Theoretical Perspectives, Methodological Approaches, and Trends in the Study of Expertise

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Abstract This chapter begins by briefly overviewing the early approaches, perspectives, and findings in the expertise research. Basically, the approaches have first focused on exceptional experts, then studies evolved into studying expert performance relative to novices, with emphases on differences in their strategies of searching for a solution, the structure of knowledge, and finally in representation. Then three constructs emphasized in current research on expertise are described. These constructs are ideas about deliberate practice, adaptive expertise, and team expertise. The last section of the chapter proposes a new perspective for understanding the acquisition of expertise, which is the idea of a perspective shift. Interleaved throughout the chapter is discussion of how the acquisition of expertise can be facilitated and/or accelerated.

Keywords Expertise trends · Perspective shift · Theoretical models

Research on expertise has spanned several decades. Because so many chapters and edited volumes have been written about expertise (see for example, Ericsson, Charness, Feltovich, & Hoffman's 2006, *Cambridge Handbook of Expertise and Expert Performance*), the goal of this chapter is not to review the many studies on expertise. Instead, the first part of this chapter overviews very briefly the evolution of the research focus and perspectives for the last four or so decades. The second part of this chapter highlights the new constructs that are currently being explored about expertise. The final section offers a new idea for how the acquisition of expertise might be facilitated, the construct of a perspective shift.

Retrospective for the Past Three Decades

Researchers and lay people have always been fascinated by experts and exceptional individuals. In the early days, exceptional individuals have been identified as those

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individuals who are generally recognized and acknowledged by the public as great people, such as popular composers (Kozbelt, 2004) and scientists who made great discoveries (Chi & Hausmann, 2003), and so on. Studying exceptional individuals has been referred to as an absolute approach (Chi, 2006).

Studying Exceptional Experts

There were four types of studies of exceptional individuals. One type of studies described how they went about making their discoveries, by studying their notes and diaries. These studies tried to capture when a discovery was made and under what circumstances. The goal was to try and capture the cognitive processes underlying their discoveries (Nersessian, 1992; Tweney, 1989).

A second type of studies looked at the societal and environmental conditions that may have led to their superiority, such as their age of onset, their productivity profile, and their parental influences (Lehman, 1953). A third type of studies tacitly assumed that there is some innate talent or mental capacity to their greatness (Simonton, 1977), so such studies might investigate differences in their cognitive structures, such as that exceptional individuals might have a larger memory capacity (Pascual-Leone, 1978).

A final type of studies looked at how exceptional individuals perform in the tasks in which they excel. For example, one might document and marvel at how a single chess master can play many different games with many different players while blindfolded (Binet, 1894), or how a great physician can diagnose a disease accurately and quickly (Elstein, Shulman, & Sprafka, 1978; Barrows, Norman, Neufeld, & Feightner, 1982; Neufeld, Norman, Barrows, & Feightner, 1981). In general, when only exceptional individuals are being examined, it is difficult to validate or refute hypotheses about how they became experts.

A Difference in Search Strategies

By the early seventies, the study of expertise introduced two new perspectives. One new perspective is methodological, in that expertise studies introduced the relative approach (Chi, 2006). A relative approach contrasts the performance of a more advanced individual (referred to as the experts) with the performance of a more novice individual. There are several advantages to the relative approach. First, the relative approach makes the tacit assumption that a novice can become an expert, because an expert is no longer viewed as a uniquely exceptional individual. Rather, an expert is someone who is relatively more advanced, as measured in a number of ways, such as academic qualifications, years of experience on the job, consensus among peers, assessment based on some external independent task, or assessment of domain-relevant content knowledge. Second, a relative approach also frees up the constraint of making sure that the level of expertise across studies are defined in exactly the same identical way, since a relative approach can tell us in what ways an expert excels over a novice, even without equating the index of expertise across studies. Third, a relative approach defines expertise by the experts' knowledge, and not by any innate hardwired capacity.

The second perspective that was introduced in the seventies was theoretical, due to the advent of computers. This new perspective – an information processing approach, required a task analysis, that is, the decomposition of a complex task such as problem solving, into three components: (a) the relevant background knowledge, (b) the problem solving strategies or ways of searching through the space of all possible moves. and (c), understanding or representing the problem in terms of a space of all possible moves. To elaborate, the first component of relevant background knowledge refers to the amount of knowledge one has, indexed in some objective way. So for instance, an expert might have more knowledge because s/he has taken four algebra courses, whereas a novice might be someone who is just starting to take algebra.

The second component of problem solving strategies can be explained more easily after we define the third component – the representation of a problem. The representation of a well-defined problem consists of its elements, all the permissible operators that can operate on the steps of the problem, the constraints on the operators, and the goal of a problem. A representation of a problem usually refers to knowing the elements in the problem, the allowable operators, the constraints on the operators and the goal. The degree to which one has a complete representation of all the components of a problem essentially is a measure of how well a student understands a problem, because knowing the elements, the permissible operators, the constraints on the operators and the goal, allows one to generate a complete representation (or problem space) of all the permissible moves. Essentially it means being able to represent the entire problem space of solution steps.

To illustrate, suppose a learner is asked to solve an algebra equation $5X + 2X + 10 = 31$ for X. What is the representation of such a problem? A representation consists of the elements, the permissible operators, the goal and so forth. Figure 1 is a partial problem space of some of the permissible moves for this problem. The permissible operators in this problem are moving numbers from one side to the other side of the equal sign, adding, subtracting, multiplying and dividing; and the goal is finding X. More specifically, the space of all possible moves are: moving the 10 to the right of the equal sign (see the first step in the last column of Fig. 1), subtracting 10 from 31, putting parenthesis around $(5 + 2)$ then multiply by X, and so forth. However, it is not permissible to decouple the X from the 2, as in making an operation such as $2(X + 10)$ from $2X + 10$. These types of student errors can typically be characterized as errors in not knowing the constraints on the operators. In any case, representing the problem means knowing all the possible moves, knowing the elements, the constraint, and so forth. Successfully solving this well-defined problem can be conceived of as finding the right path that leads to the correct solution.

