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REVIEW ARTICLE

# Domain-Specific Knowledge and Why Teaching Generic Skills Does Not Work

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**Abstract** Domain-general cognitive knowledge has frequently been used to explain skill when domain-specific knowledge held in long-term memory may provide a better explanation. An emphasis on domain-general knowledge may be misplaced if domain-specific knowledge is the primary factor driving acquired intellectual skills. We trace the long history of attempts to explain human cognition by placing a primary emphasis on domain-general skills with a reduced emphasis on domain-specific knowledge and indicate how otherwise unintelligible data can be easily explained by assumptions concerning the primacy of domain-specific knowledge. That primacy can be explained by aspects of evolutionary educational psychology. Once the importance of domain-specific knowledge is accepted, instructional design theories and processes are transformed.

**Keywords** Domain-specific knowledge · Learning · Instruction · General skills · Cognitive load theory

Psychological studies of cognitive performance have been a focus of research for over 130 years. Paradoxically, much of that research emphasised generic or domain-general cognitive skills despite domain-specific knowledge held in long-term memory being arguably the most important factor, and possibly the only factor, determining acquired cognitive performance. In this paper, we suggest an alternative to the perspective that teaching generic skills is important. Instead, we argue that all educationally relevant knowledge acquired during instruction is, and only is, domain-specific. This view provides the major point of departure of this paper from the nearly universal consensual view that can best be summarised by the suggestion that knowledge imparted during instruction includes

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some mixture of domain-general and domain-specific information (see, for example, Greiff et al. 2013).

We will define domain-specific knowledge as memorised information that can lead to action permitting specified task completion over indefinite periods of time. For example, there are many different problems that can be solved by using Pythagoras' theorem. To use the theorem to solve problems, problem solvers must not only learn the theorem, they also must learn to recognise the various problems to which the theorem can be applied and the manner in which it should be applied in each case. We define this set of problems as a "domain" and Pythagoras' theorem along with the manner in which it can be used is a constituent of the domain-specific knowledge required to solve this set of problems. That knowledge, consisting of large numbers of problem states and the moves associated with those states, is stored in long-term memory. We will argue that teachable aspects of problem solving skill are entirely dependent on large amounts of domain-specific information stored in long-term memory, rather than on other factors such as domain-general skills.

Domain-general skills, by definition, can be used to solve any problem in any area. For example, learning to solve problems by thinking of similar problems with known solutions is an example of domain-general knowledge that can be applied to all problems. Such domain-general knowledge also is stored in long-term memory, although, as will be argued next, it belongs to a different knowledge category that for biological evolutionary reasons may be learnable but unteachable because it already will have been acquired automatically without instruction, outside of an educational context. We will argue that, while people cannot learn an already learned, domain-general skill, they can learn to apply the skill in a new domain, thus providing an example of the acquisition of domain-specific rather than domain-general knowledge (e.g. Youssef et al. 2012).

## Geary's Evolutionary Educational Psychology

Geary (2008, 2012) has proposed an evolutionary educational psychology that transforms our understanding of many aspects of human cognition relevant to instruction. His proposal suggests knowledge can be divided into biologically primary knowledge that we have evolved to acquire over many generations and biologically secondary knowledge that has become culturally important but that we have not specifically evolved to acquire.

Examples of biologically primary knowledge are learning to listen and speak, learning to recognise faces, engage in social relations, basic number sense, or learning to use a problem solving strategy such as means-ends analysis (Newell and Simon 1972). Biologically, primary knowledge is acquired easily, unconsciously and without explicit tuition. Barring learning deficits such as those associated with autism, it will be acquired automatically simply as a consequence of membership of a normal society. For example, it can be argued that, despite its importance, we do not teach people how to use a means-ends problem-solving strategy because they have evolved to learn how to use the strategy automatically. Biologically, primary knowledge is modular (e.g. the modularity of number sense has been demonstrated by Mandelbaum 2013), with different skills likely to have been acquired at different evolutionary epochs. For example, we are likely to have evolved the ability to learn to recognise faces independently of learning to listen and speak.

The acquisition of biologically secondary knowledge is heavily dependent on the prior acquisition of primary knowledge. It is knowledge that we have not specifically evolved to acquire but which a particular culture has deemed to be important. Reading, writing and arguably, all other content taught in modern educational establishments provide examples of biologically secondary knowledge. Schools were invented to teach biologically secondary knowledge because it is unlikely to be acquired just by engaging in environmental or societal interactions. Secondary knowledge is acquired consciously, with active mental effort and is facilitated by explicit instruction.

We suggest that humans may have evolved to acquire very general knowledge that can be applied to a wide variety of otherwise unrelated areas. Such biologically primary knowledge is likely to be too important to human cognitive functioning to be left to the biologically secondary system. If so, domain-general cognitive knowledge will be unteachable because it will have already been acquired as biologically primary knowledge. Evidence for this suggestion comes from omission: We are unable to find a domain-general, cognitive strategy that has been described and tested for effectiveness using randomized, controlled trials varying one factor at a time with far transfer test tasks to eliminate the effects of domain-specific knowledge. Until a body of research becomes available demonstrating the existence of teachable, domain-general knowledge, it may be safer to assume that such procedures are biologically primary and so already acquired by learners. In contrast, domain-specific knowledge is biologically secondary and undoubtedly teachable.

