CHAPTER 5

Expertise: Acquisition, Limitations, and Control

Stephan Lewandowsky & Jacqueline L. Thomas

This chapter reviews the current status of research on expertise, with a tripartite emphasis on expertise acquisition, the limitations associated with expertise, and the extent to which expert skill performance is subject to conscious control. We outline how deliberate practice often enables experts to perform their skills automatically, and we explain the limitations and costs associated with this automaticity. Those limitations include its specificity, brittleness, and limited ability to be transferred to new tasks. Further costs include expediency, mediocrity, and inflexibility. We next discuss whether and in which situations experts are able to exert conscious control over their automatic skills, with the finding that the exertion of control is sometimes at a short-term cost to performance. Finally, we emphasize pragmatic means by which expert performance can be enhanced, either by avoiding known pitfalls or by increasing the level of control that experts can exert over their own behavior.

Quick, what is the value of π? Most readers will effortlessly remember the initial digits 3.14, plus perhaps the further fact that π proudly features an infinite number of additional digits. Few readers are likely to know that the 256th digit happens to be a 5 and is followed by 6, 6, 9, and 2. Indeed, one might question whether memorization of hundreds of those digits is readily possible. It is therefore of considerable psychological interest that the mnemonist Rajan Srinivasan Mahadevan has memorized π to 31,811 places—and possibly still counting (Ericsson, Delaney, Weaver, & Mahadevan, 2004; Thompson et al., 1991). Rajan is able to move through the digits of π from a randomly cued starting point with remarkable facility. Moreover, Rajan's abilities are not limited to static knowledge of a single number; his capacity to recall 75 random digits in the correct order (Ericsson et al., 2004) must be considered stunning by any measure.

Rajan's mnemonic skills are but one example of the human capability to reach outstanding levels of performance, or *expertise,* in a domain. The domains in which expertise can be displayed range from the somewhat esoteric—such as memory for the digits of π—to the surprisingly mundane, such as waiting tables (Ericsson & Polson, 1988) and transcription typing (Salthouse, 1991). Almost any human activity, when pursued with sufficient intensity, can involve rather astonishing levels of cognitive sophistication and performance. In this chapter, we review research on human expertise with a tripartite emphasis on expertise acquisition, the limitations associated with expertise, and the extent to which expertise is subject to conscious control.

We provide an illustrative overview of all three issues by revisiting Rajan, the mnemonist. Concerning the acquisition of expertise, there is now clear evidence that Rajan

DOI 10.1518/155723409X448044.

has acquired specific cognitive strategies to perform his mnemonic feats (Ericsson et al., 2004), rather than relying on some innate ability, as had been suggested at one point (Thompson, Cowan, & Frieman, 1993). Accordingly, in the first major section of this chapter, while discussing the nature of expert behavior, we suggest that expertise is the result of specific learned adaptations to cognitive processing constraints.

One consequence of the adaptive nature of expertise is that it turns out to be very specific and "brittle"; that is, experts may encounter difficulties when tasks are altered or when transfer to new problems is expected. Even Rajan's phenomenal memory span was reduced to that of mere mortals (i.e., in the range 7 ± 2) when he was confronted by stimuli—random symbol strings such as @, %, #, and so on—that defied his mnemonic strategies (Ericsson et al., 2004). We discuss the brittleness of expertise, and some of its other associated limitations, in a second major section.

In the final section, we consider the extent to which experts are in conscious control of their expertise. Do experts consciously "know" what they are doing? Can they adapt to changes in task demands, notwithstanding perhaps some initial brittleness? Rajan, for one, proved remarkably adept at overcoming the limitations that were revealed when he had to memorize sequences of random symbols: Within a few sessions, he developed a recoding scheme that allowed him to consider the symbols as digits, with an attendant increase in memory span from 7 ± 2 to 28.

THE ACQUISITION OF EXPERTISE AND ITS CHARACTERISTICS

An expert has been anecdotally described as "anyone who is holding a briefcase and is more than 50 miles from home" (Salthouse, 1991, p. 286) or "someone who continually learns more and more about less and less" (Salthouse, 1991, p. 286). However, at a technical level, there is common agreement that an expert is characterized by reproducible superior performance in a particular domain.

Any coherent set of tasks and problems that is amenable to objective performance measurement (Ericsson, 1996) can constitute a domain of expertise. Accordingly, researchers have examined domains as diverse as the linking of a series of car crimes by expert investigators (Santtila, Korpela, & Häkkänen, 2004), the ability to predict the spread of bush fires by expert firefighters (Lewandowsky & Kirsner, 2000), the performance of chess masters (e.g., Charness, Krampe, & Mayr, 1996), and expert medical diagnosis (e.g., Patel, Kaufman, & Magder, 1996). In all cases, expert performance has been consistently and reliably found to be outstanding and superior to that of novices. (By the same token, research has identified domains in which exceptional performance cannot be detected. For example, people who claim to be speed readers have been found to exhibit remarkable dexterity at turning pages without displaying any comprehension of the text [Homa, 1983]. Those "domains" are commonly excluded from consideration in research on expertise.)

In chess, for example, expertise is associated with an extraordinary ability to remember the location of pieces on a board after a few seconds of viewing time and with the ability to play several games at the same time (e.g., de Groot, 1965). In medical diagnosis, experienced radiologists reliably outperform residents when inspecting X rays

(Norman, Brooks, Coblentz, & Babcook, 1992). In the realm of mental arithmetic, at least one individual, Shakuntala Devi, has been able to multiply in her head large numbers, such as 7,686,369,774,870 × 2,465,099,745,779, rapidly and without error (the answer, incidentally, is 18,947,668,177,995,426,462,773,730). In many instances, the observing researcher took more time merely copying down the problem than Ms. Devi required for her computations (Jensen, 1990).

In sports, expertise is generally associated with either very speedy or very precise motor responses, or both (Ericsson & Lehmann, 1996). With increasing expertise, athletes such as figure skaters and gymnasts become able to perform more complex motor behavior and do so with increasing consistency (Ericsson, 2007). As a case in point, consider the ability of Olympic gymnasts to combine multiple saltos and twists in the air with the ability to land on their feet on a 10-cm-wide balance beam.

What is the most likely path by which such outstanding ability is acquired? Several competing views have been put forward, including the idea that an inherited genetic endowment is required for at least some manifestations of expertise (e.g., Simonton, 2007, 2008). The potential role of genetic factors is suggested by the fact that since 1901, Nobel prizes have been awarded to no less than six father-son pairings (Simonton, 2008). Given the extremely low base rate of this prestigious honor, its repeated award to members of the same family may seem difficult to explain without recourse to heritability of scientific talent. Accordingly, Simonton (2008) proposed that the contribution of genetic factors to a variety of broad measures of scientific prowess is moderately large. To place this magnitude into context, it is comparable to the magnitude of the relationship between receiving psychotherapy and subsequent well-being.

Simonton's (2007, 2008) argument about heritability is based on the fact that (a) expertise is statistically associated with various personality characteristics, which (b) in turn are known to involve a considerable extent of heritability. Hence, so the argument goes, (c) some proportion of expertise must also be heritable. This argument is flawed because it does not consider alternative causal paths.

To illustrate, consider the following hypothetical example. Suppose good parenting (as measured by various outcome variables such as happiness of the children, success at school, etc.) turns out to be statistically associated with physical attractiveness of the parent (paralleling Item a). Physical attractiveness, in turn, (b) is indubitably partially inherited. Does it follow therefore (c) that parenting qualities are also heritable? The answer is no, because the causal variable that determines quality of parenting need not involve physical attractiveness at all. For example, the causal variable may be marital happiness, and marital happiness happens to be facilitated by attractiveness because it increases options during mate choice. Crucially, in this scenario, when marital happiness is controlled, differences in attractiveness attributable to genetic variation would no longer be associated with parenting. It follows that indirect associations of the type cited by Simonton (2007, 2008) are therefore of little value in establishing heritability of expertise.

However, heritability estimates derived for the population at large by conventional behavioral genetics do not necessarily shed much light on the role of genetic endowment in elite performance (Ericsson, Roring, & Nandagopal, 2007b). There are several reasons that heritability estimates from the population at large need not apply to experts (Ericsson et al., 2007b). Most relevant here is the fact that the prolonged training that is inevitably associated with the attainment of expertise engenders task-specific cognitive adaptations that may circumvent the more general cognitive constraints—such as short-term memory capacity—that contribute to heritability estimates. Accordingly, exceptional individuals often do not distinguish themselves on tests that are known to have a large heritability component, such as IQ.

For example, Ms. Devi's exceptional calculating abilities were not accompanied by an equally exceptional IQ (Jensen, 1990). Likewise, numerous studies have failed to find a strong relationship between IQ and skilled chess-playing performance (e.g., Ericsson & Lehmann, 1996; Unterrainer, Kaller, Halsband, & Rahm, 2006; though see Grabner, Stern, & Neubauer, 2007, for a report of a relationship between IQ and chess performance). Moreover, in direct challenge to Simonton's (2007, 2008) claim about heritability of exceptional performance, Ericsson, Roring, and Nandagopal (2007a) reviewed evidence that both fraternal and identical twins are in fact quite unlikely to reach exceptional performance, rendering twins underrepresented among elite performers and thus preventing a reliable estimate of heritability.

