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Working Memory, Long-term Memory, and Instructional Design

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Cognitive load theory is used to design instruction. Several aspects of human cognition are critical to instructional design. First, the theory assumes we have not specifically evolved to learn the topics taught in educational and training institutions. Second, these topics require learners to acquire domain-specific rather than generic–cognitive knowledge. Third, while generic–cognitive knowledge does not require explicit instruction because we have evolved to acquire it, domain-specific concepts and skills do require explicit instruction. These factors interact with the capacity and duration constraints of working memory to delineate a cognitive architecture relevant to instructional design. The working memory limits do not apply to biologically primary, generic–cognitive knowledge acquired without explicit instruction but do apply to biologically secondary, domain-specific knowledge that requires explicit instruction. Accordingly, cognitive load theory has been developed to provide techniques that reduce unnecessary working memory load when dealing with explicitly taught, biologically secondary, domain-specific knowledge.

Keywords: Cognitive load theory, Instructional design, Relations between working and long-term memory

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Based on cognitive load theory (Sweller, Ayres, & Kalyuga, 2011), this paper discusses the role of working memory, its relations to long-term memory and changes in the characteristics of working memory with changes in the categories of information being processed. The purpose is to indicate those aspects of human cognitive architecture that can be used to devise instructional procedures. The characteristics of working memory are central to cognitive load theory and to instructional design.

With respect to instructional design, there are three related aspects of human cognition that frequently are ignored: (a) The distinction between knowledge we have specifically evolved to acquire and knowledge that we need for largely cultural reasons; (b) The differential role of generic–cognitive and domain-specific knowledge; (c) The conditions under which instruction needs to be explicit. Each of these factors is important for their own reasons but they are related through their interaction with working memory and long-term memory. I will consider each factor in sequence followed by an outline of the cognitive architecture used by cognitive load theory and some of the instructional applications that have flowed from the theory.

Biologically Primary and Secondary Knowledge

The distinction between these two categories of knowledge was made by Geary (2007, 2008, 2012). We have evolved to acquire biologically primary knowledge over countless generations. Examples are learning to listen and speak, learning to recognize faces, or generic–cognitive processes such as solving problems by using solution knowledge of related problems.

Primary knowledge and skills tend to be modular. Our ability to learn our native language may have evolved during a different evolutionary epoch and use different cognitive processes to our ability to learn to recognize faces. Most importantly from the current perspective, biologically primary knowledge tends to be acquired easily, unconsciously and without explicit tuition from other people. We do not need to be taught how to listen to speech or how to find our way from Point A to a visible Point B. These are complex skills that we acquire automatically and effortlessly.

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The working memory limitations (Shipstead, Lindsey, Marshall, & Engle, 2014) that researchers have been familiar with for decades (Cowan, 2001; Miller, 1956; Peterson & Peterson, 1959) do not apply to biologically primary material where limits may be far wider than those usually discussed in the literature. Most people do not have difficulty remembering the enormous number of points of difference needed to distinguish one face from another face nor do we have difficulty learning and retaining the large range of sounds that constitute our native language. We have evolved to acquire the knowledge needed for facial recognition and the sounds of our native language.

Biologically secondary knowledge consists of the wide variety of disparate knowledge we need for cultural reasons. Unlike the modular nature of primary knowledge, it is largely undifferentiated except insofar as secondary knowledge requires primary knowledge for its acquisition (Paas & Sweller, 2012). Almost every topic taught in educational institutions provides an example of secondary knowledge as do topics taught in the workplace and during cultural activities.

Similar cognitive processes are used to acquire all categories of secondary knowledge but those processes are very different to the ones used to acquire primary knowledge. The acquisition of secondary knowledge tends to be conscious, relatively difficult and effortful. It is greatly assisted by explicit instruction (see below). Indeed, schools and other education and training institutions were invented precisely because of the characteristics of biologically secondary knowledge. Unlike biologically primary knowledge that is acquired merely by membership of a functioning society, biologically secondary knowledge tends not to be acquired without the assistance of the specifically devised societal structures associated with schools and other education and training institutions. Almost everybody will learn to listen and speak without the need for schools. Very few will learn to read and write without school-based instruction.