The second component of a representation refers to the problem solving strategies of how one searches the problem space of all possible moves. Looking at the problem space shown in Fig. 1, one can search from top-down (or forward strategy), starting from the given equation and moving toward the goal of finding X, or one

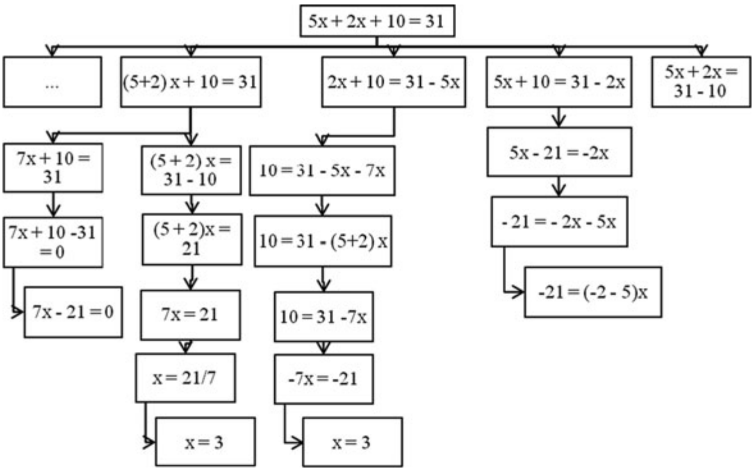

Fig. 1 A partial search space

can search bottom-up in the figure (meaning a backward strategy), starting with the goal, and working backward. Alternatively, an efficient way to search is to create a sub-goal so that it reduces the portion of the space that has to be searched. Suppose one sets a sub-goal of grouping all the X-terms. Such a sub-goal would eliminate taking the second and third path at the first level of search.

Using this knowledge-search strategy-representation framework, it was typically assumed back in the seventies, that the first and third components of problem solving – knowledge and its representation, were not significant factors that differentiated experts from novices because the problems used in problem solving research were often knowledge-lean puzzle-type problems, such as the Tower of Hanoi. For the Tower of Hanoi, the elements are the disks, the operators are the moves by each disk, and the constraints are rules such as that a larger disk is not permitted to be set on top of a smaller disk. These elements, operators and constraints are often in fact given in the problem statement, so that a complete representation can be easily generated without applying any other background knowledge. For example, for the Tower of Hanoi problem, the goal is to move a stack of three disks, one at a time, from the first peg to the last peg; and the constraints on the operators is that only one disk can be moved at a time, and a larger disk may not be put on top of a smaller disk. As can be seen in Fig. 2, it is quite simple to generate a problem space of solution steps for the Tower of Hanoi problem. (Fig. 2 shows the complete problem space of all possible moves.) Thus, understanding such a problem in the sense of representing the entire problem space is not a difficult task. Therefore, solving such a problem becomes an issue of searching for the optimum path through the problem space of different solution steps. Little background knowledge is needed in order to know how to begin to solve such a puzzle, since these puzzle-like problems required little knowledge that is not already given. In short, it is not surprising that problem solving research back then focused on the strategies by which the problem space was being searched.

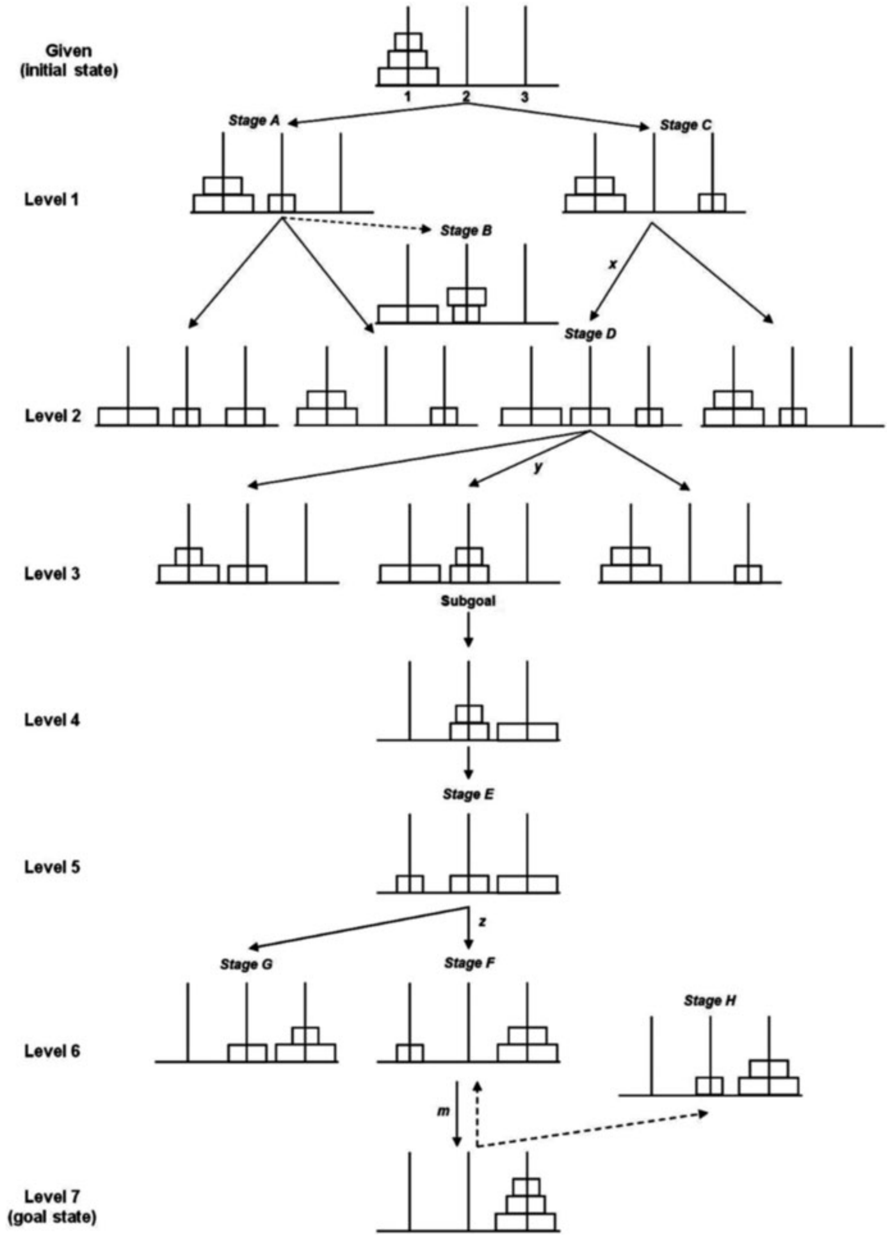

Fig. 2 A complete search space for the Tower of Hanoi problem

A Difference in the Structure of Knowledge

When researchers began to study problem solving beyond puzzle problems and focused instead on academic disciplines, such as mathematics and physics, they carried over the assumptions of solving puzzle problems. That is, they continued to ignore potential differences in representation. Therefore, the findings of such studies continued to conclude that expert and novice physics problem solvers differed in their problem solving performance primarily in the way they search their problem space. Figure 3a depicts the view that experts' superior knowledge may have dictated a difference in their search strategies in that their strategies might be superior to the novices' strategies. This approach was fostered by the work of Simon and Simon (1978). Figure 3a also shows a question mark in terms of whether or