We therefore focus here on an alternative view that has gained considerable prominence—namely, the idea that expertise is not the result of genetic endowment or "talent" but arises from extensive *deliberate practice.*

Acquisition of Expertise: Deliberate Practice

The view that expertise is acquired rather than being the result of innate talent or genetic endowment has found a theoretical focus in the work by Anders Ericsson (e.g., Ericsson, 2003, 2005). The principal tenet of Ericsson's view is that expertise arises from extensive *deliberate practice*. Specifically, there is now considerable evidence that for many domains of expertise, 10 years of deliberate practice are required to attain outstanding levels of performance (e.g., Ericsson, 1996). Some exceptions to this rule exist, such as in chess, for which expertise may be acquired in less than 10 years. Even in these exceptions, however, it is still estimated that between 1,000 and 10,000 hr of practice are required to reach expert levels of performance (Charness, Tuffiash, Krampe, Reingold, & Vasyukova, 2005).

The notion of deliberate practice is crucial because it differs from mere exposure and repetition in several important ways: First, deliberate practice involves a well-defined, specific task that the learner seeks to master. Second, task performance is followed by immediate feedback. Third, there is opportunity for repetition, and fourth, learners must actively exploit the opportunity for improvement afforded by errors.

Ericsson, Krampe, and Tesch-Römer (1993) provided an extensive characterization of these defining attributes: First, the choice of practice tasks must take into account the preexisting knowledge of the learners so that the task can be understood after a brief period of instruction. This is important in reducing the cognitive load of understanding the task so as to allow maximum attention to be paid to specific learning goals. Further, research has shown that performance is maximally improved when specific and challenging goals are set for an individual to achieve. This type of goal setting is posited to encourage individuals to apply more effort and optimize their task strategies (Locke & Latham, 1990).

Second, learners must receive immediate feedback about their performance. In the absence of adequate feedback, learning is inefficient and practice leads to only minimal improvement, even in motivated participants (Ericsson et al., 1993).

Third, learners should repeatedly perform the same or similar tasks. This requirement is nontrivial because in many situations, such as learning to fly an airplane, some task elements are not instantly reproducible—for example, it is not possible to repeatedly land an aircraft without intervening takeoffs—thus delaying the interval between repetitions.

Finally, learners must actively try to seek out new methods or refine methods in response to errors. In this respect, deliberate practice must be differentiated from work or play. Working generally requires individuals to perform at their optimal levels, thus taking away the opportunity to refine skills or explore new methods that may temporarily result in errors or reduce the level of performance. A major difference between play and deliberate practice is that deliberate practice requires effort and is often not inherently enjoyable. It is highly structured, with the explicit goal of improving performance.

The concept of deliberate practice is best illustrated by considering a variety of domains. One particularly illustrative example is chess, in which specific techniques of deliberate practice can be readily identified. One such strategy is for the learner to "replay" games between chess masters and try and select the best move—defined as the one played in the initial masters' game—for each position. If the person engaging in practice fails to pick the correct next move, he or she continues to study and analyze the board until the reasons underlying the chess master's choice of move are understood.

In the board game SCRABBLE, deliberate practice activities involve the study and memorization of word lists, activities to strengthen skills in anagramming (the ability to access words based on visual letter cues), and exercises to improve tactical strategies specific to the game (Tuffiash, Roring, & Ericsson, 2007). As the players are not required to know the meaning of words or to be able to pronounce them during the game, these skills are not incorporated into the deliberate practice (Ericsson et al., 1993).

The unique importance of deliberate practice can be highlighted by contrasting it once more with *experience*—that is, the mere amount of chronological time spent on a task. Several large-scale reviews have shown that the relationship between the amount of accumulated professional experience and attained performance is low and can sometimes even be negative (see Ericsson & Lehmann, 1996; Keith & Ericsson, 2007). For example, diary studies and retrospective estimates provided by expert musicians have found that although the total amount of time spent on domain-related activities was not associated with attained level of performance, the amount of engagement in solitary practice was (Ericsson et al., 1993). Solitary practice fulfilled all the criteria associated with deliberate practice, including in particular the fact that it was not considered fun but, rather, as tiring, hard work that led to rapid exhaustion.

In summary, there is no doubt that deliberate practice plays an important role in the development of expertise—a role that is acknowledged even by proponents of genetic factors (e.g., Simonton, 2007). Nonetheless, we must caution that the *causal* role of deliberate practice awaits final confirmation. Sternberg (1996) very eloquently drew attention to several logical problems in the interpretation of deliberate practice, two of which are particularly noteworthy.

First, there is a potential risk of circularity, because all instances in which practice fails to predict expertise could be relabeled as *nondeliberate*. What is needed, therefore, are strong a priori criteria for what constitutes deliberate practice that can be ascertained independently of the to-be-explained outcome. Some of those criteria were listed in the foregoing, offering a partial solution to this problem. Nonetheless, one must continue to guard against the circularity problem.

Second, retrospective analyses of the role of deliberate practice necessarily ignore dropout effects. Thus, there may be many people who wanted to become expert in a given domain but dropped out at various stages because, perhaps for lack of talent, they did not improve with deliberate practice. These dropout effects will result in a *correlation* between deliberate practice and expertise—but the hidden *causal* variable is self-recognition of one's talent (or lack thereof) rather than practice. This criticism appears difficult to reject altogether; nonetheless, the continuous functions relating performance to practice in the theoretically expected form (i.e., by a power function; see, e.g., Ericsson et al., 1993, Figure 15) are not readily reconciled with a dropout view.

Moreover, there have been a number of recent attempts to address the dropout problem by empirical means (e.g., de Bruin, Smits, Rikers, & Schmidt, 2008; Roring & Charness, 2007). For example, de Bruin et al. tracked young elite chess players longitudinally, comparing those who remained within the (Dutch) national training program with those who had dropped out along the way. The players' chess performance (as revealed by the usual standardized rating system) turned out to be a function of deliberate practice, and—most important in the present context—whether or not players had dropped out had no effect on that relationship.

We next turn to a more detailed examination of the specific processes underlying deliberate practice. That is, whereas deliberate practice provides a descriptive perspective on how expertise develops in the long term, we must turn to cognitive theories of skill acquisition to provide explanatory insight into the underlying mechanisms.

Theories of Skill Acquisition and Automaticity

Many theories exist that explain how new skills are initially slow and effortful to perform but become easier and faster with practice. One major theory is Anderson's (1988, 1992) Adaptive Control of Thought (ACT) cognitive architecture, which postulates that skill acquisition occurs as a result of refining and strengthening of "procedures" for performing a task.

The skill may initially rely on declarative (i.e., verbalizable) knowledge as to how to complete a task but then move to a more effective rule-based (if-then) model (Speelman & Kirsner, 1997). For example, when learning to drive a car, one's performance becomes dependent upon a set of steps whereby different actions are required in different positions. When approaching traffic lights, *if* the light is red, apply the clutch and then brake to stop; but *if* the light is green, continue to drive.

Practice of the skill can continue to refine its production and increase efficiency. One suggested reason for the increased efficiency associated with practice is that it leads to the compilation of several productions into one. Productions are small groups of actions based on the declarative rules. Combining these into more complex productions results in the execution of the same behavior in less time. For example, in the driving analogy, the separate steps of applying the clutch followed by braking to stop will eventually be compiled into a single production, "*if* red *then* stop," in which the action "stop" subsumes a number of initially separate steps.

An alternative model of skill acquisition relies on the idea that people rely on memorized instances to develop automaticity (Logan, 1988). This exemplar theory of learning proposes that performance initially relies upon a slow algorithm. Each time the task is performed using the algorithm, people store an example of its performance in memory. With practice, the number of examples stored in memory increases, thus making their retrieval faster and easier. Eventually the use of exemplars becomes more efficient than the initial algorithm, and performance of a task therefore relies on exemplars rather than the algorithm.

One consequence of prolonged skill acquisition that applies equally to Anderson's (1988, 1992) and Logan's (1988) models is that people eventually reach a stage known as *automaticity*. Anderson (1992) noted a number of characteristics of automatic performance, two of which are particularly relevant to expert skill. First, as a skill becomes automatic, it interferes less with a concurrent task and, correspondingly, is less subject to interference by a concurrent task. This allows automatic tasks to be performed in parallel with each other (at the same time) rather than serially (one at a time; Moors & De Houwer, 2006). We return to this issue later, when we consider experts' ability to perform their expert skill in addition to a secondary task. Second, automatic processes can be difficult to inhibit, thus creating interference when they are in conflict with another goal. A classic example involves the Stroop task, in which participants are slow to name the ink color of words, such as *blue,* that are printed in an incongruent color, such as red.

Later we will revisit the implications of the fact that automatic processes cannot be suppressed; here we focus on their resilience to interference. There is considerable evidence that experts are able to perform secondary tasks at the same time that they exercise their focal expert skills without disruption to their performance. For example, Beilock, Wierenga, and Carr (2002) asked experienced golfers and novices to putt a ball while simultaneously monitoring an auditory stream for a target signal. The experts' putting abilities, unlike the novices', were found not to be disrupted by this secondary task.

Similar results have been found with other experts, such as ice hockey players (Leavitt, 1979), soccer players (Smith & Chamberlin, 1992), and badminton players (Abernethy, 1988). In all cases, performance on the experts' primary task was not impaired by the presence of a secondary task. In the soccer study, for example, participants of varying levels of expertise were required to dribble a soccer ball through a slalom course while identifying geometric shapes projected on a screen located at the end of the course. In all cases the secondary task caused some decrement in performance, but the extent of that decrement decreased as the level of expertise increased (Smith & Chamberlin, 1992).