While biologically primary knowledge may be unteachable, it does not follow that it is unimportant to instruction. It can be important in at least two respects. (1) People may learn the different contexts in which an already acquired generic skill can be applied. Learning the contexts in which a generic skill can be applied provides another example of acquiring domain-specific knowledge. In other words, general problem-solving strategies are "teachable" in a very restrictive sense, i.e. indicating to learners that a primary, general problem-solving strategy, already acquired by the learner, is usable to solve a specific academic problem (e.g. Youssef et al. 2012). (2) In addition, biologically, primary knowledge may facilitate the acquisition of biologically secondary information that provides the subject matter of instruction. Pointing out to learners that a biologically primary skill that they have can be used to assist in a biologically secondary task may be useful. Similarly, instruction that is organized in a manner that facilitates the use of primary skills in the acquisition of secondary skills may be beneficial (Paas and Sweller 2012). In other words, while primary skills may be unteachable because they have already been acquired, they may be useful in leveraging the acquisition of secondary skills.

If domain-general knowledge is biologically primary and domain-specific knowledge provides the major, perhaps only form of teachable knowledge, we should be able to find evidence for this suggestion. In the remainder of this paper, we will analyse a variety of research areas, including historically important lines of investigation that placed an emphasis on either domain-general or domain-specific knowledge. Our aim is to indicate that learned skill, especially problem solving skill, derives from acquired domain-specific, rather than domain-general, knowledge.

In the following sections, we present a description of some results from the very beginnings of scientific psychology to more recent work in both general and educational psychology. Those results provide evidence that the effect of domain-specific knowledge, even in areas where it was assumed to be largely irrelevant, has always been available, but that its importance has tended to be down-played.

## The Problem of Knowledge and Intelligence

Binet's (1894) study is well known by psychologists who study human expertise (e.g. Ericsson and Charness 1994; Ericsson and Lehmann 1996; Ericsson 1985; Ericsson and

Chase 1982) and historians of psychology (Nicolas et al. 2011), probably because it was the first psychological study to discuss chess expertise. The first part of Binet's book is about great mental calculators and is still referenced more than 100 years after its initial publication (e.g. Dehaene 1997; Rikers 2009). Binet studied the case of Mr. Inaudi, a great mental calculator who could carry out seemingly impossible tasks of mental calculation. Binet asked him to perform a large number of operations and measured how long Inaudi required to carry out the calculations. He compared the calculation times with several cashiers who, in the days before mechanical or electronic calculators, were required to carry out mental calculations as a major component of their employment. Table 1 replicates a table Binet provided, dealing with mental multiplication of large numbers. The table includes the results of several participants multiplying numbers mentally without recourse to pen and paper, but we are primarily concerned with the results of Inaudi and the "1st Cashier", referred to as Mr. Lour in Binet's (1894, p. 97) quote below. (Mr. Diamandi was another prodigious mental calculator. The gaps in the table are Binet's gaps.)

> "We see that while Mr. Inaudi usually has a marked superiority, it is less, for the multiplication of small numbers, to a cashier, Mr. Lour. He is the best and fastest "Bon Marche" cashier, who takes only 4 seconds in a case where Mr. Inaudi takes 6.4 seconds to solve the same problem. These are small operations. Mr. Lour could not continue his superiority for more complex operations, because his memory failed him. The discussion of these numerical results raises an interesting question of psychology."

It is fascinating to observe that Binet was, on the one hand, an ingenious and creative psychologist, a pioneer in the history of scientific psychology, and, on the other hand, seemingly blind, unable to see that, for 7,286 × 5,397, the cashier performed much faster than Inaudi. For Binet, Inaudi was a highly intelligent freak of nature who had to be superior to a mere cashier. Binet incorrectly interpreted his results accordingly.

It is also interesting to note that, in a previous publication about Inaudi, Binet (1892) reported a well-known anecdote about Mozart and his ability to remember Allegri's Miserere. When visiting Rome as a 14-year-old, Mozart heard the piece during a Sistine Chapel Wednesday service. Later that day, he wrote it down entirely from memory, returning to the Chapel that Friday to make minor corrections. According to Binet, this feat is explained by Mozart's musical memory, which Binet attributed to a natural disposition in the same manner as he interpreted Mr. Inaudi's ability to mentally calculate. (Binet also thought that painters like Doré and Vernet have a naturally superior visual memory.)

There was little sign that Binet was able to think in terms of expertise due to domain-specific knowledge. Such knowledge can readily explain Mozart's ability to remember a musical piece. Mozart understood that Allegri's piece was tonal music, following the established rules of tonal music. Those rules are known to experienced musicians who know the structure of such music and can reproduce it in a manner very similar to Mozart. Mozart was a genius, but it does not require a genius to remember a music piece belonging to a well-known category. In other words, the transcription of this piece of music is likely to be a routine exercise for highly knowledgeable musicians. It was more than 75 years after Binet and more than 300 years after Mozart for the field to realise, following the work of Ericsson and his colleagues (Ericsson and Charness 1994; Ericsson and Lehmann 1996; Ericsson 1985; Ericsson and Chase 1982), that, when performing a cognitive task requiring domain-specific knowledge, that the presence or absence of this knowledge is the best predictor of performance.

