skinny rectangle looks very different than a short fat one, even if both have the same area, and "squareness" (equal height and width) is a perceptually salient emergent feature.

Because they are perceived easily and automatically, emergent features can be used to make critical information salient in visual displays. To be most useful, emergent features should be mapped to the higher-order data patterns that reflect the integration of lower-order variables (Bennett & Flach, 1992). We can illustrate this by describing a medical display for monitoring patient respiration developed by Cole (1986). As represented back in Row 4 of Figure 6.4, two rectangle displays can be presented side by side, one showing the natural breathing of the patient, the other the artificial breathing imposed by the respirator. The displays are coded so that the height of the rectangle represents the depth of breathing (amount of oxygen supplied on each breath), and the width represents the rate of breathing (breaths/minute). Thus, the total amount of oxygen is represented by the height × width = area of the rectangles (Row 6). The relative size of the two rectangles indicates the amount of "work" the patient is doing compared to the respirator, and because the rectangles are abutting, differences in their size are readily perceptible. Furthermore, the style of patient breathing, panting versus slow, deep breathing, can be rapidly comprehended from the shape of the rectangle (Row 8). Thus, both relative amount and style—both properties that can only be inferred by integrating multiple sources of information—can be discerned at a quick glance. Such relatively automatic perception could not be accomplished if the basic breathing variables were either presented separately or represented by heterogeneous display dimensions.

Importantly, research (and intuition) has suggested that emergent features need not be created by an object display (Sanderson et al., 1989), although they are usually encouraged by objectness. Figure 6.6 provides an example of a graph with two bars (separate objects), each perhaps representing the desired and actual temperature of some operation and supporting the divided-attention integration task of assessing that the two values (desired = actual) agree. To the left, it is easy to perceive that the system is operating normally: the height of the two bars is identical. To the right, the same integration judgment is more difficult. The reason? On the left, the bars are aligned to a common baseline, meaning that the emergent feature of co-linearity of the tops automatically signals equivalence. It is as if one could imagine a ruler laid flat across the top (shown by the dashed line). One also might notice in Figure 6.6 how different display features of similarity can work in conjunction. If the same-baseline bars are also closer together or abutting, they can be perceived as a single object, as shown at the bottom. This makes the emergent feature of co-linearity salient, since its absence will be signaled by the break in the line across the top. This is a sensory/perceptual feature (*vernier acuity*) to which humans are extremely sensitive.

Another important emergent feature is the slope of a line that may connect two objects in a graph. For example, consider the bar graphs in Figure 6.7. On the left, it is possible to note that bars are of different heights or that four bars depict an interaction between two variables in a 2 × 2 experimental design. However, when the same data are depicted in a line graph, as shown on the right, then the height differences become more salient, as represented by the slope of the lines connecting the two points. This slope is an emergent feature. Furthermore, the magnitude of the interaction is expressed visually by the emergent feature of the angle between the two lines. Indeed, when the two variables are additive, and the effect of one is the same size at both levels of the other, the parallelism of the two lines also becomes an important emergent feature. This is shown at the bottom of the figure. It should be noted that some graphical packages generate graphs as unconnected points. This is unfortunate, as it deprives the viewer of a very important emergent feature reflecting the size of an effect or trend.

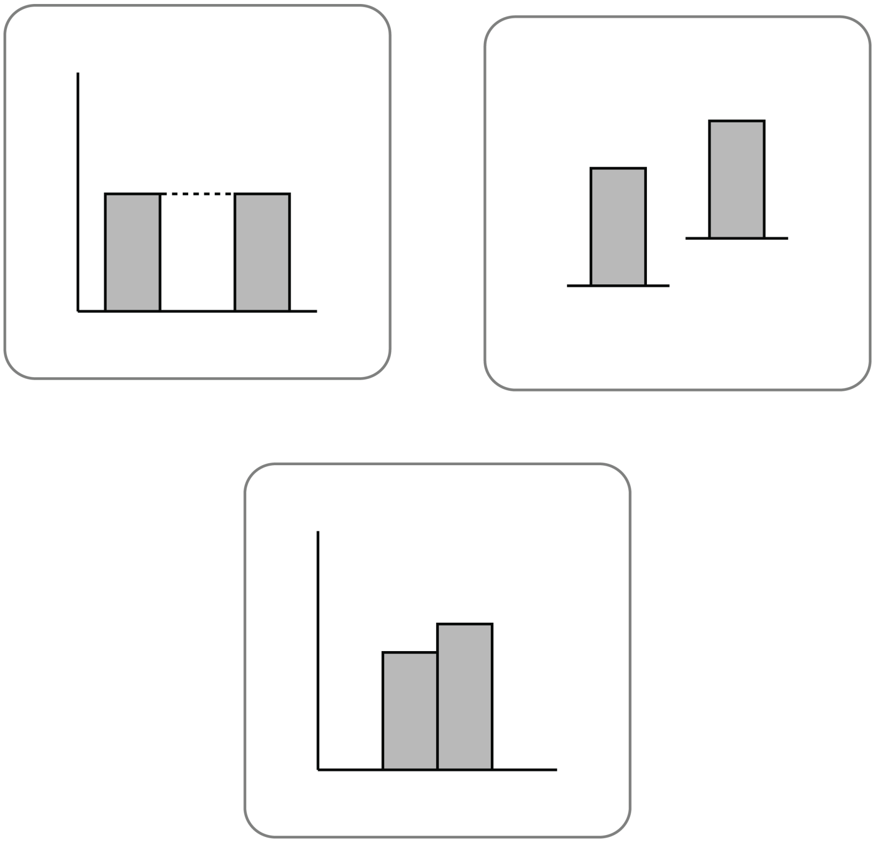

FIGURE 6.6 The role of common baseline alignment in creating an emergent feature (left side) to signal equal operating parameters. This is not available on the right side graph because the baselines are not aligned. The effectiveness of this emergent feature can be amplified when close spatial proximity or "abutment" is used (bottom row; illustrating nonequal parameters).

Before we leave the discussion of emergent features, we note one additional emergent feature that can often be created and exploited in display design, and that is the symmetry of an object or configuration (Ondov et al., 2019). The property of symmetry is one to which human perception is naturally tuned (Garner, 1974; Pomerantz & Pristach, 1989), and so if a symmetrical configuration can be directly mapped to a critically important display state, then a well-conceived emergent features display will be achieved. An example often cited is the polygon display (Beringer & Chrisman, 1991; Woods et al., 1981) such as that shown in Row 9 of Figure 6.4. Here, the normal operating levels of four parameters of a system are represented by a fixed (and constant) length of the sides of the quadrahedron (or the length of four radii from the center). When all four are at this normal level, a perfect square results, as on the left. When any variable departs from normality, symmetry is broken, and the distortion is easily noticed, as shown to the right (Ondov et al., 2019).

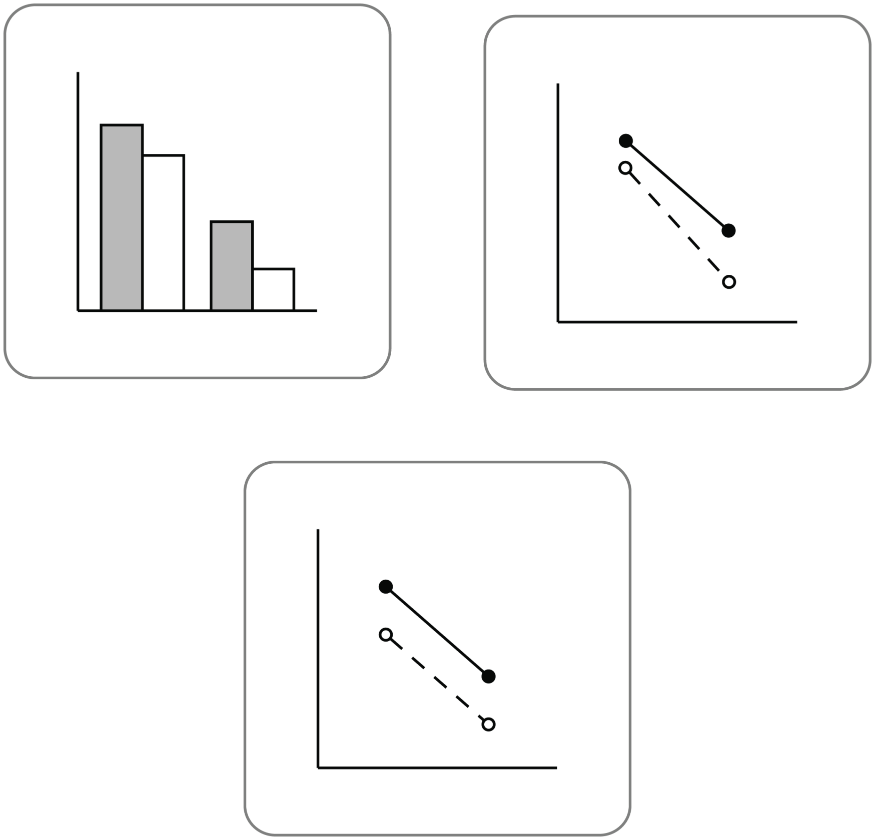

FIGURE 6.7 Contrasts the ease of understanding line graphs (right panel above) with bar graphs (left panel above) when an interaction relationship exists between two variables. On the right, divergence between the lines, an emergent feature, signals an interaction. The value of this representation increases as the number of variables increases. In the line graph below, an additive relation between the two independent variables is signaled by the emergent feature of parallelism.

In closing our discussion of information integration, we note two important aspects of emergent (homogeneous) feature object displays. First, the creation of such displays involves considerable creativity on the part of the designer—some would say as much art as science—not only to identify the critical system states to be perceived by the display user (i.e., the integration task mapping, often determined through cognitive task analysis and interviewing) but also to think of ways that this mental integration can be best supported by creative configuration of the display dimensions. Second, although we have been concerned with design of displays to aid mental integration of multiple cues, the display reader might sometimes need to know the precise value of a particular underlying dimension, e.g., what is the patient's rate of breathing? This brings us to the topic of focused attention and raises the concern that design features intended to support mental integration of multiple cues may impede the mental isolation of a single cue. A trade-off in design for divided and focused attention is the so-called "no free lunch" effect, to which we now turn.

6.4.2 Costs of Focused Attention: Is There a Free Lunch?

The PCP analytically proposes that there will be an interaction between display and task proximity, graphically depicted at the bottom of Figure 6.3. In its purest form, it predicts that closer display proximity (however achieved; see Figure 6.4) will improve performance on integration tasks but disrupt performance on focused-attention tasks (e.g., Lorenz et al., 2004). However, a more modest form of the interaction is also consistent with the principle: specifically, that increasing display proximity may aid integration tasks without hurting focused attention. By now, the costs of high task proximity on focused attention are well documented (Wickens & Carswell, 1995), even if they are typically smaller in magnitude than the benefits of close display proximity for integration (Bennett & Flach, 1992). The following are two examples of negative effects of close display proximity.

6.4.3 Overlaying Imagery: Maps, HUDS, HMDs, and Augmented Reality

The PCP can be illustrated in the design of displays for spatial understanding and guidance, which must often serve multiple tasks (Wickens, 2021). One example is the database overlay shown in Figure 6.8 (Kroft & Wickens, 2003). In this example, a spatially defined database, a terrain map, is either overlaid on a weather map of the same region (left) or displayed separately from it (right), representing high and low display proximity, respectively.

Kroft and Wickens (2003) found that overlaid displays were preferable to the separated displays when the task called for information integration, for example, when pilots were asked to judge whether a low-altitude detour around bad weather risked flying into a mountain. When the task required focused attention to a single display element, such as the altitude of a specific mountain, clutter produced by display

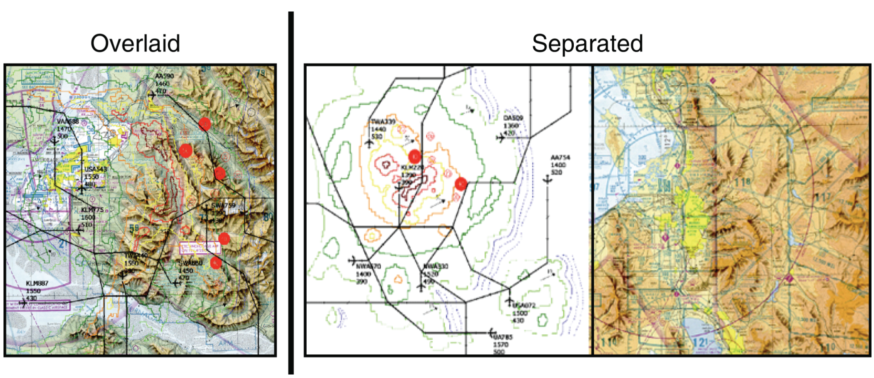

FIGURE 6.8 Database overlay (left) and separate (right) displays (Kroft & Wickens, 2003).

overlay hindered performance. For such focused-attention tasks, therefore, separated displays were best.

Interfacing with maps is sometimes provided by a *head-up display (HUD)* for ground and air vehicles (Wickens, Ververs et al., 2004) or its counterpart, the *head-mounted display* (*HMD*) (Dey et al., 2018), both of which provide a display overlaid on top of the view of the world beyond, e.g., a runway on the forward view for the airplane, a roadway on the forward view for the car, or a text message on an HMD overlaid on an everyday scene. Aspects of the natural world are referred to as the *far domain*. As compared to their head-down counterparts such as dashboard displays or mobile phone screens, spatially overlaid displays minimize the effort needed to switch attention between information sources but at the risk of high clutter. How does the cost of clutter trade off with the cost of information access effort?

Meta-analyses have found that aircraft HUDs, like that shown in Figure 6.9, tend to support better human performance than do head-down displays (Fadden et al., 2001, 2000), suggesting that the benefits of reducing information access effort outweigh the costs of clutter. HMDs show a similar advantage relative to handheld displays (Yeh et al., 2003). Yet in both cases, clutter in the overlaid displays carries a cost to focused attention, particularly in the detection of low salience targets either in the display itself or in the far domain (Fadden et al., 2001). Safety concerns about reduced awareness of the far domain have plagued recent HMD technologies like Google Glass (Lewis & Neider, 2016), and research has documented cases of distraction-related injury that resulted from users' attempts to divide attention

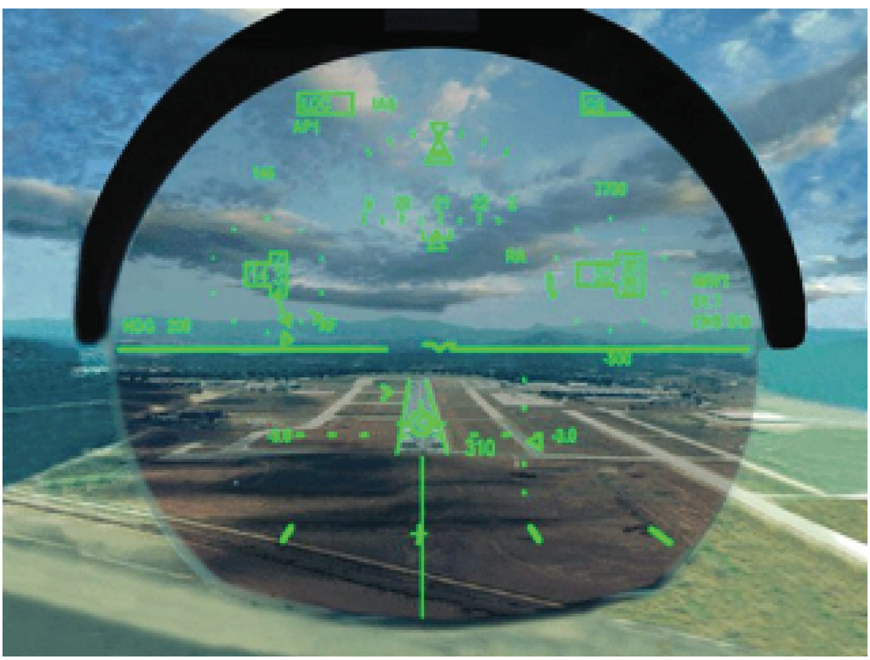

FIGURE 6.9 Example of an aircraft HUD viewed on a landing approach.

between the augmented-reality displays and the far domain (Richards et al., 2018). Such findings are entirely consistent with the predictions of object-based attention theory discussed earlier.

The trade-off of information access effort and clutter, however, is modified by one key variable reflecting the influence of object-based attention. When a display element is spatially aligned and moves in synchrony with its far domain counterpart even as the user's viewpoint changes, then the benefits of overlay to integration increase and the costs to focused attention are reduced and sometimes even reversed. In the HUD, such display images are called *conformal*. In the HMD, this property is one critical element of *augmented reality* (Claypoole et al., 2021), as shown in Figure 6.10. The relationship of this phenomenon to object-based attention is direct: synchronous motion—what the Gestalt psychologists called "common fate" (S. E. Palmer, 1999)—is a strong cue that two or more visual elements belong to the same object, even if they are separated in depth. Perceptual grouping by common motion produces "scene linking" between an overlaid display and the far domain, facilitating the division of attention between them (Levy et al., 1998).

In examining the images on the HUD or HMD, a further classification is necessary, as illustrated in both Figure 6.9 and 6.10. A text display such as a chat box or message, a digital indicator or a minimap, rendered on the display in a fixed display-referenced location, as seen in the right image of Figure 6.10, can create overlay clutter, inhibiting focused attention. In contrast, a graphics symbol on the display that overlays its far domain counterpart, such as the airport runway outline and horizon line in Figure 6.9 or the mountain identifier shown at the left of Figure 6.10, are displayed at world-referenced locations and are clearly augmenting the far-domain reality. These image properties enhance performance by scene linking. Lying between these are such elements as "AR signposts" ("Woods Point" in the left panel of Figure 6.10) that are world-referenced but also obviously can be sources of overlay clutter in focusing attention on elements of the domain.

In conclusion, both examples of overlay (HUD with conformal vs. non conformal imagery and HMD with AR-world referenced vs. screen-referenced imagery) are

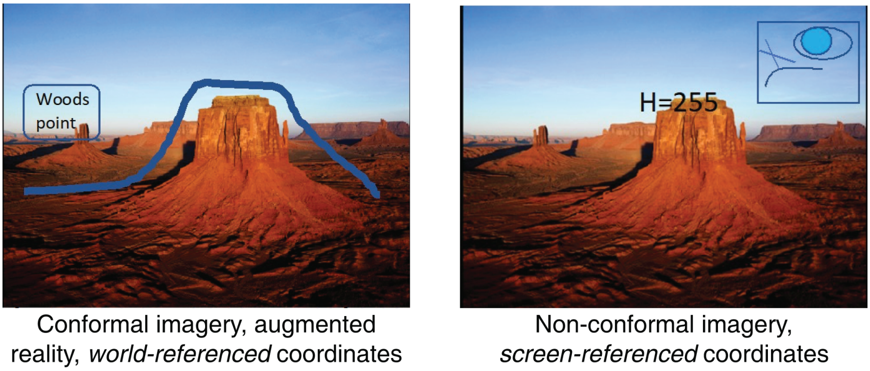

FIGURE 6.10 Example of a head-mounted display using augmented reality, world referenced imagery (left) versus screen-referenced imagery (right).

concepts designed to increase the likelihood of parallel processing between the near and far domains by exploiting object-based and space-based attention. Both concepts have indeed fulfilled that promise. However, it is important to note that neither HUD nor HMD technology guarantees that such parallel processing will be perfect. Consistent with the PCP, both reveal occasional shortcomings of focused attention on one domain or the other (e.g., Fadden et al., 2001). Indeed, both entail the risk of inattentional blindness discussed in Chapter 3 (Wickens, Hooey, et al., 2009): foveating on an event or object does not guarantee its detection, and overlay can create clutter that will interfere with both attention and perception.

In considering these and other examples of the PCP, it is important to understand that there are circumstances in which closer display proximity aids integration without hurting focused attention. For example, as we have noted, reducing the distance between elements generally doesn't hurt focused attention until separation falls below 1 degree of visual angle, where costs abruptly increase, or when objects overlap. But as we saw earlier in this chapter (and in Chapter 4, Figure 4.3), the costs of greater separation and information access effort to divided attention increase modestly across a wide range of angles above 1 degree but within the eye field. Thus, decreasing separation between information sources, say, from around 20 degrees to around 2 degrees will help integration and will not hurt focused attention. As another example, rendering two items in a cluttered display the same color will facilitate efforts to integrate or compare items and will likely not hurt the focus of attention on either. Color-coding of this form can even facilitate focused attention; it allows the operator to find a critical item more easily (Wickens, Alexander, et al., 2004). In the same vein, using a line to connect two symbols in a graph will not hinder a reader's ability to mentally extrapolate from a symbol to the y-axis, a focused-attention task, even as the slope of the line will improve the ability to perceive the difference in the two points' values.

In short, sometimes there is a free lunch, or at least a cheap one, if display proximity is used with care. A designer who must configure a display to support an array of focused and integration tasks can, by careful selection of different proximity metrics, attempt to support the "best of both worlds" in the scan–clutter trade-off. An example is the application of the proximity compatibility principle to graph design, which we discuss in the following.

6.4.4 Applications to Graph Design

The proximity compatibility principle is directly applicable to designing effective graphs that the user can process without investing unnecessary cognitive effort, although many principles of good graphics go further, of course (Gillan et al., 1998; Kosslyn, 2006; Wickens et al., 2022). Consider the graph in Figure 6.11, which depicts the hypothetical results of an experiment studying the combined effects of workload, task complexity, and age on response time. Five features in the design of this graph, relating to the features of proximity in Figure 6.4, adhere to the proximity compatibility principle:

1. *Object integration*: A heterogeneous-featured symbol represents each data point, representing age with intensity and task complexity with symbol size. There is also a redundant object integration, since the link between the two data points within each age group is coded by line type, dashed or solid.

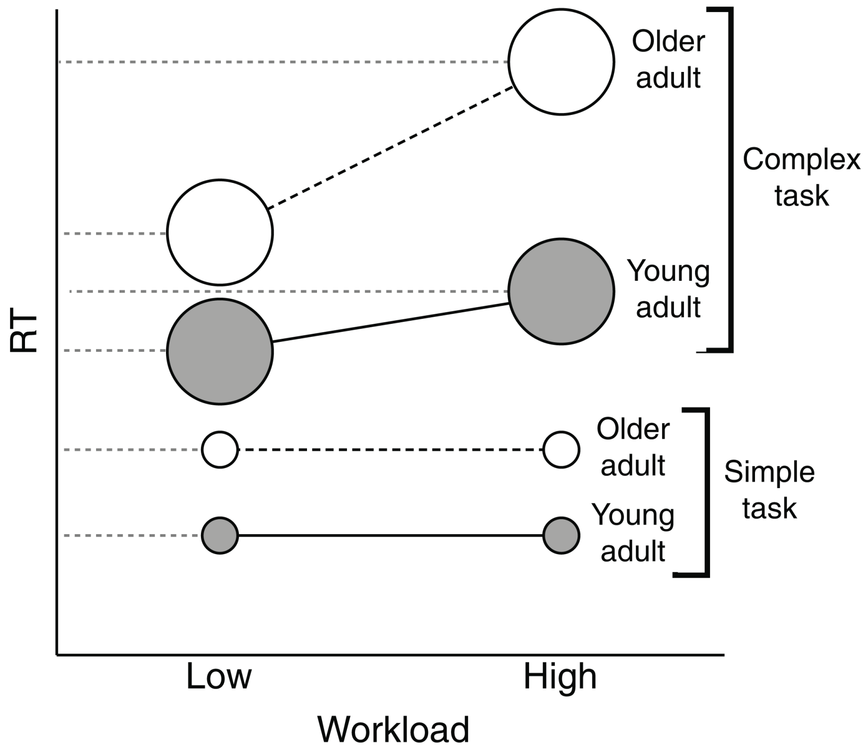

FIGURE 6.11 Application of several aspects of the PCP to the design and layout of graphs, in this case the graph of the results of a 2 × 2 × 2 experimental design.

2. *Connections*: The connections between data points reveal the workload effect (and what moderates it) through the emergent feature of line slope, as we saw in Figure 6.7. For example, this feature helps integration so we can focus attention on the large dots to see how workload affects performance with complex tasks or focus on the white dots to see how workload affects older participants. Conversely, comparing slopes allows us to check for interactions. Flat, parallel lines let us easily see that workload had no effect for either age group in the simple task, whereas sloped, nonparallel lines make clear not only that workload increased RT in the complex task but did so disproportionately more for older people.
3. *Spatial proximity*: Labels are directly adjacent to the lines that they refer to. This reduces the effort needed to mentally associate the labels and lines as compared to a design in which the labels were placed in a separate legend.
4. *Spatial proximity*: All four lines are plotted in a single panel, giving them high spatial proximity and making the three-way interaction described in point 2 easy to notice. This would not be easy if, for example, the simple task data were plotted in one graph and the complex task data were plotted

in another. Such separation would be particularly problematic if the two graphs were placed on separate pages.

5. *Focused attention*: The horizontal lines connecting data points to the y-axis allow readers to accurately estimate values for individual data points, but, because they are low intensity, do not hamper the perception of the overall integration yielded by the line slopes.

Note further that the graph in Figure 6.11 is designed to emphasize that the effect of workload is moderated by age and complexity. Hence, the influence of workload was mapped to the x-axis, with symbols representing different levels of load connected by lines. The emergent feature of line slope therefore gave a direct visual cue to represent the effect of workload. If the most important point of emphasis had been the differences between age groups, then age rather than workload would have been represented on the x-axis.

This example for applications of the PCP to graph design is actually a fairly simple one: eight data points, three independent variables, and one dependent variable. However, the PCP and its guidance for the control, direction, and support for attention are very applicable for much more complex data visualizations (Shneiderman et al., 2016; Wickens, Merwin, & Lin, 1994; Wickens, Helton et al., 2022). Here, there may be massive amounts of quantitative data, with hundreds of data points representing scores of multiple different dimensions (North, 2012; Pattanaik & Wiegand, 2021; Tufte, 2001). The ultimate challenge in designing such visualizations is to help support the user to integrate information across objects and/or dimensions in order to gain insight into relations that are not yet known. We have seen in the examples how display similarity and proximity can support such integration in simple graphs; such techniques can be extended, in many creative ways, to the more complex graphs supporting visualization (Franconeri, Padilla, Shah, Zacks & Hullman, 2021; Y. Liu & Wickens, 1992b; North, 2012; Shneiderman et al., 2016; Wainer & Thissen, 1981; Wickens, Helton et al., 2022).

6.4.5 Ecological Interfaces, Navigation, and Supervisory Displays

Discussion of the PCP and multielement displays leads us to the concept of *ecological interface design* (EID), a process that aims to support the operator in maintaining awareness of a complex, dynamic system (Bennett & Flach, 2013; Burns et al., 2008; Burns & Hajdukiewicz, 2017; Lohrenz et al., 2004; P. J. Smith et al., 2006; Vicente, 2002; Vicente & Rasmussen, 1992). This might describe the needs of supervisors in the process control industry, air traffic controllers, or anesthesiologists, among many others. Next, we highlight aspects of EID related to attention.

6.4.5.1 *EID and Emergent Features*

The concept of "ecology" in ecological interface design refers to the goal of representing elements perceptually, in a way that they are expressed in the natural world (and, it is assumed, within the mental model of the well-trained expert; P. J. Smith et al., 2006, Vicente and Rasmussen, 1992). Ecological displays are generally configural, using emergent features to represent key relationships between variables

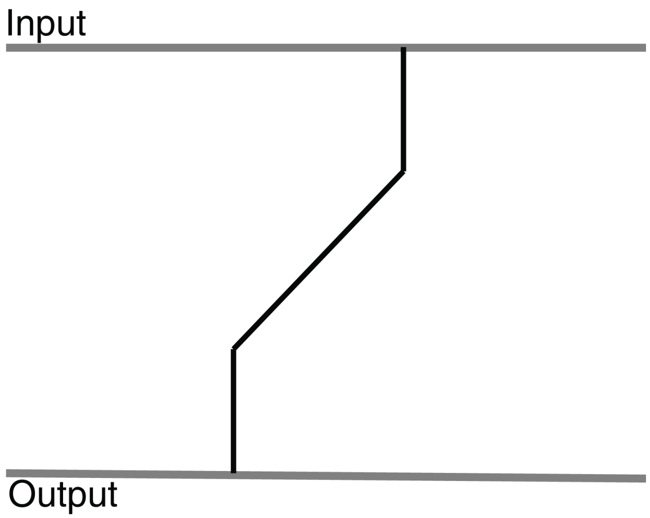

FIGURE 6.12 An example of an ecological display, showing the imbalance between two quantities (e.g., flow in vs. flow out of a reservoir). This rightward slope of the middle segment indicates that the reservoir is filling: input is greater than output. Steady-state behavior would be indicated by a vertical line—an emergent feature—connecting the Input and Output scales (adapted from P. J. Smith et al., 2006).

(Bennett & Flach, 2013). Analog displays are most appropriate for this purpose, as most of the natural world behaves in an analog fashion consistent with the laws and constraints of physics.

As an example, in many systems, there is a need to preserve a balance of processes in order to be operating normally. The flow into a chemical tank should equal the flow out of the tank, for instance, and in nuclear power facilities, it is critical that the balance between mass and energy be preserved. Such a balance can be directly and intuitively perceived by the display form in Figure 6.12. This representation relates directly to our discussions of attention because of the degree to which the single object supports the parallel processing of its attributes, and the attribute of symmetry, representing balance, can be directly perceived as an emergent feature, specifically, an unbroken vertical segment. Other examples from ecological interface design relate to object-based safety parameter displays such as those described in Figure 6.4 Row 9 (Woods et al., 1981).

6.4.6 Integration Over Space and Time

Systems in the process control industry may involve hundreds of different dynamic parameters to be displayed, presenting a risk of visual overload within a single display (Moray & Salvendy, 1997). Although strategic use of emergent features may allow some parallel processing, subsets of parameter values will likely need to be attended sequentially, and good design is therefore necessary to minimize information access effort. One solution is to present multiple displays side by side, eliminating the manual and cognitive effort needed to navigate between. However, this may require shrinking the displays and reducing their legibility (Kroft & Wickens, 2003). A preferable approach, where possible, is to employ integrated ecological displays (P. J. Smith et al., 2006).

For example, in a process control simulation, Burns et al. (2008) compared the three philosophies of sequential, simultaneous, and simultaneous-integrated information display as ways of representing the same process control information, with the simultaneous-integrated display incorporating the principles of EID. They found a compelling advantage of the simultaneous-integrated approach when an integration task (fault diagnosis) was required. Correspondingly, Jang et al. (2012) compared large, multiscreen meteorological displays depicting different databases at different time slices to "stacked" displays, wherein each display screen had to be accessed sequentially (over time) by a click or mouse hover. Across expert and novice participant groups, data consistently showed an approximately 30% reduction in the time required to answer questions that required information integration across screens in the single-screen format compared to the stacked-screen format. There was no loss in accuracy. In so doing, they added another aspect to the information access effort concept: the cost of manual retrieval.

6.4.7 Visual Momentum and Navigation

When multiple views of a complex industrial system process, database structure, or physical (geographical) space are presented to the viewer who tries to integrate information between them, the issue of how to support movement of attention while relating different views becomes critical. As a simple example, when you are in unfamiliar territory, maintaining geographical awareness often involves relating—integrating—the layout presented on a map with the visual image looking forward (Wickens, Vincow et al., 2005; Wickens, 1999). This entails linking a local view of the space to a more global view.