The idea that skilled performance is automatic may come as no surprise in the domain of physical sports; the automaticity associated with the performance of intellectual skills, such as playing chess, may be somewhat more counterintuitive. In chess, an automatic process has been identified concerning the way in which experts extract relational information about the pieces on the board. Reingold, Charness, Schultetus, and Stampe (2001) showed that when given a small section of a chess board to consider, less skilled players processed the relational position of each piece one at a time (serially), whereas experts examined all pieces of the board in parallel with one another. Specifically, the time required by experts to determine whether or not the king was being checked by an attacker on the board was unchanged by the addition of a second potential attacker. For less skilled players, by contrast, the addition of a second possible attacker slowed responses considerably. This result implies that the novices had to process the relational information of each piece individually, whereas the experts processed the two pieces in parallel and hence did not experience a significant time cost.

Further evidence of parallel processing was drawn from a second experiment, in which there were two attackers present but, in one condition, one of the attackers was identified by a red mark. The task in this condition was to decide whether or not the red attacker was checking the king. In this experiment, the novices benefited from the color cue, whereas the experts did not. One explanation of this finding is that the novices benefited from having to perform only the first step of serial processing (i.e., the relational processing of the cued piece), whereas the experts experienced no advantage because they were able to process the two pieces simultaneously, irrespective of the presence of a cue.

These findings are in line with other research that has found that experts have a substantially larger visual span than do less skilled players when processing chess configurations (Reingold, Charness, Pomplun, & Stampe, 2001). *Visual span* refers to the amount of information that a person can take in with a single fixation. One technique by which visual span is measured involves a gaze-contingent window; that is, the computer displays information only within a narrow window, the location of which is determined by the participant's eye movements. Visual span is defined as the smallest window size that does not interfere with the participant's performance. Using two detection tasks, Reingold, Charness, Pomplun, et al. (2001) found that experts (but not novices) extracted information from the parafoveal regions of the eye (in addition to the foveal region), and this larger visual span enabled experts to make fewer fixations per trial and to avoid fixating on individual pieces.

The clear role of automatic processing in both physical and intellectual manifestations of expertise gives rise to an interesting and potentially problematic issue—namely, the degree to which experts may lose conscious control over their skills as a result of automaticity. That is, once experts perform tasks automatically, does the automaticity compromise their conscious control over the task or its components? This is an issue that will be addressed in the final section of this chapter. We next examine additional outcomes of skill acquisition by considering the nature of expertise, once it has been acquired, in some detail.

Characteristics of Expertise

Circumventing known processing limitations. The capacity of human short-term memory is famously limited to 7 ± 2 units of information (Miller, 1956). For that reason, most people struggle to retain an unknown overseas phone number with its 10 or more digits, and few could imagine an easy way to expand that capacity. Perhaps somewhat worryingly, the capacity of short-term memory correlates highly with IQ and higher-level cognitive abilities. (See Unsworth & Engle, 2007, for a recent review and discussion of the differences between short-term and working memory. For the present purposes, we consider the two terms to be interchangeable.) Given the well-known stability of IQ, its association with short-term memory capacity seems to reinforce the notion that capacity, too, may be resistant to attempts to increase it. What, then, explains the exceptional performance of individuals such as Rajan, whom we introduced in the beginning of the chapter?

We noted at the outset that Ericsson et al. (2004) recently found Rajan's short-term memory abilities to be the result of the application of learned strategies, notwithstanding earlier opinions to the contrary (Thompson et al., 1993). In particular, Rajan's span was reduced to the standard 7 ± 2 when he was confronted by novel symbols that (initially at least) defied his learned strategies. This reliance on acquired strategies to "enhance" one's short-term memory capacity turns out to be of considerable generality.

There are numerous reports of individuals who gradually raised their digit span by deliberate acquisition of mnemonic techniques. In some particularly dramatic instances, a person's span increased from the standard 7 ± 2 to 80 or even higher (e.g., Ericsson, Chase, & Faloon, 1980; Staszewski, 1993), an increase of more than 70 standard deviations. These remarkable abilities relied on the acquisition of increasingly larger, richly integrated hierarchical retrieval structures (e.g., Staszewski, 1993), an observation supported by computer simulation (Richman, Staszewski, & Simon, 1995). Thus, notwithstanding the common perception that short-term memory capacity is difficult to increase, and notwithstanding its strong association with a stable characteristic such as IQ, broadly applicable means exist by which people can develop specific cognitive processes and techniques that circumvent seemingly invariant processing constraints.

The utility of such specific compensatory techniques is not limited to mnemonists; in fact, its development and refinement constitutes a common theme among virtually all forms of expertise. In chess, for example, players acquire better and more refined mental representations that allow them to evaluate and mentally manipulate chess positions better than do less skilled players. This process allows them to select the best move among a set of possible moves they have generated or to discover new and better moves (Ericsson, 2007).

Circumventing hard biological constraints. We have shown that experts can develop cognitive means by which to circumvent cognitive constraints. However, even more strikingly, expert performance also often seems to defy biological limitations that appear "hardwired" at first glance. For example, it is known that people cannot tap a finger repetitively more than about six times a second, even if they do not have to respond to specific stimuli (Freund, 1983). In conjunction with the known lower limit on response latency to successive stimuli (around 550 ms; Salthouse, 1984), these constraints seem to dictate a maximum typing speed of somewhere between 20 and 75 words per minute. Yet, expert typists can enter text at a rate exceeding 75 words per minute. How is this possible in light of the seemingly "hard" constraints just mentioned?

Salthouse (1984) showed that typists achieve this high level of performance by developing specific strategies that circumvent these biological constraints. For example, when maximum typing speeds are compared across individuals, speed is found to be correlated with the number of characters that must be simultaneously visible (i.e., the visual span defined earlier) for the typists to maintain their maximum speed. Any reduction in the number of visible characters below that limit adversely affects the typist's performance.

This correlation indicates that increasing expertise is associated with enhanced parallelism of processing.

To illustrate, parallel processing seems to be involved in preplanning keystrokes involving opposite hands. This planning is revealed by the strong negative correlation between expertise and the delay between keystrokes involving alternate hands, as when *w* is followed by *o*. That is, coordination between the two hands increases with the expertise of a typist. Further, the correlation between expertise and interkey intervals is substantially smaller for repetitions of the same letter—which necessarily involves repeated tapping of the same finger—indicating that expertise often involves the acquisition of skills to circumvent hard constraints, rather than a relaxation of those biological constraints.

Another example can be drawn from elite sport, in which experts extract new and more informative perceptual information to improve their performance. Elite athletes need to be able to plan their actions on the basis of advance perceptual cues because the greater strength and speed of elite opponents results in less available time to respond (Ericsson & Lehmann, 1996). For example, Savelsbergh, Williams, and Van Der Kamp (2002) examined the differences in anticipation and visual search behavior of soccer goalkeepers of varying levels of expertise during a penalty kick. Participants were required to move a joystick in response to penalty kicks presented on a screen in front of them. Their visual search behavior while performing this task was examined by recording their eye gazes. It was found that the experts used a more efficient search strategy involving fewer fixations of longer duration. In addition, the novices spent more time looking at the trunk, arms, and hips of the goal shooter, whereas the experts looked more at the legs (both kicking and nonkicking) and the ball area, particularly as the moment of foot-to-ball contact approached.

Finally, Ericsson (2007) recently reviewed mechanisms by which intense physical activity *can* lead to a softening of those hard biological constraints. For example, by engaging in sustained strenuous activity, individuals can induce an abnormal state in some physiological systems—such as certain muscle groups—that will cause metabolic processes to change, thus leading to a permanent physiological adaptation. In part, this adaptation relies on the activation of many different genes that would remain unexpressed in the absence of intense physical activity. Physiological adaptations of this type are the norm in all elite athletes.

Common to all mechanisms by which experts circumvent human limitations is the specificity of the adaptations to task demands: Regardless of whether the adaptation involves a new cognitive skill (as with mnemonists), a new coordination of biological constraints (typing), or indeed an alteration of biology (athletes), the end result is a new ability that is specific to the task at hand. This entails two related consequences: First, expertise is typically highly specific and limited to the trained domain (and perhaps even more so than intuition would suggest at first glance). Second, expertise is often quite brittle, and even seemingly small deviations from a routine task can be associated with surprisingly large performance decrements.

Specificity of expertise. It should come as no surprise that expert archaeologists are not necessarily also outstanding oceanographers and that expert psychologists are unlikely also to be world-class ornithologists. However, the extent of the specificity of expertise may exceed the intuition of some readers. For example, individuals who acquire a phenomenally large digit span after extended training (e.g., Ericsson et al., 1980) somewhat soberingly retain the standard limit (approximately seven symbols) on capacity for other information (e.g., Chase & Ericsson, 1981). That is, the same person may struggle to recall "C F G K L P Z" in the correct order but be able to reproduce the sequence "2 9 0 3 4 1 8 9 2 3 0 5 7 1 4 5 2 2 8 1 0" (or indeed an even longer series of digits) flawlessly. We already noted that the mnemonist Rajan displayed similar specificity; indeed, it was the specificity of his expertise that pointed toward acquired skills as the cause of his mnemonic abilities.

We consider two further examples of the specificity of expertise. First, expert pianists' acquired ability to tap fingers particularly rapidly (Ericsson et al., 1993) does not generalize to an ability to tap feet at a particularly rapid rate (Keele & Irvy, 1987). Although this may come as no particular surprise, this finding does rule out a general speeding up of motor movements as a correlate of pianists' expertise.

Second, and perhaps more surprisingly, Sims and Mayer (2002) found evidence for extreme specificity of skill in expert Tetris players. Tetris is a computer game that requires players to mentally (and then physically via key press) rotate shapes that appear on screen for a limited amount of time. Sims and Mayer compared the general spatial ability of Tetris players of varying levels of skill. The spatial tests variously involved rotation of standard Tetris shapes, shapes similar to Tetris shapes, and other shapes, such as letters and numbers. The results showed that highly skilled players outperformed less skilled players only in the rotation of Tetris (or representationally similar) shapes, revealing a remarkable specificity of skill. In a second phase of the study, novices were trained on Tetris for 12 hr. This practice improved the participants' ability to rotate the Tetris-like shapes but had no effect on their more general spatial ability, thereby again highlighting the specificity of the Tetris skill even in early phases of expertise acquisition.