**Table 1** Binet's table (Binet 1894, p. 98)

| | 3×7 | 49×6 | 63×58 | 426×67 | 638×823 | 4,279×584 | 7,286×5,397 | 61,824×3,976 | 58,927×61,408 | 729,856×297,143 |
|---|---|---|---|---|---|---|---|---|---|---|
| Mr. Inaudi | 0.6 s | | 2 s | | 6.4 s | | 21 s | | 40 s | 4 min |
| Mr. Diamandi | | 6 s | 17 s | 21 s | 56 s | 92 s | 2 min 7 s | 3 min 10 s | 4 min 35 s | |
| 1° Cashier | | | | | 4 s | | 13 s | | | |
| 2° Cashier | 0.7 s | | 4 s | | 12 s | | | | | |
| 3° Cashier | 0.7 s | | 4 s | | | | | | | |

The data refer to minutes and seconds to mentally complete the multiplication in the first row

Years after Binet's 1892 and 1894 publications, he was asked to design a standardized test to evaluate if a pupil was likely or unlikely to succeed in secondary school. Subsequently, this test, used to determine the probability of success in school, was given a new name: "Intelligence". Binet and those who followed him assumed that they were primarily measuring a natural, basic trait rather than acquired knowledge

There are more recent findings indicating the importance of acquired knowledge in intelligence. Some of the strongest evidence for the influence of knowledge on intelligence comes from an experiment conducted by Cahan and Cohen (1989). They were concerned with the differential effects on intelligence of increases in age versus increases in schooling. We know that children's intelligence increases with age because different tests are required to measure the intelligence of children and adults, but to what extent is this increase a natural increase simply due to increasing age and to what extent is it due to the increase in knowledge acquired in school? Obviously, a true experiment on this issue could not be carried out in an ethical fashion. Cahan and Cohen circumvented this problem by a quasi-experimental design using the fact that, for any given school year, children's ages can normally vary by up to 1 year. Thus, in a given school year, children with the same amount of schooling can vary in age by up to 1 year depending on whether their birthday fell just before or just after the cut-off for school entrance. Correspondingly, children in adjacent school years can be very close in age but vary in amount of schooling by one year. Cahan and Cohen found that the increase in intelligence due to one additional year of schooling was twice the increase for one additional year of age. Similar results were obtained by Cliffordson and Gustafsson (2008) and Stelzl et al. (1995). Other methods, such as assessing the effect of school reform, provide the same evidence: Increasing time spent in school increases intelligence (Brinch 2012). It should be noted that other studies that reverse the direction of causality by suggesting that intelligence has a positive effect on school performances (e.g. Herrnstein and Murray 1994) rather than that schooling can increase intelligence, are not based on controlled experiments but on correlational analyses that cannot determine causality.

While these results can be interpreted in a variety of ways, one conclusion is that knowledge plays a critical role in intelligence. Based on these results, it may be inappropriate to assume that intelligence is a basic, biologically determined measure that increases with age. The accumulation of knowledge in long-term memory during schooling provides an obvious candidate for the role of the major factor in the development of intelligence.

One hundred years after the publication of Binet's book on prodigious calculators, "The Bell Curve" was published (Herrnstein and Murray 1994), emphasising intelligence and its links with performances and achievement in many different aspects of life. In response, the Board of Scientific Affairs (BSA) of the American Psychological Association concluded that there was an urgent need for an authoritative report on these issues—one that all sides could use as a basis for discussion. Acting by unanimous vote, the BSA established a Task Force charged with preparing such a report. Neisser was appointed Chair. Here are some quotations from this report (Neisser et al. 1996):

> "… schooling itself changes mental abilities, including those abilities measured on psychometric tests. This is obvious for tests like the SAT that are explicitly designed to assess school learning, but it is almost equally true of intelligence tests themselves." (Neisser et al. 1996, p. 87).
>
> "There is no doubt that schools promote and permit the development of significant intellectual skills, which develop to different extents in different children. It is because tests of intelligence draw on many of those same skills that they predict school achievement as well as they do". (Neisser et al. 1996, p. 87).

Some of the conclusions of this work also are very important. Neisser et al. claimed that we do not know the links between (psychometric) intelligence and genetic endowment. There is an important quote on the Flynn Effect discovered by Flynn (2007) who found that, over a half century, intelligence scores had been rising substantially:

> "Mean scores on intelligence tests are rising steadily. They have gone up a full standard deviation in the last 50 years or so, and the rate of gain may be increasing. No one is sure why these gains are happening or what they mean." (Neisser et al. 1996, p. 97.)

Based on these conclusions, after 100 years, we apparently still know very little about intelligence. Of course, as these quotes suggest, many of the paradoxes associated with intelligence could be resolved had the history of intelligence testing included a heavier reliance on the acquisition of biologically secondary, domain-specific knowledge held in long-term memory. Many of the puzzling findings associated with intelligence testing including the Flynn Effect, become understandable if we assume that at the very least, the possession of a large store of domain-specific knowledge is an indispensable component of intelligent behaviour (see e.g. Ackerman 2000; Brinch 2012).

While we have attributed increasing intelligence scores to the acquisition of biologically secondary, domain-specific knowledge, these increases could just as easily be caused by changes in biologically primary, domain-general knowledge such as general problem solving skills. Our failure to identify teachable/learnable general problem solving skills argues in favour of domain-specific skills. The centrality of domain-specific skills in problem solving expertise is discussed below in the section entitled "Recognising Domain-Specific Knowledge and Expertise". In the next two sections, we continue to indicate the historical significance of a failure to recognise the importance of domain-specific knowledge and the equally important failure to find teachable, domain-general knowledge.