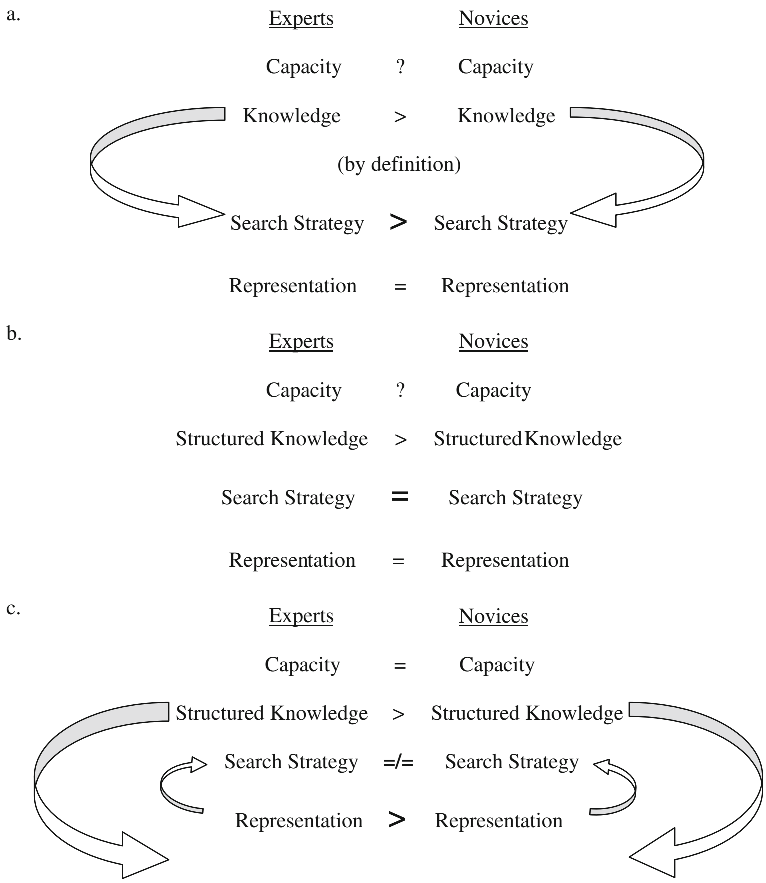

Fig. 3 Assumptions about differences in problem solving components between experts and novices

not experts' innate capacity is any different from novices, as there was no direct evidence as yet.

The idea that experts and novices differed primarily in their search strategies violated some findings in the chess literature. In non-toy and knowledge-rich domains, such as chess, it became apparent that search strategies per se did not differ significantly between experts and novices. For example, deGroot (1966) found that Master chess players searched the representation of all possible chess moves only to a depth of two or three levels, much as novice players would. Therefore, a competing assumption was that experts and novices have similar search strategies. Moreover, the representation of all possible chess moves continue to be assumed to be equivalent between experts and novices since they can be easily generated, once a player knows what are the allowable moves. These alternative set of assumptions are depicted in Fig. 3b.

From Fig. 3b, it seems that the only remaining difference between experts and novices is the knowledge component. It did not seem adequate to simply claim that experts had more knowledge. The relevant question remained: how does an expert's greater knowledge facilitate their superior performance, in terms of any kind of measures, such as speed, efficiency, search strategies, and so forth. The classic study by Chase and Simon (1973) on chess expertise basically proposed that what differed between experts and novices was not merely the amount of knowledge in a specific domain, but more importantly, how that knowledge is structured. Moreover, they refuted the idea of an innate difference in mental structures. For example, they showed that both experts and novices can recall about the same number of chess pieces and their locations if the chess pieces were randomly placed on a chessboard, suggesting that their memory capacity for chess piece locations were the same. However, if the chess pieces were placed in the context of meaningful plays, then the experts far outperformed the novices in recalling the location and identity of the chess pieces. These two types of studies put to rest the ideas that exceptional individuals have better mental capacities and more superior search strategies. Instead, these studies highlighted the importance of structured domain-relevant knowledge, as indicated in Fig. 3b.

How is domain knowledge structured? The Chase and Simon work began to capture what is the structure of greater knowledge in the chess domain. One analysis of structure was the idea of "chunks", which is a cluster of related pieces that are often placed in proximity on a chessboard. Thus these chess chunks were visual patterns. The concept of "chunks" can of course be extended to many other domains. For instance, a 3-digit number such as 100 is an important chunk or a meaningful unit to an adult, but perhaps not to a child (Chi, 1976). The concept of the structure of knowledge was important because it attempted to explain how greater knowledge can have a bearing on task performance. In the context of memory for chess board pieces, it explained how recall was a function of the size of chunks, and therefore, even if experts and novices could recall the same number of chunks, experts' chunk structures were larger, therefore accounted for their superior recall in terms of pieces. Many other studies followed in identifying and capturing the structure of domain knowledge.

A Difference in Representation

Beyond the context of recall of chess pieces, how might knowledge influence performance in more academic domains such as problem solving in mathematics or physics? In attempting to answer this question, researchers in the early eighties turned to the third component of problem solving. The third component is the component of the representation of a problem. It turns out that when the domain is not a toy domain but an academic domain, representing a problem is quite difficult, and expert and novice problem solvers focused on different elements within a problem when representing it. Chi, Feltovich, and Glaser (1981) found, for instance, that when given the same description of a physics problem to solve, advanced graduate students represented the deep principle-based aspects of a common routine physics problem whereas novice students represented the superficial surface elements of a problem, such as whether it described an inclined plane, a pulley, or friction. This representational difference can be captured by looking at what problems novices and experts considered to be similar. Figure 4a depicts the diagrams of two pairs of problems that novices considered to be similar; notice that their judgments are based on similarity in the concrete elements describe in the problem situations, such as round disks or inclined planes. Experts, on the other hand, tended to consider problems to be similar if they are governed by the same underlying principles. Figure 4b shows two pairs of problems advanced physics students considered to be similar even though they have dissimilar surface or concrete elements; but they do share similar deep principles, such as problems solvable requiring a consideration of energy, or "work is lost somewhere," or by Newton's Second Law.