Such shifts of attention between different but related or overlapping representations of a space are facilitated by establishing *visual momentum* (Aretz, 1991; Olmos et al., 1997; Wickens, 1993; Woods, 1984). This technique was originally used by filmmakers to provide the audience with a graceful cognitive transition between different cuts of the same scene (e.g., zooming and panning; Hochberg & Brooks, 1978). In the case of industrial system monitoring, one application of visual momentum, shown in the top panel of Figure 6.13, might be to provide two views, one a global view of the entire plant layout and the other a zoomed-in view of a particular region of the plant where a problem has developed. To create visual momentum, the elements of the local view are highlighted on the global view, so it is easy for the viewer to see how one relates to the other—an integration task—and move attention back and forth between them.

One visual momentum technique that has proven to be particularly valuable in navigating through real or virtual spaces is the "wedge" shown in the bottom of Figure 6.13, which shows how the information in the large forward view local display (shown below) is represented in the global map (shown as the inset above) by presenting the field of view of the former as a wedge, overlaid upon the latter (Aretz,

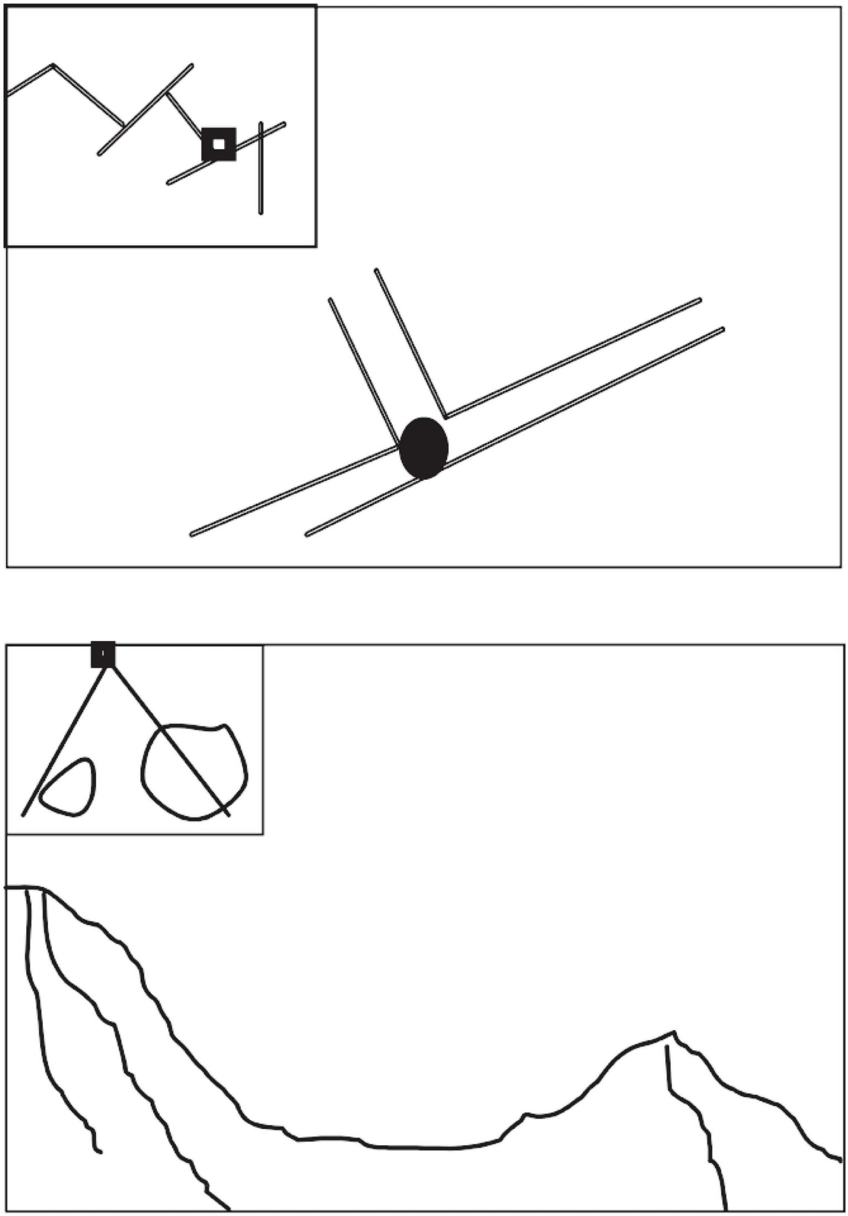

FIGURE 6.13 Two examples of visual momentum. In the top panel, a schematic representation of the piping of a full system is shown in the inset, highlighting the location of the particular valve that is rendered in the main part of the display. In the bottom panel, the pilot is flying southbound, toward the gap between two mountains, as shown in the global-view inset. The field of view of the local view, shown in the main part of the display, is rendered by the inverted wedge in the small global view. With an augmented reality HMD, the width of the wedge could be represented by two vertical lines drawn in world referenced coordinates on the display below. In both examples, the display features situate the local view within the global view, helping the user to divide or switch attention between views.

1991; Olmos et al., 1997; Wickens et al., 2000). Such a technique of attentional support is particularly advantageous when one is looking or traveling in a direction that is different from the normal orientation of the global view. This is often the situation with a north-up map when traveling southward. Levine (1982) has shown how this can be applied to "you are here" maps, commonly found in malls and city areas (see Wickens, Helton et al., 2022).

6.5 CONCLUSION

In the interfaces with which we work, displays are usually visual and almost always contain multiple elements. Hence it is not surprising that visual attention is challenged. Because of this challenge, it is the designer's goal to either foster as much parallel processing as possible or, at least, to reduce the effort of selective attention required to visually access related elements in sequence. The PCP, incorporating elements of both space- and object-based theories of attention and related elements of proximity in ecological interface displays, points to ways that this can be accomplished. Such techniques then often help the sequential access of information. We considered the important concept of information access effort in Chapter 4 and will do so again in the next chapter. Importantly, sometimes the display environment confronted by the human contains nonvisual elements as well: speech, tones, and even tactile stimulation. We describe these multimodal aspects of display design in Chapter 8.

7 Resources and Effort

The common exhortations “try harder” and “pay closer attention” are closely related. Both phrases invoke the concept of effort; mental effort in the latter case and either mental or physical effort in the former. Kahneman (1973), in his classic book *Attention and Effort*, conceived of effort as a sort of mental energy or resource (Hockey et al., 1986) that can be mobilized or demanded in continuously varying quantities. In this respect, the notion of attention as a resource contrasts markedly with the metaphor of a two-state (open or closed) bottleneck (Chapter 2) or a discrete attention switch (Tsang, 2006; see Chapter 9). The concept of effort in psychology has also been tied closely to physiological characteristics of arousal through the autonomic nervous system (Gopher & Sanders, 1984; Hockey, 1997), although the two concepts are not synonymous.

As effort pertains to task performance, it can be invoked in two different ways, characterizing either the person or the task (Kahneman, 1973). First, the person can be said to invest varying levels of effort), reflecting a kind of strategy. Second, the task can be said to demand varying levels of effort in order to achieve a particular level of performance. These two characterizations are reflected in the concepts of both mental workload and automaticity, as we discuss in what follows.

The person and task characterizations of effort are equally relevant to both single- and dual-task performance, a distinction we make in the following two sections. Following that, we discuss the issue of measuring effort, or *mental workload*.

7.1 EFFORT IN SINGLE-TASK CHOICE

The general framework for considering effort in a single-task context is that excessive mental effort, like excessive physical effort, generally produces an unpleasant or aversive state, what Shugan (1980) has called the “cost of thinking.” Hence, people tend to be inherently effort conserving (Kahneman, 2011; Kool et al., 2010; Kurzban et al., 2013; Wickens, 2014, 2017), particularly in highly demanding environments. With this effort conservation in mind, Figure 7.1 presents a very general model of effort in choice. Here, a person is confronted with a choice between two behavioral strategies. One requires little effort but might provide a modest expected value, perhaps even with the possibility of a loss—it is risky. The second requires a higher investment of effort but promises a better payoff (“no pain, no gain,” as the saying goes). We can apply this simple representation to a number of different kinds of single-task choices.

7.2 EFFORT IN THE CHOICE TO STOP SEARCH OR LIMIT SAMPLING

Chapter 5 discussed visual search. Serial search can be considered effortful (assuming that more time and more scanning translates to more work). A critical issue in

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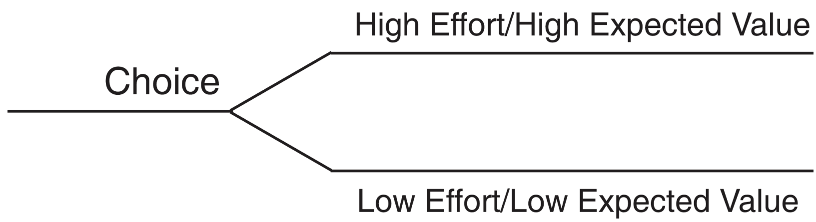

FIGURE 7.1 A general model of effort, expected value and choice.

understanding search performance, as discussed at the end of that chapter, is the stopping policy for target-absent responses: in a serial search, how does an operator decide to stop searching and conclude that the target is absent? Very often, a target-absent response is executed when the effort required to continue searching exceeds the expected value of a negative response (Drury & Chi, 1995). Thus, in many real-world environments, when the searcher reaches some total expended effort threshold, search may be terminated even if the target has not been found. This decision to stop searching corresponds to taking the bottom path in Figure 7.1. The threshold for the decision will obviously vary for a number of reasons, just as the expected cost of not finding something will vary with the value of the unfound object. As discussed in Chapter 5, for example, miss rates in visual search increase as target prevalence rates decrease, in part because observers tend to terminate search quickly (Rich et al., 2008).

The concept of effort can also be applied to other forms of real-world search beyond serial visual scanning, such as the decision to terminate a document search (MacGregor et al., 1987) or to give up searching for a particular experimental phenomenon in the laboratory. In most of these contexts, effort can be expressed fairly directly in terms of time (Gray & Boehm-Davis, 2000) or sometimes in financial resources. The two can be used interchangeably if "time is money." However, as we will see, time is not always equivalent to effort.

A different role of effort is applied to visual sampling and surveillance tasks of the form discussed in Chapter 4, where one is no longer searching in a self-terminating manner for a specified target but is monitoring for critical events over time. This may involve watching for enemy targets (Yeh et al., 2003, 1999), for example, or monitoring an air traffic display for changes in heading or altitude that might produce a conflict (Remington et al., 2000; Stelzer & Wickens, 2006). Here, as discussed in Chapter 4, and as incorporated in the SEEV model, effort-based choices may limit the spatial extent of sampling. If large movements are needed to check the periphery of a display, information access effort is high, and the effort-conserving searcher may focus scanning more heavily on the central channels (Eisma et al., 2018). Design features that make attention shifts effortful can further inhibit peripheral searches. For example, heavy HMDs may keep surveillance more centralized than desirable (Seagull & Gopher, 1997; Yeh et al., 1999). Similarly, the need to pan a camera in an immersive 3D imaging device may lead users to focus more of their attention on the default field-of-view (straight ahead) and fail to scan the sides (Wickens, Thomas & Young, 2000).

Thus, the choice to minimize information access effort can be applied directly to manual sampling as well as eye and head movements. Often, when the effort of keypresses is substantial, people will be reluctant to seek valuable information (Jang et al., 2012) and will choose to use memory-based strategies instead. With the use of a computer graphics interface, a mouse hover is a less effortful way to retrieve information than is an active key request; and the former shows a different pattern of choice than the latter where more use is made of a memory-based strategy. The way in which the costs of information access effort alters both strategies and performance outcomes has even been extended to walking. Yang et al. (2015) found that requiring doctors to walk 5 meters in order to view patient health data reduced information access by 13% and increased the doctors' reliance on their (fallible) memory, resulting in poorer performance.

7.3 EFFORT IN THE CHOICE TO BEHAVE SAFELY

As discussed earlier, the choice involved was between continuing or stopping a search. In many other situations, effort plays a role in the choice between engaging in safe or unsafe behavior, often at the workplace. Consider the two limbs of Figure 7.1 again. The lower limb in this case is the choice to behave unsafely, which can lead to costs in the form of accidents and injuries; consider, for example, the risks of failing to wear protective goggles or a safety helmet. The upper limb is safer but is penalized by compliance costs (Lee et al., 2017; Wogalter et al., 2021). These costs can often be expressed in terms of the effort (here again, often time) required to behave safely (locating and putting on the safety equipment, taking the time to read and understand the safety instructions, etc.) but might also include influences such as the discomfort of wearing the safety equipment. The cost further involves mental effort if, for example, the operator is required to read and understand poorly worded instructions for following safety procedures. Under such circumstances, this reading will often be bypassed.

7.4 EFFORT IN THE CHOICE BETWEEN DECISION STRATEGIES

A third influence of effort is in guiding the choice between two decisions strategies. This application is based on a line of research on decision-making by Bettman, Payne, and Johnson and their colleagues (Bettman et al., 1990; Johnson & Payne, 1985; Payne et al., 1993). However, the concept of effort in choice has its earlier roots in the concept of decision-making heuristics, examined by (Kahneman et al., 1982; Kahneman, 2003; Tversky & Kahneman, 1974; see Lehto & Nanda, 2021, for a review of more recent work on decision-making heuristics).

A heuristic may be thought of as a low-effort, "quick-and-dirty" means of generating what is usually a good-enough solution to a decision-making problem, in a manner that is easier than following a more formal algorithm. The latter approach will usually generate the formally optimal solution (i.e., the outcome with the highest expected value given the factors at hand) but often at the expense of a great investment of mental effort and time (i.e., the upper limb of Figure 7.1). A good example of the contrast between algorithms and heuristics can be provided by comparing the potential decision strategies for the choice between options. Consider a consumer, choosing between three products that differ on three attributes (e.g., cars that differ on gas mileage, durability, and price). Typically, the attributes will have different degrees of importance to the consumer (high, medium, low). Using an optimum decision-making algorithm, the consumer will consider all values of each option on each attribute, weighted by attribute importance. Because it allows a high-value attribute to make up for a low-value different attribute, this method of choice is sometimes described as a *compensatory* strategy (Wickens, Helton et al., 2022). A compensatory approach, if done mentally, requires an effortful reliance on working memory. In contrast, using the heuristic *elimination-by-aspects* strategy (Tversky, 1972), the decision-maker will first eliminate from consideration the options that are least favorable on the most important attribute (e.g., all cars that do not fall within the decision-maker's price range), immediately reducing the cognitive load of the decision problem.

As an example, elimination-by-aspects might quickly narrow a large range of options down to two, leaving only the two items ranked first and second on the most important aspect. Thus, a car shopper with the primary goal of saving money might quickly reject all models that fall above a price limit and consider only the two least expensive cars from among the available choices. This approach will indeed keep costs low but might not generate the best solution. One of the options eliminated from consideration because of its cost, for instance, might have actually been strong enough on its remaining attributes to compensate for its higher expense. However, elimination by aspects will always lead to an option that is acceptable, and will do so with much less mental effort than is needed to choose an option guaranteed to be optimal. Its benefits will also grow as the choice space expands.

Wickens, Helton et al. (2022) have represented algorithms and heuristics in an effort–performance space, as shown in Figure 7.2. Here, algorithms can attain very good performance but only with maximum investment of effort. Heuristics, on the other hand, can obtain pretty good performance with smaller effort investment. If the utility of a decision strategy can be characterized as a weighted sum of performance quality and effort conservation, then it is easy to think of a utility scale running from the lower right (poor performance, high effort) to the upper left (good performance, little effort). Within this representation (Navon & Gopher, 1979), it is then easy to see how a heuristic can be chosen that has overall greater utility than an algorithm.

In a similar model, Bettman et al. (1990) present a *contingent decision model* that describes the role of effort in the choice of decision strategy, identifying six elementary information processing (EIP) mechanisms that are involved to varying degrees in the decision process: READ, ADD, COMPARE, MULTIPLY, DIFFERENCE, ELIMINATE. The model characterizes decision strategies based on the number of EIPs they involve. On average, a strategy requiring fewer EIPs imposes less effort but also tends to reduce decision accuracy. The model predicts that the choice of strategy will therefore be based upon the trade-off between the desired accuracy (more EIPs needed) and the available effort (fewer EIPs wanted), corresponding to the top and bottom limbs of Figure 7.1, respectively, as well as to the upper-right and lower-left regions of Figure 7.2. Their data validate the model.

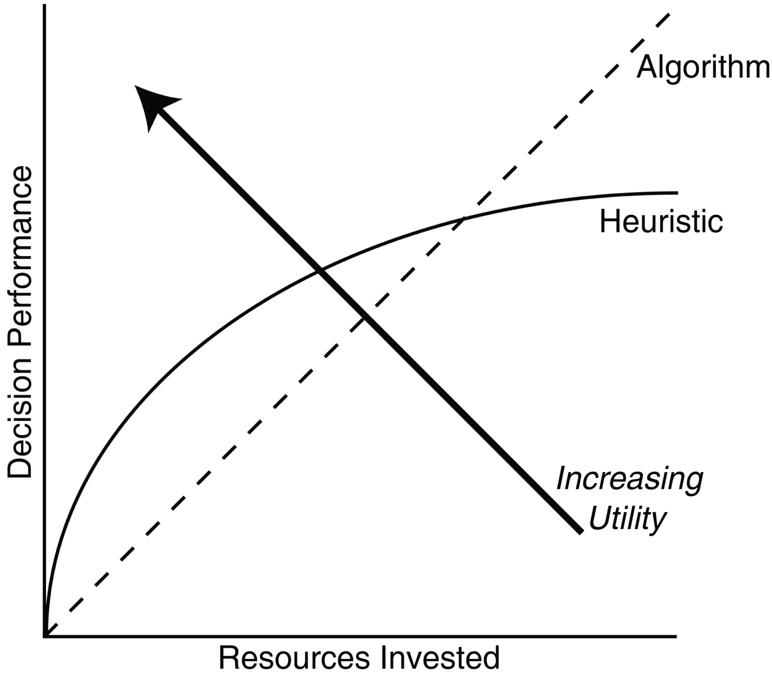

FIGURE 7.2 The effort–performance representation of algorithms versus heuristics. The higher utility of heuristic decision-making explains why it is often chosen over algorithmic decision-making.

Bettman et al. (1990) applied the contingent decision model specifically to consumer choice. As an example of such an application, Russo (1977) considered the scenario of shoppers faced with a wealth of options at the supermarket. The supermarket has a variety of options for presenting pricing information to help the shopper choose the optimal product (at least where optimality is defined by dollars/weight). These options include:

1. present separate price and weight information, ordered by product brand;
2. present unit price information (e.g., $/oz.) ordered by product brand;
3. present unit price information ordered by unit price value.

Moving from option 1 to 3 reduces the shopper's cognitive load and, as documented by Russo, improves the shopper's decision-making. Bettman et al. (1990) describe the third procedure, price-ordered marking, as an example of *passive decision support*, in which information is conveyed in such a way as to make the least effortful strategies yield the best results. Bettman et al. (1986) have applied this approach to develop guidelines for presenting product risk information, here tying back to the issue of safe behavior, discussed earlier. Note the parallel to display layout strategies discussed in Chapter 4, where displays were laid out so that expectancy for a pair of displays was inversely correlated with the distance (information access effort) between them.

Of course, a decision-maker confronted with a new way of making choices or a new kind of choice to be made may not know how much effort will be required by a particular strategy or the level of accuracy that the strategy can be expected to produce. Choice in these cases will therefore be based on anticipated effort and accuracy. Fennema and Kleinmuntz (1995) have demonstrated that people are not always highly calibrated in their estimates of these anticipated quantities.

Finally, the distinction between heuristics and more effort-consuming algorithms maps onto the distinction that some researchers have drawn between cognitive *system 1* and *system 2*, respectively (Evans & Stanovich, 2013; Kahneman, 2011; Steigenberger, 2017). Within this framework, the decision-maker may prefer to use the less effortful and more intuitive system 1 to make a decision or to solve a problem but sometimes invoke the slower and more deliberative system 2 to check system 1's output.

7.5 EFFORT IN THE CHOICE OF A FEATURE TO USE: IMPLICATIONS FOR SYSTEM DESIGN

Technology often provides multiple features to solve the same problem. Some features may be powerful but demand a heavy investment of effort, either to use (e.g., high working memory load) or to learn (e.g., complex multistep procedures). These map onto the upper limb of Figure 7.1. Other features may be less efficient but require less effort. These map onto the lower limb of Figure 7.1. An example of the first type of strategy might be to take the time and effort to write a script to automatically extract data from the tables and figures in a set of published research articles. An example of the second type of strategy might be to code the same data manually, a process that is more time consuming and potentially less accurate but also less cognitively demanding.

In this context, the choice between strategies has at least four important elements: (1) time demands, (2) cognitive demands, in particular, working memory demands, (3) the anticipated accuracy of the output, and (4) the utility of the choice option, which may reflect a weighted combination of the first three variables. That is, people may be seen to maximize utility by choosing a strategy that achieves some compromise between minimal time, minimal effort, and maximum expected accuracy. Yet circumstances can alter the weighting assigned to each of the three elements, as suggested by two experiments described in what follows.

Ballard et al. (1995; see also Draschgow et al., 2021) asked people to copy a pattern of colored blocks—the model—by picking up and transferring blocks from a resource area onto a canvas. In some conditions, the model and the resource area were close together, so that it was possible to make short eye movements back and forth between them. Under these circumstances, people tended to minimize the demands on working memory by making frequent eye movements: looking at the model to determine what color of block was needed, then looking at the resource area to select a block, then looking back at the model to determine where the block should be placed. Evidently, no more than one piece of information—color or location—was held in working memory at a time, indicating that people preferred to make many information access actions with low working memory load rather than make fewer actions with higher working memory demands. When the model and resource area were farther apart, however, such that head movements were needed to shift attention between them, performance strategy changed. Participants made fewer gaze shifts between the two areas and appeared to hold color and location information simultaneously in working memory. This is analogous to the bias observed by Yang et al. (2015) above when physicians had to take the “effortful” 5-meter walk.

Gray and Fu (2004) likewise also relying on working memory. Participants in their experiment were asked to program a simulated VCR under three conditions. In the first, the participants memorized show days, times, and channels before performing the programming task. In the second, the same information was not memorized but could be accessed by visual scanning. In the third, keypresses were needed to access the programming information. The three conditions could thus be ordered by ease of information access from easiest (direct retrieval from long-term memory) to more difficult (visual scanning) to hardest (manual interaction). Data revealed that participants in the direct memory retrieval condition made the fewest programming errors. And even within the two groups who had to access information perceptually, participants often relied on imperfect working memory for programming information instead of checking the display. Participants who were required to manually interact with the display to view the programming information relied more on imperfect memory than those who only had to make an eye movement to access the information, manifesting the costs of information access effort.

7.6 EFFORT IN INFORMATION INTEGRATION: THE PROXIMITY COMPATIBILITY PRINCIPLE

Another example of effort in single-task performance relates to the proximity compatibility principle (PCP) (Wickens & Carswell, 1995) discussed in Chapter 6. There, we described how, when information needs to be integrated from two different sources, there is an increased penalty of moving those sources farther apart or otherwise making it harder to access one source after attention leaves the other, relative to the case when the two sources are part of separate tasks or separate judgments. This effect is explained in terms of the trade-off between the effort required to retain information in working memory as attention shifts from one display source to the next, and the effort required to access the second source necessary for comparison or integration with the first. These two mental operations (working memory maintenance and information access) compete for a common pool of cognitive resources. The greater the working memory load imposed by the information integration task and the greater the distance traveled by attention as it moves from the first information channel to the second, the greater is the total effort demand of both information processing components, and thus the greater is the performance penalty (Vincow & Wickens, 1993).

7.7 EFFORT DEPLETION AND EXPANSION: THE VIGILANCE DECREMENT

If cognitive effort is indeed a limited resource drawn on by cognitive activity, it is reasonable to assume that it might wane over time with heavy use (Kurzban et al., 2013). This is perhaps best illustrated by the effect known as the *vigilance decrement* (P. A. Hancock, 2017). A vigilance task requires the observer to monitor for rare and unpredictable signals over long periods of time. Modern research on vigilance began with Mackworth (1948), who was spurred by the practical need to improve human performance in WWII. He noted, for example, that "in 1943 . . . the Royal Air Force had to determine the optimum length of watch for airborne radar operators on anti-submarine patrol. It was suspected that working efficiency was deteriorating due to overlong spells at the radar screens" (Mackworth, 1948, p. 7).

To study vigilance in the lab, Mackworth sought a task that mimicked the anti-submarine radar operators' demand to watch for occasional, barely perceptible signals, interspersed among much more common noise events, over an extended time. The result was the *clock test*, which asked observers to monitor the hand of a clock, ticking forward once per second, for occasional movements (the signals) that were twice the normal size. Mackworth's data showed that signal detection rates began to decline within the first half-hour on watch. Later studies found that a drop in vigilance can begin within just a few minutes of the start of monitoring (Craig & Klein, 2019; Nuechterlein et al., 1983; Temple et al., 2000).

What causes the vigilance decrement? Signal detection rates drop over time in part because observers gradually become more conservative in their response bias, setting a higher threshold for reporting a signal (Broadbent & Gregory, 1965), and in part because they experience attentional lapses, mentally dropping out of the task (Manly et al., 1999; McCarley & Yamani, 2021; Robertson et al., 1997). The *resource depletion model* of vigilance proposes that attentional resources can also be drained over time. By this account, sustained attention requires intense effort (Warm et al., 2008) and gradually exhausts the observer's information processing resources (Caggiano & Parasuraman, 2004), especially if the task is fast paced or imposes a heavy load on perception and memory (Nuechterlein et al., 1983; Parasuraman, 1979). The loss of processing resources increases sensory and decision noise, reducing signal detectability. Converging evidence for the resource depletion model comes from the finding that vigilance tasks impose high mental workload and create operator stress (Szalma et al., 2004; Warm et al., 2008). Contrary to the intuition that simply watching for signals is undemanding, sustaining attention over time is resource taxing.

If resources can be depleted in continuous fashion by extensive use, then an argument can be made that the size of the "tank" containing these resources can also be considered as variable or malleable (Young & Stanton, 2002). What this pool might be in terms of actual brain functioning will be addressed soon. However, Kahneman (1973) has argued that its size is not fixed. He asserts that it is simply "harder to try hard" on an easier task than on a hard task. That is, increasing task demand itself essentially mobilizes additional resources, expanding the pool, as task demand dictates. Young and Stanton (2002) provide data that are consistent with this view.

Processing becomes more efficient with a more difficult task because more resources are made available. Cognitive modeling of speeded decision tasks has produced similar findings, showing that an emphasis on fast responses doesn't just lower the operator's response threshold but speeds up information processing (Rae et al., 2014), consistent with the notion that effort marshals resources. Data also suggest that the ability to expand the resource pool may differ between people (Matthews et al., 2011; Matthews & Davies, 2001).

7.8 EFFORT AS RESOURCES: DUAL-TASK PERFORMANCE

7.8.1 The Performance Resource Function and the Performance Operating Characteristic

Kahneman (1973) has presented the most comprehensive theory of mental effort and its role in dual-task performance, equating effort with the mental resources necessary to sustain both single- and dual-task performance. He proposes that difficult tasks mobilize those resources through increasing arousal of the autonomic nervous system, but only up to a limit. This pattern of diminishing resource returns yields the supply–demand curve illustrated by the solid line in Figure 7.3. The resource shortfall that emerges as task demand increases, represented by the difference between the solid and dashed lines in the figures, causes a progressive loss in performance that we might refer to as a *task-difficulty decrement*.

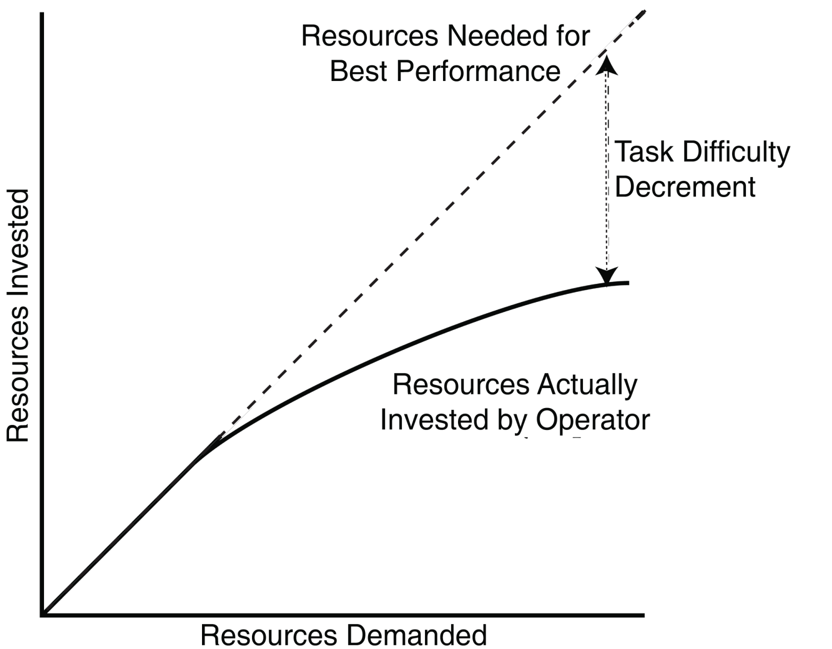

FIGURE 7.3 The resource supply–demand curve and the task-difficulty decrement.

Norman and Bobrow (1975) formalized Kahneman's qualitative theory with the development of the *performance resource function (PRF).* The PRF, three examples of which are shown in Figure 7.4, characterizes the performance of individual tasks in either a single- or a dual-task context, plotting the performance on a given task as a function of the resources invested to perform it. In this regard, the PRF is directly analogous to the function that contrasts heuristics with algorithms in Figure 7.2. From the PRF emerged the distinction between resource-limited tasks and data-limited performance. A task is a resource-limited task if devoting more resources to it—by diverting them from a concurrent task or just by trying harder—will always improve performance. In Figure 7.2, using an algorithm was such a task. The bottom line of Figure 7.4 (Task B) represents a fully resource-limited task. In contrast, a task is data limited if performance is not constrained by resource availability but by the quality of available information—thus, investing more effort will not consistently improve performance. The middle line of Figure 7.4 (Task A) represents a partially

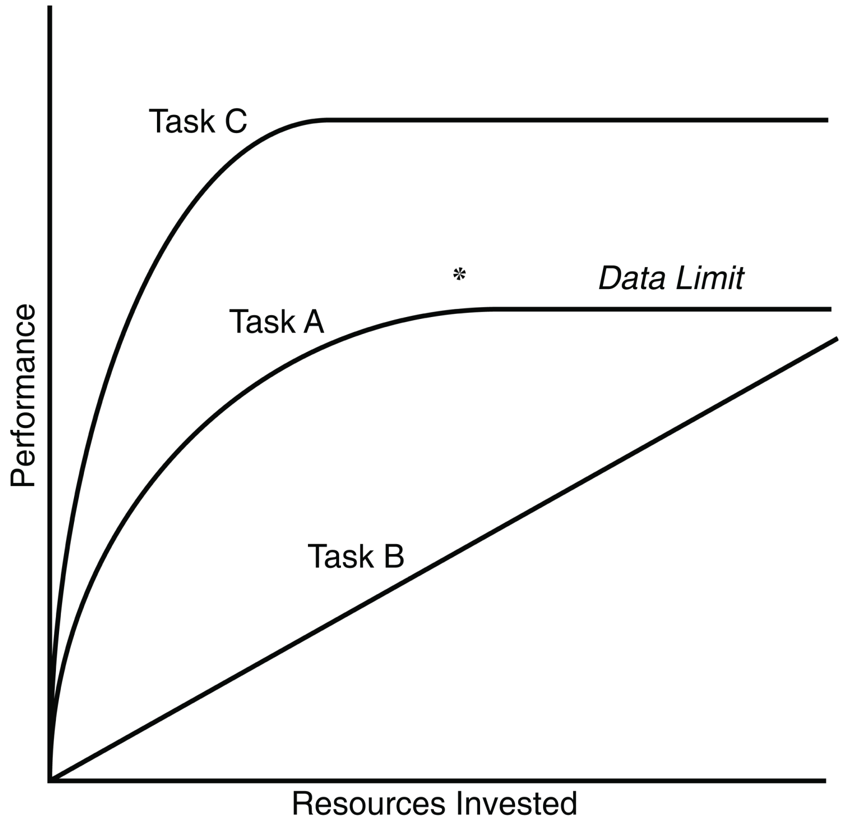

FIGURE 7.4 The performance resource function for three tasks, one that is partially data limited (Task A), one that is fully resource limited (Task B), and one that is almost fully data limited (Task C).

data-limited task, since to the right of the asterisk, further investment of resources will lead to no further gains in performance. The top line (Task C) represents a task that is almost fully data limited.