## The Problem of Expertise and Disappearing Short-Term Memory Limits

Miller's (1956) paper can be considered as one of the main events in the birth of cognitive psychology, but also, the paper that defined the concept of capacity of processing information or short-term memory capacity. Even as the short-term memory concept was progressively replaced by working memory (Atkinson and Shiffrin 1968; Baddeley and Hitch 1974; Miller et al. 1960), the linked concept of capacity did not disappear (Cowan 2005; Conway et al. 2007). The powerful idea of Miller was that this capacity is universal, applying to everyone in every domain. But, again, a short quotation from his 1956 article is relevant. In this passage, Miller reported results concerning absolute judgment of tones. After presenting some results that accorded with his argument, he wrote:

> "Most people are surprised that the number is as small as six. Of course, there is evidence that a musically sophisticated person with absolute pitch can identify accurately any one of 50 or 60 different pitches. Fortunately, I do not have time to discuss these remarkable exceptions. I say it is fortunate because I do not know how to explain their superior performance. So I shall stick to the more pedestrian fact that most of us can identify about one out of only five or six pitches before we begin to get confused." (Miller 1956, p. 84.) Of course, as is the case for intelligence, expertise in the form of domain-specific knowledge can explain these differing results between experts and novices.

The problem with the limited capacity of working/short-term memory that seems to disappear as a limit for some people should be linked to the way Miller thought about the issue. He considered working/short-term memory capacity as a general capacity, not depending on the domain being tested. In fact, it is virtually impossible to measure working/short-term memory capacity in a "pure" fashion uninfluenced by knowledge held in long-term memory for whatever material is being used such as digits, words, letters, tones, pictures, etc. There are huge differences between individuals' knowledge held in long-term memory and that is precisely what the pioneers of expertise psychology discovered in the late 1960s (see below).

## Domain-Specific Knowledge and Cognitive Development

Historically, the lack of an appropriate emphasis on biologically secondary, domain-specific knowledge has also bedevilled the field of cognitive development, in particular, Piaget's stage theory of cognitive development. His stage theory (Piaget 1972) documents a series of cognitive stages through which children develop, beginning with the sensorimotor stage and progressing through the pre-operational and concrete operational stages culminating in the formal operational stage. These stages indicate changes in the general ability of children to engage in logical thought. Each stage was initially assumed to be domain-independent (Piaget 1972). The thought processes were assumed to progress in a fixed, necessary sequence. Progress through the stages could vary in speed but not in sequence.

While the stage theory worked reasonably well, some apparent inconsistencies began to appear. Piaget demonstrated that preoperational children have difficulty conserving number, mass, and volume. Objects that are spread out frequently are usually assumed by pre-operational children to have increased in number, liquids poured into a differently shaped container may be assumed to have altered in volume while solid objects whose shape changes may be assumed to alter in mass. These errors, according to Piagetian theory, are due to the predominance of perceptual over logical reasoning in preoperational children. In the next stage, the concrete operational stage, logical reasoning becomes dominant and the errors are no longer made.

The difficulty with this explanation is that the point at which the errors disappear varies. Children may, for example, conserve number earlier than they conserve mass. If we assume that learning to conserve number, volume, and mass are simply domain-specific concepts that must be acquired, the fact that a child acquires them at different times is easily explained. If we assume that the acquisition of these concepts is dependent on the development of a biologically primary, domain-general ability to handle logic, their appearance at different times in the same child becomes problematic.

The issue became overwhelming in the case of the ultimate developmental stage, formal operational thought. Formal operational thought was assumed to develop at about 12–13 years of age. It allows us to consider issues that may or may not exist except in our minds. We can propose hypotheses in a scientifically appropriate fashion. Piaget initially tested for formal operational thought using children from some of the better schools in Geneva. The tasks included asking children to set up valid experiments testing simple scientific hypotheses such as establishing the factor or factors that determine the frequency of oscillation of a pendulum. Formal operational children could accomplish this task successfully by altering one variable at a time and observing its effect. Concrete operational children were more likely to vary multiple variables simultaneously indicating their failure to understand the logic of hypothesis testing.

Towards the end of his career, Piaget (1972) realised that there were serious problems associated with formal operations. Using his scientific tasks as a test, many apparently capable people seemed never to attain the formal operational stage. The solution, he suggested, was not to abolish the notion of formal operations but rather to only test for formal operations in an area that a person had ability, interest, and knowledge. In other words, we cannot ignore domain-specific knowledge.

We would like to go a step further. Our acquired ability to reason logically is due to biologically secondary, domain-specific knowledge. A person who is able to reason logically in science may show no such ability in his or her personal life or in any areas outside of his or her areas of science. Knowing that we should only test one variable at a time when conducting a scientific experiment is critical. Outside of hypothesis testing, it may be irrelevant, with other knowledge being pre-eminent.

The extent to which biologically secondary, domain-specific knowledge held in long-term memory can explain skill that appears to be due to highly general abilities or teachable general skills can be surprising. In the next section, we discuss research into expertise and what that research tells us of the relation between biologically secondary, domain-specific skill and biologically primary, domain-general skills.

## Recognising Domain-Specific Knowledge and Expertise

Air traffic control and chess are probably the two most common areas where the effect of domain-specific knowledge has been demonstrated. We will begin by discussing research on air traffic control.