The finding of representational differences between experts and novices has immediate and far-reaching implications. The immediate implication for expertise research was that such representational differences obviously dictated why experts and novices appeared to search the problem space differently. The difference reflects a difference in their representations, so it is not the case that experts and novices have the same problem space to search, as is commonly assumed back then in the problem solving literature, especially for knowledge-lean problems. In other words, the differences between experts and novices in their representations of the same problem dictated and resulted in different searches in their problem spaces. Essentially, this refuted the assumption made in earlier expertise research that the problem representation of experts and novices were the same, which was a legitimate assumption for toy domains but not for knowledge-rich academic domains. Thus, the origin of search differences that were uncovered by studies such as Simon and Simon's (1978), is their representations as a function of prior knowledge, and not in a difference in search strategies per se. Figure 3c depicts the assumptions of this revised view that knowledge differences allowed experts and novices to represent a given problem differently, which in turn then dictated the kind of search strategies they would use for solving the problem, which may or may not be the same. Since the eighties, representational differences between experts and novices have since been

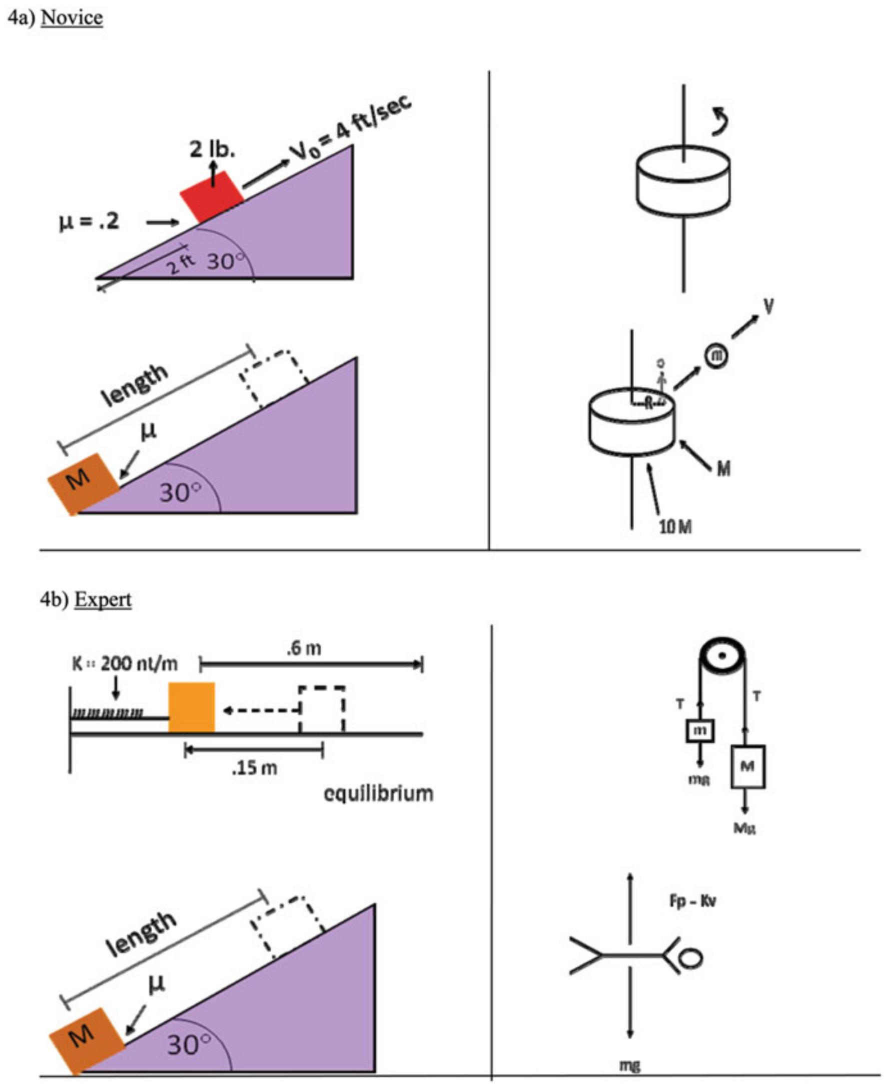

Fig. 4 Pairs of problems that novices (**a**) and experts (**b**) considered to be similar

replicated in many studies and many domains. The idea that experts and novices differ in the depth of their representations was characterized in many subsequent studies on expertise in many different domains.

A far-reaching implication of representational differences between experts and novices is that this means that teachers will generally have a normatively correct and deeper representation of a topic or concept they are teaching, whereas novice students will have a naïve, shallow, and incomplete representation. The consequence of such lack of correspondence between the representations of teachers and students will undoubtedly lead to misunderstanding of a teacher's explanations. We have shown consistently in tutoring work that students have difficulty learning from hearing a tutor's explanations, whereas they learn better when the tutor scaffolds them (Chi, Roy, & Hausmann, 2008). This inefficiency of explanations may be caused by the lack of correspondence in representations.

Issues of Training

The focus on academic domains also brought to fore the idea that expertise should be an attainable skill that novices should aspire to attain. Therefore, changes in the conception of expertise in the literature also led to research that took much more of a relative approach, in that, one should contrast more expert-like performers with less expert-like performers, and not necessarily focus on the performance of exceptional experts. Therefore, many studies could simply contrast advanced students with less advanced students, since such contrasts could potentially inform us on ways to advance a novice student to be more skillful.

The critical question remains as to how one becomes an expert in the sense of being able to represent a problem deeply. Little progress had been advanced to understand this difficult issue. Although some attempts have been made to directly teach novice students the way experts categorize problems or to directly teach them to relate key words or explicit cues with one of the deep physics principle (Dufresne, Gerace, Hardiman, & Mestre, 1992), it doesn't appear as if this kind of training can accelerate or shortcut the achievement of expertise readily, which is typically claimed as requiring 10 years of practice, at minimum. In other words, to be more specific, when a novice reads a physics problem statement, such as that

> A block of mass M1 is put on top of a block of mass M2. In order to cause the top block to slip on the bottom one, a horizontal force F1 must be applied to the top block. Assume a frictionless table, find the maximum horizontal,

the explicit words in the problem statement itself does not elicit the relevant deep physics principles. However, it is not the case that novices cannot identify the relevant and important key words: In fact, novices can identify the relevant and important key words in a problem statement quite adequately, as shown in Chi, Glaser, and Rees (1982, Study 8). The issue is that the key words themselves do not lead novices to make further inferences as they do for experts. In our data, we found that a keyword such as "frictionless" would lead an expert to infer that there are "no dissipative forces", which in turn led the expert to further infer that it's a "Conservation of Momentum" problem. In short, the key words themselves do not directly evoke the correct underlying principles; instead, intermediary or secondary cues are first derived from the key words. If this is true, then it is not clear how we can teach students to directly associate key words with the underlying physics principles, and expect deep understanding, without also teaching them how to derive the secondary cues from the keywords. If we must teach them how to derive the secondary cues from the keywords, then such instruction may not necessarily accelerate the acquisition of expertise.