Secondary knowledge is acquired with the assistance of primary knowledge (Paas & Sweller, 2012). For example, our ability to listen and speak influences our ability to read and write. All secondary concepts and skills have an underlying bed of primary concepts and skills. These underlying primary concepts and skills are likely to influence individual differences in secondary concepts and skills.

Working memory provides a major cognitive difference between primary and secondary knowledge. The well-known capacity and duration working memory limitations apply only to biologically secondary knowledge. When dealing with novel, biologically secondary information, working memory is severely constrained in both capacity and duration. In turn, those constraints have instructional consequences, discussed below (Sweller et al., 2011).

Domain-specific and Domain-general Knowledge

One of the distinctions between biologically primary and secondary knowledge is that primary knowledge frequently constitutes a cognitive skill that is generic in nature while secondary knowledge tends to be domain-specific (Tricot & Sweller, 2014), with both including conceptual and procedural information. A generic–cognitive skill is a mental process that can be applied to a wide variety of unrelated areas while a domain-specific skill is a procedure that only can be applied to a specific range of areas. A general problem-solving strategy that can be applied to a wide variety of unrelated problems provides an example of a generic–cognitive skill. Using a means-ends strategy (Newell & Simon, 1972), according to which problem solvers note each problem state reached and attempt to reduce the distance between that problem state and the goal state, provides an example of a generic–cognitive skill. We all use a means-ends strategy when faced with novel problems in any area. In contrast, learning that when faced with an algebra problem such as $(a+b)/c=d$, solve for a, the best first move is to multiply out the denominator, provides an example of a domain-specific skill that applies only to a limited class of algebra problems.

Not all biologically primary skills can be classed as generic–cognitive nor are all secondary skills domain-specific. For example, since primary skills are modular, they tend to be specific to particular areas and in that sense are domain-specific rather than general. Nevertheless, because of their importance, generic–cognitive skills commonly are biologically primary. Means-ends analysis, the general problem solving strategy discussed above provides an example. There are many others such as learning to generalize or learning metacognitive skills. We not only need to learn how to solve problems, we need to learn how to learn, how to plan or how to think. These are critical, generic–cognitive skills (or abilities) that tend to be emphasized heavily in current educational research. There are good reasons for that emphasis. Generic–cognitive skills tend to be far more important than domain-specific skills. Without generic–cognitive skills, humans may have difficulty surviving as humans. But despite their importance, they do not need to be taught because they are biologically primary skills that we have evolved to acquire and so they are acquired without tuition.

While secondary skills tend not to be generic–cognitive in nature, some have considerable generality. As an example, while learning to read is a biologically secondary skill, it is domain-general although it is not a generic–cognitive skill in the sense of the above examples. Nevertheless, the vast majority of secondary skills taught in educational institutions are domain-specific rather than generic–cognitive.

For example, humans can survive without the domain-specific skills of knowing complex mathematics or openings in chess. As a consequence, we have not specifically evolved to acquire most domain-specific skills and so they are biologically secondary. While we may have evolved to acquire general, problem solving skills, we have not specifically evolved to acquire the knowledge that in order to solve a problem of the type, $(a+b)/c=d$, solve for a, we should first multiply out the denominator. That difference has instructional implications.

Schools and other educational and training institutions were largely devised to teach domain-specific, biologically secondary knowledge (Sweller, 2015). They were not devised to teach generic–cognitive skills because most of these are acquired automatically without tuition. Students may need to be taught that a particular generic–cognitive skill applies to a particular domain-specific area but they do not need to be taught the skill itself (Youssef-Shalala, Ayres, Schubert, & Sweller, 2014).