Data limits can arise from one of three sources: (1) the operator might lack knowledge data needed to perform a task (e.g., you cannot perform well on a language whose vocabulary you do not know, even if you try hard), (2) the "perceptual data" available to support performance might be poor (you cannot detect a subthreshold signal no matter how much you strain your eyes), or (3) the task might have achieved full automaticity, as discussed in Chapter 2, allowing the operator to do just about as well as possible while investing few resources (see Task C curve in Figure 7.4). It should be noted that examples (1) and (2) have large data limits but low asymptotic levels of performance, like curve A in 7.4.

The PRF can be generated in either of two different ways. One is by manipulating the voluntary effort invested in single-task performance. Vidulich and Wickens (1986) did this through financial incentives, finding improved performance when incentives were offered. The second is through a sort of "reverse engineering" in which priorities are manipulated between two time-shared tasks. Here, the assumption is that giving full attention to one task creates maximum resource investment, putting performance for that task at the far right of the x-axis of Figure 7.4 and putting performance for the concurrent task at the far left. Giving equal priority to both tasks creates 50% resource investment, and other relative allocation instructions (e.g., 25% to 75%) map to additional points. Figure 7.5 shows how this might be done with tasks A and B of Figure 7.4. The x-axis presents the relative allocation of resources between the two tasks, in favor of Task A on the left end of the x-axis and Task B at the right end. Thus, any given point along the x-axis depicts performance of both tasks at that allocation policy along the x-axis. Then, assuming both tasks use the same resources, the PRF for both can be reconstructed. We discuss this assumption in the next chapter, in which we address multitasking in general.

Interestingly, when most PRFs are generated, single-task performance is generally better than dual-task performance with 100% priority. This difference between

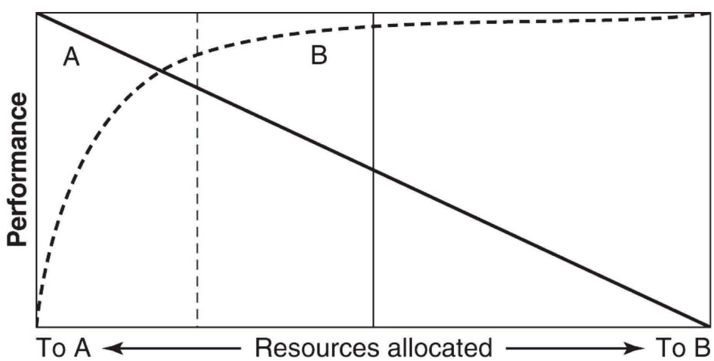

FIGURE 7.5 Two different resource allocation policies, each between a data-limited task and a resource-limited task (from Wickens, Helton et al., 2022).

doing a task alone and doing it with the possible requirements for another task in the background is called the *cost of concurrence* (Navon & Gopher, 1979) and may be thought of as sort of an executive control overhead of managing two tasks, as discussed more fully in the next chapter.

The applied value of the PRF is that it can provide guidance as to the optimal allocation of attention in multitask situations. For example, in Figure 7.5, the dashed vertical line reflects an allocation policy that is near optimal, compared to the 50/50 policy of the solid line. In the first case, high performance on both tasks is achieved. In the second case, resources are somewhat wasted on the more data-limited Task B at the expense of performance on Task A (Schneider & Fisk, 1982).

7.9 RELEVANCE OF EFFORT TO MENTAL WORKLOAD

Underlying the notion that tasks vary in the amount of effort they demand—or equivalently, in the amount of mental workload that they impose—is the idea that effort is an important commodity to be measured (G. M. Hancock et al., 2021; Wickens & Tsang, 2014; Young et al., 2015). We can consider at least two circumstances in which gauging effort is valuable.

- Equivalent levels of performance on two tasks can mask differences in workload. Tasks that demand different levels of effort can sometimes yield equivalent levels of performance when resources are plentiful, as shown by PRFs A and B in Figure 7.4. However, a task like A, which has a greater data-limited region, can be performed at its maximum level while leaving more spare capacity left over. As a consequence, it will be less vulnerable to performance loss should unexpected new resource demands be placed on the user. For example, suppose in comparing two electronic map interfaces for use in a driver navigation system, a designer discovers that one interface imposes higher demands on working memory than the other (e.g., by requiring the user to remember and enter map coordinates). While the two interfaces might produce no obvious performance difference under single-task conditions, the more memory-demanding interface may show greater interference when placed in the dual-task context of driving, particularly when other sources of workload are high (e.g., in fast-moving traffic).
- Equivalent time demands of two tasks can likewise mask differences in workload. Chapter 2 discussed the timeline model of mental workload in the context of single-channel theory of attention. Within the timeline model, workload was simply defined as the ratio $\frac{\text{time required}}{\text{time available}}$. But this simplification can be misleading when tasks that require similar amounts of time to perform also differ in the intensity of effort they demand over that time. An index of workload should differ depending on the extent to which two tasks that require the same amount of time are easy or difficult. Consider the workload of driving on a clear day with a dry road relative to that of driving on a snowy night. In both cases, the time occupied by lane-keeping may be the same; but clearly the demands on the snowy night are greater, and its

potential to interfere with other tasks will be greater as well. An implication of this is that, if there are ways of calculating the resources demanded by a task, the most valid timeline analysis of workload should be based on the ratio, $\frac{\text{resources required during time } \Delta t}{\text{resources available during time } \Delta t}$, where Δt is the window of time over which the task is performed. The challenge of how this might be calculated will be discussed in the next section.

7.10 MEASURING EFFORT AND MENTAL WORKLOAD

About half a century of work has gone into developing ways of quantifying mental workload (G. M. Hancock et al., 2021; Moray, 1979; Vidulich & Tsang, 1986; Wickens & Tsang, 2014; Williges & Wierwille, 1979; Young et al., 2015). This has produced four major categories of techniques for assessing the mental load of a *primary task*, a designation we give to the task of interest.

7.11 ANALYSIS OF PRIMARY TASK DEMANDS

Measuring primary task performance is often necessary but is rarely sufficient to understand the workload imposed by the primary task itself. As the contrast between tasks A and B in Figure 7.4 illustrates, primary tasks with different PRFs can yield the same performance when all resources are invested. However, many primary tasks can be analyzed in terms of elements that will increase their resource demands. For example, higher working-memory demands will almost always demand more resources. So too will higher-bandwidth tracking tasks or decision tasks with more alternatives. In air traffic control or multiple UAV control, the number of vehicles for which a controller is responsible is a valid measure of mental workload. Thus, even without direct measurement of human performance, it is possible to predict the level of resource demand of some of these tasks, from these "count heuristics." A limitation of primary task workload analyses is that they do not readily lend themselves to comparisons across qualitatively different tasks. For example, what level of working memory demand is equal to the resource demand of a 0.5 Hz bandwidth tracking task?

7.11.1 Analysis of Secondary Task Performance

Although primary task performance is not necessarily an adequate index of primary task workload, variations in an operator's performance of a resource-limited secondary task can be used to infer the resource demands of a primary task. The secondary task approach is based on the simple reasoning that if the primary task requires fewer resources (i.e., produces lower mental workload), it will avail more resources for the secondary task, the performance of which will increase accordingly. There are scores of different secondary tasks available, including probe detection, mental arithmetic, and time estimation. The reader is referred to Wickens, Helton et al. (2022) and G. M. Hancock et al. (2021) for more examples.

7.11.2 Subjective Measurement

There is a long history of measuring workload by simply asking operators to report the perceived difficulty of a task, and a variety of different rating scales have been developed (NASA Task Load Index: Hart & Staveland,1988; SWAT: Luximon & Goonetilleke, 2001; Nygren, 1991; the Bedford Scale and Modified Cooper-Harper Scale: Wierwille & Casali, 1983; Wierwille & Eggemeier, 1993; see Hill et al., 1992; Wickens, Helton et al., 2022 for reviews). The most frequently used of these is the NASA Task Load Index, or NASA-TLX, which solicits ratings along six subscales: mental demand, physical demand, temporal demand, performance, effort, and frustration. These ratings can then be combined in a weighted or unweighted fashion to produce a global measure of workload. In most applications, however, the added complexity of generating and combining multiple scales does not appear to provide sufficient informativeness to single-scale measures to be worth the additional effort.

Interestingly, computational primary task properties and subjective measures are integrated in the classic McCracken and Aldrich (1984) scale of task demands (Aldrich et al., 1989), for which the authors asked a large panel of workload experts to assign ratings to the difficulty of different component tasks, a sample of which is shown in Table 7.1.

7.11.3 Physiological/Neuroergonomic Measures

Because mental workload is, by definition, associated with brain activity, researchers have long sought direct measures of neural activity that would correlate both with the objective task difficulty (e.g., through the "count" measures of task load described) and with the level of effort invested (e.g., as reflected by subjective and secondary task measures). These physiological measures have been categorized under the general label of *neuroergonomic* measures (Ayaz & Dehais, 2019; Mehta & Parasuraman, 2013; Parasuraman & Rizzo, 2008).

Several of these measures, particularly in the earlier years of mental workload research, were not entirely direct but were based upon the assumption that mobilizing more resources for performance of a task would activate portions of the sympathetic nervous system related to arousal, and such activation would be reflected in measures of increased pupil diameter (Bhavsar et al., 2016; e.g., Kahneman & Beatty, 1966; see Mathôt, 2018 for review), galvanic skin response, and heart rate activity (Backs et al., 2003; G. Mulder & Mulder, 1981; L. J. M. Mulder et al., 2009; e.g., Sirevaag et al., 1993).

Because these various physiological measures are also affected by noncognitive factors—stress, lighting conditions, physical load, etc.—they can be contaminated measures of mental workload. More closely related to mental workload are two categories of brain measurement: EEG and hemodynamic measures of blood flow. Regarding EEG, frontal theta activity (4–7 Hz) increases and alpha activity (8–12 Hz) decreases as more resources are allocated to a task. Activity in these bands therefore provides a sensitive measure of mental workload (Gevins & Smith, 2008). Spectral power in these two frequency bands can be fairly easily computed

TABLE 7.1
Examples from the McCracken and Aldrich (1984) Scale. Within each of four categories (visual, auditory, cognitive, motor), different tasks are assigned different levels of resource demand.

Scale Descriptor	Value
Visual	
No visual activity	0.0
Register/detect image	1.0
Discriminate or detect visual differences	3.7
Inspect/check (discrete inspection)	4.0
Visually locate/align (selective orientation)	5.0
Visually track/follow (maintain orientation)	5.4
Visually read (symbol)	5.9
Visually scan/search/monitor (continuous/serial inspection, multiple conditions)	7.0
Auditory	
No auditory activity	0.0
Detect/register sound	1.0
Orient to sound, general	2.0
Orient to sound, selective	4.2
Verify auditory feedback	4.3
Interpret semantic content	4.9
Discriminate sound characteristics	6.6
Interpret sound patterns	7.0
Cognitive	
No cognitive activity	0.0
Automatic (simple associations)	1.0
Alternative selection	1.2
Sign/signal recognition	3.7
Evaluation/judgment (consider single aspect)	4.6
Encoding/decoding, recall	5.3
Evaluation/judgment (consider multiple aspects)	6.8
Estimation, calculation, conversion	7.0
Motor	
No motor activity	0.0
Speech	1.0
Discrete actuation (button, toggle, trigger)	2.2
Continuous adjusting (flight control, sensor control)	2.6
Manipulative	4.6
Discrete adjusting (rotary, vertical thumbwheel, level position)	5.8
Symbolic production (writing)	6.5
Serial discrete manipulation keyboard entries)	7.0

from the raw EEG data using readily available software packages, and the ratio of theta/alpha activity can sometimes be used as a simple scalar measure of mental workload.

In the 1990s, researchers began using functional magnetic resonance imagery (fMRI) to study patterns of blood flow across the brain as subjects engaged in cognitive tasks (e.g., Just et al., 2003). However, for practical purposes of assessing mental workload in working environments, fMRI was limited because of the requirement for the participant to lie relatively motionless in the measuring device. Subsequently, two neuroergonomic techniques have been developed and validated that are less restrictive.

Transcranial Doppler sonography (TCD) (Duschek & Schandry, 2003; Shaw et al., 2019) uses head-mounted ultrasound transducers to measure the speed of cerebral blood flow, a correlate of overall cerebral blood flow. TCD studies have shown that changes in the difficulty of perceptual and cognitive tasks are accompanied by increases in cerebral blood flow (Duschek & Schandry, 2003; Stroobant & Vingerhoets, 2000). In a simulated air defense task, for example, changes in cerebral flood detected by TCD closely tracked changes in workload caused by increases in the number of enemy threats (Satterfield et al., 2012; Shaw et al., 2010).

Functional Near Infrared Spectroscopy (fNIRS) (Bunce et al., 2006; Pinti et al., 2020; Yücel et al., 2017; Zhu et al., 2019) uses near-infrared light from small head-mounted sources to measure task-driven changes of oxygenated and deoxygenated blood in the cerebral cortex. Because neural activity demands oxygen, an increase in the ratio of oxygenated to deoxygenated cerebral blood flow can be taken as a measure of task demands. fNIRS provides a compromise between the high spatial resolution of fMRI and high temporal resolution of EEG recording and provides much higher spatial resolution than TCD. Additionally, because fNIRS systems can be light, wearable, and wireless, they are suitable for use in naturalistic and operational settings (Pinti et al., 2020). Ayaz et al. (2012) used fNIRS to monitor cerebral oxygenation in experienced air traffic controllers in a high-fidelity simulator and found a systematic increase in oxygenation as the number of aircraft under control increased from 6 to 12 to 18. These neural changes mirrored changes in subjective workload, as measured by the NASA-TLX. fNIRS has been used extensively in studies examining mental workload in tasks in which the operator is seated (e.g., Sturman & Wiggins, 2021; see Wickens, Helton et al., 2022 for review) and also works reasonably well in tasks requiring whole-body movement (Herold et al., 2018; McKendrick et al., 2017, 2016). Given the advantages of fNIRS compared to EEG and TCD in regard to instrumentation (actually applying the sensor to the person), fNIRS will be increasingly useful in neuroergonomic research and is probably the only cerebral measure that has been deployed in a real-world system.

7.12 CONCLUSION

Each of the discussed techniques has its strengths and weaknesses, and it is by now well accepted that the best approach to workload assessment is to choose converging methods well suited to the circumstances (e.g., avoiding use of pupil diameter in environments with rapidly changing illumination or avoiding use of heart rate variability in tasks that also have a high physical workload demand). It is important to note, however, that the techniques of computational task properties and table look-ups (e.g., Table 7.1) are the only ones in which workload demands can be inferred and predicted in the absence of actually measuring human performance or physiology. Hence these techniques are of the greatest value for computational modeling of human performance and workload (Laughery et al., 2006).

8 Concurrent Task Performance
Time-Sharing and Multiple Resources

Driving through a busy downtown area in an unfamiliar city on a rainy night, stealing glances at the GPS to keep himself oriented and searching the roadside for a parking spot, the driver hears his cell phone ring. He feels compelled to answer—it's probably his friend, wondering why he's late to dinner—and talks to the caller. Will he be successful in this multitask endeavor? What is the probability that the added demand of talking to his caller will impair safety? Could a different interface on the phone make a difference? What about a head-up display, projected on the windshield? Would the benefits of not having to glance downward offset the cost of the added clutter? In this chapter, we present a general model of time-sharing that can provide the basis for answering such questions.

In the last chapter, we presented a model of resource demand and allocation that implicitly assumed that these resources were unitary—they came from a single, general pool of mental effort—and that it did not matter much whether tasks were visual, auditory, spatial, linguistic, perceptual, or action oriented. In that undifferentiated resource model, the key factors for predicting time-sharing interference were the demand for resources and the resource allocation policy. But some everyday observations tell us that other task characteristics contribute to time-sharing efficiency. As one obvious example, it is harder (and thus more dangerous) to drive while reading a book than while listening to the same book on tape. Here, the time-sharing efficiency of the two activities is greatly improved by using auditory rather than visual input channels for language processing. In the example in the first paragraph, it is unlikely that the single-task demand of reading navigational information from a head-up display versus a head-down map would differ much; but the difference in dual-task interference with driving might be considerable. In this chapter, we consider four important factors that modulate concurrent-task performance beyond those that influence single-task difficulty: multiple resources, preemption, similarity-induced confusion, and cooperation.

8.1 MULTIPLE-RESOURCE THEORY

Multiple-resource theory is a theory of divided attention between tasks, with both practical and theoretical implications (Wickens, 1991, 2002, 2008, 2021). The practical implications stem from the predictions that the theory makes regarding the

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human operator's ability to perform in high-workload, multitask environments, such as the automobile in heavy traffic, the aircraft cockpit during landing, or the front office of a business during peak work hours. These practical implications are often expressed in a particular instantiation of multiple-resource theory, which we identify as a multiple-resource model (Wickens, 2021, 2008). In the applied context, the value of such models lies in their ability to predict operationally meaningful differences in multitasking performance that result from changes (to the operator or to the task design) that can be easily coded by the analyst and the designer (e.g., should we use a joystick or voice control in a multitask setting, and how much difference will our choice make to performance?).

In the theoretical context, the importance of the multiple-resource concept lies in its ability to predict differences in dual-task interference levels (the dual-task decrement) between different combinations of tasks, in a way that is consistent with neurophysiological mechanisms. The goal of the theory is to account for differences in task-divided attention interference that cannot easily be explained by simpler models of information processing, such as the bottleneck and filter theories discussed in Chapter 2, or by general task difficulty, as discussed in Chapter 7.

In both applied and theoretical contexts, the distinction between "multiple" and "resources" is critical, and this distinction will remain an important theme throughout this chapter. The concept of "resources" discussed in the previous chapter connotes something that is both limited and allocatable (i.e., can be distributed between tasks: Tsang, 2006). The concept of "multiple" connotes parallel, separate, or relatively independent processing, as characteristic, for example, of Treisman's perceptual analyzers, discussed in Chapter 6 (Treisman, 1985). Multiple resources formally concerns the intersection between these two concepts, but each concept on its own has much to contribute to an understanding of time-sharing (multiple-task) performance.

In what follows, we will first trace the origins and tenets of multiple-resource theory and then describe one particular version of the theory, the 4-dimensional model proposed and elaborated on by Wickens (2002, 2008, 1980; Wickens et al., 2022). We demonstrate how this model can be implemented in a computational form and conclude by describing three other mechanisms to account for differences in divided-attention and dual-task performance.

8.2 HISTORY AND ORIGINS

The origins of multiple-resource theory can be traced to the concept of a single-channel bottleneck in human information processing, a bottleneck that limited the ability to perform two speeded tasks concurrently (Broadbent, 1958; K. J. W. Craik, 1947; Welford, 1967). As discussed in Chapter 2, the single-channel model has been prominent in the analysis of response times in dual tasks and suggests that time is a limited resource that cannot be shared between tasks. As discussed in the previous chapter, however, the concept of effort as a continuously allocatable and sharable resource emerged later and proved particularly attractive in the context of mental workload measurement (Moray, 1967). Again, however, the concept was unable to fully account for performance within multitask contexts. Thus, it was elaborated to incorporate multiple resources.

Subsequent to the development of a general resource model of task interference (Kahneman, 1973), evidence emerged that considerable variance in dual-task performance could not be attributed just to the difficulty (unitary resource demand) of the component tasks nor to the resource allocation policy between tasks. Instead, differences in the qualitative demands for information processing structures led to differences in time-sharing efficiency (Kantowitz & Knight, 1976; Wickens, 1976). Such structures thus behaved as if they were separate (limited) resources. Time-sharing between two tasks was more efficient if the two utilized different structures than if they utilized common structures.

An obvious example of such a structural distinction is between the visual and auditory processing, that is, the eyes and ears. In many circumstances, dual-task performance is poorer when two visual tasks must be time-shared than in a configuration in which the equivalent information for one of the tasks is presented auditorily (e.g., Treisman & Davies, 2012). To cite a more concrete example, a driver will have an easier time controlling the vehicle while listening to a set of directions than while trying to read them (Y. C. Liu, 2001; Parkes & Coleman, 1990); the eyes and ears behave as if they are supported by separate resources. Wickens (1980) performed a sort of meta-analysis of a wide variety of multiple-task experiments in which structural changes between task pairs had been compared and found strong evidence that certain structural dichotomies, such as auditory versus visual processing, behaved like separate resources in supporting dual-task performance. These dichotomies are described in more detail next.

It should be noted that this aspect of multiplicity (to make parallel processing more feasible and improve the level of multiple-task performance) does not have to be linked to a resource model. However, in a classic article, Navon and Gopher (1979) laid out the clear intersection between the "multiplicity" and the "resource" components in the context of the economic theory of scarce resources. Their theory made explicit predictions about the trade-offs between time-shared tasks as a function of their degree of shared resources, their quantitative resource demands, and the resource allocation policy adopted by the performer. In a parallel effort, as noted, Wickens (1980) identified the particular structural dimensions of human information processing that met the joint criteria of accounting for changes in time-sharing efficiency, and being associated with neurophysiological mechanisms that might define resources. This particular set of dimensions provided the basis for the particular multiple-resource model, which we now describe.

8.3 THE 4-DIMENSIONAL MULTIPLE-RESOURCE MODEL

The multiple-resource model (Wickens, 1984, 2002, 2005b, 2008, 2021) proposes that there are four important categorical and dichotomous dimensions that account for variance in time-sharing performance. All other things being equal (i.e., equal resource demand or single-task difficulty), two tasks that both demand one level of a given dimension (e.g., two tasks both demanding visual perception) will interfere with each other more than two tasks that demand different levels on that dimension (e.g., one visual, one auditory task). The four dimensions, shown schematically in Figure 8.1, and described in greater detail in the following pages, are processing

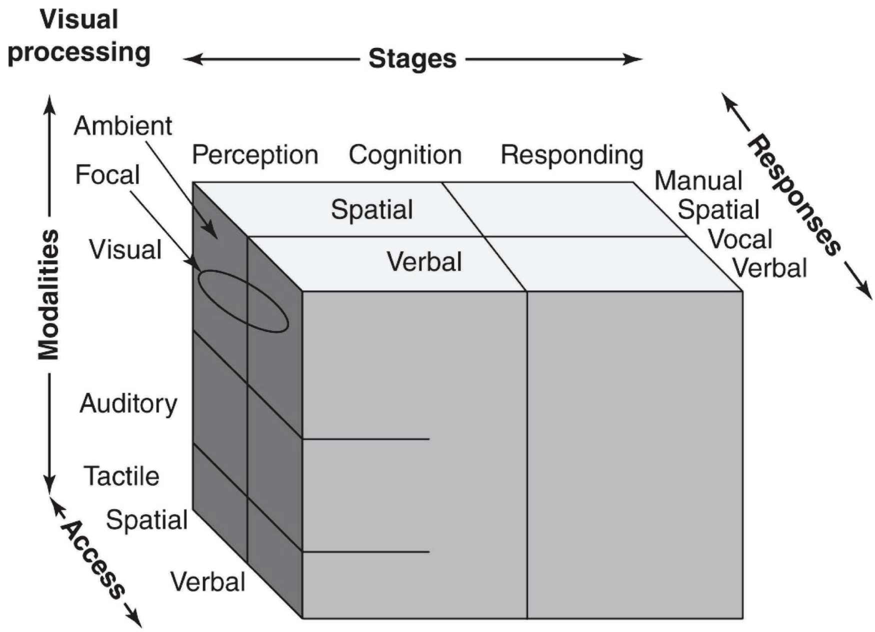

FIGURE 8.1 The structure of multiple resources (after Wickens, 2002).

stages, perceptual modalities, visual channels, and processing codes. Consistent with the theoretical context of multiple resources, all of these dichotomies can be associated with distinct physiological mechanisms.

8.3.1 Stages

The resources used for perceptual activities and for cognitive activities (e.g., involving working memory) appear to be the same, as shown in Figure 8.2, and are functionally separate from those underlying the selection and execution of responses. Evidence for this dichotomy is provided when the difficulty of responding in one task is varied and the manipulation has no effect on performance of a concurrent task whose demands are more perceptual and cognitive in nature; or conversely, when increases in perceptual-cognitive difficulty do not much influence the performance of a concurrent task whose demands are primarily response related (Wickens & Kessel, 1980). In the realm of language, Shallice, McLeod, and Lewis (1985) have examined dual-task performance on a series of tasks involving speech recognition (perception) and production (response) and have concluded that the resources underlying these two processes are partially independent, even as the tasks share linguistic resources (see the following). It is important that the stage dichotomy can be associated with different brain structures; speech and motor activity tend to be controlled by frontal regions in the brain, forward of the central sulcus, while perceptual and language

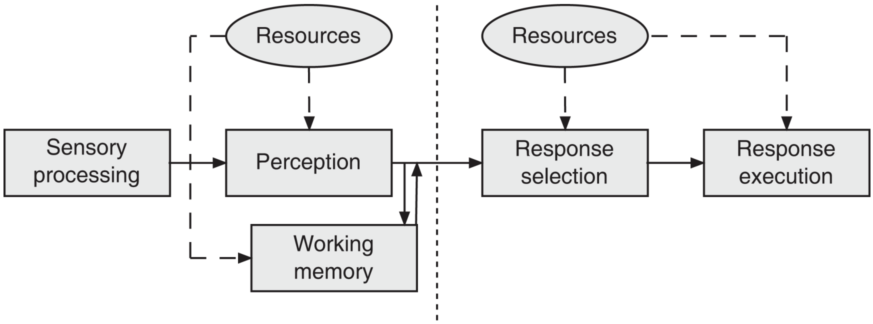

FIGURE 8.2 Stage-defined resources.

comprehension activity tends to arise in more posterior regions. Physiological support for the dichotomy is also provided by research on event-related brain potentials (e.g., Isreal et al., 1980).

As an operational example of separate stage-defined resources, the stage dichotomy would predict that the added requirement for an air traffic controller to acknowledge vocally or manually each change in aircraft state, a response demand, would not disrupt his or her ability to maintain an accurate mental model of the airspace, a perceptual-cognitive demand.

The stage dichotomy of the multiple-resource model also predicts that there will be substantial interference between resource-demanding perceptual tasks and cognitive tasks that draw on working memory to store or transform information (Y. Liu & Wickens, 1992a). Even though these do constitute different stages of information processing, they are supported by common resources. For example, visual search coupled with mental rotation or speech comprehension coupled with verbal rehearsal both provide examples of operations at different stages (perceptual and cognitive) that will still compete for common stage-defined resources and will thus be likely to interfere. The cognitive processes in cell-phone conversation, for example, clearly interfere with perceptual processes involved in noting changes in the driving environment (McCarley, Vais, et al., 2004).

Finally, we note how the stage dichotomy of multiple resources is consistent with the evidence for a bottleneck in response selection, as discussed in Chapter 2 (Pashler & Johnston, 1998). This is because two tasks both involving a response selection stage will heavily compete for the bottleneck. In contrast, response selection will compete less with tasks that rely upon perceptual cognitive processing.

8.3.2 Perceptual Modalities

It is intuitive that we can sometimes divide attention between the eye and ear better than between two auditory channels or two visual channels. This is not to say that auditory-visual (AV) time-sharing is necessarily easy: only that it is generally better than AA or VV. Classic studies by Rollins and Hendricks (1980) and by Treisman and Davies (2012) demonstrated this cross-modal advantage in carefully controlled laboratory investigations decades ago, replicated by Wickens et al. (1983).

Naturally, part of this AV advantage results because of the scanning costs between two visual sources in the VV case (think of driving while texting), which is not present in the AV case (driving while listening). Correspondingly, an auditory masking effect cost is present in the AA case (think of listening to the radio news and a conversation by a passenger). Both of these intra-modality costs are said to be peripheral because they are imposed by fundamental properties of the visual and auditory sensory systems.

Such findings would suggest the design of systems to be used in high visual environments (e.g., vehicle control and monitoring, surgery or search and rescue) that capitalize on the auditory modality to present information (e.g., voice synthesis rather than text, auditory vs. visual alerts). Indeed, applied attention research has documented the AV advantage in multiple domains such as driving (Donmez et al., 2006; Horrey & Wickens, 2004). For example, navigational information interferes with driving less when presented as speech than when presented as a map (Y. C. Liu, 2001; Parkes & Coleman, 1990; Srinivasan & Jovanis, 1997). AV benefits have also been demonstrated in other domains, including TV watching (Basil, 1994a, 1994b), health care (M. Watson & Sanderson, 2004), flying (Wickens, Vidulich, et al., 1984; Wickens, Goh, et al., 2003), UAV monitoring (Dixon et al., 2005), and education (Low & Sweller, 2014; Mayer, 2013; Mayer & Moreno, 2003). Meta-analyses have affirmed the advantage of AV over VV displays (S. A. Lu et al., 2013; Wickens, 1980) and have shown that the crossmodal advantage extends to the tactile modality as well, that is, visual-tactile displays produce better performance than VV displays (S. A. Lu et al., 2013). Studies comparing AV task combinations to AA combinations are less frequent but still indicate a crossmodal benefit (e.g., Rollins & Hendricks, 1980).

In the context of this overall AV advantage, four important caveats must be highlighted, covered next.

8.3.2.1 *Visual Scanning*

Scanning between display channels in a VV arrangement can contribute to crossmodal AV advantages, particularly when the VV channels are separated by more than a few degrees of visual angle (Wickens, Dixon, & Seppelt, 2005). This cost grows with greater separation, such as that between the roadway and the dashboard display. It is a cost based upon both the increasing information access effort (see Figure 4.3) attached to long gaze movement and the poor sensitivity of peripheral vision (see discussion of the NSEEV model in Chapter 4). Naturally, as VV costs grow, so will grow the AV benefit.

8.3.2.2 *Auditory Preemption*

In the particular instance when a continuous and ongoing visual task, like lane-keeping in the car, flight path tracking in the airplane, or performing surgery in the operating theater, is coupled with a discrete task that occasionally interrupts the operator with a message or alert, an asymmetry develops. Performance of the discrete task is best when its alerts are auditory delivery: RTs are about 30% faster to auditory than to visual alerts (S. A. Lu et al., 2013). Auditory signals in the second task generally do not improve performance on the ongoing visual task, however, because the ongoing task is subjected to two offsetting forces. On the one hand, auditory delivery of the alerts allows better time-sharing of attention between the continuous and discrete tasks. But on the other hand, the phenomenon of *auditory preemption*, discussed in more detail in what follows, appears to prompt a reflexive attention switch from the ongoing visual task to the auditory interrupting task, an effect that does not show up when the interrupting signal is visual. This effect appears to offset any benefit to the continuous task offered by multiple resources.