In contrast to the preceding examples of specificity, recent research focused upon visual or spatial attention has found more generalized effects whereby playing action video games, such as first-person "shooter" games, resulted in improved performance on spatial tasks not directly practiced in the games played (Feng, Spence, & Pratt, 2007; Green & Bavelier, 2003). It has been posited that these generalized improvements are the result of improved lower-level attentional capacities, which stands in contrast to games such as Tetris, in which improvement is specific to the higher-level *cognitive* skill of mental rotation.

Brittleness of expertise. A corollary of the specificity of expertise is what we call its *brittleness*—that is, the deterioration in performance that is observed when a domain-relevant task is altered slightly and thus becomes atypical. A classic example of this brittleness involves memory for chess positions. (By *position,* we refer to the configuration of all pieces on the board.) One characteristic attribute of expert chess players is their remarkable ability to remember the current game position. Chase and Simon (1973) found that chess expertise was associated with recall of the identity and location of pieces on the board after fairly brief (5-s) exposure with remarkable accuracy. Even more strikingly, Gobet and Simon (1996b) showed that chess grand masters can retain multiple different chess positions—each involving 25 pieces—with considerable accuracy (>80% for two positions and around 60% for four separate positions). In terms of the number of recalled pieces, grand masters were found to place 60 pieces from four positions correctly after a total exposure time of around 20 s; this ability is remarkable by any standard.

However, the experts' ability is largely limited to plausible positions that might arise during an actual game. In virtually all relevant studies conducted to date, when pieces were quasi-randomly arranged and hence no longer formed a meaningful pattern, the performance of the chess experts deteriorated dramatically. The deterioration of expert memory when domain-relevant stimuli are rendered meaningless by randomization or some other disruption is a fundamental attribute of expertise that has been observed in many domains: A review by Ericsson and Lehmann (1996) cited areas as diverse as the games of bridge, Go, Othello, snooker, basketball, field hockey, volleyball, and football as well as professional disciplines such as medicine, computer programming, and dance.

Another intriguing aspect of these results, specifically those involving chess, arises out of detailed comparisons between experts and novices. For meaningful game positions, the reproduction skills of chess masters are indubitably far superior to those of novices, even if the novices are respectably able players themselves. For example, Gobet and Simon (1996b) observed that whereas grand masters could recall 60 pieces from four positions correctly, performance under equivalent conditions was below 20 for Class A players—the skill of Class A players is between 1.5 and 2.5 standard deviations above the mean of the Elo scale (Bilalic, McLeod & Gobet, 2008).

For random chess positions, by contrast, it used to be a matter of consensus that the expert advantage (at least after brief exposure durations) was completely eliminated. The belief that experts and novices did not differ in their memorial abilities for random board positions was sufficiently entrenched to be echoed in textbooks (e.g., Medin, Ross, & Markman, 2001). However, when the evidence from numerous studies was considered jointly in a meta-analysis, increasing expertise was found to be associated with a small but clear memory advantage even for random board positions (Gobet & Simon, 1996a). This small advantage is most likely attributable to the experts' ability to discover even small regularities in otherwise random positions by matching board positions against a vast repertoire of chess patterns stored in long-term memory. Estimates of the size of this repertoire range from 50,000 (Simon & Gilmartin, 1973) to around 300,000 (Gobet & Simon, 2000).

Accordingly, when the degree of randomness (defined by the extent to which basic game constraints are violated) is manipulated, players with greater expertise have been found to be better able to exploit any remaining regularities than players with lesser expertise (Gobet & Waters, 2003). Thus, the specificity of expertise extends to highly subtle regularities indeed.

The fact that expertise is brittle and tightly circumscribed hints at the possibility that it might also be limited in other ways. Indeed, as we show next, there are a number of known ways in which experts' performance can be compromised.

THE LIMITATIONS OF EXPERTISE

There is growing recognition that the analysis of performance errors and limitations contributes in fundamental ways to understanding the nature of expert knowledge (e.g., Johnson, Grazioli, Jamal, & Zualkernan, 1992). We highlight three particular limitations here—namely, expediency, mediocrity, and inflexibility.

Expediency

Expediency arises primarily during the acquisition of expertise and refers to the fact that experts emphasize efficiency when acquiring a skill. They may, for example, trade knowledge for extended search where many cues could be considered (Charness, 1991; Johnson, 1988). Thus, the accumulation of a large knowledge base allows experts to select the key features of the problem, thereby reducing the number of variables chosen for consideration.

An illustrative case of expert expediency was reported by Lewandowsky and Kirsner (2000), who asked experienced wildfire commanders to predict the spread of simulated wildfires. In actuality, the spread of wildfires is primarily determined by two physical variables: Fires tend to spread with the wind and uphill. It follows that with light downhill winds, the outcome depends on the relative strengths of the competing predictors. If the breeze is sufficiently strong, the fire spreads downhill with the wind, whereas if the wind is light, the fire spreads uphill against the wind. Lewandowsky and Kirsner found that experts largely ignored slope and based their predictions entirely on wind. Although this gave rise to correct predictions in most circumstances, any fire in which light winds were overridden by a strong slope was systematically mispredicted. We suggest that this systematic error arose because during training, firefighters learned about the role of wind, which typically is overwhelming, while neglecting to place much weight on the more subtle role of slope.

It must be noted, however, that the experts in Lewandowsky and Kirsner's (2000) study were aware of the role of slope in another context and, often, when verbally prompted. Moreover, the expedient focus on wind at the expense of slope is not entirely maladaptive, given that the effects of wind transcend local idiosyncrasies and apply to the fire as a whole, whereas the effects of slope are necessarily limited in physical extent.

Mediocrity

Imperfect expert performance has been associated with situations in which probabilistic cues must be used to predict uncertain outcomes. For example, in predicting the likely success of applicants to medical school from their prior record (e.g., grades, letters of recommendation), expert accuracy is often inferior to that achieved by simple linear regression models and only slightly superior to that of novices (Camerer & Johnson, 1991; Johnson, 1988). Similar results have been obtained in a variety of other domains, such as predicting recidivism of criminals, financial investment, and weather forecasting. Although widespread, this expert "mediocrity" is not universal; for example, auditors often perform at great levels of reliability, and there is evidence that weather forecasters can also be well calibrated (see Shanteau and Stewart, 1992, for a more detailed review).

Most reports of mediocrity have relied on domains in which there are no unequivocally correct rules, only sets of more or less accurate heuristics (Johnson, 1988). It turns out that human experts have considerable difficulty applying and combining those heuristics in the correct statistical manner. By contrast, the properly weighted linear combinations of probabilistic cues are readily obtained by linear regression using so-called actuarial models (Camerer & Johnson, 1991).

Human experts use a variety of alternative combinatorial strategies that do not match the long-run statistical accuracy associated with linear regression. One of them, known as *configural reasoning,* consists of considering predictor variables in a categorical manner rather than by weighted addition. For example, a configural rule in medical diagnosis might be "if the patient experiences headaches that have a gradual onset, with no periods of remission, and has high levels of spinal fluid protein, then diagnose a brain tumor" (Schwartz & Griffin, 1986, p. 94). Configural reasoning is often observed in experts, but unlike weighted linear regression, its all-or-none character renders it vulnerable to small variability in measurements (Camerer & Johnson, 1991). A statistical examination of expert performance, based on analysis of residual variance, has found that only about 40% of expert error reflects random variation; the remainder (60%) is likely attributable to systematic use of configural rules and other statistically inappropriate heuristics (Camerer, 1981).

Somewhat encouragingly, experts' performance can be improved by a rather counterintuitive process known as *bootstrapping.* Bootstrapping involves the construction of a regression model of the experts' *judgments*—rather than the to-be-predicted outcome—using objective indicators as predictor variables. For example, one might use the expert's admission decisions to graduate school as dependent measures and variables such as grade point average as the independent variables in a regression. The predictions of that regression model turn out to correlate more with the actual outcomes than do the experts' judgments (Camerer & Johnson, 1991). Bootstrapping is of particular value because it can be conducted in the absence of any knowledge of the true outcome, hence permitting improved prediction on the basis of available indicators and expert judgments—but without using the experts' responses directly.

Inflexibility

Inflexibility is revealed when experts are confronted with novel task demands and fail to adjust their performance in response. Thus, unlike the earlier demonstrations of brittleness and expediency, which illuminated the static boundaries of expertise, research into inflexibility traces the dynamic abilities of expertise (or lack thereof) by noting how experts adapt to changes.

In those situations, the need for adaptation may prove to be more challenging to experts than to novices (Frensch & Sternberg, 1989; Sternberg & Frensch, 1992). For example, Sternberg and Frensch (1992) compared expert and novice bridge players and examined the effects of various arbitrary rule changes on their performance. In general, perhaps somewhat counterintuitively, experts were found to suffer *more* than novices from any rule change, although the extent of their impairment differed with the type of change. When the rule change involved surface modifications, such as introducing new nonsense names for suits and honor cards, experts suffered less of a performance decrement than when the deep structure of the game was changed—for example, by altering the rule determining the opening of each play. The fact that expert disruption was maximal after a change to the deep structure suggests that the experts, unlike the novices, routinely processed the task at that deep level, a finding that is consonant with much prior research (e.g., Chi, Feltovich & Glaser, 1981; Dunbar, 1995). Highly skilled performance may thus entail the general cost of reduced flexibility in the face of novel task demands.