Another example can illustrate the potential flaw of this intervention approach of directly teaching the relationship between the keywords and the principle. In a study of 32 expert physicians in four different specialties (cardiologists, hematologists, infectious disease specialists, and internists), we presented them with individual patient cases and asked them to diagnose the disease of the patient cases and give reasons for their diagnoses (Hashem, Chi, & Friedman, 2003). We then coded the number of cues in the cases that they used to come up with their diagnoses. We found that when a case matches the physicians' specialty so that they have expertise (such as a blood disease case diagnosed by a hematologist), they tended to use multiple cues in the case statement to come up with the diagnoses. However, when the case does not match their specialty (so that they are more novice), then they tended to use only single cues to come up with the hypothesized diagnoses. Presumably, using multiple cues is more accurate and physicians with more expertise in a case were able to use multiple cues. Table 1 shows the frequency with which they used single cues versus multiple cues as a function of whether the cases matched or did not match their specialties. With respect to the training question raised above, does this mean that we can accelerate the acquisition of expertise by teaching physicians to use multiple cues? It does not seem obvious that one can accelerate the association between cues and hypothesized diagnoses by telling physicians what the cues are, since presumably they were taught the cues already. Perhaps expertise involves not only the detection of individual cues within a case, but in addition, perhaps the acquisition of expertise requires the development of knowledge of the interaction of multiple cues and their relationship to a specific diagnosis.

In summary, this section raced through three decades of work on expertise by highlighting the underlying assumptions and conclusions of the different theoretical and methodological perspectives and approaches to the study of expertise. Expertise was always defined as having more knowledge, but knowledge originally played a very minor role. Instead, expertise was defined by one's ability to search efficiently and effectively. In light of new evidence, it became clear that expertise did not necessarily result in more efficient searches, rather expertise can be defined as having more structured knowledge. Structured knowledge in turn dictated how experts represented a to-be-solved problem. Thus, the differences in the representation between

Table 1 The use of single or multiple cues as a function of the match between the case to-be-diagnosed and the physician's specialty (data taken from Hashem et al., 2003)

Cues and Specialty		
	Cases match their specialty	Cases outside their specialty
Single cues	29	190
Multiple cues	61	45

experts and novices dictated how they searched. Finally, we still have no obvious insights about how expertise can be taught, or how we can accelerate the acquisition of expertise.

The Current Constructs

Many questions remain about expertise, such as how to accelerate and facilitate its acquisition. Three new constructs have been introduced and emphasized in the last decade. The first construct is the idea of deliberate practice, attempting to answer the question of how some individuals reach elite status of expertise and others remain mediocre. The second construct is the idea of adaptive expertise, exploring the notion of a more innovative expert, one who is not rigid and conventional. The third construct is the idea of a team, group, or system-level expertise, bringing forth new challenges in understanding how an expert team can be construed, since an expert team does not appear to be composed of expert individuals, measured either in terms of a team's performance or learning. These three constructs are explored briefly in this section.

Deliberate Practice

Deliberate practice is a construct advanced primarily by Ericsson (Ericsson & Lehmann, 1996). The construct was introduced to account for the fact that not all experts achieve elite status, some remain mediocre in the sense that some individuals are satisfied in reaching an acceptable level of performance and continue in maintaining that level of performance with minimal effort for years on end. In understanding how some individuals reach elite status, Ericsson proposed the construct of "deliberate practice." The assumption is that those experts who reach elite status are the ones that engage in deliberate practice, even though they spend about the same amount of time practicing as non-elite experts.

Deliberate practice is defined as expanding intentional efforts to achieve further improvement through focused, concentrated, well-structured, programmatic, and goal-oriented practice. Moreover, the goals of practice are set to go beyond one's current level of achievement, and evaluated by identification of errors, and so on. For example, elite figure skaters spent more time on challenging jumps than less elite skaters; the interpretation of this kind of practice is that they intentionally attempt to achieve more challenging jumps in order to improve and move themselves up in their level of expertise (Deakin & Cobley, 2003). They seek challenges because they view failures as opportunities to improve. Deliberate practice is contrasted with mindless performance or playful engagement (p. 15), or "merely executing proficiently during routine work" (Ericssson, 2006, p. 683, Chapter 38, *Handbook*). As Ericsson (2006, p. 691) puts it, "Those select group of individuals who eventually reach very high levels do not simply accumulate more routine experiences of domain-related activities, but extend their active skill-building period for years or even decades." For example, musicians who are the more elite experts are the ones who concentrate on practicing with the intention of achieving beyond the level that they are currently capable of performing (Ericsson, Krampe, & Tesch-Romer, 1993). It is as if they are always reaching beyond their "zone of proximal" achievement.

Deliberate practice does involve many other players as well. It involves a coach or a teacher who designs the targeted practice task, who continually guides, monitors, and gives feedback to the expert in performing the task. Family members also play a huge role in helping their children develop elite expertise. According to Ericsson (2006), parents of elite experts are actively involved in helping them find a good teacher, helping them with their practice, spending large amounts of money for equipment, driving them to lessons, sometimes even relocating to be closer to a specific teacher or training opportunities. These parental involvement and sacrifices are reminiscent of parents of immigrant families, resulting in high success rates of immigrant children on measures such as college completion, but it is not clear whether children from immigrant families also achieve elite status. If not, then these parental factors may only guarantee success, but not necessarily elite expertise.

It is very difficult to say whether deliberate practice is the result of some personality or individual attributes, such as motivation or persistence, or whether it is the nature of the designed deliberate practice task that is critical for achieving elite status. For example, elementary and secondary students seem to fall into two types: intrinsically motivated versus extrinsically motivated (Dweck, 2000). Intrinsically motivated students persist through challenging tasks by adopting high-quality learning behaviors, while extrinsically-motivated students tend to adopt tasks and behavior that may produce rewards or satisfies the requirements without worrying about whether they have actually learned. In short, one type of learner might be more likely and inclined to engage in deliberate practice to achieve elite status.