8.3.2.3 *Compatibility*

An issue that cannot be neglected is that of compatibility. When a structural change is made to a task by the designer, for example, a change from visual to auditory display of discrete alerts, it may be that the new interface is less compatible with the central processing demands of the task. For example, spoken words and digits are a less compatible way of communicating precise direction and magnitude than are arrows. If the designer decides to present precise spatial information using spoken words so as to reduce resource conflict with a concurrent visual task, the benefits gained by the appeal to multiple resources may be offset by the greater resource demands of the incompatible mapping of spatial information to a verbal format (trying to describe precise directional information with words). This issue of stimulus–central processing–response (SCR) compatibility, and its effects on resource demand and hence task interference, is addressed in depth by Vidulich and Wickens (1985; Wickens et al., 1983, 1984).

8.3.2.4 *Redundancy Gain*

It is important to consider some aspects of the redundant or multimodal presentation of auditory and visual information, as when synthetic speech echoes a printed text (Helleberg & Wickens, 2003) or when a foreign film has both dubbing (auditory) and subtitles (visual). Data suggest that in a dual-task context, redundant auditory-visual display can improve processing of the displayed information but may fail to improve performance of an ongoing visual task, as visual display of the discrete message distracts the operator from the ongoing task. When navigational messages are displayed redundantly as speech and as text on a dashboard visual display, for instance, a driver may look from the road to the text display even when it's not necessary to do so (S. A. Lu et al., 2013, 2012). There is some evidence that training of attention allocation strategies can help operators achieve the "the best of both (auditory and visual) worlds" from redundant displays (Wickens & Gosney, 2003).

8.3.3 Visual Channels

In addition to the distinction between auditory and visual modalities, there is evidence that two aspects of visual processing, referred to as *focal* and *ambient* vision, constitute separate resources in the sense of (a) supporting efficient time-sharing, (b) being characterized by qualitatively different brain structures, and (c) being associated with qualitatively different types of information processing with design implications (Horrey et al., 2006; Leibowitz et al., 1982; Previc, 1998, 2000). Focal vision, which is nearly always foveal, is required for perceiving fine detail and pattern and object recognition, for example, reading text or identifying small objects. Ambient vision relies heavily (but not exclusively) on peripheral vision and is used for perceiving orientation and ego motion, that is, the direction and speed with which one is moving through the environment. When we manage to successfully walk down a corridor while reading a book, we are exploiting the parallel processing or capabilities of both focal and ambient vision, just as we are when keeping the car moving forward in the center of the lane (ambient vision) while reading a road sign, glancing at the rear-view mirror, or recognizing a hazardous object in the middle of the road (Horrey et al., 2006). Aircraft designers have considered several ways of exploiting ambient vision to provide guidance and alerting information to pilots while their focal vision is heavily loaded by perceiving specific channels of displayed instrument information (Nikolic & Sarter, 2001; Reising et al., 1998; Stokes et al., 1990).

8.3.4 Processing Codes

The processing code dimension reflects the distinction between analog/spatial processing and categorical/symbolic (usually linguistic or verbal) processing. Data from multiple-task studies (Wickens, 1980) indicate that spatial and verbal processes, or codes, whether functioning in perception, cognition, or response, depend on separate resources and that this separation can often be associated with the two cerebral hemispheres (Polson & Friedman, 1988; Baddeley, 2010; see Baddeley, 2003; Logie, 1995, 2011 for parallel views on the important distinctions between spatial and verbal working memory or cognitive operations).

The distinction between spatial and verbal resources accounts for the relatively high degree of efficiency with which manual and vocal responses can be time-shared, assuming that manual responses are usually spatial in nature (tracking, steering, joystick or mouse movement) and vocal ones are usually verbal. This conclusion has been supported by several investigations in applied contexts, particularly flying and driving (Dingus et al., 2011; G. L. Martin, 1989; Sarno & Wickens, 1995; Shutko & Tijerina, 2011; Tsang & Wickens, 1988; Tsimhoni et al., 2004; Vidulich, 1988; e.g., Wickens et al., 1983; Wickens & Liu, 1988). The interference of spatial responding with driving is particularly evident when the former involves the processing of visual feedback for data entry (Tippey et al., 2017). In driving, manual control of side tasks leads to substantially more time with the driver's eyes off-road (Reimer et al., 2016), although voice control does not eliminate interference with driving altogether (He et al., 2015; E. E. Miller et al., 2018; Simmons et al., 2017). Also consistent is the finding from microanalyses of behavior revealing that discrete manual responses using the nontracking hand appear to interrupt the continuous flow of the manual tracking response, whereas discrete vocal responses do not (Wickens & Liu, 1988). We also see the multimodal advantage of speech and manual activity in human–computer interaction, when operators can specify an action with words ("put it there") and the action location with a pointing gesture to "there" (LaViola et al., 2014).

Note that typing constitutes a hybrid operation. In the context of Figure 8.1, it can best be described as a manual response that is fed by verbal cognition, or by visual-verbal input if it is simple transcription.

An important practical implication of the processing codes distinction is the ability to predict when it might or might not be advantageous to employ vocal versus manual control. Manual control may disrupt performance in a concurrent task that engages spatial working memory (e.g., driving), whereas voice control may disrupt concurrent performance of tasks with heavy verbal demands or be disrupted by those tasks depending on resource allocation policy. Thus, for example, the model predicts the potential dangers of manual dialing of cellular phones given the visual, spatial, and manual demands of vehicle driving, and it suggests the considerable benefits to be gained from voice dialing (Dingus et al., 2006; Goodman et al., 1999). (Note that this benefit clearly does not imply that hands-free phones will be interference free. As discussed more in Chapter 11, there will still be some resource competition between conversing and driving at the perceptual-cognitive stage: Strayer et al., 2011.) The model also predicts and research confirms the greater ease of using voice control rather than touchscreen or keyboard control for secondary in-vehicle tasks while driving (Ranney et al., 2005; Tsimhoni et al., 2004).

The verbal-spatial code dichotomy also accounts for finding that background music disrupts reading comprehension more if it includes vocals than if it does not (R. C. Martin et al., 1988). In driving, verbal-spatial code dichotomy explains the finding that driving while navigating from a memorized map, a spatial representation, is more difficult than driving while navigating from a memorized route list, a verbal representation (Wetherell, 1979).

8.4 THE MULTIPLE-RESOURCE MODEL REVISITED

Figure 8.1 presented the four dimensions of the multiple-resource model in a graphical form. Each boundary in the 3-dimensional cube separates the two categorical levels of a given dimension. The figure shows that the distinction between verbal and spatial codes is preserved across all stages of processing and that the stage-defined resource distinction is preserved in both verbal and spatial processing. It also depicts the way in which the distinction between auditory, tactile, and visual processing is defined at perception but not within cognitive processing and the way in which the distinction between ambient and focal vision is nested only within the visual resources. Thus, within this dichotomous dimensional structure, to the extent that two tasks share more common levels along more of the four dimensions, this will engender greater dual-task interference.

To correct a common misconception, it is important to note that the multiple-resource model does not predict perfect parallel processing whenever two separate resources are used for two different tasks. This is evident from the model structure in Figure 8.1. For example, just because an auditory and visual task use separate resources on the modality dimension, they may still share demand for the common perceptual-cognitive resources within the stage dichotomy, particularly if both use the same code. For example, consider the high interference of reading while listening to a conversation.

It is also important to raise the question of whether there is any general pool of resources for which all tasks compete. A commodity of this form has often been referred to as a “cost of concurrence” and would produce some interference between tasks that share no common resources within the model of Figure 8.1 (Vergauwe et al., 2010). As we described in Chapter 7 and will again in Chapter 9, this may be conceived of as reflecting the resource demands of the *executive manager* or *executive control* that coordinates the interleaving of tasks and decides how to allocate resources continuously when perfect parallel processing is possible (Chapter 7) or decides whether and when to discretely switch attention when it is not (Chapter 9).

8.5 A COMPUTATIONAL MODEL OF MULTIPLE-RESOURCE INTERFERENCE

As represented in Figure 8.1, multiple-resource theory makes qualitative predictions about multitask performance by implying that tasks sharing common resources will produce more mutual interference than tasks drawing on separate resource pools. Efforts have been made to make the model quantitative, allowing absolute measures of predicted performance that can be used to compare a set of systems, tasks, and/or interfaces (Horrey & Wickens, 2005; Sarno & Wickens, 1995; Wickens, 2002, 2005b; Wickens, Dixon & Ambinder, 2006). Such models typically include two additive components: one based on the total resource demand and one based on conflict for the resources within the multiple-resource space.

The total demand component reflects the plenary demands of the concurrent tasks and can be estimated by simply assigning each task a value of 0 (fully automated), 1 (easy), or 2 (difficult) and summing the values across the two time-shared tasks, thus availing a predicted range of scores between 0 (minimum) and 4 (maximum) in a dual-task situation. Alternatively, demand can be assigned using a subjective workload scale such as the NASA-TLX discussed in Chapter 7, so long as total scores are rescaled from 0 (minimum) to 4 (maximum). (More elaborate scales, such as that depicted in Table 7.1 from the previous chapter are also possible, where the analyst might prefer them: Laughery et al., 2006).

The resource-sharing component may be computed by establishing the number of the four dimensions along which the two tasks share common resources, here again a value that can range between 0 and 4. In an easy-to-use version of the model, the demand and conflict components can be summed to provide a predicted total interference measure that ranges between 0 and 8. This model, though simple, has been validated to account for a good deal of variance in dual-task interference (over 50%) across a set of heterogeneous task combinations and interfaces used in aviation (Sarno & Wickens, 1995), driving (Horrey & Wickens, 2005), and robotics/unmanned vehicle control (Wickens, Dixon & Ambinder., 2006).

Importantly, while the model predicts the total interference between two tasks, it says nothing about the extent to which one task or the other bears the brunt of the interference, that is, the resource allocation policy (Broeker et al., 2017). For example, revealing a greater potential for interference between driving and manual cell phone dialing versus voice dialing might be of little consequence to safety if the only effect of the interference was to hinder the dialing. On the other hand, if the additional interference is manifest in driving performance, then the difference would have serious safety consequences. Thus, the multiple-resource prediction must be accompanied by a prediction of the operator's resource allocation policy, just as was the case with the single-resource model we saw in Figure 7.4 in the previous chapter. The modeling of the joint effects of priority and multiple resources is complex (Navon & Gopher, 1979; Tsang, 2006; Tsang & Wickens, 1988; Broeker, 2017) and remains in need of further study and validation. One approach that merits study would be to predict resource allocation using the SEEV model (Chapter 4), where scan preferences on task-relevant AOIs can be linked directly to resource allocation, embedded within the multiple-resource model (Wickens, 2007b). Further discussion of priority-based resource allocation policy in the context of executive control and task management will come in the next chapter.

8.6 OTHER SOURCES OF INTERFERENCE: PREEMPTION, COOPERATION, AND CONFUSION

A hallmark of the mechanisms of dual-task interference that we have described so far is that they are associated with resource demand, with strategic allocation, and with four relatively gross and anatomically defined dichotomies within the brain. Yet there appear to be additional sources of variance in time-sharing efficiency that cannot be described by these mechanisms but are instead related to other characteristics of human information processing. We describe here briefly the role of preemption and, in more detail, the roles of cooperation and confusion.

8.6.1 Auditory Preemption

As noted, research asking whether information delivery along separate rather than shared perceptual modalities (e.g., AV vs. VV) supports better dual-task performance has not produced entirely consistent findings. One reason for the inconsistency has been that the arrival of a discrete auditory message will be more likely to capture attention away from an ongoing visual task than will arrival of the same message visually (Helleberg & Wickens, 2003; Horrey & Wickens, 2004; Iani & Wickens, 2007; Latorella, 1996, 1998; Wickens, Dixon, & Seppelt, 2005; Wickens & Colcombe, 2007b). This asymmetry has a number of underlying causes, including the need to rehearse a long auditory message as soon as it is heard (an operation that is not necessary for a printed visual message, Helleberg & Wickens, 2003) and the intrinsic alerting properties of the auditory channel, as discussed in Chapter 3 and in the next chapter. Importantly, as discussed earlier, the preemption mechanism makes the identical predictions to multiple-resource theory when performance of the discrete task whose modality is varied is considered (auditory delivery is better than visual). However, opposite predictions of the two theories are offered when considering performance of the concurrent (usually visual) task; multiple-resource theory favors auditory delivery of the discrete task, and preemption theory favors visual delivery.

In resolving these competing explanations for modality interference, two points emerge. First, the two theories or mechanisms are not incompatible or mutually exclusive. They can both function at the same time and can offset each other, such that there may be little difference at all in performance of an ongoing visual task as a function of whether the interrupting task is auditory or visual (Lu et al., 2013). For example, Horrey and Wickens (2004) found essentially equivalent interference with driving between an auditory and visual (HUD) presentation of in-vehicle task information. Second, the advantage of cross-modal (AV) over intramodal (VV) performance for both tasks grows as the separation between visual sources in the latter condition increases, extending into the eye and head fields and thus increasing the need for visual scanning, as discussed in Chapter 4 (Wickens, Dixon, & Seppelt, 2002, 2005).

8.6.2 Cooperation

Time-sharing efficiency improves when a common display property, mental set, processing routine, or timing mechanism can be cooperatively shared between the tasks. We noted in Chapter 6 that the close proximity fostered by an object representation can improve parallel perceptual processing (e.g., Duncan, 1984). Object-based proximity and other forms of similarity between two display sources have been found to improve tracking performance in multitask situations (Fracker & Wickens, 1989), such as when operators must maintain concurrent lateral and vertical aircraft control (Haskell & Wickens, 1993) or perform concurrent tracking and discrete tasks (A. F. Kramer et al., 1985). That is, integrating information for two tasks into a common object allows cooperative perceptual processing of the two task-related streams of information, which can help dual-task performance. Thus, the pilot can easily control altitude and attitude (i.e., left-right tilt) because both are supported by a single object display, the moving horizon, that provides error information for both axes by its deviation off of "straight and level."

With regard to central processing operations, there is some evidence that two-dimensional tracking tasks is better if the dynamics—position, velocity, or acceleration control—are the same on both axes than if they are different (Chernikoff et al., 1960). Even when the performance of two identical but difficult tasks is not actually better than the performance of a difficult–easy pair, performance of the paired difficult tasks is less degraded than would be predicted by a pure resource model (Braune & Wickens, 1986; Fracker & Wickens, 1989). Pairing tasks of the same dynamics improves tracking performance in a way that can compensate for the cost of baseline tracking difficulty.

A similar phenomenon has been observed in the domain of speeded decision-making (Duncan, 1979). Here, time-sharing was better between two incompatibly mapped RT tasks (e.g., left stimulus mapped right response) than between a compatibly and an incompatibly mapped task in spite of the fact that the average single-task difficulty of the incompatible pair was greater. Again, the common rules of mapping between the two tasks helped performance. A related series of investigations has demonstrated superior time-sharing performance of two rhythmic activities when the rhythms are the same rather than different (Klapp, 1979; Peters, 1981) or when they can be represented as an integrated pattern (Klapp et al., 1998). Investigators have also noted that when manual and vocal responses are redundantly mapped to a single stimulus (i.e., both responses are based on the same information), then the bottleneck normally associated with simultaneous response selection is eliminated (Fagot & Pashler, 1992; Schvaneveldt, 1969).

These examples illustrate that similarity in information-processing routines can lead to cooperation and facilitation of dual-task performance. In contrast, in other circumstances, similarity can lead to negative outcomes of interference, confusion, and conflict, an issue that we now address.

8.6.3 Confusion

We have just discussed ways in which increasing the similarity between processing routines can improve dual-task performance. The opposite trend, in which the increasing similarity of processing material may reduce rather than increase time-sharing efficiency, is also possible. For example, time-sharing between a spelling and mental arithmetic task (involving letters and digits, respectively) is easier than time-sharing between two spelling tasks (both letters) or two mental arithmetic tasks (both digits) (Hirst & Kalmar, 1987). Likewise, distinctive acoustic features reduce the difficulty of dichotic listening by minimizing confusion between messages (Hirst, 1986). Many of these confusion effects may be closely related to interference effects in working memory. Indeed, similar effects are observed when tasks are performed successively, so that the memory trace of one interferes with the processing of the other (Venturino, 1991). It is such confusion that causes, for example, greater disruption when trying to do math while listening to basketball scores or a stock market report (confusing digits and digits) than while listening to a story (less confusing digits and words).

Although these findings are similar to the concepts underlying multiple-resource theory (greater similarity producing greater interference), it is probably not appropriate to label the elements in question as "resources" in the same sense as the stages, codes, and modalities of Figure 8.1. This is because such items as a spelling routine or distinctive acoustic features hardly share the gross anatomically-based dichotomous characteristics of the dimensions of the multiple-resources model (Wickens, 1991). Instead, it appears that interference of this sort is more likely based on confusion or a mechanism that Navon (1984; Navon & Miller, 1987) labeled *outcome conflict*. Responses (or processes) relevant for one task are activated by stimuli or cognitive activity for a different task, producing confusion or crosstalk between the two. The most notorious example of this phenomenon is in the Stroop task, discussed in Chapter 6, in which the semantic characteristics of a color word name interfere with the subjects' ability to report the color of ink in which the word is printed. The necessary condition for confusion and crosstalk to occur is high similarity. That is, "color" (its semantic or visual expression) enters into both the interfering and disrupted tasks. Stroop effects are minimal or absent when people try to report the color of noncolor words. While the Stroop task represents a failure of focused attention rather than a failure of divided attention, this explanation can also well account for similarity-induced confusion in the latter case.

In summary, although confusion and crosstalk due to similarity can contribute to task interference, it is not always present (Fracker & Wickens, 1989; Pashler, 1998). Their greatest impact probably occurs when an operator must deal with two verbal tasks requiring concurrently working memory for one and active processing (comprehension, rehearsal, or speech) for the other, or with two manual tasks with spatially incompatible motions. In the former case, similarity-based confusions in working memory probably play an important role.

8.7 CONCLUSION

In conclusion, this chapter and the preceding one have generated a growing list of things that can affect the efficiency with which two (or more) tasks can be time-shared; that is, the efficiency of divided attention between tasks. In Chapter 7, we discussed the obvious candidate of single-task difficulty, which drains resources that would otherwise be available for the concurrent task. Here, we described the similarity of demand for global structural resources and the similarity between tasks in both mappings (more similarity helps via cooperation) and material (greater similarity hurts because of confusion). We can think of the mechanisms discussed in this chapter, then, as emergent features that grow out of the relation between the time-shared tasks but are not properties of either task by itself.

However, as noted, predicting such dual-task interference, complex as it may be with the five mechanisms of difficulty, multiple-resource similarity, preemption, confusion, and cooperation, is still only part of the picture. The issue of which task suffers more when there is interference and which is preserved is determined by the overall task management strategy of resource allocation. One example of such a resource allocation effect we described briefly was auditory preemption, favoring a discrete task that is delivered aurally over one delivered visually. Another, referred to in the opening anecdote, is the *engaging* nature of certain tasks, like conversation, which can leave other tasks entirely neglected until such time as attention is discretely switched to them. Indeed, task management and strategic task switching are such critical aspects of attention that we address them at different levels in the following chapter, where we describe overall task or workload management strategies and the concept of executive control, which implements these strategies.

9 Sequential Multitasking
Attention Switching, Interruptions, and Task Management

Aviation accidents are often the result of poor task management (Loukopoulos et al., 2009); the operator switches attention away from airplane guidance and stability control to deal with an interruption (for example, a communication from air traffic control or a possible failure of a landing gear) then fails to bring attention back to the high-priority, safety-critical task. In Los Angeles, in 1991, an air traffic controller positioned a plane on an active runway, switched attention to a number of unrelated items, and then failed to return attention to the vulnerable airplane and move it to a different runway. Another plane was then cleared to land on the runway where the first plane had been left. Several fatalities resulted from the ensuing crash. In Detroit, in 1987, pilots configuring an airplane for takeoff switched attention to address a request from ATC, then returned attention to the wrong step on the checklist of guided preparation activities, skipping the critical step of setting the flaps as necessary to gain adequate lift on takeoff (Degani & Wiener, 1993). In the resulting crash, more than 100 lives were lost.

These are examples of breakdowns in selective attention, the element of attention we described in Chapter 4. Here, though, we consider attention shifted between different tasks rather than between perceptual channels, and the topic thereby can be relabeled *task management* (Adams et al., 1991; Damos, 1997; Dismukes & Nowinski, 2007; Dornheim, 2000; Funk, 1991; Wickens, Tsang, et al., 2003). This treatment is in contrast to that of Chapters 7 and 8, where our concerns were the allocation of resources during parallel or concurrent processing activities, such as driving while conversing with a passenger or listening to the radio. There, we identified characteristics that made concurrent multitasking easier (separate resources, automaticity) or more difficult (common resources, high cognitive load, or task similarity). In this chapter, the focus is on attention-switching between sequential activities, where parallel processing either does not or cannot take place.

An important observational study by Walter et al. (2014) of medical professionals in the ward and in the emergency department revealed that both forms of behavior, concurrent performance and discrete task switching, manifest in real-world settings but to different degrees under different circumstances. In the ward, concurrent time-sharing occurred approximately 8 times as often as discrete switching. However, in the higher-tempo emergency department, time-sharing was only 1.5

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times more common than task switching. These results imply that at very high levels of workload, performance can "regress" to more of a sequential processing mode.

The role of fluency in discrete attention switching between tasks is highlighted in the accidents mentioned earlier and relates to a form of cognitive tunneling whereby attention is focused on one task for so long that others are totally neglected, a phenomenon well documented in aviation by Funk (1991) and Chou et al. (1996). The importance of appropriate task prioritization is high in dynamic and complex environments such as the cockpit or the hospital operating room, where system status changes rapidly, the number of tasks to be juggled is large, and the consequences of poor management can be fatal (Chou et al., 1996). The typical nurse may have as many as 10 tasks in a queue waiting to be performed, and the delay of some of these could have serious consequences for patient safety (Wolf et al., 2006).

In the current chapter, we first describe some basic laboratory research on attention switching, the processes that underlie the "meta-task" of task management. We then turn to applied research that deals with this issue in complex real-world domains, first examining the phenomenon of interruption management, then multitask management, and finally looking at individual differences in these processes.

9.1 TASK SWITCHING

Early studies of task switching focused on its time cost, an effect first demonstrated by Jersild (1927). Participants in Jersild's study were presented lists of items, similar to those in Figure 9.1, and asked to work their way through each list, performing either or both of two different tasks. In some cases, for example, the stimuli were lists of numbers, and the participants' task was either to add or subtract 3 from each item on the list (Figure 9.1, left column). In *pure blocks*, the participant performed the same task on each item in the list. In *mixed blocks*, the participant alternated back and forth between the two different tasks while working through each list. The time necessary to complete the mixed blocks was substantially longer than the average time needed for the pure blocks. The need to alternate back and forth between different tasks, that is, imposed processing demands beyond those associated with the mathematical operations themselves. Jersild's experimental procedure has become known as the *task-switching paradigm* and the RT increase produced by the alternation between tasks as a *switch cost*. Switch costs can be measured by examining trial-by-trial RTs for blocks in which tasks alternate in pairs (A, A, B, B). As illustrated in Figure 9.2, the switch cost is the difference between RT following a task switch and RT following a task repetition. As likewise illustrated in the figure, RTs in mixed-tasks blocks can also show a more general *mixing cost*. This can be measured by comparing RTs for task repetitions in mixed blocks to the mean RTs for pure blocks. Frequently, RTs for repetitions in the mixed blocks are longer than pure-block RTs, indicating an additional slowing of mixed-block performance even after specific, trial-by-trial switch costs are accounted for (Kray & Lindenberger, 2000; Monsell, 2003).

Multiple effects contribute to task-switch costs. One is uncertainty about which task to perform on a given stimulus. Jersild demonstrated that switch costs were eliminated when the stimuli for the alternating tasks were mutually incompatible, so

18	90	32 + 3
26	COLD	80 - 3
41	44	38 + 3
45	NEAR	50 - 3
73	77	68 + 3
69	TOP	79 - 3

FIGURE 9.1 Stimuli like those used by Jersild (1927) and Spector and Biederman (1976) to study task switching. Subjects proceed down each list as fast as possible, performing a mental operation on each item in sequence.

that the nature of the stimulus implicitly stipulated which task to perform. For example, when one task was to add 3 to a two-digit number and the second task was report the antonym of a common word (Figure 9.1, middle column), switching costs were minimal. An experiment by Spector and Biederman (1976) replicated this effect, and also found that the effects of mixing addition and subtraction within blocks were reduced when a +3 or –3 was provided to indicate which task should be performed at each step (Figure 9.1, right column). Thus, switch costs are greatest when stimuli are compatible with either task and no cue is provided to signal which task is to be performed, are reduced when a disambiguating cue is provided, and are minimized when the stimulus unambiguously specifies which task to perform. In the absence of external cues, operators tend to rely on rehearsal in verbal memory to remind themselves which task to perform on each new stimulus. The costs of uncued task switches therefore increase when operators are prevented from talking to themselves, either out loud or subvocally (Baddeley et al., 2001). The need to maintain multiple task sets in memory can also contribute to the mixing costs shown in Figure 9.2, since additional memory load will be present even on task repetition trials. This is an example of the cost of concurrence generally observed in dual-task paradigms, as discussed in Chapter 8.

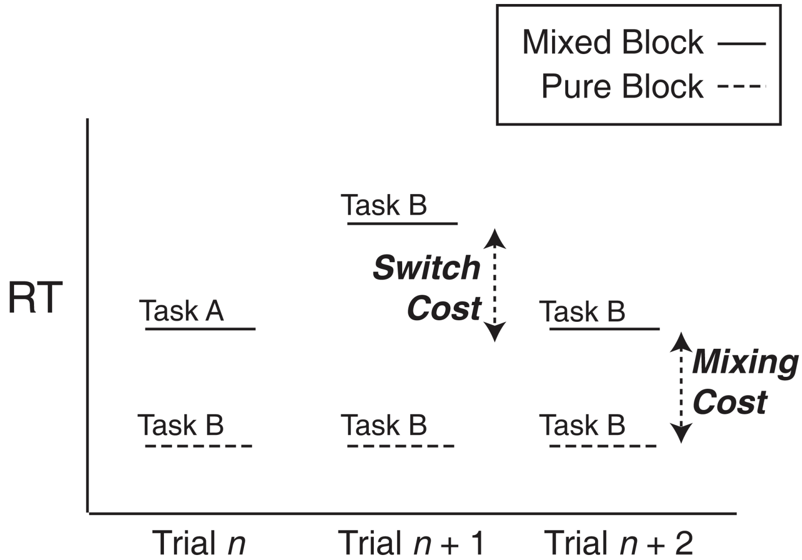


FIGURE 9.2 Hypothetical pattern of RTs illustrating switch costs and mixing costs. A switch cost is the difference between RT for a given task after a task alternation and RT for the same task when it is repeated. Here, the switch cost is the difference in RT for Task B on trial $n + 1$ and trial $n + 2$ of the mixed trial block. A mixing cost is the difference between nonswitch RTs for a given task in the mixed block and RTs for the same task in the pure block.

The need to remember or determine which task to perform on a given stimulus, however, does not entirely account for task switch costs. A transition from one task to another also appears to necessitate a *task set reconfiguration*, "a sort of mental 'gear-shifting'" (Monsell, 2003, p. 136) that may include changing goals, activating new stimulus–response mappings (Rubinstein et al., 2001), and adjusting the parameters of subordinate perceptual and attentional processes (Gopher et al., 2000; Logan & Gordon, 2001). This reconfiguration accounts for at least part of the specific switch cost. The time needed for reconfiguration can be estimated using a procedure in which the order of tasks varies randomly, and a cue is presented before each target stimulus to indicate which task should be performed. Data from such experiments indicate that switch costs increase with task complexity. It takes longer, for example, to establish the proper mental configuration for a task with difficult stimulus–response mappings than for a task with simpler or more natural mappings (Rubinstein et al., 2001). Conversely, switch costs decrease as the interval between the cue and target grows longer. However, even when the operator is given a long preparation period, the switch cost is not entirely eliminated. These results suggest that the operator can begin task set reconfiguration when cued but that the process cannot be completed until the target stimulus arrives to provide an exogenous trigger (Meiran, 1996; see also Rogers & Monsell, 1995).

A general finding is that task switching, like visual scanning, is itself effortful: it demands resources, and hence switching between two tasks will be less fluent, slower, or done less often when the operator is devoting resources to yet a third task, whether visible or purely cognitive (Wickens, Gutzwiller, & Santamaria, 2015).

Importantly, the phenomenon of switching costs scales up very nicely from the basic laboratory research to more applied environments. For example, Wickens et al. (2006) observed relatively large (> 1 sec) costs as pilots switched between subtasks of controlling and supervising two unmanned air vehicles. Switching costs appear to manifest in two different forms of applied tasks: *interruption management* and *multitask management*.

9.2 INTERRUPTION MANAGEMENT

You are deeply engaged in revising a manuscript and have several thoughts running through your mind as to how to describe a particular concept. Unexpectedly, the phone rings. You answer and spend a few minutes in an engaging conversation. Finally, you hang up and return to the paper but find that you cannot remember your thoughts, and unfortunately, you neglected to write them down before you took the call. The neglect to record your thoughts before starting the conversation is a failure of *interruption management*. In this example, we can refer to your working on the manuscript thought as the *ongoing task (OT*) and taking the phone call as an *interrupting task (IT).*

The high frequency of interruptions has been documented in specific workplaces such as those involving information technology (González & Mark, 2004), human–computer interaction (McFarlane & Latorella, 2002), aviation (Loukopoulos et al., 2009; McFarlane & Latorella, 2002), and health care (Grundgeiger et al., 2010; Koh et al., 2011; McCurdie, Sanderson, Aitken, & Liu, 2017; Sanderson et al., 2019; Wolf et al., 2006). Figure 9.3 provides a schematic representation of the interruption cycle. We can point to factors that affect interruption management, in particular the smooth return to the OT after the IT, at each of the two switching points: Switch 1, away from the OT to the IT; and Switch 2, from the IT back to the OT). We can also consider how properties of the OT and IT themselves influence interruption management.

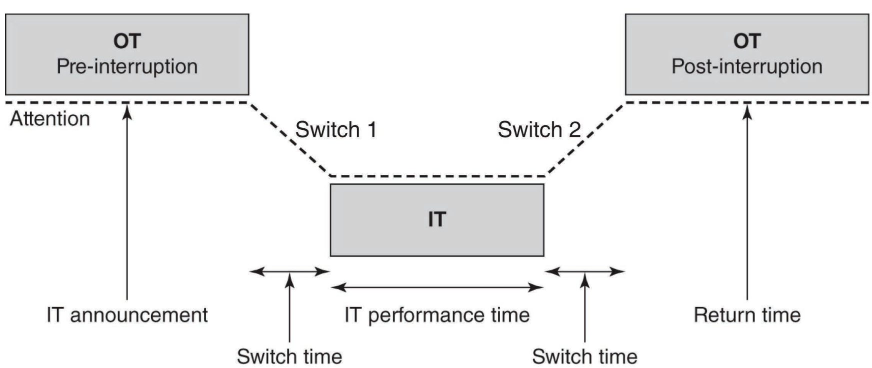


FIGURE 9.3 An interruption management switch cycle. From Wickens, Helton et al. (2022).