Inflexibility is not limited to situations in which the domain itself is altered by creating anomalous challenges, as in the case of bridge, but it may also be observed when the domain remains intact and novel (but legitimate) choices are presented. As a case in point, consider two studies involving successive presentation of chess positions to players of varying levels of expertise (Bilalic et al., 2008; Saariluoma, 1990). In both studies, participants were presented with a sequence of midgame positions and were asked to choose the best solution for each stimulus. Of greatest interest here are the Einstellung effects that arose (e.g., in Saariluoma's Experiment 2) when the first four positions were all solvable by the well-known "smothered mate" motif. The fifth, critical, position was again solvable by smothered mate but additionally contained two other much shorter—and hence objectively better—solutions. Although experts recognized the better solutions when presented on their own, 10 out of 12 players failed to recognize them when they were preceded by the four Einstellung stimuli.

The Einstellung effect was replicated by Bilalic et al. (2008), who found that Einstellung reduced the experts' ability to detect the optimal solution by an extent equivalent to a reduction in skill level of about 3 standard deviations. Bilalic et al. also found that "superexperts," defined as grand masters, were impervious to Einstellung. Bilalic et al. concluded that "although experts can be trapped by the immediate appeal of a well-known solution to a problem, the more expertise players possess the more likely they are to find the optimal solution once they start to look further" (2008, p. 90). Note, however, that only the most expert of experts (grand masters are more than 5 standard deviations above the mean of all rated chess players) escaped the Einstellung effect; all other experts exhibited inflexibility in both studies.

The notion that experts' behavior may change qualitatively when they are forced to pause or are given additional time finds support in the further fact that with prolonged exposure durations, experts' recall of random chess positions is strikingly superior to that of novices (rather than just barely so, as reviewed earlier for the case of brief exposure durations; see Ericsson, Patel, & Kintsch, 2000, for a brief review of the effects of exposure duration and Gobet and Simon, 2000, for a detailed exploration). This suggests that expert performance need not be automatic and inflexible but can be "nudged" into a more flexible and strategic mode.

The finding that experts' performance can be quite inflexible, even within their domain and without presenting anomalous challenges, raises at least two important questions. First, one might wonder about the experts' ability to *transfer* knowledge from one task to another. We have already shown that people's ability to rotate Tetris shapes does not transfer to the rotation of other shapes, but what about the ability to transfer a proven solution from one problem to another? Second, the observed inflexibility raises the larger issue concerning the extent to which experts are in conscious control of their activities. Can experts choose to perform differently if they decide to do so? We take up both of those issues in the next section, beginning with the issue of conscious control.

EXPERTISE AND CONSCIOUS CONTROL

We noted at the outset that the mnemonist Rajan quickly learned to recode arbitrary symbols as familiar digits and thus rapidly adapted to a situation that was incompatible with his mnemonic skills. In consequence, Rajan's symbol span quadrupled over just a few short sessions. Intuitively, this recoding effort would not have been possible without some conscious control. In general, one might expect the extent of conscious control to determine the extent to which experts are able to avoid errors and adapt to novel situations. We examine this possibility in the following.

Consciousness

We frame our discussion within the taxonomy proposed by Block (1995), who differentiated among four types of consciousness, the most relevant of which to the present discussion is *access consciousness*. Access consciousness refers to situations in which mental representations have become accessible for use in rational thought and controlling action. This occurs when attention is paid to a stimulus, resulting in the representation of that stimulus being amplified and made available to the cognitive system for further processing (Rossano, 2003). Thus, access consciousness can be thought of as the mental state resulting from attending to a particular stimulus. Access consciousness is therefore relevant to examining the skills of experts because it allows for the manipulation of thoughts and the control of action. Therefore, the amount of control an expert has over his or her actions can be seen as a direct indication of the extent to which thought processes are subject to access consciousness.

We noted earlier that much of expert performance develops to a point approaching automaticity; here, we are interested in whether this automaticity reduces the amount of conscious control experts have over their skills and knowledge. There is no simple answer to this question, and the following sections will present evidence in which some conscious control is present in expert performance, followed by situations in which performance of expert skill appears to be beyond conscious control.

Strategic Control of Expertise

Deliberate practice creates a number of consciously controlled strategies from which experts can choose. The conscious use of strategies is a relevant aspect of expertise, but it must be differentiated from the amount of conscious access that experts have to the subcomponents of automatically performed skills.

An example of consciously controlled strategies in expertise can be drawn from analysis of the behaviors adopted by expert orienteers to maximize their performance. Orienteering is a sport that is essentially a running race in which participants use a special map and compass to navigate their way through diverse terrain and visit designated checkpoints during completion of the course. Race participants all start at different times and so must navigate their own way through the course.

Expert orienteers have been reported to adapt their navigational equipment to reduce the cognitive load associated with the navigational requirements of the sport (Eccles, 2006). For example, they fold the map to reduce the search space, "thumb" the map to keep track of where they are, annotate the notes that describe the location of the control bases they must pass through, and attach it to their sleeve for easy reference. They also typically set and reset the map to align with the direction in which they are heading so that they do not have to mentally rotate the map while running. Eccles, Walsh, and Ingledew (2002) reported a number of other methods expert orienteers use, such as early anticipation of the terrain to be covered to reduce the need to refer to the map, selecting the most functional information from a map and blocking out the rest, and planning their next moves at a time when attentional requirements are low.

Another example of environmental manipulation as a strategy to increase performance was reported by Kirsh (1995). He noted that experienced jigsaw puzzlers often group pieces into piles that are similar in shape or color. By sorting the pieces, players reduce the expected time needed to perceptually locate appropriate pieces and allow fine distinctions between pieces to be made more readily, owing to their physical proximity.

Clearly, there are cases in which experts have control over their actions. We next consider whether that control may be lost because of the automatization of performance.

Automatization, Access Consciousness, and Cognitive Control

One implication of the automatization of skill is that performance may no longer require access consciousness. According to Moors and De Houwer (2006), the individual components of an automatic sequence reside only briefly in short-term memory. Given that a component must receive a sufficient amount of attention before it can come into consciousness, tasks that are implemented by automatic processes may therefore be performed without necessarily rising to (access) consciousness.

This absence of access consciousness has two consequences: On the one hand, owing to automatization of their skills, experts—but not novices—may be able to perform a primary task (their expert skill) without disruption while attending to a secondary task. Novices, by contrast, must devote attention to perform the primary task, which is therefore disrupted by a secondary task. On the other hand, the fact that experts need not be consciously aware of their skilled performance raises the question of whether they might even be able to consciously control their expertise should they choose to do so. That is, once it is possible to perform a task without access consciousness, can one still revert back to a controlled manipulation of its components?

Evidence suggesting a lack of conscious control over expertise can be drawn from a number of sources suggesting that experts are unable to prevent the automatic activation of domain-relevant knowledge. For example, Baird (2003) tested recall for domain-relevant and domain-irrelevant lists of words in experts and novices in investment. Participants were read aloud a list of 26 words; 13 were investment-related words (domain relevant) and 13 were not. In the domain-relevant category, experts recalled more items correctly but also exhibited more false recalls of investment-related words. This is suggestive of the possibility that experts could not inhibit their automatic responding with investment terms.

Stronger evidence that experts cannot suppress the retrieval of domain-relevant knowledge, even when warned that their knowledge may be inappropriate or misleading in the current task setting, was provided by Wiley (1998). Wiley used a remote association task, in which people have to generate a word that can form a familiar phrase with each one of three presented items. For example, given the stimuli *plate, broken,* and *rest,* the word *home* can be used to form the meaningful phrases *home plate, broken home,* and *rest home.* Readers with expertise in baseball may have found this example particularly easy because the target phrase *home plate* represents a crucial concept in baseball. But what if the stimuli had instead been *plate, broken,* and *shot*? The intended word here is *glass,* although the first word is compatible with the baseball-consistent completion *home.*

Wiley (1998) found that baseball experts, unlike novices, had great difficulty with items that implied—but did not permit—a domain-consistent completion, such as the triplet *plate, broken,* and *shot.* It was found that the baseball experts were least able to solve these misleading problems. Experts' response times were slower, and there were more baseball-related intrusions in their answers than in the novice group. The experts' difficulty persisted even when they were warned beforehand that their domain knowledge would be misleading, suggesting that activation of expert knowledge is automatic and cannot be suppressed.

A study by Gray (2004) complemented the work of Wiley (1998) by examining the effects of the obverse. That is, whereas Wiley showed that automatic activation that cannot be suppressed may impair performance, Gray investigated whether attempts to convert automatic activation into conscious access may also be harmful.

In Gray's (2004) experiment, expert and novice baseball players completed a virtual batting task in one of two conditions. In both conditions a tone occasionally sounded during batting. In the attentional condition, participants were required to judge the frequency of the tone, whereas in the skill-focused condition they were required to indicate the direction in which their bat was moving when the tone sounded. It was found that the experts were better than the novices at judging the frequency of the tone. This result supports the contention that experts' automatic skill execution left more resources available to complete secondary tasks. However, the experts' batting performance was degraded when they were required to make the skill-based judgment. Thus, when experts were forced to focus on the declarative aspects of their skill, this interrupted the automatic processes that supported their expert performance. Furthermore, the experts made significantly more errors when judging the direction of movement of their bat than did novices.