If the hypothesis is true that some experts achieve elite status because of motivational or other reasons rather than the nature of deliberate practice itself, then we should see that having the guidance and help of a coach in designing tasks for students will not succeed with all students, because these alternative factors may come into play. Some related evidence might be interpreted in this context. In the Chi et al. (2008) study, an expert tutor guided 10 students individually in solving physics problems. These 10 students were asked to read and learn the relevant materials from which the to-be-solved physics problems were taken. After their independent unguided learning, they took a pre-test, so the pre-test in essence assessed how well they could learn on their own. All 10 students had similar background knowledge about physics. The hatched bars in Fig. 5 show the amounts the students could learn on their own (pre-test) and the dark bars show how much more the tutor could help the students gain. As Fig. 5 shows, not surprisingly, there is a difference in how much the sample of 10 students could learn on their own. What is surprising is that the poorest three students gained the least amount whereas both the intermediate students and the best students gained substantially more. What this data tells us is that the same tutor could not design guidance and feedback that

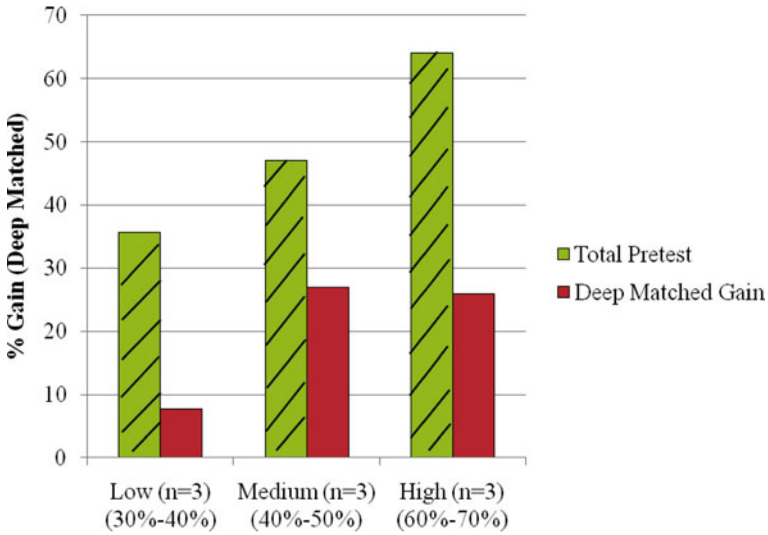

Fig. 5 Hatched bars show the tutees, divided into low (30–40%), medium (40–50%), and high (60–70%) on the basis of their pre-test scores, and the solid bars show how much they improved after tutoring

allows all the students to gain maximally. This suggests that individual differences in learning and/or differences in one's success in achieving elite expertise may not be caused by deliberate practice necessarily (although no doubt engaging in deliberate practice can help), but by a myriad of other factors, such as a desire to excel, persistence, ability to learn, and so forth. Thus, the basic question about achieving elite status is not answered by the finding that the elite experts undertake deliberate practice, because this finding basically regresses the basic question to another question of understanding why some individuals engage in deliberate practice while others do not.

Adaptive Expertise

The second construct that is currently intriguing scholars of expertise is the notion of an adaptive expert. The construct of an adaptive expert was introduced prominently by Hatano and Inagaki in 1986, as a contrast to a routine expert. Routine experts, according to Hatano and Inagaki (1986, p. 266) are experts who are efficient and are outstanding "in speed, accuracy, and automaticity of performance but lack flexibility and adaptability to new problems." Thus, routine experts are "able to complete school exercises quickly and accurately without understanding," whereas adaptive experts have "the ability to apply meaningfully learned procedures flexibly and creatively." (Hatano, 2003, p. xi).

Adaptive experts, in short, are ones who "understand" the procedure or skill, in the sense of understanding the principles and conceptual knowledge guiding the execution of the procedures or skills. With such deeper understanding, adaptive experts obviously can "generalize" their skills to other non-routine problems. Of course this definition of adaptive expertise requires further elaboration in defining what is meant by "understanding" and "generalization." Suppose we simply operationalize the meaning of "generalization" in an objective way without defining it, such as by measuring in some graded way a learner's ability to solve more and more distantly related problems. With such an operational definition of what "generalization" is, we can provide two senses of the term "adaptive expertise" that have been used in the literature. In so doing, we add our elaborations of what we think "understanding" means in each sense.

The first and most common idea of adaptive expertise is the notion of knowing not only how to execute or apply a procedural skill, but an adaptive expert is one who also has conceptual understanding of that skill (Schwartz, Lin, Brophy, & Bransford, 1999). This dichotomy of knowing a procedural skill versus having conceptual understanding of it exists at all stages of skill acquisition, not necessarily only at the expert level. Here is one way of thinking about it. Suppose we have a skill of solving a mathematical problem. The solution can be decomposed into a set of If-Then rules as follows:

> If A, Then do Y. [after doing Y, the resulting pattern is C];
> If C, Then do Z.

For example, if the unknown variables of Xs are on both sides of the equal sign (condition A), then use legitimate operators to move all the Xs onto one side of the equal sign (execute action Y). Now the resulting equation has changed the condition from A to C. Now If C is true, then action Z can be executed.

One can learn these two rules so well that one can solve all kinds of problems efficiently and accurately in applying these two rules when the problems are similar to the conditions of each rule (i.e., the A's and the C's), as in the case for routine experts. However, if the conditions presented change from A to A + B, then a routine expert would not know what to do. In order to know what to do when conditions A + B show up, one must have reflected on the If A, Then Y rule when one is acquiring it. Reflection can include numerous processes, such as self-explaining why action Y works when condition A is true, seeking what is the characteristics of A for Y to apply. For example, if A is the number 5, one can reflect on whether Y follows because A is a prime number, or because A is less than 10, and so forth. The idea is basically to construct knowledge about A, in a way that generalizes beyond the specific instance of A, thereby allowing the learner to have greater conceptual understanding of A. Thus, we can say that procedural knowledge is simply knowing the two rules, If A, Then Y and If C, Then Z; whereas having conceptual understanding can include understanding the nature of the conditions A and C, their characteristics, the principles that explain their categorical structure, and so forth. Thus, this first idea of adaptive versus routine expertise can be conceptualized as being very much related to the distinctions between conceptual and procedural understanding, a contrast and dilemma that have been around for decades.

However, a more intriguing second idea of adaptive expertise is the notion of a propensity or predisposition to learn while performing. That is, the idea is that while practicing or executing a skill, adaptive experts are ones who seek to learn more from the experience, seek help from others, experiment with new ideas, as if they are not satisfied with what they already know and can do (Bransford & Schwartz, 2009). Thus, this definition of adaptive experts is similar to the characterization of elite experts who intentionally seek challenges in their deliberate practice. In effect, adaptive experts as defined here resemble all "effective learners," and not just adaptive experts. Perhaps only effective learners can become adaptive experts.