## The Nature of Air Traffic Controller Expertise

Air traffic controller memory has been widely studied during the past 50 years (see Bainbridge 1975; Stein et al. 2010 for reviews). The first reported results that we can find are those of Yntema (Yntema and Mueser 1960, 1962; Yntema 1963). Yntema's goal was to understand why "card players, air-traffic controllers, and people going about their ordinary business demonstrate an ability to keep track of a number of things at once" (Yntema and Mueser 1960, p. 18). His hypothesis, in conformity with the times, was contrary to a domain-specific knowledge hypothesis. Following Miller (1956), Yntema tested whether air traffic controllers had an enhanced general ability to chunk information. Accordingly, he tested air traffic controllers on laboratory tasks such as letters associated with shapes, colours, signs, etc. The results indicated that air traffic controllers were no better at chunking information than the general population.

Ten years later, Bisseret (1970) used the same kinds of tasks but approached them from a different perspective: understanding performance at work using meaningful materials rather than laboratory tasks unrelated to an enhanced knowledge base. His experiment included a description of several aircraft with each description using seven variables. Two factors were manipulated: The number of aircraft and the experience of the air traffic controller. He found an increase in memory scores with an increase in experience. The average number of variable values recalled was 22.8 for advanced air traffic control students and 30 for more expert professionals, with both of these scores far in excess of Miller's 7+/−2. Knowledge had a dramatic effect on working memory.

These effects on performance depending on levels of expertise provided an early suggestion that working memory capacity depends on domain-specific knowledge. In a personal communication, Bisseret provided an interpretation of his results 40 years later. He indicated that he would have been better positioned to interpret his results had Ericsson and Kintsch's (1995) concept of long-term working memory (see below) been available to him at the time of publication.

## Why Chess Masters Win

Historically, the above work concerning the consequences of domain-specific knowledge on cognition using aircraft controllers had minimal impact. The work on chess had a much greater impact, although the full implications of that work are still to be realised, we believe. That work was initiated by De Groot (1965).

De Groot's work was first published in 1946 in Dutch and had a limited impact on the field. It was re-published in 1965 in English. It had a substantial impact on the field of cognition, especially after Chase and Simon's (1973) work (see below), but only a limited impact on issues associated with instructional design.

De Groot was concerned with the factors that allow chess masters to consistently defeat lower ranked players. Chess is validly seen as a game of problem solving, but the problem solving factors that allow masters to defeat lower-ranked players were obscure. One possibility is that masters engage in a greater search in depth by considering more possible moves ahead or a greater search in breadth by considering more alternative moves at each choice point. We might expect that increased search would increase the possibility of finding a good move, but De Groot found no evidence of increased search by chess masters compared with lower-ranked players. Differential problem solving search did not distinguish masters from other players.

The only distinction De Groot could find between masters and lower-ranked players was in memory for board configurations taken from real games. Players were shown a board configuration for 5 s before the board was removed, and the players were asked to replicate the configuration they had just seen. Masters were good at this task with a 70–80 % accuracy rate. Lower-ranked players had an accuracy rate of 30–40 %. Chase and Simon (1973) replicated these results but in addition demonstrated that, if random board configurations were used, the difference between masters and lower-ranked players disappeared with all having a low success rate.

These results altered our view of human problem solving and, indeed, of human cognition. Masters were superior to lower-ranked players not because they had acquired complex, sophisticated general problem solving strategies, nor general memory capacity, but rather, because they had acquired an enormous domain-specific knowledge base consisting of tens of thousands of problem configurations along with the best move for each configuration (Simon and Gilmarti 1973). No evidence, either before or after De Groot's work has revealed differential, general problem solving strategies, or indeed, any learned, domain-general knowledge, that can be used to distinguish chess masters from lower ranked players. The only difference between players that we have is in terms of domain-specific knowledge held in long-term memory. Furthermore, no other difference is required to fully explain chess problem solving skill.

In our view, these results provide some of the strongest evidence for the suggestion that learned skill, especially problem-solving skill, derives primarily from the accumulation of a large store of biologically secondary, domain-specific knowledge stored in long-term memory. As far as we are aware, there is no evidence that learned problem solving skill in chess derives from domain-general knowledge. Domain-general strategies such as means-ends analysis (Newell and Simon 1972) clearly exist and are presumably used by chess masters, but there is no body of evidence indicating that they are teachable. We suggest that for evolutionary reasons, we have been selected for our ability to acquire domain-general knowledge. Such knowledge is too important for us to not acquire it. As a consequence, we may acquire domain-general knowledge automatically as biologically primary knowledge. If so, we cannot be taught domain-general knowledge in educational institutions because it already has been acquired.

## Generalisation of the Work on Chess to Other Areas

Unsurprisingly, similar results have been obtained in a variety of other areas including areas of greater interest than chess to the education research community. Findings indicating that experts have a better memory for problem solving states than novices have been obtained in areas such as understanding and remembering text (Chiesi et al. 1979), electronic engineering (Egan and Schwartz 1979), programming (Jeffries et al. 1981), and algebra (Sweller and Cooper 1985). Based on these results, competence in any area requires knowledge of the problem states that can be found in the area along with the best moves associated with those states. For complex, extensive areas that knowledge may consist of tens of thousands of problem states (Simon and Gilmarti 1973). Those innumerable problem states and the best moves associated with those states are stored in long-term memory. It is that knowledge that constitutes expertise. We should at least consider the possibility that such knowledge is all the teachable skill that is required for expertise and competence.