The findings of this study become more complex when one considers situations in which the expert batters experienced a slump in performance. During this time, their skill-focused judgment was found to increase in comparison with the judgments made during a hot streak in their batting. Moreover, when players were placed under high pressure to perform well at the batting task, they were also better at the skill-focused judgment. The finding that the experts were able to change the way in which they processed their skill indicates that they were able to consciously control its execution. That is, people could choose whether or not to pay sufficient attention to the procedure to result in access consciousness.

Taylor (1988) suggested that the reversion to focused attention helps a batter to break out of the slump. The general idea that "an individual self-observes and strategically adjusts his or her overt performance, such as when a tennis player double faults when serving and decides to adjust his or her ball toss" (Zimmerman, 2006, p. 706) has been labeled *behavioral self-regulation* and may be present in experts across diverse disciplines. Gray (2004) similarly concluded that reverting to conscious control may hurt performance in the short term but may also serve to improve skill execution in the longer term. Thus, just as conscious control is required to learn a skill to expert levels, reverting to conscious control of an expert task may be a necessary long-term strategy to allow continued improvement, notwithstanding any detrimental effects on performance in the short term.

A possible explanation for the contrast in findings between Wiley (1998) and Gray (2004) is the extent to which the task assessed was related to the expert activity. The Wiley experiment assessed a cognitive task involving words common to the expert domain, although the task (remote association task) was not a part of baseball. By contrast, the task in the Gray study was baseball batting and therefore assessed the participants' actual area of expertise.

Expert Transfer

We have extensively noted the specificity of expertise and the associated fact that one cannot expect transfer of skill outside the expert's domain. Here, we address the extent to which skill can transfer within a domain, from one relevant problem to another.

There is considerable support for the notion that experts show large within-domain transfer. For example, Novick (1988) and Novick and Holyoak (1991) showed that mathematical expertise predicts the degree to which solution strategies are transferred from one algebra word problem to another when the two problems appear different at the surface but share the same deep structure. In one study, the amount of transfer among experts was found to be up to nine times greater than among novices (Novick, 1988, Experiment 1), and expert transfer was observed even when the two problems were presented under two separate experimental cover stories.

Likewise, in the domain of accounting, Marchant, Robinson, Anderson, and Schadewald (1991) showed that experts (experienced tax practitioners) in general exhibited significantly more transfer than novices (introductory tax students) between problems involving the application of taxation laws. The study investigated the amount of transfer between a source problem with which participants were initially presented and a target problem they subsequently had to solve.

Why are experts better able to transfer their skills to novel problems than novices? A study by Hinds, Patterson, and Pfeffer (2001) provided an interesting perspective on the underlying processes. In their study, novices and experts in an electronics construction task instructed other novices in how to complete a task. On a subsequent test, the novices who were instructed by novices performed better on that same task than did novices who were instructed by experts. However, when tested on a different task within the same domain, those instructed by the experts outperformed their novice-instructed counterparts. Hinds et al. suggested that the more abstract and advanced concepts conveyed by experts facilitated the transfer of learning across tasks. Other evidence suggests, however, that this tendency for within-domain transfer may not always be beneficial to experts.

Consider again the study just mentioned involving tax accountants (Marchant et al., 1991). An interesting accompanying finding in that study was that when the problems were anomalous—that is, constituted exceptions to a general taxation principle—the experts' transfer was often reduced to the level shown by novices. Marchant et al. argued that processing of the first exceptional case "increased the salience of a highly proceduralized strategy that overrides transfer from the analogy in the more experienced group" (p. 283). Accordingly, Marchant et al. also found that when attempts were made to facilitate transfer by asking lead-up questions to induce transfer-appropriate processing or by providing multiple source analogs (shown to improve participants' ability for transfer by Gick & Holyoak, 1983), these manipulations raised the performance of the novices but further decreased that of the experts.

In summary, although expertise generally facilitates within-domain transfer, it may not do so in cases involving exceptional problems, because experts cannot help but activate their general knowledge even when exceptions to that knowledge must be processed.

Expertise and Consciousness: Conclusions

Research into expertise reveals numerous situations in which experts exhibit both flexibility and control, as well as situations in which neither is present. We draw two conclusions from the preceding review.

First, experts have considerable conscious control over their expertise. Thus, in many instances they can manipulate their knowledge and skills to solve novel problems and can revert to conscious skill execution if their expert performance levels are dropping, as was shown in Gray's (2004) study of baseball batters and, indeed, as was shown by Rajan in response to being confronted with stimuli that did not align with his mnemonic strategies. However, when experts revert to conscious control, their performance levels are generally not as high as they are when tasks are performed automatically.

Second, experts possess many skills that are automatic and can be completed without access consciousness. This generally results in high levels of performance within the domain—for example, by rendering performance impervious to secondary task demands—but it comes at a cost. Specifically, experts may have difficulty suppressing their automatic responses, as in the case of the baseball experts who were solving remote associations or the tax accountant whose transfer between anomalous problems was impaired.

CONCLUSION AND OUTLOOK

Expertise in a Few Words

The depth and scope of the literature on expertise prevent a meaningful summary in a few words. Nonetheless, we offer the following statements as a concise take-home message: (a) We suggest that expertise, rather than being the result of innate talent, is the result of 1,000 to 10,000 hr of practice (Charness et al., 2005). (b) As predicted by theories of skill acquisition, much of the resultant expert performance relies on automatic processing. (c) Automaticity entails the benefit of allowing parallel task execution but (d) comes at the cost of contributing to some of the limitations of expert skill, such as specificity, inflexibility, brittleness, and limited transfer. (e) Some of those limitations can be overcome when experts are able to gain conscious control of their task performance, but (f) this is not always possible, and even if it is possible, (g) it often comes at a cost to their performance level (although this cost may be limited to the short term).

Finally, we must point out that the expansive body of research on expertise prevents coverage of all of the relevant literature or areas of research in a single chapter. For a more comprehensive source of information on expertise, we therefore point the reader toward other sources: for example, the *Cambridge Handbook of Expertise and Expert Performance* (Ericsson, Charness, Feltovich, & Hoffman, 2006).

We now turn our attention to how people may be able to develop expertise but avoid the limitations we have previously highlighted.

Avoiding the Limitations of Expertise

Notwithstanding experts' generally outstanding performance, we have emphasized a cluster of related limitations that revolve around brittleness, inflexibility, and the inability to transfer knowledge to novel situations. How might those limitations be resolved? Are there ways in which experts can be trained to be less specific and more flexible?

One possible answer to these questions cites the distinction between routine and adaptive expertise. Thus far, we have limited our discussion to what some have called *routine* experts—that is, highly skilled people who "have learned complex and sophisticated sets of routines and apply them efficiently and effectively in their practice" (Mylopoulus & Regehr, 2007, p. 1161). Routine expertise stands in contrast to *adaptive* expertise (e.g., Gott, Hall, Pokorny, Dibble, & Glaser, 1993; Kimball & Holyoak, 2000), which has been defined as "an advanced level of problem-solving performance...characterized by principled representations of knowledge...as opposed to representations dominated by surface features" (Gott et al., p. 259).

Routine and adaptive forms of expertise are often seen as two contrasting concepts (e.g., Kimball & Holyoak, 2000), and on this dichotomy, routine experts are assumed to persist with their routine approaches, thus failing to adapt to new circumstances. By contrast, adaptive experts are thought to use (and seek out) new problems to challenge and stretch the boundaries of their knowledge. They are characterized by more flexible and creative competencies rather than speed, accuracy, and automaticity (Mylopoulus & Regehr, 2007).

Although this dichotomy is attractive at first glance, we are reluctant to accept it, for a variety of reasons. First, we are not aware of any independent criteria that identify a particular expert, or a particular domain of expertise, as adaptive. Instead, expertise appears to be considered adaptive whenever it transfers well and is resilient to inflexibility and brittleness, and it is considered routine whenever it does not. It follows that the distinction between routine and adaptive expertise amounts more to a post hoc redescription of the data than to an a priori explanation.

Second, empirical examinations of adaptive expertise converge on identification of the same, or similar, cognitive principles that are also involved in nonadaptive settings. For example, Barnett and Koslowski (2002) presented experienced restaurant managers and business consultants without any experience in the hospitality industry with problems relating to the management of hypothetical restaurants. The specific problems were novel to both groups of participants, however, so Barnett and Koslowski considered them to represent transfer problems.

Notwithstanding their lack of domain-specific expertise, the business consultants were found to outperform the restaurant managers, suggesting perhaps that the consultants were "adaptive" experts whereas the managers' expertise was more "routine." Further analysis identified the amount of prior consulting history (i.e., strategic business advisory experience) as the crucial variable underlying the performance difference. A principal characteristic of business consulting, in turn, is the extreme breadth and variability of the problems that consultants tend to encounter. Barnett and Koslowski (2002) therefore concluded that "a possible explanation for the observed differences is…the wide variety of business problem-solving experience to which the consultants, but not the restaurant managers, have been exposed" (p. 260).

We therefore propose that adaptive expertise does not differ qualitatively from routine expertise and that the observed differences in transfer ability and conscious control are best explained within known principles of knowledge and expertise.

By implication, we point to the known effects of training regime on the breadth of transfer as the preferred alternative to avoid expert brittleness and inflexibility. Lewandowsky, Little, and Kalish (2007) recently summarized the variables that facilitate transfer. For example, transfer tends to be better after learning that requires participants to generate solutions to problems or actively test hypotheses, as compared with transfer after rote learning; transfer is proportional to the breadth of problems considered during training; and transfer is facilitated by self-initiated discovery of similarities between tasks or problems (see Lewandowsky et al., 2007, for more detail).