Even though this "effective learner" definition of adaptive expertise emphasizes the learning aspect whereas the first definition proposed above emphasizes the conceptual understanding aspect, the two definitions are related in that they have a common component, namely that in order to acquire conceptual understanding, one must reflect and self-explain the concepts or conditions of a rule, much like one must reflect and self-explain while solving a problem or practicing a skill in order to maximize learning. Both definitions can be said to require a constructive component, where new knowledge is constructed while trying to understand the concepts and conditions of rules or while performing the rules.

Not only are the two definitions of adaptive expertise described here similar to the idea of the elite experts engaging in deliberate practice, but moreover, deliberate practice seems to have the components of engaging in reflective practice. That is, in deliberate practice, one can be either reflecting on the conditions of the rule, or reflecting on the outcome of the procedural execution, in order to seek more challenging practice. In short, one could say that to achieve adaptive expertise is to engage in constructive reflection during practice and performance, and such constructive reflection allows one to further learn, generalize, and acquire deeper conceptual understanding. The real question though, is why some learners engage in such constructive reflection and others do not. We have alluded earlier to the notion that motivation and other social and personal factors might be mitigating reasons, but no evidence addresses these issues directly.

Team or Group Expertise

The third construct that has not been pursued very much in the literature is the idea of group expertise. The idea of group expertise has many related and intriguing issues and questions. For example, we know that groups most often perform better than individuals, whether the group is a size of two (dyads), or three (triads), or more (e.g., Barron, 2000; Pfister & Oehl, 2009; Schwartz, 1995; Webb, Nemer, Chizhik, & Sugrue, 1998). But what we don't understand is why. The most mundane reason is to say that groups perform better because different individuals within the group know different aspects of the to-be-solved problem, so that the combined knowledge of the individuals allows more problems to be solved (Ploetzner, Fehse, Kneser, & Spada, 1999). This is a "complementarity" idea. But more intriguing is the notion that even if the individuals in the group have the same knowledge, it seems that they too, can solve more problems correctly (Hausmann, Chi, & Roy, 2004). This is the "co-construction" idea, that two or more people, together, can create some new understanding that neither of them could create alone. Several additional questions arise with respect to group expertise such as: What is the best combination of group members in terms of levels of expertise to optimize the co-construction of new ideas? What is collective knowledge? How can it be measured?

More recently, the challenge involves understanding group and team learning, and not just team or group performance. A team is a pre-determined group in which each member might have a pre-defined role. The question is how to create an expert team that can not only perform effectively but also learn effectively, since groups and teams often have to learn new innovations? That is, a team that performs and learns expertly is not necessarily a team of individual experts, nor necessarily a team led by an expert (Edmondson, Bohmer, & Pisano, 2001). There are other potent factors such as coordination among team members. What is the nature and characteristics of expert coordination (such as timing) is an issue that is being actively explored currently (Cooke, Salas, Cannon-Bowers, & Stout, 2000).

In summary, the three constructs that are being explored in the expertise research currently – deliberate practice, adaptive expertise, and group learning and performance – are silent on the issue of how we can help learners become adaptive experts. Besides the relatively new area of group learning, the first two constructs seem to be mediated by some other unknown factor, such as motivation. There are also many other social (family values, parental guidance) and cultural factors that seem difficult to reproduce for specific learners in order to make them more adaptive. In other words, there are no obvious solutions for how we can train learners to become adaptive and elite experts. Two of the five catalysts mentioned by Martin and Schwartz (2009) seem feasible to implement in training. One is the idea of providing variability instead of reducing variability as usually done in formal instruction. That is, by intentionally introducing variability (as for example, in the condition of rules), then students can see the variability more directly and easily, rather than having to reflect on potential variability, as we postulated above. A second idea is what Martin and Schwartz called "fault-driven adaption". The idea is that if a situation contains either new crisis or chronic bothersome snags, then an individual or a group might decide to adapt. Fault-driven adaption is essentially an effective change caused by an altered situation, in much the same way as conflict-driven conceptual change. And we can imagine a training regime that can include faults such as new crisis, chronic errors, or bothersome tedious repetitive actions. Both of these ideas can be readily implemented in training so as to produce more adaptive experts.

Expertise as Perspective Shift

Besides the question of how to produce elite and adaptive experts, the more fundamental question of how we can accelerate the acquisition of expertise without a decade of practice, is not a question that has a ready answer. One of the reasons is that many of the results from contrastive studies on expertise (i.e., contrasting experts versus novices) do not translate easily into instructional intervention about training for the acquisition of expertise. For example, if we find that experts can see more patterns in an X-ray that novices cannot see (Lesgold et al., 1988), what can we do to accelerate training other than going through what training already is doing, which is to have experts point out x-ray flaws to novices? Similarly, if we find experts to categorize and sort physics problems (Chi et al., 1981) or trees (Medin, Lynch, Coley, & Atran, 1997) or birds (Tanaka & Taylor, 1991) differently from novices, it is not clear how we can teach the categories to novices in a way that can accelerate their learning. That is, they still have to learn the relationships between the features in the objects that are relevant to the categories that the objects belong.

Occasionally, there are more mundane reasons for the length of time it takes to acquire expertise, such as the need to encounter unusual situations. In that case, simulations built to mimic the rare incidents would help accelerate the training of novices, since they can encounter those incidents more often in a simulator (Gott, Lesgold, & Kane, 1996). Lack of access also occurs in other scenarios, such as in apprenticeship. In some workplace apprenticeships, the apprentices do not have good access to the master, therefore they cannot acquire their skills readily and quickly. These kinds of access issues (either accessing rare incidents or accessing an expert) require solutions that can be more easily implemented, if feasible.