If domain-specific knowledge and skills largely are biologically secondary, they require the same working memory characteristics in order to be processed as all biologically secondary skills. Working memory capacity and duration limits will apply and instructional procedures need to take those limits into account (Sweller et al., 2011). In contrast, if generic–cognitive knowledge tends to be biologically primary, acquisition of the knowledge will not impose a heavy working memory load but attempts to teach it are likely to fail (Redick et al., 2013) because like all biologically primary knowledge, it is acquired without explicit tuition.

Explicit Instruction

Instructional implications flow from the biologically secondary, domain-specific characteristics of knowledge that is dealt with in educational contexts. We may automatically and unconsciously learn the biologically primary, generic–cognitive knowledge associated with listening and speaking, recognising faces and using means-ends analysis to solve problems. We do not automatically and unconsciously learn the biologically secondary, domain-specific knowledge associated with most of the topics taught in educational contexts. That knowledge needs to be explicitly taught by talking to learners or writing for learners (Kirschner, Sweller, & Clark, 2006). We should never assume that the relatively easy acquisition of biologically primary knowledge outside of formal education is due to the lack of formal guidance, while the more difficult acquisition of secondary knowledge is due to formal guidance. The difference in ease of learning between the two contexts is due to their evolutionary difference, not due to instructional procedures. Minimal guidance in educational contexts decreases ease of learning.

Why is explicit instruction important in educational contexts? The answer lies in the working memory characteristics when dealing with novel, biologically secondary, domain-specific information. Given that this category of information is the category where the limitations of working memory occur, it is important that instruction reduces all sources of extraneous cognitive load. Explicit instruction is likely to reduce the working memory load imposed compared to instructional procedures that rely on minimal guidance. There is strong evidence supporting that hypothesis. The worked example effect is one of the empirical effects generated by cognitive load theory. It occurs when learners shown the solution to a problem subsequently outperform learners who must solve the problem themselves (Cooper & Sweller, 1987; Renkl, 2014; Renkl & Atkinson, 2003). Based on the worked example effect, the empirical evidence overwhelmingly favors explicit instruction, providing support for the cognitive architecture that underpins the theory. That cognitive architecture will be discussed next.

Human Cognitive Architecture

Human cognition, when dealing with biologically secondary information, can be described as a natural information processing system analogous to the information processing characteristics of evolution by natural selection (Sweller et al., 2011; Sweller & Sweller, 2006). The analogy between biological evolution and human cognition has been suggested frequently (Campbell, 1960; Darwin, 1871/2003; Popper, 1979). There are many ways of describing natural information processing systems (Sweller, 2003). One way is in terms of five basic principles.

The Information Store Principle

In order to deal with a complex, constantly changing environment, natural information processing systems require a very large store of information. Genomes provide that store in the case of evolution by natural selection while long-term memory has an analogous role in human cognitive architecture.

The role of long-term memory in human cognition was considerably clarified by work on expertise in chess (De Groot, 1965). The obvious hypothesis was that chess masters consider a greater range of moves than less able players. In fact, chess masters showed no sign of engaging in greater search than weekend players despite masters usually choosing better moves. De Groot solved the mystery by showing chess masters and weekend players a chessboard configuration of pieces taken from a real game for 5 s, removing the board and asking the players to reproduce the board they had just seen. Chess masters could replace over 80% of the pieces accurately while weekend players were only able to replace less than 30% of the pieces accurately.