9.2.1 Properties of the OT

9.2.1.1 *Engagement*

OTs can vary in the level of engagement they engender (Charney, 2013; Horrey, Lesch, & Garabet, 2009; Matthews et al., 2010), a property that makes it difficult for an IT to "break through" and prompt a switch. In the extreme, high engagement, whether driven by the operator's interests or by task demands (Lavie, 2010), becomes cognitive tunneling and can lead to inattentional and change blindness (Wickens & Alexander, 2009; see Chapter 3). Though it is intuitively obvious that a task will be less susceptible to interruption when the operator is highly focused on it, this effect has been somewhat difficult to capture experimentally or parametrically for the purposes of modeling. Interest plays a role; interesting tasks are engaging, and we are reluctant to leave them, just as boring tasks can be easily interrupted. The role of interest is revealed by the results of a meta-analysis of the distracting effects of cell phones on driving (Horrey & Wickens, 2006). Data revealed that naturalistic conversations produced more interference than did controlled but less-engaging tasks meant to simulate the information processing demands of natural conversations. The latter tasks did not involve interesting semantic content, whereas the former were generally explicitly designed to engage the interest of the participant (e.g., discussing current topics, personal stories, etc.).

At least two other properties of the OT can also encourage cognitive or attentional tunneling (Regis et al., 2014). First, highly immersive 3D displays can encourage tunneling (Wickens, 2005a). For example, a form of cockpit navigational display known as the *3D highway-in-the-sky* (Alexander et al., 2005) was found to engage head-down attention to such a degree that pilots sometimes failed to notice critical events in the outside view of the world. Such failures were less observed when pilots flew with more conventional 2D flight instruments (Wickens, 2005a; Wickens & Alexander, 2009). Wickens and Yeh (2018) further discuss the properties of engagement/compellingness.

Second, problem-solving or troubleshooting operators can produce cognitive tunneling, with people failing to notice concurrent important events (Dismukes & Nowinski, 2007; Moray & Rotenberg, 1989). This phenomenon was manifest in the Eastern Airlines Everglades crash in 1972, when pilots, trying to diagnose a landing gear problem, were entirely unaware of a salient auditory alert that signaled their impending crash into the ground. Dehais and colleagues (Dehais et al., 2011; Saint-Lot et al., 2020) have developed a repertoire of techniques to "break through" the cognitive attentional tunnel in fault management, along with methods for detecting the tunneling behavior (Regis et al., 2012).

9.2.1.2 *Subgoal Completion and Memory Load*

Altmann and Trafton (2002) proposed a theory of interruption management based on the idea that the operator's memory trace of OT status decays while attention is directed to the IT. The model suggests that OT subgoals that are interrupted before they are achieved are highly vulnerable to failures upon return from the IT at Switch 2, as was seen in the aviation examples at the beginning of the chapter. Interruptions are therefore less disruptive if they occur at a time when a particular subgoal of the OT has just been completed—a natural breakpoint—and people can manage interruptions by delaying Switch 1 until subgoal completion (Janssen et al., 2012; Janssen & Brumby, 2010; Monk et al., 2004, 2008; Trafton & Monk, 2007). For example, reading will be less disrupted if an interruption occurs at the end of a paragraph instead of mid-paragraph. Thus, the reader can reduce interference by waiting until the paragraph is completed before addressing the interruption. Unfortunately, workers too often choose not to defer an interruption, even when it threatens to degrade working memory (Katidioti & Taatgen, 2014).

A closely related task characteristic found to influence switching strategy is the working memory demand of the OT. For a task that depends on auditory working memory, like writing down a long phone number just heard on an answering machine, there should be reluctance to leave until the task is completed, as much of the critical information is likely to have been forgotten after the interruption (Gutzwiller, Wickens, & Clegg, 2016). This would not be the case when dialing from a written phone number. Here it is noteworthy that visual rather than auditory presentation of complex information allows better task management and more optimal task switching (Wickens & Colcombe, 2007a), because with a persisting visual text display of an OT, Switch 1 can occur without fear that the information will be gone upon return. This is, of course, not the case with working-memory demanding auditory information.

One important implication of the subgoal completion effect is that intelligent computer automation can potentially reduce human error and stress by withholding interruptions (e.g., a text message alert) until it infers that the user is between subgoals (B. P. Bailey & Konstan, 2006; Dorneich et al., 2012; C.-Y. Ho et al., 2004). As an example, when the information worker is creating text, an interruption could be imposed only after the new-paragraph key is hit.

9.2.1.3 *Importance and Priority of the OT*

It is intuitive that an OT with high priority should be less susceptible to interruption than a task of lower priority. This effect was found by Janssen et al. (Janssen et al., 2012; Janssen & Brumby, 2010) in driving and also in aviation by Iani and Wickens (2007) as a primary flight task was interrupted by the delivery of discrete weather information. Turning to ground transportation, the fact that driving is as safe as it is, despite all the multitasking that goes on (much of it head down, as people have begun texting), suggests that people's switching strategies tend to prioritize out-the-window viewing over head-down activity, as if the out-window tasks are less interruptible. However, this prioritization strategy clearly fails at times, and accidents occur as a result of in-vehicle distractions (Dingus et al., 2016). One important constraint on performance is the ability of operators to know the priority of the IT before deciding whether to abandon the OT. This points to the importance of preattentive referencing in alarms (Woods, 1995), as discussed in Chapter 3, and systems that do use preattentive referencing have been found to be effective in task management (C.-Y. Ho et al., 2004). Systematic observations from the flight deck indicate that pilots often let lower-priority communications tasks interrupt those of higher priority involving navigation (Damos, 1997). This departure from optimality may be related, as mentioned, to modality (auditory communications versus visual navigation). Clearly, the Detroit crash involved a departure from priority optimization.

9.2.2 Properties of the IT

9.2.2.1 *Importance*

As with the OT, the importance of the IT is a relevant factor for Switch 1, as it is indeed the relative importance between the two tasks that matters most. A less important IT will delay Switch 1 away from an OT. The role of relative importance in governing scanning between head-up and head-down driving tasks, for example, has been well documented by Horrey and Wickens (2006), and in Chapter 4, we saw that for visual tasks, task value in the SEEV model is highly predictive of attention allocation.

9.2.2.2 *Salience*

Probably the most characteristic of IT at Switch 1 is its salience. If the IT is salient, it will rapidly and reliably cause a switch away from the OT (Trafton et al., 2003). If it is not salient, it may not trigger a switch at all, and cognitive tunneling on the OT will occur. Both tactile and auditory interruptions are more salient than visual interruptions, leading to 15% more rapid attention switches (S. A. Lu et al., 2013), particularly if the visual interruptions are distant from the OT's central point of visual interest (Wickens, Dixon, et al., 2002; Wickens, Sebok, et al., 2016a, 2016b). The ability of auditory alerts to break through ongoing processing is sometimes referred to as *auditory preemption* (Wickens & Colcombe, 2007b), and it leads to an inherent tendency for operators to switch attention rapidly to auditory tasks (C.-Y. Ho et al., 2004; Latorella, 1996).

One cause of auditory preemption is related to the cognitive demands of rehearsing and processing fragile auditory linguistic information, as discussed earlier (Damos, 1997; Latorella, 1996); there is a demand to attend to an auditory signal "right now," before it is forgotten. This can explain why synthetic voice messages are more disruptive of ongoing visual flight tasks than are equivalent visual text messages (Helleberg & Wickens, 2003; Wickens & Colcombe, 2007b). However, because preemption also applies to nonlinguistic and tactile interruptions, a mechanism different from (although consistent with) the need for rehearsal of auditory material may be at work. We can call this second mechanism *sensory preemption*.

In this regard, we note that auditory preemption may offset the benefits of separate resources (Chapter 8) for an OT–IT combination that would create an AV benefit. Consequently, an auditory IT may still disrupt a visual ongoing task, even as, consistent with multiple-resource theory, the separate resources used by an auditory IT may facilitate the OT in an offsetting fashion. The IT, on the other hand, will clearly always benefit from an auditory over a visual presentation because of the benefits of both preemption and multiple resources. This explanation can account for findings wherein the auditory (versus visual) delivery of IT information has little impact on the performance of a visual OT but a large benefit for the IT (S. A. Lu et al., 2013).

An important concept that has emerged in considering IT properties at Switch 1 is that of preattentive referencing (Woods, 1995), by which the IT can register its presence in a nonsalient, nondisruptive form, making the operator aware that an interruption is pending (e.g., as a variable is trending toward an alert-threshold level) but without requiring a full attention switch away from the OT. The operator can also be informed of the priority of an interruption before a full switch is implemented (Ho et al., 2004).

Just as high salience of the IT makes a Switch 1 switch more rapid, so low salience makes the switch slower and less likely. In the extreme, a *zero-salience IT* provides no alert at all and instead depends entirely on the operator's prospective memory to be initiated (Dismukes & Nowinski, 2007). Such a situation imposes a demand on "knowledge in the head" rather than "knowledge in the world" (Norman, 2013). This would characterize the status of a task like "remember to check the altitude" imposed on a pilot who is busy with other tasks. The fact that these zero-salience ITs often fail to trigger attention switches can account for the high frequency of "altitude busts" in aviation as well as the prevalence of controlled flight into terrain (CFIT) accidents in which a pilot flies a perfectly airworthy aircraft into the ground (Wiener, 1977). Such an accident generally results from the failure to remember to perform the altitude check task. Although in modern aircraft this task will be triggered by the alert of a ground proximity warning system, such alerts might occur too late to be fully useful and are themselves subject to problematic false alarms (see Chapter 3).

9.2.3 OT Properties Influencing Task Return and Reengagement

Here, we address those characteristics of the OT that influence the circumstances of returning to it after Switch 2.

9.2.3.1 *Strategies Carried Out at Switch 1*

The ease of returning to the OT depends on the strategy adopted for leaving it at Switch 1, as discussed. For example, if the OT is interrupted in the middle of a subtask rather than between subtasks, return is more likely to be difficult (S. L. Miller, 2002; Monk et al., 2004). Indeed, in some cases, an interruption may be so disrupting that after completing an IT, the operator has to re-start the OT from the beginning, such that the time taken to complete the OT post-interruption (see Figure 9.3) is just as long as the time that would have been needed to carry it out uninterrupted. As also noted, an intentional delay at Switch 1 can facilitate the later return to the OT. This delay can be used to rehearse the state of the OT at the interruption (Trafton et al., 2003), encoding it into memory so that it is easy to recover upon return from IT. Alternatively, it can be used to set up an explicit reminder, such as by placing a mark on the page where text editing was suspended. In an especially clever use of reminders, ICU nurses often keep a small object related to the OT in-hand during the interruption (Grundgeiger et al., 2010). Such actions are helpful (Dismukes & Nowinski, 2007; McDaniel & Einstein, 2007).

9.2.3.2 *Delay in Return*

Delaying the resumption of the OT can compromise performance in three ways. First, there will be a simple decay of working memory for the status of the OT. If the OT had loaded working memory at Switch 1, then there will be a decay of the material in the task itself (remember the phone dialing example). Second, if the OT is a dynamic one, like vehicle control, the status of the system is likely to have changed—and potentially become unstable—while attention was diverted. Thus, a car will be more likely to have drifted out of its lane the longer the driver's head was down. As described in the context of scanning in Chapter 4, a long first passage time away from the OT leads to increasing vulnerability of missing a critical event (Horrey & Wickens, 2007; T. Sheridan, 1970). Third, the longer the operator stays on an IT, the greater the possibility the OT will have been forgotten entirely—its goal memory will have decayed below threshold (Altmann & Trafton, 2002), and a failure of prospective memory will have occurred (Dismukes & Nowinski, 2007; McDaniel & Einstein, 2007).

9.2.3.3 *Difficulty of the IT*

The longer an IT lasts, the more compromised Switch 2 will be. But independent of length, a difficult IT will also tend to reduce the fluency of Switch 2 (Grundgeiger et al., 2010; Monk et al., 2008). In the context of memory-for-goals theory, a long IT will prolong the period during which OT goals may decay, while a difficult IT will prevent goal rehearsal through dual-task interference. For instance, a disorganized menu structure in a dashboard display used to perform an IT can disrupt the fluency of a driver's return to normal scanning (Kujala & Saariluoma, 2011).

9.2.3.4 *Visibility of the OT*

Any property of the IT that obscures visibility of the OT workspace will also disrupt return fluency, whether this property involves a blanked computer screen (Ratwani & Trafton, 2010) or simply looking away farther from the OT workspace (Grundgeiger et al., 2010). Ratwani and Trafton (2010) have shown the impact of visual–visual resource competition in degrading interruption management. When the IT demands visual attention, even if it does not actually obscure the view of the OT working surface, it will still disrupt return more than when the IT only taxes auditory attention.

9.2.3.5 *IT–OT Similarity*

Finally, similarity between the OT and IT degrades resumption of the OT at Switch 2 (Cellier & Eyrolle, 1992; Dismukes & Nowinski, 2007; Gillie & Broadbent, 1989). This effect appears to result from confusion and crosstalk discussed in the previous chapter. During the interruption, OT/IT similarity causes greater disruption of OT-related information in working memory (retroactive interference). And after the interruption ends, lingering activation of IT-related information in working memory will cause persistent interference with the OT (proactive interference).

9.3 TASK AND WORKLOAD MANAGEMENT

The area of strategic task and workload management integrates the findings on switching and interruption discussed already and places them in a broader context. This context might be represented as "zooming out" from the OT-IT-OT cycle of a single interruption to a view of lots of cycles in sequence, often involving multiple heterogeneous tasks "clamoring for attention" like a room full of unruly kindergartners. Here, the distinction between OT and IT becomes blurred. Rather than speaking of an IT, we will therefore use the label *alternate task (AT)* to refer to any one of several tasks that are available but are not currently being performed at a given moment. We can consider task and workload management over the time scale of minutes or hours, as when surgical nurses attempt to manage their responsibilities in the operating room, or over the time scale of days and weeks, as when a university student attempts to juggle the demands of five classes over the course of a semester.

How well do people manage multiple heterogeneous tasks? Often poorly (Puffer, 1989). Unfortunately, this includes even expert performers such as highly skilled airplane pilots (Chou et al., 1996; Funk, 1991; Loukopoulos et al., 2009; Wickens & Dehais, 2019). To understand task management failures, we can turn to a broader perspective that borrows from queuing theory and operations engineering (Moray et al., 1991), specifying the optimal strategies for maximizing collective performance across tasks. What strategies should influence the human in deciding what task to perform next, having just completed another task?

Raby and Wickens (1994) found that although skilled pilots were reasonably optimal at task scheduling, they did not optimally reschedule the higher-priority tasks as workload increased. This suggests that pilots do not maintain perfectly optimal strategies, for the plausible reason that the task scheduling itself demands resources that could otherwise be devoted to task performance. Such a conclusion is consistent with Kahneman (1973)'s effort-conserving view of decision-making heuristics (see also Moray et al., 1991). Notably, better-performing pilots tend to be more proactive, initiating high-priority tasks earlier (Zsambok et al. 1997). Procrastination hurts! However, too much early preparation in an uncertain world can be counterproductive, especially if formulated plans are rigidly maintained despite changing circumstances (McCoy & Mickunas, 2000).

While scheduling may be described in terms of an overall top-down macro strategy, it can also be considered in terms of a bottom-up decision of which task to choose to perform next and, by extension, which tasks to defer. Thus, a model from Wickens, Gutzwiller, and colleagues (Gutzwiller et al., 2019, 2015; Gutzwiller & Sitzman, 2017; Wickens, Gutzwiller, et al., 2016; Wickens, Gutzwiller, & Santamaria, 2015; see also Barg-Walkow et al., 2021) represented task management in high-demand overload situations as a multiattribute decision-making process. Here, at any given time, one is performing an OT with one or more ATs "waiting in the wings" and clamoring for attention. The decision of whether to stay with the OT or switch to an AT and, if switching, which AT to choose, is a multiattribute decision (see Figure 9.4).

In predicting the choice of what to do, this account, the *Strategic Task Overload Management (STOM) model*, posits one fundamental bias and four attributes that make any task more or less attractive to be chosen next. The fundamental bias is not to switch at all: once engaged in an OT, a sort of cognitive inertia biases us to keep doing what we are doing. In the extreme, this results in cognitive tunneling (Arrington & Logan, 2004; Wickens, Gutzwiller, & Santamaria, 2015). This bias may be seen as reflecting the effort-cost of attention switching described earlier and the fact that people are often effort-aversive in their decisions. The strategy of sticking with a task until the ongoing subgoal has been completed, as shown in Figure 9.4, amplifies the resistance to switching (Gutzwiller, Wickens, et al., 2016).

Counteracting this general switch aversion, in some cases fatigue or resource-depletion with prolonged performance on one ongoing task will actually increase the likelihood of switching to another task (Kurzban et al., 2013), particularly if one of

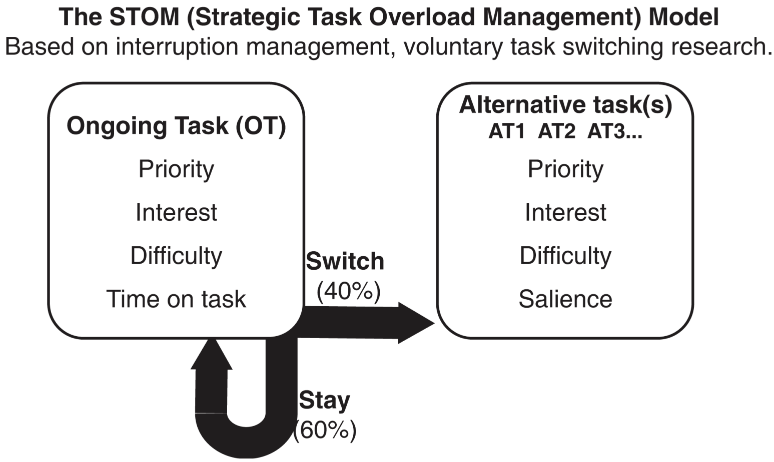


FIGURE 9.4 The STOM model of task management, depicting the four attributes that influence switch likelihood.

the waiting tasks uses different resources from the ongoing task (Brzezicka et al., 2013). Nevertheless, the operator's tendency is toward inertia.

Superimposed on this overall bias are the four STOM attributes that determine the attractiveness of a task, applied to both the OT and the AT(s). These are as follows:

9.3.1 *Priority*

Task priority can be defined jointly by urgency and by the cost of not doing it at all. In health care, skilled ER physicians have rated urgency as the most important attribute to consider when choosing which patients to prioritize (Barg-Walkow et al., 2021). Examples across other domains include:

- in a dual-task experiment, the distinction between the primary and secondary tasks;
- in driving, the difference between hazard detection, precise lane-keeping, cell phone conversation, and in-vehicle technology.
- in aviation, the difference between aviating (keeping the plane in the air; highest priority), navigating (heading in a precise direction), communicating, and systems management (lowest priority).

Of course, priority is not unchanging. Some OTs produce diminishing returns over time, as in foraging for low-hanging fruit, such that the payoffs for not switching dwindle, either because the task is stable or because there are simply fewer and fewer events to handle (Gutzwiller et al., 2019).

Somewhat surprisingly, priority as a task attribute seems to have little influence on actual task choice when assigned by other authorities (e.g., experimental investigations: Wickens, Gutzwiller, et al., 2016), but priority appears to influence choice when it is assigned by the participants themselves (Gilbert & Wickens, 2017).

9.3.2 *Interest*

Interest exerts a powerful influence on an operator's choice of what activities to perform (Charney, 2013; Jin & Dabbish, 2009). Wickens, Gutzwiller, et al. (2016) found that self-rated task interest actually dominated other STOM factors in task switching in a safety-critical dual-task overload simulation.

9.3.3 *Salience*

Just as the salience of a display alert captures visual attention, so the salience of task arrival helps determine the probability of switching from an OT to an AT. Thus, the loud ring of a phone is more salient than the softer "earcon" of an arriving text message, which, in turn, is more salient than the soft ping of an email arrival, which in turn is more salient than the silence of email sitting entirely dependent upon the operator's prospective memory for a response.

9.3.4 *Difficulty*

A meta-analysis of 11 published experiments found that on average, operators were about twice as likely to switch to an easy AT rather than to a difficult one. This effect, like the tendency to avoid switching altogether, implies an influence of "cognitive laziness" or effort conservation. Interestingly, this preference for easy tasks does not seem to apply to the OT. Once engaged, the operator is just as likely to stay with a harder OT as with an easier OT, reflecting the offsetting tendency of switch inertia. This is likely an adaptive tendency. Once one is engaged in a hard task, less effort will be required to complete it than to switch away and resume it later, particularly if it contains working memory demands (Gutzwiller, Wickens, et al., 2016). This effect could account for the cognitive tunneling of the Eastern Airlines crew on the task of diagnosing a landing gear failure, leading to their crash into the Everglades (Wiener, 1977).

Figure 9.4 presents the STOM model. In the model, which updates its state at equal intervals of time (perhaps once per second), the operator is performing an OT in the oval at the left. At each update, a decision is made whether or not to switch tasks. On average, the operator chooses to remain with the OT about 60% of the time. In the gray boxes at the top are the attributes that bias the operator toward staying, with weights established from a meta-analysis (Wickens, Gutzwiller, & Santamaria, 2015). However, on the 40% of updates when a choice is made to switch to AT, then the attribute values in the boxes below indicate what makes an AT more or less attractive. After a switch is made, the selected task becomes the new OT, and the previous OT becomes an AT. STOM was found to predict attention allocation reasonably accurately in a simulation that required operators to time-share a robotic arm payload movement task with an environmental atmosphere control task (Wickens, Gutzwiller, et al., 2016). Importantly, operators' relative interest in the two tasks was a strong predictor of individual differences in attention allocation.

9.4 INDIVIDUAL DIFFERENCES IN ATTENTION-SWITCHING AND MULTITASKING SUCCESS

In this chapter and the previous two, we have described conditions that make multitasking easier (e.g., automaticity) or more difficult (e.g., competition for common resources, interruptions in the middle of task goals). Here we consider differences between people in their multitasking success.

9.4.1 Categories of Individual Differences

Because task switching may be a relevant predictor of individual differences, we now consider two aspects of that switching: how fast and how often.

9.4.1.1 *Switching Speed*

Early research found that the speed of switching between channels in a dichotic listening task was negatively correlated with the accident rate in bus driving (Kahneman et al., 1973) and with pilot training success (Gopher & Kahneman, 1971). Other work (Braune & Wickens, 1986; Hunt et al., 1989; Lansman et al., 1983), observed relatively stable individual differences in switching speed that generalized across the auditory and visual modalities, although these did not correlate with other measures of dual-task performance. The US Navy was sufficiently impressed by the stability of a dichotic listening switching measure that they included it in their test battery to select candidates for flight school.

9.4.1.2 *Switching Frequency*

Damos and Wickens (1980) identified two distinct groups of participants in a dual-task training study: those who switched frequently and regularly between two discrete cognitive tasks ("alternators") and those who stayed for long blocks of one task before switching to the other ("blockers"). Dual-task performance was similar between the two groups. Other work has likewise observed null effects of switch frequency on task performance (Gutzwiller et al., 2015), though Arrington and Yates (2009) found that more frequent switching was associated with a reduced dual-task decrement. Adler and Benbunan-Fich (2012) observed substantial individual differences in the frequency with which operators switched between ongoing cognitive tasks and found that more frequent switching was associated with lower multitasking efficiency and higher risk of error. Rapid switching appeared to interrupt task goals, as described in our discussion of interruption management.

The simple conclusion that more rapid switching may be associated with poorer performance is contradicted by the results of Raby and Wickens (1994), who found that better-performing pilots tended to switch attention more frequently between tasks, being less inclined toward cognitive tunneling or task inertia. The conclusion that rapid switching is detrimental is also complicated by the findings from a third group of participants that Damos and Wickens (1980) identified, also identified by Brüning and Manzey (2018). These were people who chose not to switch at all, whether rapidly or slowly, but rather to process two discrete tasks in parallel, making concurrent responses to both. This group showed superior multitask performance. Such findings are also consistent with those of J. M. Watson and Strayer (2010), who identified a minority subset of participants—so-called *supertaskers*—who appeared to drive and carry out cellphone conversations simultaneously without costs (see also Fischer & Plessow, 2015). Research shows that a concurrent processing strategy may be largely immutable, in that those who do not demonstrate it naturally cannot easily be trained to effectively deploy it (Brüning & Manzey, 2018; Damos et al., 1983).

In sum, there is no doubt that stable individual differences in the frequency, speed, and timing of switching exist, as well as in the preference for multitasking and in the ability to process concurrently (i.e., without switching at all). These differences can be associated with the high quality of multitask performance (low dual-task decrement), although the form of this association is not simple. Concurrence may be more effective than switching, but rapid switching is not necessarily better and may be worse than slower switching, particularly when working memory and discrete goal states are involved with one or both of the tasks, so that switches more likely occur before subgoal completion. We have more confidence that knowledge of when to switch is a more stable individual difference, as discussed in what follows but are uncertain if this strategy can be trained. We now ask what stable individual differences in cognitive ability may be associated with switching effectiveness, pointing first to three prominent candidates, working memory, executive control, and fluid intelligence.

9.4.2 Correlates of Individual Differences in Switching

9.4.2.1 *Working Memory*

Working memory is associated with switching in two ways. Its first role is direct: when a task is suspended with subgoals uncompleted, people with better working memory will have an easier time remembering task state (Borst et al., 2010) and goals (Salvucci & Taatgen, 2010; Trafton & Monk, 2007) upon resumption. Its second role is indirect: there is good evidence that attention-switching itself is a resource-intensive cognitive task (Arrington & Logan, 2004; Wickens, Gutzwiller, et al., 2015), which will therefore compete with other cognitive tasks in the multitasking ensemble. Greater working memory capacity should thereby avail more reserve capacity to enable better multitasking and hence a reduced cost for switching.

The research associating increases in WM capacity with better multitasking ability is both ample and consistent (Bühner et al., 2006; Colom et al., 2010; Konig et al., 2005; Morgan et al., 2013; Redick et al., 2016; Redick, 2016). While all these studies found better multiple-task performance associated with higher working memory, they did not directly examine the dual-task *decrement*, which, of course, is the key difference between single- and multiple-task performance.

9.4.2.2 *Executive Control*

The concept of executive control is multifaceted (Banich, 2009; Miyake & Friedman, 2012), and tests of executive function sometimes include working memory tasks. However, a key component of executive control is the resistance to distraction (Friedman & Miyake, 2004). In a multitask setting, it is reasonable to conclude that those who are more resistant to distractions (here, the distraction of other tasks waiting in the wings) would be less likely to abandon an ongoing task and switch to a concurrent one when it is not a desirable time to do so—and would therefore multitask more efficiently. Consistent with this view, Arrington and Yates (2009) found that people with poorer executive control performed more poorly in dual-task situations. Medeiros-Ward et al. (2015) found that supertaskers showed less activation of executive regions of the brain while multitasking, as if they needed fewer resources to suppress unwanted distraction, and Gutzwiller et al. (2015) found that those with better executive control chose more opportune times to switch away from an ongoing tracking task, even if they did not switch more frequently. Sanbonmatsu et al. (2013) found that those with lower executive control rated themselves as doing more multitasking and, as reported, were poorer at performing a concurrent multitask ensemble.

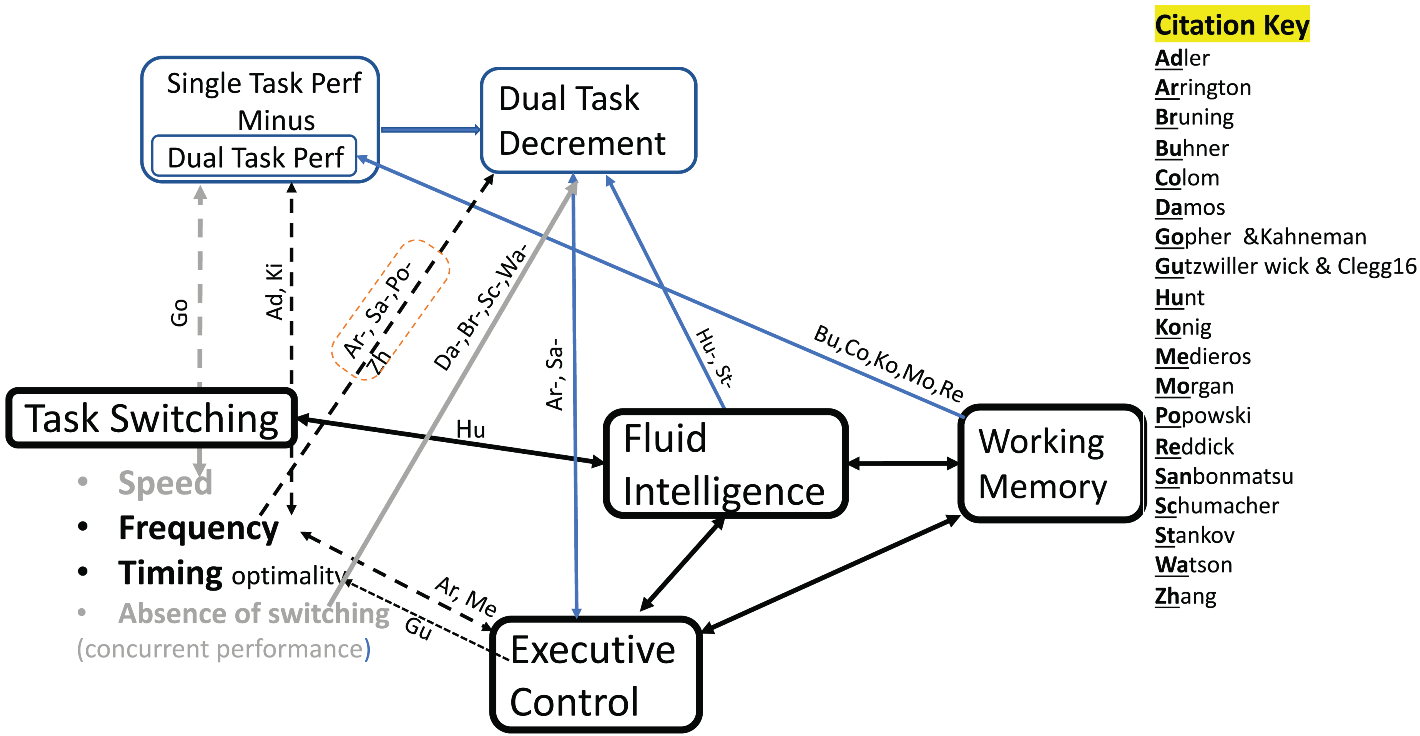
9.4.2.3 *Fluid Intelligence and the General Time-Sharing Ability*

General intelligence—as measured by the IQ test—has sometimes been partitioned into two components: acquired knowledge, or *crystalized intelligence*, and a more dynamic capability associated with logical reasoning and analysis, termed *fluid intelligence* (Cattell, 1971). General IQ tests tap both types, producing a score, *g*, that has been used successfully to predict performance in the dynamic, multitasking world of aviation (Carretta & Ree, 2003; Causse et al., 2011; Hunt et al., 1989; Wickens & Dehais, 2019). Hunt et al. (1989) found a measure of fluid intelligence to correlate with both switching speed and measures of general attention control in integrating different sources of information.

It is not surprising that investigators have also found fluid intelligence to be a predictor of dual-task performance. In particular, multiple studies (Ackerman et al., 1984; Fogarty & Stankov, 1982; Jennings & Chiles, 1977; Stankov, 1988, 1983; Wickens et al., 1981) have had participants perform a wide variety of different dual-task combinations, demanding various skills and resources, and have examined the correlations between single- and dual-task performance. Not surprisingly, performance on task pairs that share the same single tasks correlate highly. So do the decrements of dual-task pairs sharing similar tasks, indicating task-specific time-sharing skills. But notably, these researchers have also identified shared variance between very diverse dual-task pairs, variance that cannot be accounted for by the similar task pairs and appears to reflect a general time-sharing ability. Correspondingly, Redick et al. (2016) found unique variance in the performance of three different multitask "games," which they associated with a general multitasking ability. Importantly, Stankov's (1988, 1983) research indicates that fluid intelligence is a good predictor of this general time-sharing ability, and Redick et al. (2016) found that fluid intelligence predicted general multitasking ability as well as did working memory, both of which were more predictive than was attention control. We don't know the extent to which this predictor is also related to executive ability and task switching.