Aside from these access issues, no novel approaches have been taken to see if expertise acquisition can be accelerated. One idea to be explored here is perspective shift. Although perspective can be interpreted in many ways, such as spatial perspective, the idea proposed here is a perspective shift across ontological categories (Chi, 1997). For example, a shift between objects and processes can be considered a shift across ontological categories, or a shift between seeing the parts versus seeing the whole might be a second example, or a shift between individual entities versus a system might be a third example. Let us consider two examples. In the old data of experts and novices solving physics problems (Chi et al., 1981), there were some protocols reported in which we asked experts and novices what kind of cues in the problem statement allowed them to decide what kind of a problem it is or how it should be solved. In analyzing two expert and two novices' citations of cues, gross differences emerged (Chi et al., 1981, Table 11, 1982, Table 14). The cues could be either a specific object or concept in the problem statements, such as a spring, an inclined plane or friction, or the cues could be more system level processes, such as that the problem is a "before-and-after" situation, or there are "interacting objects". Table 2 below shows the difference of a single expert and a single novice in the cues they cited as important for determining how a problem is to be solved. The expert cited 21 concrete cues, whereas she cited 74 process cues. The novice did just the opposite: he cited 39 object cues and 2 process cues. Thus, the

Table 2 Physics problem cues (data taken from Chi et al., 1981)

	Object	Process
Expert	21	74
Novice	39	2

Table 3 Ratings of four swimmers (data taken from Leas & Chi, 1993)

	Time	Experts (N=2)	Novices (N=2)
Swimmer 1	51.7	8.00	8.50
Swimmer 2	53.1	6.50	7.50
Swimmer 3	60.2	4.75	6.50
Swimmer 4	61.0	4.75	7.50

experts focused on the processes occurring among the elements within the problem statement, whereas the novices focused primarily on the elements themselves. This constitutes a concrete-object to process shift.

Another example comes from our work on examining expert swimming coaches (Leas & Chi, 1993). In this study, expert swimming coaches (as recognized by the US Swim Association, and with 12 years of coaching experiences) and novice coaches (with 2 years of coaching experience) were asked to view underwater tapes of four swimmers. Their task was to rate each swimmer on a scale ranging from 1 (bad) to 10 (good) and to diagnose what might be wrong with each swimmer's stroke. Table 3 shows the mean ratings of the two expert and two novice coaches, compared with the actual swim times of each swimmer. As one can see from Table 3, novices and experts had the same ranking of ratings, and moreover, these rankings corresponded to the ranking of the swimmers' times. This means that with a minimum of 2 years of coaching experiences, coaches can adequately pick out the good swimmers and differentiate them from the poorer swimmers. The accuracy of the novice coaches makes sense because even a naïve spectator can often tell who is a better swimmer (or dancer, or any other physical performer), and so forth, based on qualitative overall features.

However, we further asked the coaches to give us the cues that they had used to decide on their ratings of the swimmers. Here we found little overlap in the cues cited by the expert and novices coaches. Moreover, there are characteristic differences between the types of cues the novices cited versus the type that experts cited. (Table 4 gives some examples of the cues they had used.) The

Table 4 Swimming diagnoses (data taken from Leas & Chi, 1993)

	Object	Process
Expert		Unequal body roll Rotates to right Wide pull Stroke unbalanced Breathes to one side
Novice	Elbow bent Elbow lock out Right arm not underneath Left arm not extended	Nice body roll

differences can be characterized again as either an object-process difference, or a part-whole difference, or a static-dynamic difference. For example, novices tend to cite a single body part ("elbow bent" or "right arm not underneath") as the flaw in a specific swimmer's stroke, whereas experts tend to refer to the entire holistic movement ("unequal body roll" or "stroke unbalanced") as a flaw in a swimmer's stroke.

These characteristic differences are not incremental, but rather, represent significant shift in perspectives. For example, if we view the difference as one between objects and processes, these two perspectives are distinct ontological categories (Chi, 1997). The difference is similar to the difference in physics cues cited earlier, between citing an explicit concrete object (inclined plane or pulley) as the cue for the kind of problem it is, versus citing cues referring to the entire system, such as a before-and-after situation, meaning that the forces acting on the entire system are equal before some interactions and after some interactions. The question of interest is whether this perspective shift is trainable. For example, in solving simple mechanics problems, would it be feasible to teach students to look for concepts such as a balance-of-forces for the whole system, rather than to teach them to seek individual forces acting on each mass? Similarly, for swimming coaches, can instruction for diagnosis focus on movement of the entire body, rather than individual body parts? Other related areas might be the difference between a focus on individual agents or objects in a dynamic system (such as an eco system), versus teaching students to focus on the entire population (Chi, 2008). This type of instructional approach has not been tried, to our knowledge, to see if the acquisition of expertise can be accelerated.

Conclusion

This chapter is not a review of the expertise literature. Instead, this chapter first outlined the major shifts in the literature in terms of understanding what makes experts excel. Of course, more knowledge is assumed, by definition. But the first approach to the study of expertise had assumed that what differentiated experts from novices were the experts' superior search strategies. However, in light of new empirical evidence, this idea was replaced by another assumption, that what differed between experts and novices was the structure of their greater knowledge. Finally, it was shown that differences in the structure of knowledge led to differences in the way a problem is represented by experts and novices. And the way a problem is represented led naturally to more efficient and more correct solutions. Although this difference in representations offers many insights (for example, in understanding the discrepancy between a teacher's representation of a problem and a student's representation, thereby students will inherently misunderstand a teacher's explanations), how one can teach learners to construct better structured knowledge so that they can construct a better representation remains a challenge. This instructional challenge can be couched as how can we accelerate a learner's understanding or how can we create a more adaptive expert.

The second part of this chapter highlights the three constructs that are being emphasized in the current literature – deliberate practice, adaptive expertise, and team expertise. On the surface, the first two constructs appear to refer to different aspects of expertise: deliberate practice refers to how experts practice in order to achieve elite status, and adaptive expertise refers to some experts who can generalize their understanding to new situations. But in some ways, these two constructs are quite similar: they are both concerned with the production of some exceptional experts, those who have deeper understanding and can generalize and transfer their understanding to non-routine problems. The third construct is concerned with a more concrete practical problem: how to create expert groups or teams, given the nature of collaborative and team work that is required in the real world. Many questions remain unexplored so far about group and team expertise, such as what is the best composition of an expert team, how to optimize a group's learning, and so forth.

The last section of this chapter proposes a new way of thinking about differences between experts and novices. Instead of thinking about experts or more elite and adaptive experts as ones who have conceptual understanding in addition to procedural understanding, or as ones who can generalize their knowledge to non-routine problems, or as ones who practice deliberately, we might want to explore the source of this greater conceptual understanding or greater generalized understanding. One source might be the achievement of an ontological perspective shift. That is, to achieve a certain level of eliteness and adaptive expertise means that one has acquired another perspective. Viewed this way, it makes sense to consider adaptive expertise at all levels of expertise. To enable the acquisition of adaptive expertise then means that we have to understand what is the perspective of the experts, and develop instruction from this perspective. Whether this approach will be more successful at producing adaptive experts remains an empirical question for now.

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