Several points concerning these results need to be noted. First, the difference largely disappears when random board configurations are used, with both weekend players and masters poor at this task (Chase & Simon, 1973), although there is a small but consistent advantage for masters in recall of random boards. Chess masters only perform well on a board configuration task when they are faced with configurations taken from real games. Second, it takes many years of practice to become an expert in any substantive area including chess (Ericsson & Charness, 1994). Third, the major change, possibly the only change during this period, is the transfer of information to long-term memory. Over many years of practice, chess masters have stored tens of thousands of board configurations along with the best moves for each configuration in long-term memory (Simon & Gilmartin, 1973). When playing a game, they recognize most of the configurations they encounter and know the best move or moves for each configuration. Weekend players, in contrast, must try to work out the best moves in a few seconds resulting in the likely choice of sub-optimal moves compared to someone who knows the best moves. Exactly the same process occurs in all areas of human expertise including educationally relevant areas (Chiesi, Spilich, & Voss, 1979; Egan & Schwartz, 1979; Jeffries, Turner, Polson, & Atwood, 1981; Sweller & Cooper, 1985). For example, while a chess expert learns to recognize board configurations, an expert reader needs to recognize the sets of marks that constitute the written word. An expert is someone who has an enormous store of domain-specific, biologically secondary information concerning his or her area of expertise held in long-term memory.

It needs to be emphasized that while individual differences are heavily influenced by differential knowledge held in long-term memory, it does not follow that there are no other factors influencing individual differences. For example, Meinz and Hambrick (2010) found that a substantial part of the variance between more and less skilled pianists was due to differences in working memory. Of course, the proportion of the variance determined by working memory differences will be also determined by the size of the differences in knowledge held in long-term memory. For example, differences in knowledge between people who do and do not know how to play the piano are likely to overwhelm any differences in working memory. Working memory differences are likely to be more important between slightly more knowledgeable and slightly less knowledgeable pianists. As another example, if people with knowledge of written English when asked to reproduce the marks that constitute a sentence of this paper are compared with people with no knowledge of written English, the immense differences between them will largely reflect their differential knowledge base rather than their differential working memory capacity. Under those circumstances, differences in knowledge may be critically important. With decreases in differential knowledge between individuals, we should expect increases in the contribution of the role of working memory differences.

The Borrowing and Reorganizing Principle

Most information acquired by natural information processing systems is borrowing from other stores. In the case of biological evolution, sexual and asexual reproduction provide the required processes. Asexual reproduction provides an exact copy of ancestors' genomes apart from mutations. Sexual reproduction borrows information from both male and female ancestors but reorganizes it.

Most of the contents of long-term memory are borrowed from the long-term memories of others because we learn from others. We imitate what other people do (Bandura, 1986), we listen to what they say and we read what they write. Our propensity to obtain information from other people is biologically primary. We do not need to be taught to imitate other people nor do we need to be taught to listen to them and speak to them. We do need to be taught to read and write because these skills are biologically secondary but once we have sufficiently acquired these biologically secondary skills, we do not need to be encouraged to use them. We have evolved to communicate with others as a biologically primary skill even if the particular transmission procedure is the secondary skill of reading and writing. While communicating with other humans is biologically primary, the information communicated frequently is biologically secondary. It is information that we have not specifically evolved to acquire but need for cultural reasons. In modern societies, much of that information is acquired in education and training institutions.

The borrowing and reorganizing principle not only results in large amounts of information being borrowed, that information is reorganized. We rarely reproduce information precisely. It is reorganized by combining new information with old information stored in long-term memory. When required to memorize something, those aspects of the material that conform with what we already have stored in long-term memory are sharpened or emphasized while novel information that does not correspond to information held in long term memory is leveled or flattened (Bartlett, 1932). As a consequence, the same information is reorganized in different ways when stored in long-term memory by different people, analogous to the different genomes that result from sexual reproduction.

Evidence for the importance of the borrowing and reorganizing principle in human cognition comes from the worked example effect (Glogger-Frey, Fleischer, Gruny, Kappich, & Renkl, 2015; Renkl, 2014; Sweller et al., 2011). As indicated above, learners presented worked examples consisting of a problem and its solution to be studied, perform better on subsequent problem solving tests than learners just presented the problems alone for them to solve. We learn more by being shown a problem solution that we can borrow from someone else than by solving the same problem ourselves.