## Expertise Theory

Ericsson and his collaborators provided data and theory for the phenomena associated with expertise and its reliance on domain-specific knowledge held in long-term memory. Initially, the emphasis was on the outstanding performance of particular individuals on memory test tasks such as memorising a list of dozens of randomly presented digits after one presentation (Chase and Ericsson 1982). Contrary to popular opinion, studies indicated that the techniques used by exceptional performers to memorise lists of random digits or random letters are readily learnable. People who perform at a high level in memory tests are simply experts in memory test tasks because they have domain-specific knowledge concerning these tasks. Investigation of the strategies used indicated that they were domain-specific rather than general (Ericsson and Charness 1994). Learning to remember long strings of digits does not transfer to learning to remember long strings of letters.

Subsequently, in work on deliberate practice, Ericsson and his collaborators demonstrated that expertise in any substantial domain requires years of practice with the intention of improving performance (Ericsson and Charness 1994; Ericsson et al. 1993). It is likely to take a minimum of 10 years of practice to reach the highest levels of performance such as attaining grand master status in chess. Interestingly, the three cashiers who participated in Binet's (1894) experiment indicated that a period of about 10 years was required to reach their high levels of mental calculation. Due to the work of Ericsson and his colleagues, it is reasonable to assume that, during those 10 years, experts are acquiring domain-specific knowledge held in long-term memory.

In effect, the work carried out by Ericsson and his colleagues indicated that the well-known capacity and duration limits of working memory disappear when working memory deals with familiar information from long-term memory. Working memory's capacity and duration limits apply only to novel, not familiar, information. From a theoretical perspective, there are two ways of handling this fact. We can assume that working memory deals differently with organised information stored in long-term memory compared with information obtained from the environment that is yet to be organised. Alternatively, we can specify a structure to deal with information from long-term memory that differs from short-term working memory. Ericsson and Kintsch (1995) chose to specify a new structure, long-term working memory to explain how working memory handles information from long-term memory. Long-term working memory does not have the same capacity and duration limits as short-term working memory. It may have no measurable limits.

Whether we subscribe to a working memory with differing characteristics depending on the source of its information or separate structures to deal with environmental information and information from long-term memory, the outcome is identical. In both cases, knowledge held in long-term memory dramatically changes performance.

In sum, the psychology of expertise has shown that the major factor determining the performance of experts is acquired, domain-specific knowledge. The more complex is the domain, the more important is domain-specific knowledge. As indicated above, data on expertise in areas such as chess can be fully explained by the assumption that the only factor that alters as expertise develops is the accumulation of domain-specific knowledge held in long-term memory. As far as we are aware, there is no evidence that chess experts have acquired some form of domain-general knowledge that permits them to play at such a high level. There is every reason to suppose that the same cognitive factors apply to educationally relevant curriculum areas.

According to Ericsson and Charness (1994), it probably took such a long time to discover the importance of knowledge because we are fascinated by exceptional performance and genius. This fascination may have led us to seek extraordinary explanations. Nevertheless, Ericsson and Charness' emphasis on the role of our fascination with genius may only be partially correct because when considering non-exceptional people, the contribution of domain-specific knowledge has also tended to be overshadowed by an assumption that learners are also acquiring domain-general knowledge. In fact, we suggest that expertise in complex areas can be fully explained by the acquisition of domain-specific knowledge.

## From Expertise Research to Educational Psychology

The influence of expertise research with its emphasis on domain-specific knowledge has affected educational psychology and the process is ongoing. In this section, we look at the changing role of biologically secondary, domain-specific knowledge.

### Categorisation and the Representation of Physics Problems by Experts and Novices

Some of the earliest work concerning the effect of domain specific knowledge in education was provided by Chi and her colleagues (Chi et al. 1981). The 1981 study described four experiments devoted to problem solving in physics. Chi and her colleagues examined the differences between experts and novices in problem representation, i.e. "the cognitive structure corresponding to a problem, constructed by a solver on the basis of his domain-related knowledge and its organization" (p. 122). Prior to the Chi et al. (1981) paper, Simon and Simon (1978) and Larkin et al. (1980) had found that novices work backwards from the goal on physics problems using a means-ends strategy (Newell and Simon 1972) in which problem solvers locate differences between a current problem state and the goal state and search for problem solving operators to reduce those differences while experts work forward from the givens. These results were interpreted as indicating differences in problem solving strategies between experts and novices.

Chi was convinced that these differences between experts and novices in physics problem solving could be interpreted in terms of representation (see Chi 1993, for the genesis of the Chi et al. 1981, article). She presented novices and experts with a task in which they were presented with a variety of physics problems that they had to sort into categories. The experts were advanced PhD students in physics, and the novices were physics undergraduates. The results showed that experts sorted the problems based on structural cues relevant to problem solution while novices used superficial, physical cues. For example, novices might group problems together because they included an inclined plane while experts were more likely to group problems together because, for example, they all relied on conservation of energy for their solution. “The basic expert-novice result, that experts’ knowledge is represented at a "deep" level (however one characterizes "deep"), while novices’ knowledge is represented at a more concrete level, has been replicated in many domains, ranging from knowledge possessed by scientists to taxi drivers” (Chi 1993, p. 12).