9.4.3 The Tangled Web

The picture created from the findings of individual differences in multitasking is not a simple one, but we have tried to distill its most critical relations in "the tangled web" of Figure 9.5. In the upper left corner, we show that time-sharing ability can be most purely represented by the dual-task decrement: Single minus dual-task performance. The arrows connect nodes from studies that have examined correlations between key elements in the figure, with letter pairs along the arrows corresponding to studies listed at the bottom of the table.



Key: The first 2 letters designate the 1st author of the study along a line in the figure. The full list of authors for each study is found in the text.

FIGURE 9.5 The tangled web, showing relations between different components frequently involved in multitask performance. All arrows indicate a direction of positive correlation between an increase in the variable listed in the two connected nodes.

The figure clearly indicates the presence of several associations, and the likely value of using certain tests, particularly those of working memory, to predict success in jobs with heavy multitasking components. But several uncertain relationships exist, exposing many fruitful areas for future research.

9.5 CONCLUSION

In conclusion, task switching and task management become of concern whenever concurrent multitasking breaks down, which happens often in high-workload situations when demands are over the "redline" of workload, as discussed in Chapter 7, and in situations in which interruptions are frequent. Here a number of features determine how rapidly an interruption is handled and how fluently the ongoing task is resumed. Many of these features also determine which task is chosen when two or more must be switched between. Underlying all is the attention-switching strategy and proficiency, which has shown many important individual differences.

10 Attention and Human Interaction with Automation and AI

Between 2018 and 2021, multiple crashes occurred involving a particular brand of self-driving car, crashes that led to increased scrutiny by the National Highway Transportation and Safety Administration. Most of them involved situations in which a cognitively disengaged driver neglected to correct an inappropriate maneuver by the autopilot. In the language of this book, these were failures of driver attention coinciding with failures of automation, that is, double failures.

Throughout this book, we have identified attention limitations that constrain information processing. These have included:

- vigilance decrements—resource depletion and mind wandering in the midst of tasks that require sustained focus;
- inappropriate scanning, driven too much by suboptimal weighting of the factors in SEEV;
- amplified costs of imperfect alerting systems under conditions of dual-task loading;
- insufficient depth of processing resulting in the failure of later memory (as discussed more in the last chapter);
- the general toll of one task's resource demands on other concurrent task's performance.

It is often the goal of automation to offload the resource demands of information processing from the human operator (Parasuraman et al., 2008, 2000). Yet it has also been long understood that automation and attention are linked in more pernicious ways that can allow automation, ironically, to undermine human performance (S. I. Chen et al., 2017; Parasuraman & Manzey, 2010). Bainbridge (1983) labels this an *irony of automation*. In this chapter, we will review a number of the ways that human attention and automation are linked.

10.1 VISUAL MONITORING OF AUTOMATION: ALARMS AND ALERTS

Since the classic work of Sorkin and Woods (1985) and Molloy and Parasuraman (1996), researchers have been concerned with how humans and automation work in tandem when monitoring an ongoing process for malfunctions or other critical events; this obviously relates to the role of alarms and alerts as discussed in Chapter 3 (Figure 3.2).

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Most often, the data supporting the task are visual, and so the automation-assisted monitoring paradigm entails scanning between the raw data, the automation's classification itself, and other visual tasks. From the viewpoint of optimal visual scanning, it makes sense that a continuous visual task, such as monitoring air traffic control (Metzger & Parasuraman, 2005; Wickens, Rice, et al., 2009), unmanned air vehicles (Dixon & Wickens, 2006; Foroughi et al., 2019; Wickens et al., 2010), a self-driving car (Hergeth et al., 2016), or an automation-controlled robotic arm (Wickens, Sebok, et al., 2015), will have a lower bandwidth when performed by automation than when performed manually. According to SEEV, this will reduce the optimal frequency with which the operator should sample the raw data of an automation-controlled process.

The bandwidth of automation events (whether representing failures or not) drives human scanning, as reflected directly in eye movements or indirectly in the accuracy and RT for failure detection. For example, pilots are slower to notice flight deck automation state changes that are less expected (Sarter et al., 2007), and operators are less likely to scan a robotic arm when it is controlled by automation, even if that automation is imperfect (Wickens, Sebok, et al., 2015). Parasuraman and colleagues (Parasuraman et al., 1993; Parasuraman & Manzey, 2010) have extensively discussed the phenomenon of *complacency*, the tendency for operators to neglect AOIs supporting systems that are monitored by reliable automation. Moray and Inagaki (2000) defined the word *eutactic* to mean optimally calibrated, and noted that when automation reliability is high, eutactic behavior is to check the automation very infrequently (N. R. Bailey & Scerbo, 2007).

However, it is *not* optimal to ignore such automation completely, as operators sometimes do. In terms of the SEEV model decribed in Chapter 4, this is because detecting a failure is always of the highest value, no matter how high the automation reliability (and, hence, how low the expectancy of a failure). This is why SEEV can be structured to impose an additive, not a multiplicative relationship on expectancy and value, so that even if expectancy goes to zero, a high value of an AOI will still have a positive impact on how frequently the automation should be sampled (Wickens, 2015).

The sensitivity of attention to automation failure rate is evident in visual scanning metrics (e.g., Wickens, Dixon, Goh, et al., 2005) and in performance of concurrent visual tasks (e.g., Dixon & Wickens, 2006). Operators in a self-driving car monitor the vehicle more when they trust it less (Hergeth et al., 2016) or when external conditions such as poor weather threaten to degrade the vehicle's reliability (Kunze et al., 2019). In this context, trust is a subjective measure of perceived vehicle reliability. And yet this calibration of scanning to expected automation failure rate is not inevitably found. For example, Foroughi et al. (2019) found that humans monitoring automation scanned multiple onscreen UAV displays with roughly equal frequency despite large differences in their reliability. They attributed this to what Keller and Rice (2009) have described as *systemwide trust*, a tendency for people to base their trust in system components upon the average reliability of all the components and not the reliability of each one individually.

While much of the research on attention to automation systems has focused on the simple effects of reliability (or trust), some investigators have examined more closely the effects of different kinds of automation monitoring errors. In particular, Dixon and Wickens (2006) and Wickens et al. (2006) have contrasted the degrading effects of miss-prone versus false alarm–prone automation in the context of the contrast between reliance and compliance, discussed in Chapter 3. The ratio of these two types of automation errors is determined by the threshold of the alarm setting: how much evidence is needed to trigger the alarm. Both kinds of errors can be present a given system with, for example, 80% reliability, as the 20% errors can be expressed in automation misses, false alarms, or some combination of both. Data indicate that miss-prone automation induces a larger shift in visual attention toward the automated process monitored than does false alarm–prone automation, at the expense of concurrent visual tasks (Wickens, Levinthal & Rice, 2010). However, the effects of false alarm–prone automation are more disruptive overall, both because of the need to switch attention to the automated task after every alarm, whether true or false, and because of the overall degrading effects of FA-prone automation on trust (Bliss, 2003; Dixon et al., 2007) which may in turn lead to the “cry wolf” effect.

As described in Chapter 3, the design of alarm and alerting automation is also informed by the joint influences of salience, eccentricity, and expectancy, all incorporated in the NSEEV attention capture model (Steelman et al., 2017). Hence, when such alerts are visual, as in the cockpit, automobile, or process control workstation, the relevance of these NSEEV parameters to selective attention, change blindness, and attention capture becomes vital to understand (Wickens, Sebok et al., 2015).

10.2 ATTENTION CUING

Alarms and alerts serve to inform the user of automation’s inference as to what is happening. In contrast, attention cuing is based on an inference of where the operator should be looking for critical information, as, for example, the attention cue directing the soldier to look for a suspected hostile threat (Devlin et al., 2020; Yeh et al., 2003) or guiding where the radiologist should look to find an abnormality in a low-quality image (Alberdi et al., 2004). Often, the raw sensory data upon which the automation makes such an inference are noisy, and the inference rules used to categorize the object as worthy of attention or not are imperfect. The errors that result may sometimes be benign, but Yeh et al. (2003) have identified circumstances in which an automated cue to look one place for a difficult-to-see target can divert attention from other critical objects and events in the visual scene, creating a sort of cognitive tunneling. This can be particularly dangerous the first time the user experiences an automation error. Analogously, consider also the way in which an intelligent email software may prioritize information for the user by placing what it believes are the most important messages at the top of the inbox. Here, sources of automation error will include the uncertainty inherent in the content of a message and the automation’s misunderstanding of the user’s values and priorities. As with alerts, the costs of automation error in such attention cuing functions must be carefully considered.

10.3 ATTENTION AND EFFORT: LEVEL OF ENGAGEMENT

In the next chapter, we will describe the role of mental effort in long-term memory formation. This phenomenon is closely linked to the *generation effect* (Slamecka &

Graf, 1978). When generating a response in a learning environment that is either internal and covert (e.g., mentally rehearsing material just encountered) or explicit and visible (e.g., taking notes or vocally generating quiz answers), the material upon which that response is based is better retained. Such retention can either be in long-term memory or a more temporary *long-term working memory* (Ericsson & Kintsch, 1995). This latter form of dynamic memory is functionally equivalent in many ways to Endsley's (1995) level 2 situation awareness, understanding the state of a dynamically changing environment, and here is where attention and effort are so inexorably linked to automation.

Research on human–automation interaction has produced a taxonomy of *degree of automation (DOA)*, with a higher DOA corresponding to a higher amount of cognitive work by the automation (the level of automation) and to a later stage of human information processing that automation supports (Onnasch et al., 2014; Parasuraman et al., 2008, 2000; Wickens, 2018). These four stages are (1) event detection and attentional guidance, (2) diagnosis and situation assessment ("what is"), (3) decision support ("what to do") and (4) action selection ("doing it"), as shown in Figure 10.1.

This taxonomy was originally offered by Parasuraman et al. (2000) to account for the fact that a higher degree of automation appeared to support better performance when automation was working as intended but led to worse performance and less fluent and sometimes catastrophic human intervention when automation failed (or at least failed to work as expected by the human operator: Sebok & Wickens, 2017). A meta-analysis (Onnasch et al., 2014) confirmed this relationship and also revealed that an increasing degree of automation led to a loss of situation awareness. This loss can be attributed to the operator's lack of engagement. Both trends become particularly evident as the stage of automation (the x-axis of Figure 10.1) crosses the border from situation assessment to decision support. At the third stage, the automation either decides what to do or at least recommends what should be done, allowing the operator to simply act without checking the raw data. This tendency to act blindly

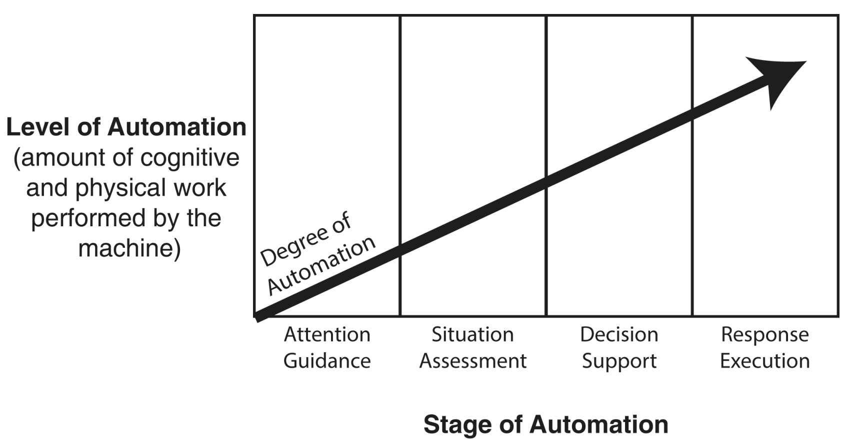

FIGURE 10.1 Stages and levels of automation define the degree of automation.

on an aid's recommendation has been termed *automation bias* (Mosier et al., 1998; Mosier, 2009; Parasuraman & Manzey, 2010).

While loss of situation awareness is the main finding relevant to attention here, the other finding revealed by the meta-analysis of DOA research (Onnasch et al., 2014) was a pronounced decrease in mental workload associated with increasing DOA. In this regard, it is surprising that increasing DOA does not produce better situation awareness rather than worse, because lower workload of higher DOA should leave the operator with more free resources to maintain awareness of what automation is doing and the raw data that it is processing. But it appears that those freed resources are often not used productively to support greater situation awareness.

One recent and frequently suggested solution to the loss of situation awareness of what automation is doing is to make the automation "transparent." Automation transparency can be created by, among other techniques, providing an explanation for why an automated aid has made a given decision or by providing a graphic display of the raw data that automation is processing (Trapsilawati et al., 2021). Such techniques are indeed often useful in mitigating a poor failure response (Wickens Helton et al., 2022). But caution must be exercised that the added display or verbal explanation to create transparency does not create unnecessary mental workload or divert visual attention away from the task that is to be monitored.

10.4 AUTOMATION, WORKLOAD, AND HAI TEAM PRODUCTIVITY

Automation and attention have also been linked in the often-asked question by system designers about whether increased productivity can be obtained by assigning more tasks to automation and hence availing more spare capacity to the human worker. Two examples from aviation illustrate this issue. First, in the 1970s, aircraft manufactures made the decision to eliminate the flight engineer from the cockpit, downsizing the aircrew from three to two. This was to be achieved by automating most tasks performed by the flight engineer. Did the remaining two crew members, the pilot and co-pilot, have the available resources to carry out the remaining tasks (including monitoring the automation itself for failures)? This is a question about mental workload (Ruggiero & Fadden, 1987), and many of the techniques of predictive modeling of pilot workload were deployed to find out the answer, including, particularly, timeline analysis as shown in Figure 2.3.

The second example concerns the supervision of multiple unmanned air vehicles (UAVs). How many UAV's can a human fly/supervise effectively (Cummings & Guerlain, 2007; Goodrich et al., 2007; Goodrich, 2013; Wickens, Gosakan, et al., 2013)? This is also a question about workload, as the supervisor/pilot's attentional resources are now divided between the multiple UAVs under their supervision. Clearly the answer is probably "1" if the UAV flies like a single aircraft. However, deploying higher degrees of automation on the UAVs, up to total autonomy, should decrease the resources required for each. And this has been frequently observed, but only under conditions in which automation is working correctly (Dixon et al., 2005; Wickens, Levinthal & Rice, 2010). As a systems analysis readily reveals, the higher the DOA and the more automated units under supervisory control, the greater is the probability that some component will fail, reducing overall system reliability. Such a trend can offset any gains achieved by more automation because of the excessive resource demands often required to deal with system failures.

10.5 ADAPTIVE AUTOMATION, ATTENTION, AND WORKLOAD

Over the past few decades, there have been frequent suggestions to make automation adaptive (Dorneich et al., 2016; Kaber et al., 2005; Kaber & Endsley, 2004; Kaber & Kim, 2011; Li et al., 2013; Sauer et al., 2012; Sauer & Chavaillaz, 2018), that is, to vary the level of automation conditional upon the operator's transient need. An example might be the logic of a self-driving car that decides, at a particular instance, that the driver is no longer capable of steering and automatically imposes a steering autopilot. Studies comparing the value of adaptive and fixed automation have produced mixed results (see Wickens, Helton et al., 2022). Most relevant to a discussion of attention is the question of when to adapt. A plausible assumption is that a higher DOA is desirable whenever human mental workload is increasing and particularly when workload approaches the red line of full resource utilization, as discussed in Chapter 7.

But how does the system know? Designers can turn to the full array of mental workload measures discussed in Chapter 7 (Regis et al., 2014), but two considerations are particularly critical. First, the designer does not want the measurement process to interfere with the adapting task. Second, the designer needs the mental workload assessment technique to be sensitive over short time scales, allowing it to reliably infer a workload increase or decrease that might have taken place within the last few seconds. A lagging workload inference might invoke automation when it is no longer needed or, perhaps worse, mistakenly infer that workload has dropped and return control to the human at the very moment that true workload is on the rise. Clearly, any measure that requires, say, 30 seconds to infer a change in workload level will not be satisfactory in adaptive automation. Hence, the dynamics of attention, task demands, and resource allocation are important to understand if adaptive automation is ever to become a reality (Wickens, Tsang & Pierce, 1985).

10.6 CONCLUSION

In conclusion, we see how automation links with attention in many ways, from the attention-grabbing properties of alerts, to the reduced attention and workload demands availed by automation, to the fact that those tasks may still require effortful attentional monitoring if the automation is less than perfect. All of these aspects and more discussed in the chapter dictate that automation designers be aware of the various properties of attention and how they can be used to improve the fluency of human–automation interaction or at least not degrade it.

11 Applications (with Tobias Grundgeiger and Yusuke Yamani)

Throughout this book, we have blended attention theory with many different applications to design, training, procedures, and error analysis in the workplace and elsewhere beyond the laboratory. In this final chapter, we draw these findings and more together in describing their applications to five different applied domains: aviation, driving, health care, education, and cybersecurity. While some of this coverage is a little redundant with that presented in the earlier chapters of the book, we believe that the reader who has a particular interest in one of these domains will benefit from seeing how the diverse attentional threads covered earlier can be knitted together to support design and safe practice in the domain of interest.

11.1 AVIATION

We have frequently used aviation as a context to illustrate the general principles of attention in design, for example, the "object display" of aircraft attitude or the spatial configuration of aircraft flight instruments. In this section, we recap these examples and present more, specifically considering the role of attention in aircraft cockpit design and pilot performance and procedures, by sequencing through the chapter topics of the book in a way that roughly parallels the stages of pilot information processing (Vidulich et al., in press; Wickens, 2021, 2022).

11.1.1 Chapter 2. Single-Channel Theory and Automaticity

There are few occasions in which the pilot is truly overloaded, to the extent that they must operate as a single-channel processor and in doing so sacrifice the safety of the flight. Yet some circumstances do impose such limitations, particularly in the face of unexpected emergencies (Pinet, 2016), as when the plane is dangerously close to either stalling, colliding with the terrain or another aircraft, or overrunning the runway. Here, in the terminology of the psychological refractory period, a delay of even less than a second in controlling the aircraft (R2) while processing the totally unexpected and potentially catastrophic event, often signaled by a high-intensity auditory warning (S1), could cause an accident.

Unfortunately, these circumstances can very rapidly multiply in complex, automated aircraft, with scores of alarms and warning indicators, in which each failure or dangerous aircraft state may trigger several more alarms—so called "alarm

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flooding" (Martensson, 1995; Wickens, Sebok, et al., 2016). These constitute a plethora of S2s, each one further delayed in its appropriate R2 response.

Such circumstances are unusual, but, ironically, it's just this rarity that makes them unexpected and can prolong the pilot's response to the triggering event (R1), thereby delaying the second response: one of controlling the aircraft to avoid a stall or collision (R2: Wickens, 2009).

At the opposite end of the attentional spectrum, automaticity is frequently expressed in pilot cognition and performance, particularly for the highly skilled pilot. We see this in almost any consistently mapped behavior in the cockpit, from proceeding through the routine checklist to the precise control of the flight surfaces on takeoff and landings on a windless day (Degani & Weiner, 1993). It is of course the proliferation of such automated behavior that enables highly proficient multitasking by the well-trained pilot (Damos, 1978; but see Loukopoulos et al., 2009). However, a word of caution is necessary. When a skill becomes so thoroughly automatized that its execution is not monitored by conscious attention, there is a danger that top-down processing may cause the operator to perceive what is expected and fail to notice a departure from expectations. For example, this may characterize a pilot going through a checklist who does not notice a slight departure from the routine and typical settings of the aircraft switches (Degani & Wiener, 1993).

Nevertheless, because automaticity is a generally desired state of pilot proficiency, it is often pursued through pilot training (e.g., the decisions to use part-task training vs. whole-task training so that a part can be extensively trained to reach automaticity; see the section on education).

11.1.2 Chapter 3: Alarms and Alerts

The issue of alarms and alerts, raised in the context of single-channel behavior, leads naturally to the questions of attention control and capture, addressed in Chapter 3. This is precisely what cockpit alarms are intended to do: capture attention. Furthermore, with the possible exception of the nuclear power console (Strobhar, 2014), the pilots' cockpit probably contains more visual and auditory alerts than any other platform within which the human does cognitive work. Many of the lessons on appropriate alarm design (Mårtensson & Singer, 1998; Noyes, 2004; Wickens, Sebok, et al., 2016a, 2016b), false alarms (Bliss, 2003; Mumaw, 2017; Olson & Olszta, 2010; Wickens, Hooey, et al., 2009), multimodal alarms (Nikolic & Sarter, 2001; S. L. Riggs et al., 2017), and alarm logic (Singer & Dekker, 2000) have been drawn directly from aviation research.

11.1.3 Chapter 4. Supervisory Control

The aircraft pilot is ultimately the supervisor of a complex dynamic system, monitoring visual channels that include both dynamic instruments and the outside world, watching for disturbances that need correcting or commands that need following (Wickens, 2022). Thus, understanding and modeling the influences that lead the pilot to attend to some channels and neglect others becomes critical in improving aviation safety (Billman et al., 2020; Dehais et al., 2017; Helleberg & Wickens, 2003; Peißl et al., 2018; Steelman et al., 2011; Steelman et al., 2013; Talleur & Wickens, 2003; Wickens, Goh, et al., 2003; Ziv, 2016). This concern is amplified as aircraft automation takes on progressively more control and the pilot increasingly becomes just a monitor whose primary responsibility is just to look and understand (Sarter et al., 2007: see also Chapter 10). A key element in modeling scanning is to predict periods of time in which some areas are neglected, leading to the risk of change blindness (Thomas & Wickens, 2004; Wickens, Hooey, et al., 2009; Wickens & Alexander, 2009). This, in turn, leads to a focus on the properties of displays that may enhance such tunneling (St. Lot et al., 2020; Wickens & Yeh, 2018) or, in contrast, may mitigate it, for example, by the use of superimposed HUD imagery or of high salience alerts (Nikolic et al., 2004).

11.1.4 Chapter 5. Visual Search

Visual search is a close cousin of supervisory control. But supervisory control involves visual monitoring over time for specific events on particular AOIs, whereas visual search entails looking for an object in space. In aviation, there are several search domains, defined by both the task and the object or target of the search. These include, (1) for both the pilot and air traffic controller, the never ending search for an aircraft that might be on a collision course (Helleberg & Wickens, 2003; Remington et al., 2000; Talleur & Wickens, 2003; Wickens, McCarley et al., 2008; Wickens, 2009); (2) the pilot's search across the instrument panel for the out-of-tolerance indicator that has just triggered an auditory alert; (3) the search through a complex multilevel computer menu to find a page or entry relevant to the task at hand (e.g., addressing an in-flight emergency); (4) for the maintenance worker, the search across the aircraft hull for a faint crack.

The importance of such searches is self-evident. Thus, equally important are those environmental and task factors, described in Chapter 5, that hinder search, or the design and task features, such as intelligent cuing or good menu organization, that can speed it up.

11.1.5 Chapter 6: Attention in Space

The pilot flies through a 3-dimensional space and also gazes across a spatially arrayed instrument panel and across the world beyond to understand the state of the aircraft with regard to stability and airspace hazards (Wickens, 2022). In Chapter 6, we discussed two theories of the allocation of attention in space, both directly relevant to cockpit display layout and format (Lim et al., 2018).

Space-based theory, conceptualizing visual attention as a spotlight, is highly applicable to the layout of cockpit warnings and alerts, in which a primary visual area is defined as a 30-degree circle surrounding the attitude display indicator (ADI), which is typically the pilot's center of view. Aviation design regulations mandate that all visual alarms and alerts are presented within this circle (Wickens, Sebok et al., 2016a, 2016b). This serves two purposes. First, this design facilitates the quick detection of new alerts and alarms. Second, it ensures that the attitude indicator remains within the pilot's field of view even when the source of an alert or alarm is foveated.

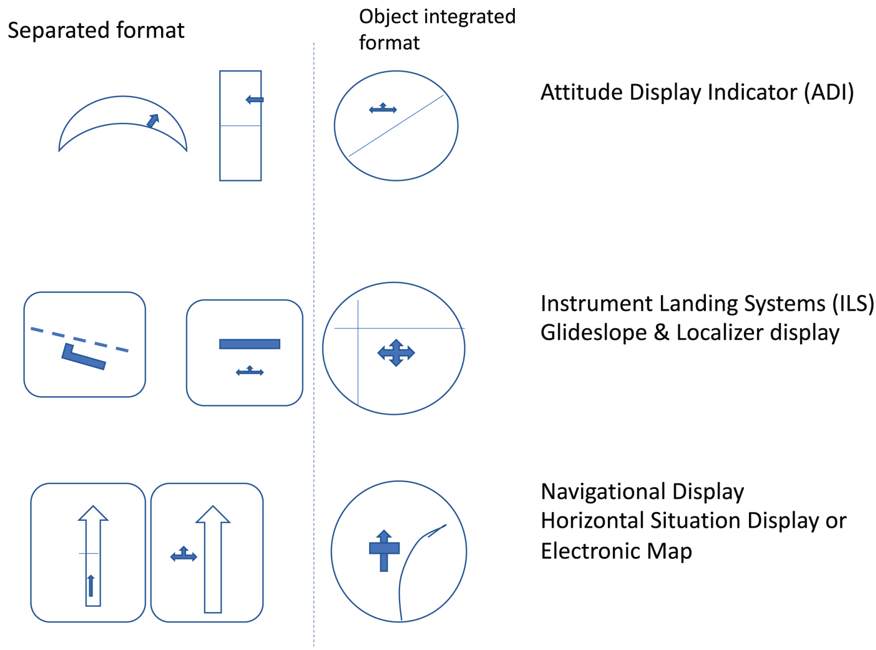

FIGURE 11.1 Three examples of cockpit displays that exploit the object-based theory of attention to create a single perceptual object that combines two dimensions of space (right column). These can be contrasted with the separated representations (left columns).

Equally applicable to display configuration is object-based theory (Andre et al., 1991), which holds that the pilot can effectively divide attention across all attributes of a single object. Although the attitude display indicator was not designed with object-based theory in mind, it is a paradigmatic example of an object display, with the bank and pitch of the aircraft signaled by the two attributes of the line representing the horizon. The top row of Figure 11.1 contrasts this design (right side) with a design in which bank and pitch are displayed separately (left side). We can also see a close correlation to this in the display of the horizontal and lateral deviation from the path toward the runway on a landing. This is illustrated by the Instrument Landing System glide slope localizer display shown in the middle row, right side of Figure 11.1. Again, for comparison purposes, this may be compared with the separated representation on the left.

In a corresponding fashion, the electronic map (sometimes referred to as the horizontal situation display or navigation display), shown in the bottom row, right side of the figure, now depicts the two critical aspects of the plane's navigation over the ground, lateral deviation and along-track position, with a single aircraft icon. This is in contrast to the earlier navigation displays that presented separate representations of the two, as shown on the left side of the bottom row.

To combine two dimensions of an electronic map, add a representation of vertical deviations from a flight path or the vertical separation from hazards, or to combine the two dimensions of the flight display, lateral and vertical with a representation of along-track deviations, designers have created a single-object 3D perspective display (Haskell & Wickens, 1993; Prinzel & Wickens, 2009; Theunissen, 1997; Wickens & Prevett, 1995). Such displays, integrating all three dimensions of space into a single object—a perspective view of the airplane and/or the surrounding airspace—have been found to be effective for guidance (staying on the desired flight path) compared to its separated 2-object counterpart (Wickens, 2007a), but suffer other limitations in terms of the line of sight ambiguity imposed by any 3D display (Wickens, Vincow, et al., 2005). However, this is a matter of spatial cognition and perception, not an attentional issue, and is addressed elsewhere (Wickens et al., 2022).

In a third section of Chapter 6, we addressed an important attention-based design principle relevant to aviation display design. This is the proximity compatibility principle (PCP) (Wickens & Carswell, 1995), which advises that two or more display items that must be compared or integrated in the pilot's mind should be of close proximity in the display. Close display proximity can be created by several means, most importantly closeness in space as dictated by space-based theories. Accordingly:

- The layout of the cockpit instrument panel is such that pairs of displays that need to be integrated for a coordinated control (e.g., a change in altitude) are co-located (Wickens, 2022).
- When two databases are both relevant for a pilot to select a safe trajectory (e.g. traffic and weather, or traffic and terrain in low-altitude flight), they should be overlaid on a single map rather than separated in two adjacent displays (Kroft & Wickens, 2003; Wickens & Ward, 2017: see Figure 6.8).
- When the pilot must integrate the representation of a target flight path toward the runway with the actual view of the runway in the world beyond, there are substantial advantages to presenting the former on a head-up display that overlays (close display proximity) the outside world (Fadden et al., 2001; Wickens, Ververs et al., 2004: Figure 6.9). Here, principles of space-based theory are joined with those of object-based theory, in that the greatest benefits of a HUD overlay are realized when the image is conformal with its counterpart in the outside world—an *augmented reality*—and therefore the two objects form a single "fused" percept (Fadden et al., 2001; Wickens, 2022; Wickens & Long, 1995; see section 6.4.3).
- As we can see from Figure 11.1, object-based attention theory is also relevant to navigation and guidance displays. Given the cross-coupling of lateral and vertical flight dynamics, changes in one axis often cause changes in the other axis. Hence, the pilot must integrate information across axes to maintain fluent flight. This is particularly true of the pitch and bank dimensions of the attitude display indicator.
- As illustrated in Figure 6.5, color, like space, is a continuous perceptual dimension that can be used to create display proximity. In that figure, common color was used to represent two aircraft of the same altitude and heading toward each other, which helps the display viewer to mentally integrate information about the position and movement of the two aircraft and therefore to recognize that they are on a conflict path.

The PCP is also relevant to maintenance and flight manuals, where text may be directly related to graphics (e.g., a picture of a piece of equipment). Here, the reason for mental or task integration is obvious, and presenting the text adjacent to or at least on the same page as the graphic is vital. Computer menu pages as well as paper pages also need to be designed with the PCP in mind. Two pages containing task-related information should be at most a "click" away from each other if not, ideally, integrated into a single page.

11.1.6 Chapter 7. Resources and Effort

Dominating all other applications of the concept of effort to aviation is the study of pilot mental workload. Indeed, some of the earliest published research on mental workload was specifically applied to aviation (Williges & Wierwille, 1979). Research on pilot workload—the effort required to perform a set of aviation tasks—was key to the FAA's decision to authorize downsizing of commercial aircraft flight crew from three to two (Ruggiero & Fadden, 1987). That is, could the pilot and co-pilot now handle the tasks previously assigned to a flight engineer without crossing the red line of workload overload? Arguably the most popular measure of mental workload, the NASA-TLX scale, indeed originated in aviation applications with the work of Sandra Hart within the aerospace branch of the NASA agency (Hart & Staveland, 1988). Within the context of mental workload, we need only emphasize the importance of keeping pilot workload sufficiently below the red line under normal circumstances so that it is not exceeded by the added task demands under emergency conditions, as we discussed in Chapter 9.