The Randomness as Genesis Principle

While natural information processing systems acquire the vast bulk of their information via the borrowing and reorganizing principle, that information must be created in the first instance. The randomness as genesis principle provides the necessary machinery.

The ultimate origin of all genetic variation between individuals, whether they belong to the same species or not, is random mutation. Other processes may distribute the unique combinations of variations initiated by random mutation, but that distribution only can function because of previous sequences of mutations.

The process by which random mutation has its effects is generate and test. Random mutation only can be of value if it is followed by a test of effectiveness. The vast majority of random mutations are likely to have either no function or a negative effect. Mutations with a negative effect are likely to be jettisoned while those with a positive effect are likely to be retained. Mutations generate novelty that is then tested for effectiveness with only effective changes retained.

Biological evolution is a natural, creative system. Human creativity uses the same logical process during problem solving (Sweller, 2009). When determining a problem-solving move, there are two separate processes that can be used. First, if the problem state is recognized and a move appropriate for that state is known, that known move can be retrieved from long-term memory and used in the same way as an established genome will determine routine activity such as protein formation. As indicated below under the environmental organizing and linking principle, generating action that is appropriate to a given environment is the primary function of the information store.

Second, when humans are faced with a novel problem, by definition, at least one or more of the required moves cannot be determined simply by retrieval from long-term memory. The only alternative to retrieving information from long-term memory is to use a generate and test procedure. Most commonly, generate and test is incorporated into a means-ends problem solving strategy. Both the use of that strategy and the retrieval of moves from long-term memory are biologically primary activities that cannot be taught because they are learned automatically without tuition. Frequently, there are several possible moves that might reduce differences between a current problem state and the goal state. If knowledge is available, the best move can be chosen. If knowledge is not available, the only alternative is to use a random generate and test procedure. A possible move is chosen randomly and tested for effectiveness. If it reduces differences between the current problem state and the goal state, it is accepted, a new current state is attained and the process can be repeated. Successful moves can be stored in long-term memory for future use just as successful mutations are retained by a genome for future use.

The Narrow Limits of Change Principle

There are structural consequences that flow from the randomness as genesis principle. An information processing system that randomly generates combinations of elements runs the risk of combinatorial explosions as the number of elements increases. For example, while there are $3! = 6$ permutations of 3 elements, there are $10! = 3{,}628{,}800$ permutations of 10 elements. When using a generate and test process, determining which of 6 permutations should be used may be relatively simple. Determining which of 3,628,800 permutations is useful is much more challenging and takes much longer. For this reason, natural information processing systems require a mechanism to ensure that the number of combinations to be tested is kept to manageable proportions. In the case of human cognition, the characteristics of working memory play this role. In the case of evolution by natural selection, the epigenetic system can be hypothesized to play a similar role.

The epigenetic system acts as a connector between the environment and the genetic system. It can turn genes on and off, discussed in the next section, and also, under the narrow limits of change principle, can determine the location and frequency of mutations. In order to maintain the integrity of a genome, mutations must be relatively infrequent since a massive change in a genome is unlikely to be adaptive.

Working memory plays the same role in human cognition as the epigenetic system plays in biological evolution. It acts as a conduit between the external environment and the information store that is long-term memory in the case of human cognition. As indicated above, working memory is a structure that has very well-known limitations when dealing with novel, biologically secondary information.

The limitations of working memory apply only to novel information from the environment. Random generate and test can function when dealing with a limited number of novel elements at a time. It cannot function when dealing with a large number of elements simultaneously. The limitations of working memory ensure that a large amount of novel information is never handled simultaneously. Since only a small amount of information can be processed by a limited working memory, any changes to long-term memory are themselves limited, reducing the chance of damage to knowledge structures that have developed successfully over long periods of time. Similarly, genomes do not change rapidly. The narrow limits of change principle ensures that changes are small and incremental.