In summary, the type of practice engaged in when developing expertise may affect its ultimate flexibility. Focus on the refinement of procedures to produce automatic performance may lead to reduced conscious control of performance and is therefore more at risk of error in new situations. By contrast, practice strategies that involve the investment of cognitive strategies into problem solving and create a deeper understanding of problems within a domain, rather than simply enhancing efficiency of performance, may be more resistant to inflexibility (Bereiter & Scardamalia, 1993).

The crucial issue, then, becomes one of balance between those two broad strategies—not only during the acquisition of expertise but also subsequently, when experts must detect anomalies and revert back to consciously controlled performance and therefore regain some degree of flexibility.

ACKNOWLEDGMENTS

Preparation of this chapter was facilitated by a Discovery Grant from the Australian Research Council to the first author and an Australian Professorial Fellowship to the first author.

REFERENCES

Abernethy, B. (1988). Dual-task methodology and motor-skills research—Some applications and methodological constraints. *Journal of Human Movement Studies, 14,* 101–132.

Anderson, J. R. (1988). Acquisition of cognitive skill. In A. Collins & E. E. Smith (Eds.), *Readings in cognitive science: A perspective from psychology and artificial intelligence* (pp. 362–380). San Mateo, CA: Morgan Kaufmann.

Anderson, J. R. (1992). Automaticity and the ACT* theory. *American Journal of Psychology, 105,* 165–180.

Baird, R. R. (2003). Experts sometimes show more false recall than novices: A cost of knowing too much. *Learning and Individual Differences, 13,* 349–355.

Barnett, S. M., & Koslowski, B. (2002). Adaptive expertise: Effects of type experience and the level of theoretical understanding it generates. *Thinking and Reasoning, 8,* 237–267.

Beilock, S. L., Wierrenga, S. A., & Carr, T. H. (2002). Expertise, attention, and memory in sensorimotor skill execution: Impact of novel task constraints on dual-task performance and episodic memory. *Quarterly Journal of Experimental Psychology Section A—Human Experimental Psychology, 55,* 1211–1240.

Bereiter, C., & Scardamalia, M. (1993). *Surpassing ourselves: An inquiry into the nature and implications of expertise.* La Salle, IL: Open Court.

Bilalic, M., McLeod, P., & Gobet, F. (2008). Inflexibility of experts—Reality or myth? Quantifying the Einstellung effect in chess masters. *Cognitive Psychology, 56,* 73–102.

Block, N. (1995). On a confusion about the function of consciousness. *Behavioural and Brain Sciences, 18*, 227–287.

Camerer, C. (1981). Gene conditions for the success of bootstrapping models. *Organizational Behaviour and Human Performance, 27*, 411–422.

Camerer, C. F., & Johnson, E. J. (1991). The process-performance paradox in expert judgement: How can experts know so much and predict so badly? In K. A. Ericsson & J. Smith (Eds.), *Toward a general theory of expertise: Prospects and limits* (pp. 195–217). New York: Cambridge University Press.

Charness, N. (1991). Expertise in chess: The balance between knowledge and search. In K. A. Ericsson & J. Smith (Eds.), *Toward a general theory of expertise: Prospects and limits* (pp. 39–63). New York: Cambridge University Press.

Charness, N., Krampe, R. T., & Mayr, U. (1996). The role of practice and coaching in entrepreneurial skill domains: An international comparison of life-span chess skill acquisition. In K. A. Ericsson (Ed.), *The road to excellence: The acquisition of expert performance in the arts, sciences, sports and games* (pp. 51–80). Mahwah, NJ: Erlbaum.

Charness, N., Tuffiash, M., Krampe, R., Reingold, E., & Vasyukova, E. (2005). The role of deliberate practice in chess expertise. *Applied Cognitive Psychology, 19,* 151–165.

Chase, W. G., & Ericsson, K. A. (1981). Skilled memory. In J. R. Anderson (Ed.), *Cognitive skills and their acquisition* (pp. 141–189). Mahwah, NJ: Erlbaum.

Chase, W. G., & Simon, H. A. (1973). Perception in chess. *Cognitive Psychology, 4,* 55–81.

Chi, M. T. H., Feltovich, P. J., & Glaser, R. (1981). Categorization and representation of physics problems by experts and novices. *Cognitive Science, 5,* 121–152.

de Bruin, A. B. H., Smits, N., Rikers, R. M. J. P., & Schmidt, H. G. (2008). Deliberate practice predicts performance over time in adolescent chess players and drop-outs: A linear mixed models analysis. *British Journal of Psychology, 99,* 473–497.

de Groot, A. D. (1965). *Thought and choice in chess.* The Hague, Netherlands: Mouton.

Dunbar, K. (1995). How scientists really reason: Scientific reasoning in real-world laboratories. In R. J. Sternberg & J. E. Davidson (Eds.), *The nature of insight* (pp. 365–395). Cambridge, MA: MIT Press.

Eccles, D. W. (2006). Thinking outside of the box: The role of environmental adaptation in the acquisition of skilled and expert performance. *Journal of Sports Science, 24,* 1103–1114.

Eccles, D. W., Walsh, S. E., & Ingledew, D. K. (2002). A grounded theory of expert cognition in orienteering. *Journal of Sport and Exercise Psychology, 24,* 68–88.

Ericsson, K. A, Patel, V., & Kintsch, W. (2000). How experts' adaptations to representative task demands account for the expertise effect in memory recall: Comment on Vicente and Wang (1998). *Psychological Review, 107,* 578–592.

Ericsson, K. A. (1996). The acquisition of expert performance: An introduction to some of the issues. In K. A. Ericsson (Ed.), *The road to excellence: The acquisition of expert performance in the arts, sciences, sports and games* (pp. 1–50). Mahwah, NJ: Erlbaum.

Ericsson, K. A. (2003). Memorizers are made, not born. *Trends in Cognitive Science, 7,* 233–235.

Ericsson, K. A. (2005). Recent advances in expertise research: A commentary on the contributions to the special issue. *Applied Cognitive Psychology, 19,* 233–241.

Ericsson, K. A. (2007). Deliberate practice and the modifiability of body and mind: Toward a science of the structure and acquisition of expert and elite performance. *International Journal of Sport Psychology, 38,* 4–34.

Ericsson, K. A., Charness, N., Feltovich, P., & Hoffman, R. (Eds.). (2006). *Cambridge handbook of expertise and expert performance.* Cambridge, UK: Cambridge University Press.

Ericsson, K. A., Chase, W., & Faloon, S. (1980). Acquisition of a memory skill. *Science, 208,* 1181–1182.

Ericsson, K. A., Delaney, P. F., Weaver, G. A., & Mahadevan, S. (2004). Uncovering the structure of a memorist's superior "basic" memory capacity. *Cognitive Psychology, 49,* 191–237.

Ericsson, K. A., Krampe, R. T., & Tesch-Römer, C. (1993). The role of deliberate practice in the acquisition of expert performance. *Psychological Review, 100,* 363–406.

Ericsson, K. A., & Lehmann, A. C. (1996). Expert and exceptional performance: Evidence of maximal adaptation to task constraints. *Annual Review of Psychology, 47,* 273–305.

Ericsson, K. A., & Polson, P. G. (1988). An experimental analysis of the mechanisms of a memory skill. *Journal of Experimental Psychology: Learning, Memory and Cognition, 14,* 305–316.

Ericsson, K. A., Roring, R. W., & Nandagopal, K. (2007a). Giftedness and evidence for reproducibly superior performance: An account based on the expert performance framework. *High Ability Studies, 18,* 3–56.

Ericsson, K. A., Roring, R. W., & Nandagopal, K. (2007b). Misunderstandings, agreements, and disagreements: Toward a cumulative science of reproducibly superior aspects of giftedness. *High Ability Studies, 18,* 97–115.

Feng, J., Spence, I., & Pratt, J. (2007). Playing an action video game reduces gender differences in spatial cognition. *Psychological Science, 18,* 850–855.

Frensch, P. A., & Sternberg, R. J. (1989). Expertise and intelligent thinking: When is it worse to know better? In R. J. Sternberg (Ed.), *Advances in the psychology of human intelligence* (Vol. 5, pp. 157–188). Mahwah, NJ: Erlbaum.

Freund, H. J. (1983). Motor unit and muscle activity in voluntary motor control. *Physiological Review, 63,* 387–436.

Gick, M. L., & Holyoak, K. J. (1983). Schema induction and analogical transfer. *Cognitive Psychology, 15,* 1–38.

Gobet, F., & Simon, H. A. (1996a). The roles of recognition processes and look-ahead search in time-constrained expert problem solving: Evidence from grandmaster level chess. *Psychological Science, 7,* 52–55.

Gobet, F., & Simon, H. A. (1996b). Templates in chess memory: A mechanism for recalling several boards. *Cognitive Psychology, 31,* 1–40.

Gobet, F., & Simon, H. A. (2000). Five seconds or sixty? Presentation time in expert memory. *Cognitive Science, 24,* 651–682.

Gobet, F., & Waters, A. J. (2003). The role of constraints in expert memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 29,* 1082–1094.

Gott, S. P., Hall, E. P., Pokorny, R. A., Dibble, E., & Glaser, R. (1993). A naturalistic study of transfer: Adaptive expertise in technical domains. In D. K. Detterman & R. J. Sternberg (Eds.), *Transfer on trial: Intelligence, cognition and instruction* (pp. 258–263). Norwood, NJ: Ablex.

Grabner, R. H., Stern, E., & Neubauer, A.C. (2007). Individual differences in chess expertise: A psychometric investigation. *Acta Psychologica, 124,* 398–420.

Gray, R. (2004). Attending to the execution of a complex sensorimotor skill: Expertise difference, choking, and slumps. *Journal of Experimental Psychology: Applied, 10,* 42–54.