The Chi et al. article emphasised the differences between experts and novices in educationally relevant problems. In the field of problem solving, moving from puzzle problems treated as a prototype for all problems, to educationally relevant problems was a major step in recognizing the importance of domain-specific knowledge in education. We can see the change by considering the Anzai and Simon (1979) paper concerned with problem solving using the Tower of Hanoï puzzle. There is no mention in this important paper concerning the effects of knowledge on problem solving or on knowledge acquisition as a factor in problem solving performance. The Chi et al. paper was one of the first to apply to educationally relevant problems the information described above concerning the importance of domain-specific knowledge on problem solving performance.

Schneider et al. (1989) replicated the domain specific knowledge effect in a very different way. They presented memory tasks and text comprehension to two groups that differed in domain-specific knowledge and in verbal aptitude (vocabulary, sentence completion, and word classifications) measured by a cognitive ability test. The participants were soccer experts and novices. The results indicated that low aptitude experts outperformed high-aptitude novices on all memory and comprehension measures. These results were analogous to those obtained by Chi (1978) who found that younger, chess-playing children had a better memory for chess board configurations taken from real games than older children with less knowledge of the game.

Chi’s work contributed to the body of evidence concerning the domain-specificity of expert knowledge. It was particularly important because the subject matter, physics, was unambiguously educationally relevant, and the novices and experts were all students with differing levels of expertise rather than established experts. Following Chi’s work, several studies took domain-specific knowledge into account by controlling it, but only a few focused on analysing the effects of domain-specific knowledge on learning (see Fayol 1994 for a review; and more recently Amadieu et al. 2009; Duncan 2007; Gijlers and de Jong 2005). A very limited number of studies have demonstrated the effect of domain-specific knowledge when it is presented a few minutes before a main learning task (Mayer et al. 2002; Pollock et al. 2002). Thus, if domain-specific knowledge is central to the intellectual performance of students, techniques designed to assist students in acquiring domain-specific knowledge seemed to be a logical next step.

## Cognitive Load Theory

If domain-specific knowledge held in long-term memory is central to learnable aspects of intellectual performance, we might expect instructional design research and theories to place their emphasis on the acquisition of biologically secondary, domain-specific knowledge. One theory that places a heavy emphasis on the acquisition of domain-specific knowledge is cognitive load theory (Chanquoy et al. 2007; Sweller 2011, 2012; Sweller et al. 2011).

Cognitive load theory was designed and has been continuously developed to account for cognitive processes that facilitate the acquisition of domain-specific knowledge via new instructional procedures. The current version of that cognitive architecture places a heavy emphasis on biological evolution in two respects. First, it uses Geary's evolutionary educational psychology (Geary 2008, 2012) to distinguish between biologically primary and secondary knowledge. It is the cognitive architecture associated with biologically secondary knowledge that is used by cognitive load theory. The information processes used by that architecture are closely analogous to the information processes used by evolution by natural selection and that analogy provides the second way in which cognitive load theory relies on evolutionary theory.

As applied to human cognition, the relevant information processes require: a store of information in the form of a long-term memory holding very large amounts of domain-specific information; machinery to obtain that information from other people; the ability to create novel information through a random generate and test process during problem solving; a structure, working memory, to limit the amount of novel information that is acquired during random generate and test to ensure that useful information held in long-term memory is not destroyed, and lastly; either a structure such as long-term working memory or processes to allow information held in long-term memory to be brought into working memory to govern knowledge-based activity. Together, these cognitive structures and processes constitute a cognitive architecture that can be used to generate instructional procedures. (See Sweller and Sweller 2006, for details of the analogy between this cognitive architecture and evolution by natural selection.) These instructional procedures are concerned entirely with facilitating the acquisition of biologically secondary, domain-specific knowledge. Recent summaries of the various cognitive load effects and their instructional implications can be found in Sweller (2011, 2012). Detailed, comprehensive summaries may be found in Sweller et al. (2011) and will not be repeated here. While all of the effects are intended to facilitate the acquisition of domain-specific knowledge, two of the effects, the worked example effect and the expertise reversal effect, provide particularly good examples of the importance of biologically secondary, domain-specific knowledge to instructional design issues. These two effects will be discussed within a context of acquiring domain-specific knowledge.

*The worked example effect* This effect is demonstrated when learners, provided problems to solve, learn less than learners provided the same problems using a worked example format. In a worked example, each problem is associated with a detailed solution. Despite solving fewer problems, on subsequent problem solving tests, the worked example condition characteristically performs at a higher level. Why is this result obtained?

According to cognitive load theory, studying a worked example reduces extraneous (or unnecessary) working memory load compared with having to search for a problem solution and that reduction allows working memory resources to be devoted to learning to recognise problem states associated with their appropriate moves. In other words, studying a worked example is congruent with the biologically secondary, domain-specific knowledge hypothesis that suggests that good problem solvers have learned to recognise a large number of problem states and the best moves associated with each state. Work examples place their emphasis on precisely those problem states and their moves, leading to the worked example effect.

*Expertise reversal effect* The worked example effect occurs using novices in a domain. As levels of expertise increase, the effect first disappears and then reverses with problem solving proving superior to studying worked examples (Kalyuga et al. 2001). While novices require worked examples to help them acquire the domain-specific knowledge that is central to problem-solving skill, why are worked examples deleterious to the acquisition of skill once levels of expertise increase?