11.1.7 Chapter 8. Multiple Resources

Following from the previous section, the ability to sustain multitask performance in high-demand situations without crossing the red line can be supported by distributing the pilot's information processing load across multiple attentional resources, as we discussed in Chapter 8. Resource distribution is particularly effective and has been investigated in an aviation context through the use of synthetic auditory displays of important discrete information in the heavily visual world of the pilot (S. A. Lu et al., 2013; Sarno & Wickens, 1995; Wickens, Sandry & Vidulich, 1983; Wickens, Vidulich, et al., 1984). Increasingly tactile channels, as a separate perceptual resource, are also being used (S. L. Riggs et al., 2017). Regarding responses, a corresponding advantage for the use of multiple resources has been observed for the use of voice for discrete tasks that must be performed concurrently with the requirements for continuous manual control (Sarno & Wickens, 1995; Wickens, Sandry & Vidulich, 1983).

11.1.8 Chapter 9. Interruption and Task Management

As we have mentioned previously, concurrent multitasking may often break down under overload, and effective task management often becomes key. This is no more true than in the cockpit of an aircraft under emergency circumstances. Theories of multitask switching and task management were founded in aviation research, particularly Funk's (1991) development of the concept of cockpit task management (CTM) and Chou et al. (1996)'s subsequent review of failures of CTM, as revealed in both aircraft incidents and accidents. Laudeman and Palmer (1995) and Raby and Wickens (1994) both examined the manner in which optimal task management in the cockpit was often dropped under increases in mental workload. The research of Latorella (1996, 1998) examined many details of interruption management in the cockpit associated with auditory preemption. Dismukes and his colleagues at NASA Ames carried on this theme with extensive theory-driven work on cockpit interruption management in general, with a particular emphasis on the role of prospective memory, to remind the pilot or air traffic controller to return to the ongoing task following an interruption (Dismukes & Nowinski, 2007). The book *The Multi-Tasking Myth* (Loukopoulos et al., 2009) is replete with examples of task-switching failures from actual aircraft accidents and incidents.

Concern for interruption management is closely linked to the issue of electronic checklist design and procedure following (Degani & Wiener, 1993). When appropriately designed, checklists and procedures provide very explicit placeholders for the pilot to return to after an interruption. But while checklists can be effective in assuring that all steps for a given task, such as preparing the aircraft for takeoff or landing, are followed, they do not offer any guidance for priority management between tasks, for example, between communicating with air traffic control, and cockpit fault diagnosis (Dismukes & Nowinski, 2007).

11.2 DRIVING (WITH YUSUKE YAMANI)

Motor vehicle crashes are a significant public health concern in the United States and abroad. In 2019, in the U.S. alone, more than 22,000 passenger vehicle occupants were killed due to traffic crashes, and roughly 2.5 million occupants were injured (National Center for Statistics and Analysis, 2021, November). Failures of attention, in various forms, are a major (Beanland et al., 2013; Dingus et al., 2016; McKnight & McKnight, 2003; Sundfør et al., 2019) and growing (National Highway Traffic Safety Administration, 2015) risk factor for crash involvement. Not surprisingly, attentional processes are interleaved through the driver's tasks; Strayer and Fisher (2016) propose a general model of attention and situation awareness in driving, with stages that include scanning for threats, predicting the occurrence of such threats, identifying threats and other road objects around the driver, deciding whether and when mitigation action is necessary, and executing appropriate responses. Research on driver attention has indicated various ways that the attentional processes involved in driving can fail and, in some cases, ways they can be improved.

11.2.1 Driving Experience and Visual Scanning

Drivers aged between 16 and 19 years face a fatal crash rate roughly 3 times higher than that of drivers aged 20 years and older (Insurance Institute for Highway Safety, 2022). Their crash rate is exceptionally high during the first few months of independent licensure (Gershon et al., 2018; Mayhew et al., 2003). Though young drivers' elevated crash risk is often attributed to immaturity and risky driving behaviors, an analysis of 2,000 accidents involving young drivers revealed that a large majority of the accidents were due to cognitive factors such as inattention to the forward roadway, visual search, and poor hazard recognition (McKnight & McKnight, 2003). This implies that visual attention plays an important role in traffic safety and operates differently between novice and experienced drivers.

Differences in visual scanning between novice and experienced drivers were first noted in seminal work by Mourant and Rockwell (1972), who demonstrated that novice drivers concentrate their fixations within a narrow visual area directly in front of the vehicle, while experienced drivers spread their fixations more broadly across the forward roadway. Subsequent research since has consistently found that, compared to novice drivers, experienced drivers scan more broadly in the horizontal direction (Chapman et al., 2002; Crundall & Underwood, 1998; Falkmer & Gregersen, 2001) and check their exterior mirrors more frequently (Underwood, Crundall, et al., 2002). Experienced drivers also flexibly adapt their visual scanning to changing road demands, while novice drivers scan more rigidly (Crundall & Underwood, 1998; Falkmer & Gregersen, 2005).

One potential cause of novice drivers' constricted visual scanning on the road or in a simulator is that the demands of controlling the vehicle itself distract from the task of monitoring the exterior mirrors and peripheral roadway (Mackenzie & Harris, 2015). Experienced drivers, having largely automatized the skill of lane-keeping (Charlton & Starkey, 2011; Ranney, 1994), would presumably have spare capacity to allow them to sample the visual world more broadly. Consistent with this possibility, data from experiments using a secondary probe-detection task to measure cognitive load have found that under equivalent conditions, experienced drivers generally have more free attentional resources than novice drivers (Crundall et al., 2002, 1999). However, differences in the breadth of scanning show up even when novice and experienced drivers are asked to monitor for hazards in roadway videos without actually controlling a vehicle (Crundall et al., 2002; Underwood, Chapman, et al., 2002). This result indicates that inexperienced drivers' narrow scanning isn't caused by the cognitive demands of controlling the vehicle but that novice drivers are not as well calibrated as experienced drivers to the distribution of useful information across the driving scene (Underwood, Chapman, et al., 2002). In the language of SEEV, novice drivers have a poorer understanding than experienced drivers of the bandwidth and value of different areas of interest (Horrey et al., 2006).

Of course, experienced drivers can also experience scanning failures resulting from deficiencies in their mental model of the environment. Experienced drivers often fail to notice traffic signs or hazards such as bicyclists—high-value objects—when they appear in unexpected locations (Borowsky et al., 2008; Shinoda et al., 2001; Theeuwes, 1996; Theeuwes & Hagenzieker, 1993). In a striking example, Summala and Rasanen and colleagues (Rasanen & Summala, 2000, 1998; Summala et al., 1996) noted that in a country where drivers use the right-hand lane, a disproportionate number of crashes between cars and bicycles at T-intersections and roundabouts involved a driver turning right with a cyclist approaching from the right. These crashes appeared to be largely the result of expectancy-driven failures in scanning. Drivers, turning into the inside lane, need only to scan leftward for oncoming automobile traffic and neglect to check rightward for low-probability bicycle or pedestrian traffic. Their scanning fails to weight the low probability of a target approaching from the right-hand direction against the high value of spotting the target.

Can drivers be trained to calibrate their scanning better with an expected value model? Studies of novice drivers indicate that the answer is yes. Recording eye movements in a driving simulator, Pradhan and colleagues (Pradhan et al., 2005) noted common situations in which novice drivers failed to scan the sites of unexpected hazards, such as the crosswalk entry hidden behind the parked truck shown in the top panel of Figure 11.2. To counteract these scanning failures, the research team developed a training program in which novice drivers were asked to examine map-view representations of driving scenes like that shown at the bottom of the figure and to point out sites at which hazards might be located (Pollatsek, Fisher, et al., 2006). Posttest data indicated that trained drivers were almost twice as likely as untrained drivers to scan sites of potential hidden hazards. This effect was evident in a simulator (Pollatsek, Narayanaan, et al., 2006; Yamani, Bıçaksız, Palmer, et al., 2018) and on the road (Pradhan et al., 2009).

11.2.2 Multitasking and Driver Distraction

Drivers often engage in concurrent tasks while operating a vehicle, from interacting with in-vehicle visual displays and driver assistance technologies to conversing with a passenger or over the phone (Dingus et al., 2016, 2019) to mind wandering (Galera et al., 2012; Glaze & Ellis, 2003; Treat et al., 1979). *Driver distraction* exists when the diversion of attention toward alternative activities compromises the performance of safety-critical activities (Pettitt et al., 2005; Regan et al., 2011). Distracted driving has been identified as a critical risk factor for crashes and fatalities. In the U.S. in 2019, driver distraction was identified as a contributing factor in roughly 9% of all fatal crashes (Insurance Institute for Highway Safety, 2021).

Distracted driving can occur as a result of either visual, manual, or cognitive interference (Engström et al., 2017; Strayer et al., 2011). Visual interference results from the demand for the driver to take eyes off the road or mirrors. Manual interference results from the need to carry out physical responses. Cognitive interference results from information processing load and can come even from tasks that allow the driver to keep eyes on the road and hands on the wheel. A messaging app that required the driver to read and type messages on a dashboard screen would impose visual, cognitive, and manual interference. An app that read messages aloud and let the driver send messages by voice would impose cognitive load but no visual or manual load. Though these three forms of load are often conflated in real-world tasks, research has managed to isolate effects of visual and cognitive load.

The information needed to maintain vehicle control and avoid hazards is of course largely visual (Sivak, 1996; Wallis et al., 2007), and as expected under multiple-resource theory (Wickens, 2008), visual-manual activities are more distracting to drivers than are purely cognitive or vocal activities. Estimates of the real-world risk associated with distracting activities have come from a study of naturalistic driving involving 3,400 participants and more than a million hours of driving data (Dingus et al., 2016). Activities taking the drivers' eyes off the road produced substantial

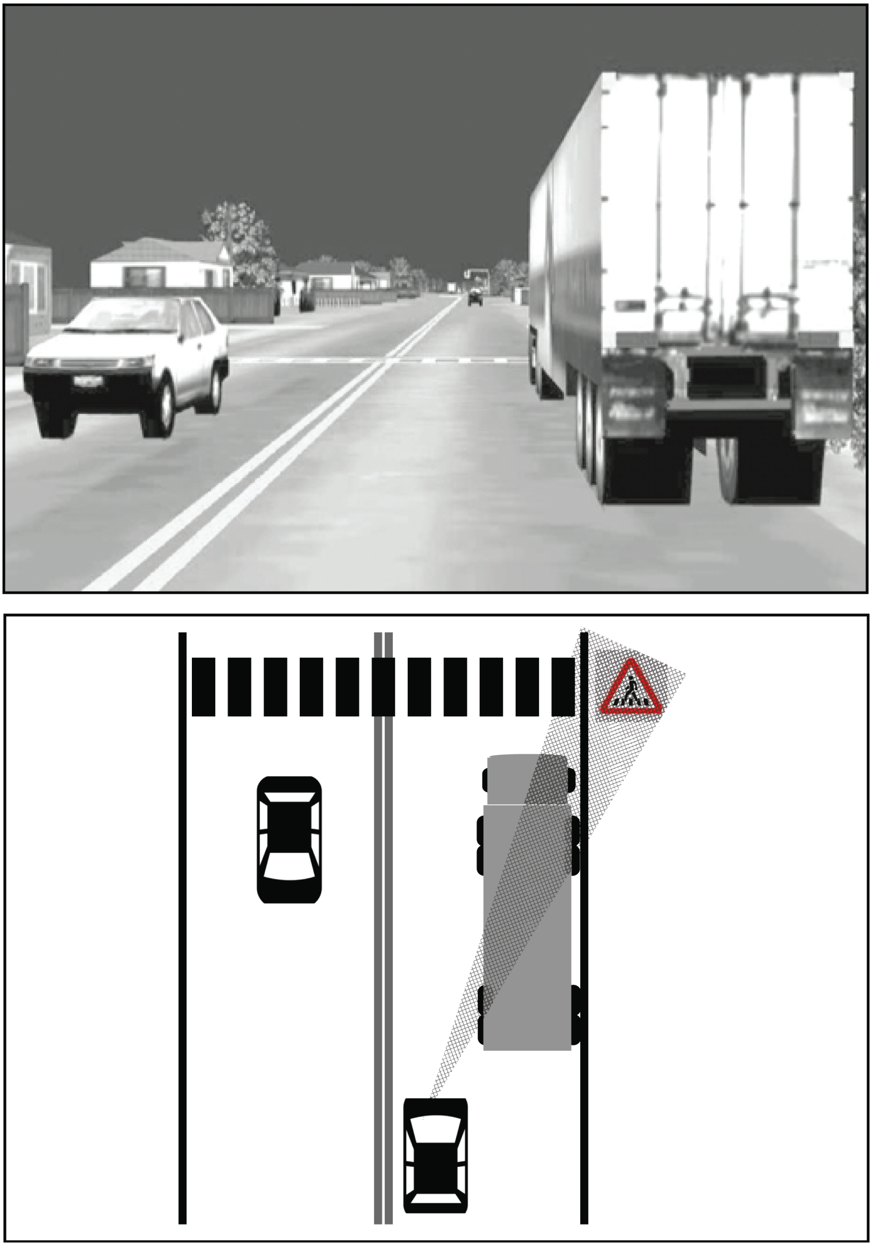

FIGURE 11.2 Test and training materials like those used by Pollatsek, Narayanaan, et al. (2006). The top panel shows a snapshot from a high-fidelity driving simulation in which participants' visual scanning behaviors were tested. The bottom panel shows a map-view representation of the scene like those used to train participants' hazard anticipation skills. The bottom car in the map view represents the driver's own vehicle, and the hashed cone illustrates that the driver's view of the crosswalk entrance is obstructed.

increases in crash risk, with the risk growing as the duration of the distraction increased (Arvin & Khattak, 2020; cf., Horrey & Wickens, 2007; Liang et al., 2012). Among the most dangerous activities were dialing a hand-held cellphone (12× risk increase), texting on a handheld phone (6×), reading or writing (10×), or simply staring too long at a roadside object (7×) (Dingus et al., 2016). Controlled studies, conducted in simulators and on test tracks, have found that visual distractions lead to poor lane-keeping and slow hazard responses (Drews et al., 2009; e.g., Engström et al., 2005; Liang & Lee, 2010). Consistent with the predictions of space-based attention theory, reading text messages off of a head-mounted display overlaid on the driver's view was less distracting than reading the messages off of a handheld phone. Even head-up messages, though, compromised lane-keeping and increased RTs as compared to a baseline of undistracted driving (He et al., 2015; Sawyer, Finomore, Calvo, et al., 2014). To reduce risk of visual-manual distraction, in-vehicle interfaces should be designed to minimize the difficulty of encoding visual information (e.g., Yamani, Bıçaksız, Unverricht, et al., 2018) and of selecting and executing responses (e.g., Lee et al., 2012).

The effects of cognitive interference are smaller but nonnegligible. Naturalistic data indicate that as compared to attentive and sober driving, driving with a primarily cognitive distraction such as talking to a passenger or carrying on a cell phone conversation produces a roughly 1.25× increase in crash risk (Dingus et al., 2019), though some data suggest these effects are concentrated among teenage and young adult drivers (ages 16–29 years) and minimal among middle-aged drivers (ages 30–64 years) (Guo et al., 2016; D. Lu et al., 2020). Simulator and on-road studies have found that cognitive distraction increases driver workload (Alm & Nilsson, 1994, 1995; e.g., Brookhuis et al., 1991; Recarte & Nunes, 2000; Strayer et al., 2017), delays braking responses (Alm & Nilsson, 1995; Harbluk et al., 2007; e.g., Strayer et al., 2003; Strayer & Drews, 2004), and causes the driver's gaze to concentrate narrowly on the road ahead, reducing the breadth of scanning and the frequency of lateral glances and mirror checks (Engström et al., 2005; e.g., Harbluk et al., 2007; He et al., 2011; Recarte & Nunes, 2000). Mechanisms of cognitive interference include the psychological refractory period (Levy et al., 2006) and inattentional blindness (Strayer et al., 2003). Surprisingly, a large number of studies have found a tendency for cognitive load to improve lateral vehicle control, that is, to reduce weaving (Brookhuis et al., 1991; Engström et al., 2005; He et al., 2014; Kubose et al., 2006; Medeiros-Ward et al., 2014). A number of explanations for this effect have been proposed, though the question of which is correct remains unsettled (see Engström et al., 2017 for review).

Reviewing the literature on cognitive distraction and driving, Engström et al. (2017) suggest that cognitive load will not tend to affect automatized elements of driver cognition and behavior but will interfere with controlled elements. This implies that cognitive distraction can be eliminated only for the driving subtasks that involve consistently mapped stimulus–response pairings (Schneider & Shiffrin, 1977), that is, subtasks for which a given stimulus always demands the same response. As driving inherently demands flexibility—Is it better to accelerate through this yellow light or stop for it? Should I slam on the brakes if that car pulls out in front of me or try to veer around it?—it is impossible to fully automatize or make immune to cognitive interference. And in fact, simulator experiments have found that practice driving with a cognitive distracting task has little effect on dual-task costs (Cooper & Strayer, 2008; Engström et al., 2010).

More optimistically, research has suggested that drivers can be trained to strategically regulate dual-task engagement, learning to shorten their off-road glances (Divekar et al., 2013; Yamani, Horrey, et al., 2015) and to postpone or avoid in-vehicle distractions (Krishnan et al., 2019). Other work has examined technological protections against cognitive driver distraction. A strategy that has been recommended to mitigate cell phone–induced distraction is to display a view of the forward roadway to driver's conversation partner, helping them to modulate their talking when the driver is under high workload (Gaspar et al., 2014; though see Charlton, 2009). Another promising approach would use measures of driving performance and driver behavior and physiology to recognize periods of distraction (McDonald et al., 2020) then intervene to refocus the driver's attention (e.g., Charlton, 2009; Donmez et al., 2008; Lee, 2009; C. Schwarz et al., 2016).

11.2.3 Automated Driving

The past decade has seen an increasing amount of work on automated, connected, and intelligent vehicles (Fisher et al., 2020) in transportation human factors, reflecting the urgent need to understand interactions between humans and automated driving systems (ADSs). A taxonomy from the Society of Automotive Engineers (On-Road Automated Driving (ORAD) Committee, 2016) defines five levels of driving automation. At Level 1, the automation assists with either speed or steering. At Level 2, it assists with both. At level 3, the driver is permitted to temporarily disengage from the vehicle unless the automation requests otherwise. At Level 4, the vehicle operates with full autonomy within a limited operational domain, and at Level 5, finally, it operates with full autonomy and no constraints on operational domain. Possibly the most problematic stage is Level 3, as it changes the human driver's role from active participant to passive monitor with the responsibility of being ready to take over vehicle control.

Research on automated driving thus far has largely focused on characterizing human limits in takeover scenarios (de Winter et al., 2021; Eriksson & Stanton, 2017; Merat et al., 2014) and examining the effects of distractions on takeover performance (Carsten et al., 2012; de Winter et al., 2014; Dogan et al., 2019; Llaneras et al., 2013; E. E. Miller & Boyle, 2019; Radlmayr et al., 2014). Future research further is expected to transition from relatively simple road environments like highways to more complex scenarios involving other road users such as other vehicles, automated or manual, bicyclists, and pedestrians in smart cities (Tabone et al., 2021). How can theories of applied attention guide systematic research?

Yamani and Horrey (2018) proposed a theoretical framework based on a general human information-processing model (Wickens, Helton et al., 2022). The framework posits a reciprocal relationship between task demand and functions replaced by automation across the four different information-processing stages at which automation operates (Parasuraman et al., 2000), as discussed in Chapter 10. It is assumed that the driver possesses a limited pool of attentional resources (Kahneman, 1973) supporting interconnected information-processing stages. Resources freed by automation can be mobilized to support cognitive activities different from the driving task. For example, a lane-departure warning system (Level 1) can free up resources at the stages of information acquisition and analysis but does little to relieve demand at the stages of response selection and execution. On the other hand, adaptive cruise control (Level 2) covers additional functions supporting the driver's response selection and execution, making more resources available for other tasks.

How do the drivers allocate attentional resources that are freed by vehicle automation? Ideally, the driver of an ADS would allocate attention to the surroundings as necessary to remain prepared for a takeover request. Samuel et al. (2020) examined the impact of Level 2 and 3 ADS on latent hazard anticipation in a high-fidelity driving simulator. Drivers navigated scenarios in which they could voluntarily (Level 2) or involuntarily (Level 3) take over the control of the vehicle. Data showed poorer latent hazard anticipation with higher levels of ADS, suggesting that the drivers with Level 3 automation devoted attention to tasks other than the primary driving task.

Takeover performance in Level 3 ADS may depend on not only the total amount of resources that are freed but also which pools of resources (Wickens, 2002, 2008, 2005b) are involved. For example, if a side task is verbal and a driver is required to resume the driving task, which is primarily visual, the resources used for the verbal task may not be used for enhancing the driving task performance. Work by Wandtner et al. (2018) specifically addressed this question. Drivers of Level 3 automation were presented short sentences and asked to repeat them across different input and output modalities, including auditory-vocal, visual-vocal, visual-manual using a tablet computer mounted in the central console, and visual manual with the tablet held by the driver's hand. Consistent with the comparisons of visual-manual and cognitive distraction discussed earlier, measures of RT, minimum time to collision, and hands-on time all indicated that takeover performance was poorest when the secondary task was in the visual-manual modalities using a handheld tablet. Notably, though, the majority of drivers in the visual-manual condition with the handheld tablet opted to cancel the side task and shift attention to driving when the takeover situation developed. In contrast, drivers in the alternative side-task conditions generally chose to continue the side task while they performed the takeover. This implies that the potential benefits of the audio-visual, visual-visual, and visual-manual with mounted tablet modalities might have been offset by participants' perception that they could perform the side task without distraction.

11.3 ACUTE HEALTH CARE (WITH TOBIAS GRUNDGEIGER)

Acute care (i.e., perioperative anesthesiology, emergency medicine, intensive care) involves the treatment of patients that need medical interventions to stay alive. The patients' conditions are likely to be changing continuously. As a result, clinicians need to manage multiple task threats and monitor multiple areas of interest (AOIs) (Gaba et al., 1995). A failure to perceive or a misperception of information was related to death or brain damage in 31% of closed anesthesia malpractice claims (Schulz et al., 2017). Although various researchers have investigated overt visual attention in acute care (e.g., Boquet et al., 1980; Law et al., 2020; Schulz et al., 2011;

Seagull et al., 2000; Weinberg et al., 2020), their analyses of attentional distributions have generally been limited to descriptive analyses or comparisons of single AOIs. Applied attention theory can provide a foundation for studying attention distribution in acute care more comprehensively.

11.3.1 Medical Simulation Environments

An early study on attention distribution during the induction of general anesthesia observed that anesthesiologists spent more time looking at the monitoring equipment when working in a medical simulation using a patient manikin than when working in the operating room with a real patient (Seagull et al., 2000). This behavior is commonly explained by the fact that the manikin does not provide clinical cues (e.g., sweating or muscle rigidity) as does a real patient. Furthermore, the anesthesiologists may expect a crisis in medical simulations and therefore be more alert (Dieckmann et al., 2007; Grundgeiger et al., 2017; Seagull et al., 2000). Grundgeiger, Wurmb, et al. (2020) replicated the initial finding of Seagull et al. (2000), but also used the expected value (EV) model version of the SEEV model, as discussed in Chapter 4, to analyze the data. The EV model analysis revealed a better model fit in the simulated environment than in the real one. Considering that the EV model is interpreted as the optimal attention distribution, these modeling results suggest that anesthesiologist did not spend too much attention on monitoring equipment in the simulated cases, but rather spent too little attention on the monitoring equipment in real cases. Grundgeiger, Wurmb, et al. (2020) suggest that the potentially more distracting and demanding operating room environment might explain this pattern.

11.3.2 Work Experience

Behavioral differences between clinicians with different levels of work experience are a frequently studied topic in health care human factors. Schulz et al. (2011) reported that experienced anesthesiologists in a medical simulation spent more attention on a manual task during a crisis than during an uneventful scenario, whereas the pattern reversed for less experienced anesthesiologists. Overall, the experience differences were more pronounced in the crisis scenario than in the uneventful scenario. The EV model analyses of two data sets of simulated noneventful scenarios produced good fits and showed no differences between experienced and less experienced anesthesiologists (Grundgeiger, Hohm, et al., 2021; Grundgeiger, Wurmb, et al., 2020). However, a significant interaction between experience and case (real vs. simulated) emerged in one study (Grundgeiger, Wurmb, et al., 2020). Experienced anesthesiologists showed worse model fit in real cases compared to simulated cases, whereas less experienced anesthesiologists showed good model fit in both cases.

One explanation of this expertise-based difference might be that experienced anesthesiologists encountered more distractions during the real cases than less experienced anesthesiologist. Alternatively, experienced anesthesiologists may have approached real cases differently than simulated cases, falling back to a “textbook” procedure only in the simulated cases in which they might not have been able to apply their tacit knowledge. In contrast, less experienced anesthesiologists would have lacked this tacit knowledge and therefore followed "textbook" procedure in both cases.

In contrast, investigating the attention distribution of scrub nurses during caesarean-section surgery cases, Koh et al. (2011) reported better model fits for experience nurses compared to less experienced nurses. The explanation for this difference in outcome might be that Koh et al. (2011) did not restrict the cases in any way, whereas Grundgeiger, Wurmb, et al. (2020) restricted the real cases to match them closely to the uneventful simulated case. Experience differences in EV model fits might be more pronounced in more demanding cases than in routine cases. Such an interpretation is also in line with the findings of Schulz et al. (2011), who observed more pronounced dwell-time differences between highly experienced and less-experienced anesthesiologists in crisis scenarios than in uneventful scenarios.

11.3.3 "Good" Attention Distribution

A crucial question is what a good or optimal attention distribution should look like. Wickens, McCarley et al. (2008) and Wickens (2015) made the point, as discussed, that the EV version of SEEV can be considered an optimal attention distribution because only expectancy and value should guide attention; clinicians should not avoid information access because it is effortful nor attend to an AOI simply because it is very salient. In the context of anesthesiology, this claim is supported by an analysis that showed that a model including effort produced worse model fits than a model based on expectancy and value alone (Grundgeiger, Beckh, et al., 2020). Furthermore, Grundgeiger, Hohm, et al. (2021) reported a significant correlation between a situation awareness level 1 score (i.e., perceiving and noticing changes in the environment) and EV model fit.

11.3.4 Cognitive Aids

Medical crises such as an allergic reaction during an operation or a cardiopulmonary resuscitation (CPR) are fast-paced, stressful, and time-critical events. In case of a CPR, for example, staff need to coordinate and monitor several tasks such as providing chest compressions, checking the heart rhythm, collecting information about the patient's history, and administering medication. To support staff during a crisis, check lists and other cognitive aids have been developed. These artifacts support an individual or a team by providing an algorithm that can be followed or a list of steps that should be considered (S. Marshall, 2013). As the name "cognitive aids" indicates, the idea is that the cognitive processes of a human operator are supported (McLaughlin & Byrne, 2020). However, the effect of these artifacts on cognitive processes has been investigated only to a limited extent (Grundgeiger et al., 2019). Grundgeiger, Michalek, et al. (2021) used the EV model to assess the attention distribution of resuscitation team leaders in a simulated resuscitation scenario. One group of team leaders used a cognitive aid that was designed to support a guideline-conforming resuscitation according to CPR guidelines. Another group did not use the aid. The cognitive aid group showed a better model fit than the control group during the first two phases (arrival phase: 0.26 vs. 0.52; early CPR phase: 0.33 vs. 0.45) of the resuscitation event, and both groups showed good model fits in the later phase, with a slightly but significantly better fit in the control group than the cognitive aid group (late CPR phase: 0.79 vs. 0.73). Furthermore, when considering the EV model of optimal attention distribution, the cognitive aid improved attention distribution during the arrival and early CPR phases, which are frequently described as confusing and chaotic (Sjöberg et al., 2015). These results demonstrate the beneficial effect of a cognitive aid on visual attention.

11.3.5 Interruptions and Task Management

In health care, particularly in the operating room, the intensive care unit, and the emergency department, distractions and interruptions are frequent (for reviews, see Grundgeiger & Sanderson, 2009; Hopkinson & Jennings, 2013; McCurdie, Sanderson, & Aitken, 2017; Rivera-Rodriguez & Karsh, 2010). Many studies have examined the effects of distractions and interruptions in a health care setting on a descriptive level (e.g., counting the number of interruptions, distinguishing interruption sources, etc.), but several have also considered theories and models of task management (see Chapter 9).

Using the memory for goals theory, Magrabi et al. (2010) reported that physicians performing simulated patient medication tasks needed longer to resume an ongoing task that involved a complex patient case than one that involved a simple patient case. They reported no differences between interrupted and noninterrupted cases in terms of error rates and suggested that this may have been due to environmental cues. Grundgeiger et al. (2010) investigated the resumption lag of interrupted intensive care nursing tasks. In line with Magrabi et al. (2010), they reported no resumption errors and observed that nurses used several behavioral strategies that reduced cognitive demands, for example, finishing a task before attending to an interruption or holding a task artifact in the hand while dealing with the interruption. They furthermore observed that the length of the interruption and a change of ongoing task context due to the interruption increased the resumption lag, whereas factors that depended on active rehearsal (such as interruption lag) did not affect the resumption lag. These results support the idea that interrupted goals decay in memory and can eventually be forgotten but also suggest that nurses rely on incidental or intentional environmental cues in place of rehearsal. These cues may be in the form of the behavioral strategies, the organization of the intensive care environment, or artifacts such as electronic patient records. Finally, Fong et al. (2017) showed that the length of the interruption, workload, and the time of day could predict whether emergency physicians remembered to return to an interrupted task.

11.4 LEARNING AND TRAINING

Attention theory can be applied to learning and training in terms of three different categories of research.

1. To what extent does expertise in a given task entail specific attentional skills?

2. To what extent can these skills be explicitly trained?
3. How should our knowledge of attention theory influence classroom instruction, which is focused more on semantic knowledge acquisition than on skills training?

11.4.1 Expertise and Attention

There is no doubt that experts time-share more efficiently than novices in many complex tasks. A straightforward explanation of this benefit is that the experts have automatized the component tasks, as the term was discussed in Chapters 2 and 7. Thus, the performance-resource function for the skills at which people demonstrate expertise looks more like those of Figure 7.4 Task A, with a large data-limited region, than like those of Figure 7.4 Task B. Such differences have long been offered as (at least partial) explanation for the expert's multitasking proficiency (Bahrick et al., 1954; Bahrick & Shelly, 1958; Damos, 1978; Fisk et al., 1987), and there is little doubt that this explanation is valid. It is important to realize that differences between the curves A and B in Figure 7.4 might not show up in single-task performance, when full resources are devoted to the task, but will be expressed in a resource-limited multitasking environment. It is also important to realize, too, that the development of full automaticity may take many years to accomplish (Fitts & Posner, 1967; Ward et al., 2020). Furthermore, as Schneider and Shiffrin (1977) documented, the development of automaticity will proceed more rapidly to the extent that the skill involved has actions that are consistently mapped to perceptual features of the environment. Hitting a golf ball on a windless day with a familiar club is an example of a consistent mapping. Hitting a baseball thrown by a skilled pitcher or climbing a rock route is not, since the environmental input is unpredictable, and the actions mapped to a given input are not consistent (Epstein, 2019).

But is single-task automaticity the only source of difference between the expert and novice? If so, then the development of expertise in complex multitask activities like driving or flying, or in multitask sports like basketball, would be acquired most efficiently by training part-tasks to a high level of performance in isolation and then assembling them. This is because part-task training allows the learner to pay full attention to the subtasks of the multitasking activity, one at a time, allowing their more rapid refinement. But the data reviewed in what follows suggest that in fact, whole-task training is usually more efficient than part-task (Wickens, Hutchins et al., 2012, 2013). Thus, something unique is learned in dual-task training. We call this a *time-sharing skill* (Damos et al., 1983; Damos & Wickens, 1980), an emergent feature that is not a part of any single task alone, but manifests when tasks must be performed concurrently. What is the form of this skill? Here, we offer some possibilities that are supported by research.