Green, C. S., & Bavelier, D. (2003). Action video game modifies visual selective attention. *Nature, 423,* 534–537.

Hinds, P., Patterson, M., & Pfeffer, J. (2001). Bothered by abstraction: The effect of expertise on knowledge transfer and subsequent novice performance. *Journal of Applied Psychology, 86,* 1232–1243.

Homa, D. (1983). An assessment of two "extraordinary" speed-readers. *Bulletin of the Psychonomic Society, 21,* 123–126.

Jensen, A. R. (1990). Speed of information processing in a calculating prodigy. *Intelligence, 14,* 259–274.

Johnson, E. J. (1988). Expertise and decisions under uncertainty: Performance and process. In M. L. H. Chi, R. Glaser & M. J. Farr (Eds.), *The nature of expertise* (pp. 209–228). Mahwah, NJ: Erlbaum.

Johnson, P. E., Grazioli, S., Jamal, K., & Zualkernan, I. A. (1992). Success and failure in expert reasoning. *Journal of Organizational Behaviour and Human Decision Processes, 53,* 173–203.

Keele, S. W., & Irvy, R. I. (1987). Modular analysis of timing in motor skill. In G. H. Bower (Ed.), *The psychology of learning and motivation* (Vol. 21, pp. 183–228). San Diego, CA: Academic Press.

Keith, N., & Ericsson, K. A. (2007). A deliberate practice account of typing proficiency in everyday typists. *Journal of Experimental Psychology: Applied, 13,* 135–145.

Kimball, D. R., & Holyoak, K. J. (2000). Transfer and expertise. In E. Tulving & F. I. M. Craik (Eds.), *The Oxford handbook of memory* (pp. 109–122). London: Oxford University Press.

Kirsh, D. (1995). The intelligent use of space. *Artificial Intelligence, 73,* 31–68.

Leavitt, J. L. (1979). Cognitive demands of skating and stick handling in ice hockey. *Canadian Journal of Applied Sports Science, 4,* 46–55.

Lewandowsky, S., & Kirsner, K. (2000). Knowledge partitioning: Context-dependent use of expertise. *Memory & Cognition, 28,* 295–305.

Lewandowsky, S., Little, D., & Kalish, M.L. (2007). Knowledge and expertise. In F. T. Durso (Ed.), *Handbook of applied cognition* (pp. 83–110). Hoboken, NJ: Wiley.

Locke, E. A., & Latham, G. P. (1990). *A theory of goal setting and task performance.* Englewood Cliffs, NJ: Prentice Hall.

Logan, G. D. (1988). Toward an instance theory of automatization. *Psychological Review, 95,* 492–527.

Marchant, G., Robinson, J., Anderson, U., & Schadewald, M. (1991). Analogical transfer and expertise in legal reasoning. *Organizational Behaviour and Human Decision Processes, 48,* 272–290.

Medin, D., Ross, B. H., & Markman, A. B. (2001). *Cognitive psychology* (3rd ed.). Chichester, UK: Wiley.

Miller, G. A. (1956). The magical number seven, plus or minus two: Some limits on our capacity for processing information. *Psychological Review, 63,* 81–97.

Moors, A., & De Houwer, J. (2006). Automaticity: A theoretical and conceptual analysis. *Psychological Bulletin, 132,* 297–326.

Mylopoulus, M., & Regehr, G. (2007). Cognitive metaphors of expertise and knowledge: Prospects and limitations for medical education. *Medical Education, 41,* 1159–1165.

Norman, G. R., Brooks, L. R., Coblentz, C. K., & Babcook, C. J. (1992). The interdependence of feature and category identification in diagnostic radiology. *Memory & Cognition, 20,* 344–355.

Novick, L. R. (1988). Analogical transfer, problem similarity and expertise. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 14,* 510–520.

Novick, L. R., & Holyoak, K. J. (1991). Mathematical problem solving by analogy. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 17,* 398–415.

Patel, V. L., Kaufman, D. R., & Magder, S. (1996). The acquisition of medical expertise in complex dynamic decision-making environments. In K. A. Ericsson (Ed.), *The road to excellence: The acquisition of expert performance in the arts and sciences, sports and games* (pp. 127–165). Mahwah, NJ: Erlbaum.

Reingold, E. M., Charness, N., Pomplun, M., & Stampe, D. M. (2001). Visual span in expert chess players: Evidence from eye movements. *Psychological Science, 12*, 48–55.

Reingold, E. M., Charness, N., Schultetus, R. S., & Stampe, D. M. (2001). Perceptual automaticity in expert chess players: Parallel encoding of chess relations. *Psychonomic Bulletin and Review, 8,* 504–510.

Richman, H. B., Staszewski, J. J., & Simon, H. A. (1995). Simulation of expert memory using EPAM IV. *Psychological Review, 102,* 305–330.

Roring, R. W., & Charness, N. (2007). A multilevel model analysis of expertise in chess across the lifespan. *Psychology and Aging, 22,* 291–299.

Rossano, M. J. (2003). Expertise and the evolution of consciousness. *Cognition, 89,* 207–236.

Saariluoma, P. (1990). Apperception and restructuring in chess players' problem solving. In K. J. Gilhooly, M. T. Keana, R. H. Logie, & G. Erdos (Eds.), *Lines of thinking: Reflections on the psychology of thought* (Vol. 2, pp. 41–57). Oxford, UK: Wiley.

Salthouse, T. A. (1984). Effects of age and skill in typing. *Journal of Experimental Psychology: General, 13,* 345–371.

Salthouse, T. A. (1991). Expertise as the circumvention of human processing limitations. In K. A. Ericsson & J. Smith (Eds.), *Toward a general theory of expertise: Prospects and limits* (pp. 286–300). New York: Cambridge University Press.

Santtila, P., Korpela, S., & Häkkänen, H. (2004). Expertise and decision-making in linking car crime series. *Psychology, Crime & Law, 10,* 97–112.

Savelsbergh, G. J. P., Williams, A. M., & Van Der Kamp, J. (2002). Visual search, anticipation and expertise in soccer goalkeepers. *Journal of Sports Sciences, 20,* 279–287.

Schwartz, S., & Griffin, T. (1986). Evaluating medical information. In *Medical thinking: The psychology of medical judgement and decision making* (pp. 59–96). New York: Springer-Verlag.

Shanteau, J., & Stewart, T. R. (1992). Why study expert decision making? Some historical perspectives and comments. *Organizational Behaviour and Human Decision Processes, 53,* 95–106.

Simon, H. A., & Gilmartin, K. J. (1973). A simulation of memory for chess positions. *Cognitive Psychology, 5,* 29–46.

Simonton, D. K. (2007). Talent "and" expertise: The empirical evidence for genetic endowment. *High Ability Studies, 18,* 83–84.

Simonton, D. K. (2008). Scientific talent, training, and performance: Intellect, personality, and genetic endowment. *Review of General Psychology, 12,* 28–46.

Sims, V. K., & Mayer, R. E. (2002). Domain specificity of spatial expertise: The case of video game players. *Applied Cognitive Psychology, 16,* 97–115.

Smith, M. D., & Chamberlin, C. J. (1992). Effect of adding cognitively demanding tasks on soccer skill performance. *Perceptual and Motor Skills, 75,* 955–961.

Speelman, C. P., & Kirsner, K. (1997). The specificity of skill acquisition and transfer. *Australian Journal of Psychology, 49,* 91–100.

Staszewski, J. J. (1993). A theory of skilled memory. In *Proceedings of the 15th Annual Conference of the Cognitive Science Society* (pp. 971–975). Mahwah, NJ: Erlbaum.

Sternberg, R. J. (1996). Costs of expertise. In K. A. Ericsson (Ed.), *The road to excellence: The acquisition of expert performance in the arts and sciences, sports and games* (pp. 347–354). Mahwah, NJ: Erlbaum.

Sternberg, R. J., & Frensch, P. A. (1992). On being an expert: A cost-benefit analysis. In R. R. Hoffman (Ed.), *The psychology of expertise: Cognitive research and empirical AI* (pp. 191–203). New York: Springer-Verlag.

Taylor, J. (1988). Slumpbusting: A systematic analysis of slumps in sports. *Sport Psychologist, 2,* 39–48.

Thompson, C. P., Cowan, T. M., & Frieman, J. (1993). *Memory search by a memorist.* Mahwah, NJ: Erlbaum.

Thompson, C. P., Cowan, T. M., Frieman, J., Mahadevan, R. S., Vogl, R. J., & Frieman, J. (1991). Rajan: A study of a memorist. *Journal of Memory and Language, 30,* 702–724.

Tuffiash, M., Roring, R. W., & Ericsson, K. A. (2007). Expert performance in SCRABBLE: Implications for the study of the structure and acquisition of complex skills. *Journal of Experimental Psychology: Applied, 13,* 124–134.

Unsworth, N., & Engle, R. W. (2007). On the division of short-term working memory: An examination of simple and complex span and their relation to higher order abilities. *Psychological Bulletin, 133,* 1038–1066.

Unterrainer, J. M., Kaller, C. M., Halsband, U., & Rahm, B. (2006). Planning abilities and chess: A comparison of chess and non-chess players on the Tower of London task. *British Journal of Psychology, 97,* 299–311.

Wiley, J. (1998). Expertise as mental set: The effects of domain knowledge in creative problem solving. *Memory & Cognition, 26,* 716–730.

Zimmerman, B. J. (2006). Development and adaptation of expertise: The role of self-regulatory processes and beliefs. In K. A. Ericsson, N. Charness, P. Feltovich, & R. Hoffman (Eds.), *Cambridge handbook of expertise and expert performance* (pp. 705–722). Cambridge, UK: Cambridge University Press.