More expert problem solvers have already acquired the knowledge necessary to solve a given class of problems. They do not need to be shown how to solve such problems because they do not need to engage in an extensive problem-solving search process to find a suitable solution. Reading a worked example is a redundant activity (see Sweller, et al. 2011, for a discussion of the redundancy effect) that increases extraneous cognitive load. Instead, learners may need practice at solving the problems so that they can automatically recognise the relevant problem states and their associated moves. For these reasons, worked examples are needed by novices while problem solving is more important for more expert problem solvers in a domain leading to the expertise reversal effect. Again, the effect was generated by cognitive load theory and relies on the central importance of biologically secondary, domain-specific knowledge to skilled problem solving. (It should be noted that the expertise reversal effect modifies a range of cognitive load effects, not just the worked example effect.)

Both the worked example effect and other associated effects such as the expertise reversal effect are predicated on the assumption that the purpose of instruction is to allow learners to acquire vast amounts of biologically secondary information stored in long-term memory. It is assumed that that information transforms our cognitive processes and indeed, transforms us. This assumption can be contrasted with alternative views of human cognition that place a greater emphasis on the acquisition of domain-general knowledge (see Kirschner et al. 2006). We suggest it can be argued that domain-general information is unteachable because it consists of biologically primary knowledge that is acquired easily and automatically without instruction. We have evolved to acquire such knowledge.

## Discussion

We have argued that expertise based on biologically secondary, domain-specific knowledge held in long-term memory is by far the best explanation of performance in any cognitive area. Furthermore, in contrast to domain-general cognitive knowledge, there is no dispute that domain-specific knowledge and expertise can be readily taught and learned. Indeed, providing novice learners with knowledge is the main role of schools. We might guess that most school teachers in most schools continue to emphasise the domain-specific knowledge that always has been central, making little attempt to teach domain-general knowledge. Based on our argument, they should continue to do so. At school, children acquire knowledge that overcomes the need to engage in inefficient problem solving search and other cognitive processes. That knowledge allows people to function in a wide variety of tasks outside of school. Given the overwhelming importance of domain-specific knowledge, indeed, its sole importance if the argument presented in this paper is valid, it is puzzling that our field has tended to place considerable emphases elsewhere for most of its existence as an area of research. There are several possible reasons.

At any given time, we are unaware of the huge amount of domain specific knowledge held in long-term memory. The only knowledge that we have direct access to and are conscious of must be held in working memory. Knowledge held in working memory tends to be an insignificant fraction of our total knowledge base. With access to so little of our knowledge base at any given time, it is easy to assume that domain-specific knowledge is relatively unimportant to performance. It may be difficult to comprehend the unimaginable amounts of organised information that can be held in long-term memory precisely because such a large amount of information is unimaginable. If we are unaware of the large amounts of information held in long-term memory, we are likely to search for alternative explanations of knowledge-based performance. Those alternatives tend to consist of domain-general strategies. We have suggested that such strategies are likely to be unteachable because they are too important for humans not to acquire. As a consequence, we have evolved to acquire very general strategies easily and quickly as biologically primary knowledge.

Not only is the amount of domain-specific knowledge held in long-term memory hidden from us, the nature of that knowledge tends to be hidden from us as well. We may know that we have learned Pythagoras' theorem because it is explicitly learned. We may not know that we must also learn to recognise the various problem states to which the theorem applies and that knowledge may be considerably more extensive and difficult to learn than simply learning the theorem itself because the problem states to which the theorem applies are effectively infinite. Based on the current, predominant literature, it is still easy to assume, for example, that learning mathematics involves no more than learning the rules of mathematics or learning to play chess is no more than just learning the rules of chess. Mathematicians and chess players are fully aware that they need to learn the appropriate rules in order to function in their area. They may be quite unaware of what else needs to be learned in order to function at a high level. It may not be surprising that, in the absence of information concerning the extensive knowledge of problem states and their moves, hypotheses associated with frequently unnamed and undescribed general cognitive strategies arose instead. It took us a very long time to discover exactly what is learned when dealing with a substantial domain.

Once we have learned a substantial domain, we tend to forget how difficult and how long it took us to learn it. As many secondary teacher trainers can testify, it can be difficult to convince trainees that they should not enter their first classroom and attempt to tell students everything they have learned about a particular topic in 45 min. Once we have learned something, we tend to assume it is simple and obvious (because it is simple and obvious for us) and forget how complex and difficult it was to learn.

For these reasons, the extent, complexity, difficulty, and sheer time needed to acquire domain-specific knowledge can be hidden from us. Suggestions that domain-specific knowledge held in long-term memory may be all that is needed to explain very high and very sophisticated levels of performance may appear to be counter-intuitive. Instead, complex but frequently unspecified cognitive strategies may appear to be the main drivers of our cognitive processes. While sophisticated, general strategies are likely to exist, we should expect them to be biologically primary.

The search for powerful, general strategies that transform and enhance our performance can provide an irresistible siren-call but such strategies, because of their importance and power, are likely to be biologically primary and so automatically acquired without assistance from instructors. Humans are likely to have evolved to acquire important cognitive strategies and do so easily and automatically. In contrast, biologically secondary information is rarely obtained easily or automatically. We should at least consider the possibility that all learning of the biologically secondary information that is central to modern education is based on the acquisition of domain-specific rather than domain-general knowledge. If so, an appropriate role for cognitive processes and instructional design researchers is to devise techniques to assist students to acquire this domain-specific knowledge rather than already learned generic skills. As indicated in the previous section, such a strategy can lead to novel instructional procedures.

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