- *Visual scanning*. Experts scan in a multitask environment differently from novices (Bellenkes et al., 1997; Borowsky et al., 2008; Fisher & Pollatsek, 2007; Koh et al., 2011; Mourant & Rockwell, 1972; Pollatsek, Narayanaan, et al., 2006; Pradhan et al., 2005; 2009; Schriver et al., 2008; Ziv, 2016). As in the expected value model of scanning (SEEV) discussed in Chapter 4, so here we can assume that experts know when and where to sample for critical information. For example, compared to novices, skilled drivers sample farther down the highway to support lane-keeping (Mourant & Rockwell, 1972) and have shorter downward scans away from the road (Pradhan et al., 2011). Similarly, skilled pilots sample task-critical display channels more frequently than do learners (Bellenkes et al., 1997). We can say the experts have a better mental model of the information within the multitask ensemble, a mental model used to drive their scanning. Even within a group of well-trained pilots, Dehais et al. (2017) found that better performers on an emergency go-around have a different scanning strategy for altitude information than do those who are less proficient.

- *Interruption management*. Koh et al. (2014) have found that in the multitask environment of the operating room, expert nurses are more resistant than are novices to interruptions of the critical foreign-object count task. Given the wealth of strategies that can govern interruption management, as discussed in Chapter 9, it is not surprising that experience and training protect against costs of interruption (Cades et al., 2011; Dismukes, 2010; Hess & Detweiler, 1994; Wickens, Sebok et al., 2021).
- *Attention flexibility*. Both of these scenarios are related to task management, and so it is reasonable to hypothesize that experts are better at flexibly allocating resources to tasks as they are needed (Gopher, 1993) and that this attentional subskill emerges from extensive practice (but see Wickens, Sebok et al., 2021). In the context of Figure 7.5, this might describe the abila ity to adaptively set the resource allocation proportion between two tasks at the optimum level.

These three features of expertise in attention, and more, are reflected in the research on how to more explicitly train time-sharing skill through deliberate practice and instruction rather than to simply allow them to emerge naturally from dual-task practice.

11.4.1.1 *Training Expertise in Time-Sharing Skills*

Just because experts differ from novices in an identifiable aspect of performance (here, multitasking) does not necessarily mean that there are shortcuts to developing expertise. But there is evidence that the attentional skills described can be directly trained.

- As discussed in Chapter 4, training to help novice operators build an appropriate mental model of the task environment—that is, to help them understand the bandwidth and value of different information channels—can improve sampling behavior. Limits on the analyst's ability to "reverse engineer" the mental model driving experts' visual scanning, though, may sometimes hinder the efficacy of this approach (e.g., Bellenkes et al., 1997).
- Dismukes and Nowinski (2007) have advocated that pilots be explicitly taught interruption management techniques, and Cades et al. (2011) have reported that practice responding to interruptions improves interruption

management skills. To the extent that practice comes from responding to interruptions that are artificially imposed in a learning environment, this represents a form of implicit learning. It should be noted, though, that the improvements that come from practice are highly specific and do not appear to generalize across changes to either the primary task or the interrupting task (Cades et al., 2011).

- Research has also indicated that the ability to flexibly prioritize tasks in a dynamic environment can be trained in a way that not only produces better multitasking on the trained task pair (Gopher et al., 1982) but carries over at least partially to new dual-task combinations (Boot et al., 2010; Gopher et al., 1994). Again, in the context of Figure 7.5, a proficient multitasker can know when resources may be temporarily unneeded in one task (e.g., the task is in a data-limited region in the context of Figure 7.4 and can be safely shifted to a task with higher momentary resource demands (Gopher, 1993, 2007; Schneider & Fisk, 1982). The skill of rebalancing attentional priorities in this way is not entirely task independent, as generalization from a trained task combination to a new one is strongest when the training and transfer tasks are similar to one another (Boot et al., 2010). Nonetheless, it is a teachable skill and one that shows some near transfer. *Varied priority training*, a technique that develops multitasking flexibility by inducing the operator to experiment with different task prioritization strategies, is one useful approach for developing multitask skill; training under varied priorities speeds the mastery of the trained component task combination and produces at least some carryover of multitasking ability to new component tasks similar to the trained ones (Boot et al., 2010; H. Lee et al., 2012).
- As described, some whole-task training of subtasks in combination with one another is necessary to teach time-sharing skills and efficient multitasking (Damos & Wickens, 1980). The benefits of this training reflect, in part, the acquisition of some of the general skills described earlier. However, it is also important to realize that interactions between concurrently performed subtasks enhance the value of whole-task over part-task training (Lintern & Wickens, 1991; Naylor & Briggs, 1963). Such interactions are characteristic of circumstances in which the responses of one task directly affect the perceived information, or necessary responses, in another. Examples include manipulating the clutch and gear shift on a stick-shift car; simultaneously controlling altitude and heading in an aircraft; or strumming while chording on the guitar. The cross-coupling required between tasks in these circumstances simply cannot be learned when each task is practiced alone.

A final concept, little investigated but whose importance was hinted at earlier, concerns the various ways that one's own knowledge of "what works" in a multitasking environment, the so-called metacognition of multitasking (Finley et al., 2014), might be a trainable skill. The importance of this concept is suggested by studies that reveal people do not always spontaneously adopt a strategy of multitasking that produces best performance (Katidioti & Taatgen, 2014; Nijboer et al., 2013), don't always know what's best for their own performance (Andre & Wickens, 1995), and might not be well calibrated in judging how well (or poorly) they are performing in a dual-task setting (Finley et al., 2014; Horrey, Lesch, & Garabet, 2008, 2009; Horrey, Lesch, Kramer, et al., 2009; Horrey & Lesch, 2009). That is, they are overconfident in their dual-task abilities. To the extent that training of metacognitive skills has shown some success in other domains (Rhodes, 2019), such as learning or decision strategies, there may be room for success in training multitasking.

11.4.2 Attention and Effort in Studying and Learning

The material on mental workload or cognitive load discussed in Chapter 7 is relevant to the choice of training and learning strategies in the classroom, in terms of both single-task choices and dual-task performance (Wickens, Helton et al., 2022).

11.4.2.1 *Study Strategies*

Many of the choices that students make in study strategies result, in part, from their belief that more fluent performance during study implies better retention, retrieval, and transfer of the studied information (Dunlosky et al., 2013; Healy & Bourne, 2012; Putnam et al., 2016; Rhodes et al., 2020; Wickens, 2017). In other words, learners believe that if they are producing the correct answers or performing a skill adeptly as they study, they are learning well (Benjamin et al., 1998; Bjork, 1999; Koriat & Bjork, 2005). A study strategy that makes information acquisition less effortful (Chapter 7) is therefore appealing not just because it reduces workload but because it seems to imply better learning. Often, though, the study and training techniques that make knowledge acquisition feel fast and easy in fact lead to poor retention and transfer (Schmidt & Bjork, 1992). Bjork (1999) used the term *illusion of competence* to describe learners' mistaken belief that ease of performance during the study phase will lead to good retention, retrieval, and transfer and used the term *desirable difficulty* (Bjork, 1994) to denote a study strategy that is effortful and slows knowledge acquisition but consequently leads to good long-term retention and transfer.

Table 11.1 provides examples of contrasting low- and high-effort learning or training strategies, listed in each row. On the left is a low-effort strategy that, for the first four examples, mistakenly signals better retention or transfer to the learner and hence, in the context of the decision branches in Figure 7.1, will likely to be chosen.

TABLE 11.1
Tradeoff of Effort and Long-Term Learning in Study Strategies. From Wickens (2017).

Low-effort, poor long-term learning	High-effort, good long-term learning
Massed rehearsal	Spaced rehearsal
Passive listening	Note-taking
Rereading	Self-quizzing
Part-task training	Whole-task training
Error prevention (training wheels)	Self-choice

On the right is a contrasting higher-effort strategy that has been empirically shown to produce higher retention and retrieval of studied material or better transfer of skill learning (Dunlosky et al., 2013; Rhodes et al., 2020; Wickens, Helton et al., 2022). We elaborate on each as follows.

- *Massed rehearsal* involves lumping all study or practice into a single continuous block of time. Spaced rehearsal involves breaking study or practice into smaller blocks, spread out over time. Spacing of material may occur within a single study session, as when the learner interleaves different material or skills for rehearsal. Alternatively, spacing may occur over multiple days. Massed rehearsal seems easier, can indeed produce faster learning and better immediate recall than spaced rehearsal (Rawson & Kintsch, 2005). However, for longer-term retention and transfer, the alternative strategy of distributing rehearsal over time is far more effective (Carpenter et al., 2012; Dunlosky et al., 2013). Learning is best when rehearsal is distributed across days instead of just within a single session. As a rule of thumb, optimal spacing between study sessions ranges between a day and a few weeks, with longer gaps within that time frame leading to longer retention (Cepeda et al., 2009). Multiple different cognitive mechanisms seem to contribute to the benefits of spacing (Smolen et al., 2016).
- Passive listening, even when a lecture is engaging, requires less effort than note-taking, which entails both the physical effort of writing and the cognitive effort of identifying key points and summarizing or paraphrasing them (Jansen et al., 2017; Piolat et al., 2005). The effort of translating the material into organized summary notes, though, leads to better retention than does passive listening (Bretzing & Kulhavy, 1979; Bui et al., 2013), a result that has been termed the *encoding effect* (Di Vesta & Gray, 1972). The encoding effect itself might be an example of the more general *generation effect*, discussed in Chapter 10, the finding that memory is better for material that is actively generated by the learner than for material that is passively processed (Richland et al., 2007; Slamecka & Graf, 1978). Alternatively, the encoding effect might result from the greater depth of semantic processing (F. I. M. Craik & Lockhart, 1972) that is required to actively take notes than for passive processing.
- A common (Carrier, 2003; Karpicke et al., 2009) and intuitive method of study is to reread material that is to be learned, and data confirm that as long as the readings are spaced over time, rereading can aid long-term learning (though back-to-back rereading seems to be of little benefit; see massing, above) (Callender & McDaniel, 2009; Rawson & Kintsch, 2005). A more effective strategy than spaced rereading, however, is for learners to actively quiz themselves on the material after reading it once (Karpicke & Roediger, 2008; Roediger & Karpicke, 2006). Self-quizzing requires the effortful process of retrieving the material from long-term memory, a skill that will be essential when the material is retrieved later in a different context (Karpicke et al., 2014). And yet, because self-quizzing is effortful and sometimes discouraging, students usually adopt the easier practice of rereading their notes or text (Karpicke et al., 2009).

- As discussed, complex skills such as flying an aircraft, translating speech to a different language, or playing an instrument with two hands require concurrent subtask performance or divided attention between multiple sources of information. The easier training strategy, part-task training, is to practice each subtask by itself. Yet empirical data indicate that despite its greater effort demands, whole-task training is more effective for transfer (Wickens, Hutchins, et al., 2013).
- The final row of the table presents an exception to the general finding presented in the first four rows that easier processing leads to less effective learning. Here, the data suggest that various techniques to prevent errors in learning a skill, perhaps by imposing scaffolding or "training wheels" on the learner, can reduce the cognitive load in a way that leads to better learning than when errors are allowed without correction (Hutchins et al., 2013). But even here, a close examination of the research reveals that such a strategy should be employed with caution: eliminating the possibility of any errors during training can result in destructive and effortful "thrashing about" if the training wheels scaffolding is suddenly removed before transfer (Wickens et al., 2022). A thrashing and confused learner is not likely to learn very well.

11.4.2.2 *Instructional Materials*

The role and measurement of cognitive effort lie at the core of Sweller's *Cognitive Load Theory (CLT)* of instruction (Paas et al., 2003; Paas & van Gog, 2009; Sweller, 1994; cf. Mayer, 2014). CLT rests on the premise that learning requires multiple, disparate elements of information to be held and related to one another within working memory. Learning is therefore impeded when the limits of working memory are exceeded.

CLT thus places learning distinctly within a multitask context. It elaborates on the concept of effort to distinguish between three sources of load imposed in the learning environment, sources that can compete with each other for limited resources (Paas & Sweller, 2014):

1. *Intrinsic load* is the inherent cognitive load imposed by the material to be learned. In particular, intrinsic load is high when the studied material comprises many informational elements high in interactivity (Sweller, 1994).
2. *Germane load* is the productive effort that the learner invests in processing the material to be learned. The learning strategies on the right side of Table 11.1, for example, impose heavier germane load than the strategies on the left side.
3. *Extraneous load* is processing effort that is imposed by the design of instructional materials or the learning task but contributes nothing to learning; only distraction. Extraneous load can result from obviously undesirable characteristics of the instructional design, such as cluttered slides or a clunky interface in computer-based learning. However, it can also result from apparently appealing aspects of the instructional design, aspects that

invite attention but don't contribute to learning. Examples include distracting ornamentation on a slide or irrelevant jokes and anecdotes from a lecturer (Mayer et al., 2008; Sundararajan & Adesope, 2020). Processing of extraneous load can be considered an example of the failure of focused attention. Extraneous load consumes scarce processing resources, diverting them away from processing of sources of intrinsic and germane load. Furthermore, extraneous load can amplify the undesirable tendency to choose the reduced-effort learning strategies on the left of Table 11.1.

Building on CLT, researchers have proposed principles for managing cognitive load in the design of instructional materials (Mayer & Moreno, 2003). Several of these dovetail with guidelines for display design discussed in earlier chapters. For example, the *split-attention principle* (Ayres & Sweller, 2005: cf., Chapter 6) holds that instructional materials should not require learners to divide attention between spatially or temporally separate channels of information. Consider a set of instructions explaining how to operate a piece of electrical equipment (Chandler & Sweller, 1991). In a conventional design, written instructions will be placed below a diagram of the equipment and will refer the learner to elements of the diagram as they are needed. This requires the learner to divide attention between spatially separated sources of information, the text and the diagram, and to mentally integrate the information presented on the separate channels. In a more effective design, the written instructions and diagram will be integrated, or *spatially contiguous* (Mayer & Moreno, 2003), with one another, with each step of the text appearing alongside the part of the diagram to which it refers (Chandler & Sweller, 1991), if necessary, providing line linking between text and figure (See Figure 6.4).

A second guideline derived from CLT, *the modality principle* (Low & Sweller, 2014: cf., Chapter 8), holds that learning will be better if information is distributed over visual and auditory channels than if it is presented in a single modality. By reducing visual load, for instance, instructional materials that pair a visual diagram with spoken narration will allow better learning than materials that pair the diagram with written text. Of course, in a dynamic presentation, this presumes that information in the speech is *temporally contiguous* with information in the visual channel (Mayer & Moreno, 2003), as required by the split-attention principle. A third guideline, *the cuing principle* (van Gog, 2014: cf., Chapter 3), states that learning will be improved if bottom-up and top-down cues are available to direct attention toward critical pieces of information in the instructional materials as they become relevant. In an audiovisual presentation, for instance, visual highlighting and backgrounding might be used to cue attention to elements of a diagram as the spoken narration refers to them (de Koning et al., 2011).

In conclusion, many aspects of attention discussed throughout the previous chapters are highly relevant to instruction, teaching, and learning and can be employed both to enhance the efficiency of these cognitive activities and to avoid their pitfalls.

11.5 CYBERSECURITY

Cybersecurity is a relatively new area of practice and one that deserves the attention of psychologists and engineers looking to improve human performance. Unlike health care or education, there is less general population familiarity, and exposure to these core concepts. Cyber operations differ from an area known as user security and privacy. Privacy and user-based decisions in cybersecurity are likely familiar to many readers with experience interacting with their home Wi-Fi networks, computers, and smartphones. These aspects revolve around relatively novice people adjusting predefined settings that dictate how technology connects to the internet, updating virus or malware protection software that runs automatically on their machine, changing, resetting, or updating passwords, or turning on or off capabilities in their smartphone applications that share information with the app developer or others, such as GPS location. Cyber operations, in contrast, are the professional monitoring and security practices in place across corporate and government information technology that attempt to find and stop intruders. Every system is a potential vector, an entry point into the network that can be exploited by malicious actors to steal information, compromise systems or access, and generally disrupt business and military operations.

Cyber operators then are the humans behind the scenes monitoring the traffic and attempting to protect these systems from attack as part of a very large sociotechnical system. As one would expect, this is an enormous undertaking when scoped to the corporate enterprise level or across services in the military—imagine just how many devices are interconnected at any given time, with various levels of access—and how these devices are communicating through hundreds of different software services and protocols, all of which are potential targets of compromise. In 2021 alone, several major attacks disrupted everything from Microsoft Exchange services (compromising email over 250,000 servers: "2021 Microsoft exchange server data breach", 2022), to key oil pipeline systems (Colonial Pipeline ransomware attack which disrupted oil supply, led to President Biden declaring a state of emergency, and resulted in a reported payment of more than $5 million to the attackers (Lab, 2021) and innumerable other attacks on critical infrastructure like hospitals (Rundle & Nash, 2021). In 2020 alone, one study found 92 different ransomware attacks that affected over 600 separate health clinics (Bischoff, 2021).

The world of the cyber defender is thus one of major information overload (Pfleeger & Caputo, 2012), invoking all of the same attentional challenges covered in this book, particularly as workers may be sometimes pushed over the "red line" of mental workload discussed in Chapter 7. In the context of this chapter, we will limit the focus to those challenges understood and potentially solved or improved, through the application of attention theory, and elements of human-factors science (Gutzwiller et al., 2015). Fortunately, there are a significant number to discuss, including how attention is needed across visual displays to create and maintain situation awareness of the cyber environment, beginning with Level 1 monitoring behaviors; how information overload could be addressed through appreciation of multiple resources and the study of mental workload (Chapter 8); and how displays could benefit from ecological design principles that avail greater efficiency of visual attention (Chapter 6). Throughout, these issues are further entangled with cognition and attention in the form of increased artificial intelligence and automated security systems, which are being researched, developed and put into practice. As we saw in Chapter 10, increased automated aspects of performance can be problematic but are created to address human limitations in monitoring and comprehension of vast amounts of information—a clear characteristic of cyber defense work.

The real goal of cybersecurity and in particular network defense is to understand what is occurring and, by doing so, derive what can be done to improve the security of the network. The realm of cyber dictates that most activities and actions occur in virtual space. Unlike in aviation, driving, or health care, the ability to look and see the state of this cyber-based world is compromised, so it is difficult to know for sure what is going on and to develop situational awareness through paying attention.

Much of the work of analysts, depending on level and job role, is in monitoring and understanding the information available and making predictions about what it means about the state of the network. Learning what these operators do has been a function of study in the form of cognitive task analyses conducted frequently over the last decade or two (D'Amico et al., 2005; D'Amico & Whitley, 2008; Gutzwiller, Hunt, et al., 2016; Mahoney et al., 2010; Trent et al., 2016). What these analyses reveal are the inner cognitive workings and processes of operators parsing large amounts of information and trying to make sense of it before working to take actions to protect networks. This leads to a multitude of challenges in the design and development of the computer interfaces to facilitate the work—most notably the representation of much of the information in various forms of visualizations. Because cybersecurity operates across a variety of levels of detail, this display problem too flows up, from the basic defenders to the leadership who must try to make sense of the 'common operating picture.'

11.5.1 Challenge: Situation Awareness

Three general processes are associated with the Endsley model of situation awareness, including perception, understanding, and prediction (Endsley, 1995, 2015). Attentional components of these tasks are relatively clear; for example, one must allocate appropriate attention to perceive important information in the cyber operations center, whether it is on a nearby display or being spoken during a briefing. Operators must also have an understanding of the information they have and what may occur (or be possible to occur, such as a successful intrusion by an attack) in the near future—essentially, situation awareness (Gutzwiller et al., 2020). The research available regarding operator situation awareness here and with teams that would comprise a more ecologically valid context is very sparse in the open literature.

To improve SA one could focus on any of the levels and associated factors; but for attention-based improvement Level 1 SA is the natural choice, since it deals with how people notice, search, and recognize relevant information. The early need to search and recognize information across data sources is clearly related to effective visual scanning. Models such as SEEV and NSEEV discussed in this book may be applied to displays those cyber analysts use and may allow for the rapid redesign of interfaces and information display to enhance performance and noticing without disrupting the activities of the analysts or needing their limited time (as would be required through user research, UX testing, and standard experimentation). On the other hand, one of the challenges is that analysts routinely flip between many different programs within a single display, which would complicate assessments based on eye and gaze tracking and may necessitate innovation in how attention is tracked over time. The most obvious factors in the SEEV model that may aid cybersecurity are improvements in saliency of important information (which could improve situation awareness and detection), and reduction in the attentional effort it may take to access that information, both of which are likely to predict how analysts allocate attention during their work. In such an application, SEEV is relevant beyond simple visual scanning, to include information access accomplished by key presses and mouse clicks as well. In particular, effort is likely to emerge based on how analysts' workstations and operation floors are setup; while many different programs are accessed visually on a single machine, there are also monitor display setups, and sometimes large-screen displays frequently found in watch floors. Naturally, allocating attention between them becomes subject to information access cost (as discussed in Chapter 4).

11.5.2 Challenge: Attention Overload

Overload is problematic throughout the cybersecurity workforce and often is observed as burnout and fatigue (Paul & Dykstra, 2017). At least one of the highly demanding aspects is a high rate of false alarms (Chapter 3) present in particular network defense tasks, such as intrusion detection, in which systems over-cue cyber analysts to potential (but ultimately benign) malicious actions that may indicate the presence of attackers or attacker activity. These systems can be set at a variety of sensitivities, leading to various rates of false indications—but regardless, it often becomes the analysts' job to investigate whenever they are alerted, in addition to other work they may be tasked to do. These high false alarm rates are an artifact of computer systems that attempt to track suspicious activity on the network, and although modern systems are improving and beginning to reduce this rate of false alarms, this phenomena has been tied closely to operator fatigue (Alahmadi et al., 2022). Therefore, the attention impact to operations and defensive success is at least twofold: false alarms are likely to misdirect the limited attention of defenders, resulting in a lack of attention to other critical tasks; and the large number of these alerts is itself a burden that results in some amount of burnout.

The rate of these alerts and their accuracy are one clear cognitive element related to attention. In other words, the amount of information available to process by an analyst will be at the mercy of the limits of attention; while alerts are a way to improve the "filter" of attention in selection of the correct information, it does not address the demand element or what attention is required to do the work itself, the "fuel". In simulated security tasks (such as monitoring numeric IP addresses over time for malicious indications), the rate of incoming information is quite high and therefore leads to a generally high demand on sustained attention to the task. Combined, the low (relative) rates of actual attack and high penalties for missing attacks appear remarkably close to the characteristics and demands on attention found in vigilance tasks, as discussed in Chapter 7. Vigilance tasks tend to be mentally taxing (Warm et al., 2008), and simulation of this type of cyber work has shown the notorious vigilance decrement in a 40-minute vigil (Sawyer, Finomore, Funke, et al., 2014).

In addition to the demands imposed by vigilance, as covered in Chapter 7, limitations to human information processing and attention are particularly clear when concurrent demands are placed in a single modality (such as multiple visual tasks). Monitoring the many displays related to cyber operations then is one such case, and a method to alleviate this condition would be to convey some information in another modality, such as using auditory outputs or representations, "sonification" (Ballora et al., 2011). In fact, this idea has been explored to some extent in cyber defense and continues to be an interesting avenue to improving performance; in terms of attention, multiple-resource theory would generally predict any V-V combination of concurrent task demands could be reduced if one of them was made auditory (A-V). In a single-task experiment in which Wireshark data was shown either in a visualization or with a sonic auditory display, sonification did not appear to provide a clear advantage in workload (Mancuso et al., 2015). However, others have provided initial demonstrations of effectiveness (Axon et al., 2019; Debashi & Vickers, 2018a, 2018b) and sometimes even improvement compared to industry-standard methods. Most interesting is Debashi's suggestion that the combination of sonified alerts and visual displays will ultimately be required to improve network detection performance above either alone (Debashi & Vickers, 2018b). However, more work remains, particularly to validate these findings in more realistic conditions (Axon et al., 2016).

Another strategy to deal with the limits of attention has been to leverage automated services and sometimes "bots," which help a cyber defender gather or make initial assessments of data (such as log files). While various automated tools are often seen as useful, as we saw in Chapter 10, they can also lead to a mistrust problem similar to that seen with autopilots, automated process control, and automated vehicles. With this issue is another misallocation of attention—where analysts may overtrust an automated system's information, conclusion, or recommended action—and therefore not check the data at its source. Creating these types of advanced tools for analysis is a difficult process and reliant upon understanding analysts' cognitive and attention needs alongside the need to only automate that which will enhance the total system's performance and to avoid the "ironies" of automation (Bainbridge, 1983; and see Gutzwiller & Van Bruggen, 2021). While strides have been made in understanding the work (Champion et al., 2014; Trent et al., 2016; Trent et al., 2019; Vieane et al., 2016), less has been explored in different human–automation and human–AI teaming configurations; nevertheless, the knowledge gained in task analysis is likely a good path forward in improving the design.

11.5.3 Challenge: Display Design

Design itself is a clear focus of human-factors work in cybersecurity (Mckenna et al., 2015; Staheli et al., 2016; and see Giacobe, 2013, Goodall, 2009). The benefits described in Chapter 6 on display design are likely to improve and impact cybersecurity defense. The multitude of tools and interfaces available to be applied to cyber defense work is enormous; some report more than 75 different tools in use at any given time (Silva et al., 2014). However, though hundreds of companies and people design these visualization interfaces, a review found only around half actually conduct a design evaluation, and a very limited number (3, in their review of over 100

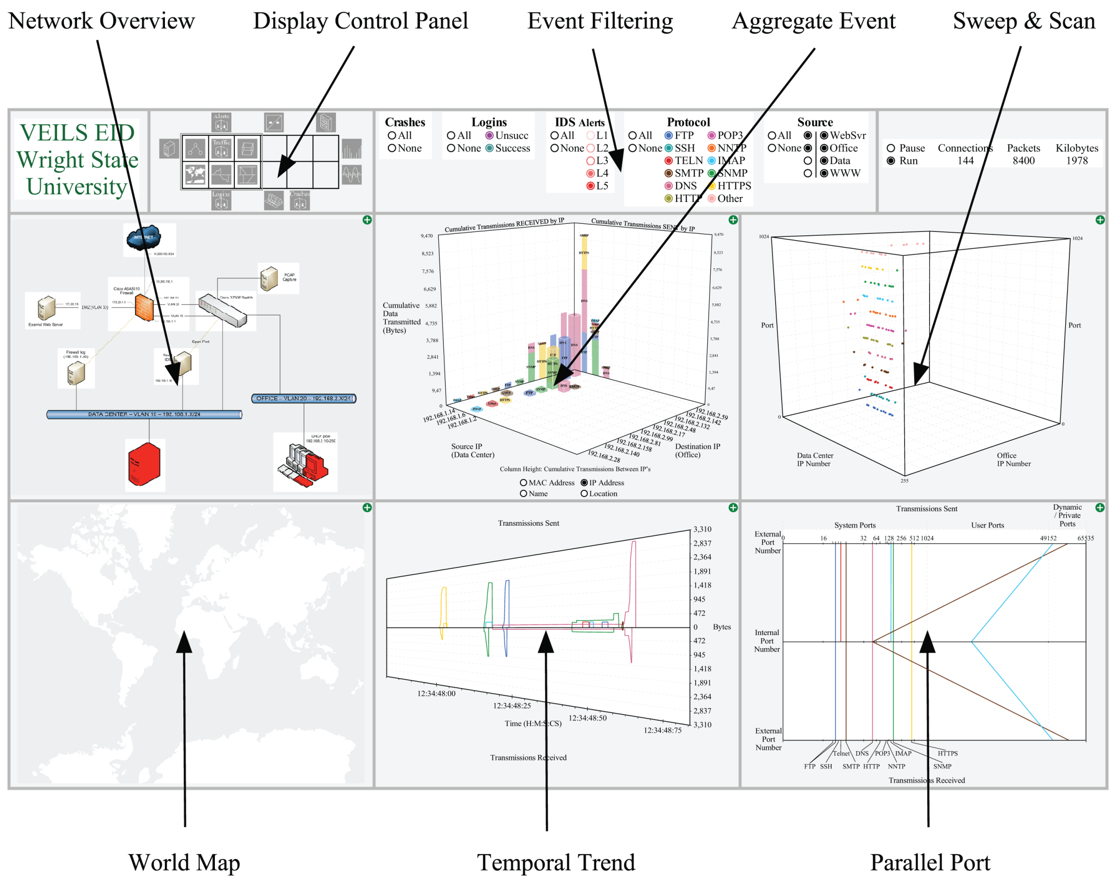

FIGURE 11.3 The VEILS interface for cyber defenders, designed to facilitate and improve multiple cyber defender tasks through ecological interface design. Image used with permission from Bennett, Bryant, & Sushereba (2018). Ecological interface design for computer network defense. *Human Factors*, *60*(5), 610–625, (c) Sage Publishing.

papers) actually test the interface with a human operator in a rigorous way to see whether it improves performance (Staheli et al., 2014), though there are increasing improvements by human-factors engineers in this area (Sushereba et al., 2020).

There is much that the application of attention principles of design could do for cybersecurity operations. Display design evaluations are increasing and improving. In particular, there has been success in using the ecological interface design recommendations for building tightly defined cyber tools (Bennett, 2014; Bennett et al., 2018; Burns et al., 2003). These tools are often better than industry standard (Burns et al., 2003) and are more principled in their design (Bennett, 2014) in dealing with very large quantities of information, their representation, and the general organization of a dashboard style display (see Figure 11.3, from Bennett et al., 2018). It remains to be seen if deeply rooted but problematic visualization systems and displays that are in current operations can be redesigned by these principles.

11.5.4 Challenge: Degree of Automation

As discussed in the previous chapter, and based on the Parasuraman et al. (2000) framework for integrating human information processing with automation capabilities, one can first consider that since automation performs something a human would do otherwise, it too follows a general four stage information processing series across information acquisition, information analysis, decision-making, and action implementation (Onnasch et al., 2014; Parasuraman et al., 2000). An early-stage system might highlight a suspicious entry into the network—the source of the false alarms mentioned earlier. This may help analysts allocate their attention to priority alerts but may also distract them from other activities. A later, more diagnostic stage of a cyber tool may help process the why and bring to bear other information—a suspicious IP attempting a connection on a particular port and even recommend an action to the user. Truly advanced systems may do all of this nearly automatically and even be authorized to take actions on the network, such as shutting systems down or implementing new rules on their own or doing so automatically unless the human supervisor vetoes the automation decision. But, as discussed in Chapter 10, being more out of the loop because the automation has been responsible for those decisions, the human operator may not possess the necessary situation awareness to make such an informed decision. Thus, as with most automated systems, it is highly likely that a higher degree of automation, when imperfect, as it will almost always be, will lead to greater problems and reflect what Bainbridge (1983) and Strauch (2018) term “ironies of automation.”

11.6 CONCLUSION

The scope of the successful applications of attention research we’ve covered here is impressive and reassuring. The attentional demands we contend with at home, in the vehicle, and in the workplace seem never to abate. As information systems and sophisticated automation seep further into our lives, the world claims less from our motor resources but more from our cognition: more focus, more vigilance, more mental juggling of sensory inputs and task demands. That we can identify attentional principles and guidelines that span domains of application, though, gives us confidence that effective training and design can mitigate the threat of information overload. By sharing knowledge between the lab and the world—drawing applications from theory and motivating theoretical advances with the promise of new application—we can understand our evolving attentional challenges and meet them.

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