The Environmental Organizing and Linking Principle

This principle justifies the preceding principles. Like the narrow limits of change principle, it connects environmental information with the information store but in a very different way to the narrow limits of change principle. Rather than adding restricted amounts of information from the environment to the information store as does the narrow limits of change principle, the environmental organizing and linking principle takes cues from the environment to allow stored information to direct appropriate action. The epigenetic system and working memory again provide the conduits.

The importance of the epigenetic system can be seen most clearly through the environmental organizing and linking principle. Consider two human cells, a skin cell and a liver cell from a single individual. Both have vastly different structures and functions but both have identical DNA structures in their nuclei. They are genetically identical but phenotypically very different. That phenotypic difference is directly caused by the epigenetic system which turns genes on or off according to environmental signals. While information stored in the genome determines the potential activities of the cells, the actual information that is activated is determined by the epigenetic system.

The environmental organizing and linking principle is equally important to human cognitive architecture. Working memory is very different when it is used to add information to long-term memory under the narrow limits of change principle as opposed to directing the use of already stored information to determine action under the environmental organizing and linking principle. Using the environmental organizing and linking principle, environmental signals indicate which information stored in long-term memory should be retrieved by working memory. That information then is used to control activity.

Whereas working memory is limited in capacity and duration when it is used to add information to long-term memory via the narrow limits of change principle, no such limits apply when it is used to retrieve information from long-term memory via the environmental organizing and linking principle. Once information is organized and stored in long-term memory, indefinitely large amounts of that information can be transferred to working memory for indefinitely large periods of time.

The ability to process information in working memory will differ between individuals. These differences can affect performance (Meinz & Hambrick, 2010) but once information is stored in long-term memory, the effects may overwhelm individual differences in working memory. Working memory always is severely limited when dealing with novel, biologically secondary information but effectively unlimited when dealing with familiar information stored in long-term memory. The possession of information held in long-term memory provides an advantage that reduces the consequences of differences in working memory. Due to the environmental organizing and linking principle, an expert in a complex area with extensive information stored in long-term memory is likely to outperform a novice in a relevant domain irrespective of any differences in their working memories.

The vast differences in the properties of working memory when it is used to gather information from the environment as opposed to transferring information from long-term memory has resulted in some theorists postulating an entirely different structure, long-term working memory, to handle information retrieved from long-term memory (Ericsson & Kintsch, 1995). For present purposes, a single structure with dual functions depending from where it obtains its information, or two separate structures with different functions, are functionally equivalent.

These five principles constitute a cognitive architecture that organizes the processing of biologically secondary information. That architecture, while dealing with biologically secondary information, itself derives from the biologically primary system. In summary, our ability to store information in long-term memory using the information store principle; borrow information and reorganize it using the borrowing and reorganizing principle; generate novel information via the randomness as genesis principle; process novel information in working memory using the narrow limits of change principle; and transfer large amounts of information from long-term to working memory to generate appropriate action using the environmental organizing and linking principle, all constitute biologically primary skills. We do not teach nor do we have to teach these immensely complex, critical skills. We have evolved to acquire them. In that sense, the biologically secondary system is acutely dependent on primary skills.

Applications

Cognitive load theory uses this cognitive architecture to devise instructional procedures. Based on this architecture, the theory assumes that the major function of instruction is to facilitate the acquisition of domain-specific, biologically secondary information that is stored in long-term memory for later use. Before it can be stored, that information must first be processed by a limited capacity, limited duration working memory. Once stored, the information can be used to guide action, again using working memory but without the capacity and duration limits attendant on the acquisition of novel information.

Based on these structures and processes, it follows that a major consideration in organizing instruction is the limitations of working memory when dealing with novel information. Cognitive load theory has been used to devise a large range of instructional prescriptions based on cognitive load effects derived from the results of randomized, controlled trials (see Sweller et al., 2011 for summaries). Most cognitive load effects reduce extraneous cognitive load by reducing the number of elements of information introduced by instructional procedures. If elements of information introduced by instructional procedures must be simultaneously processed in working memory during learning because they interact, extraneous working memory load will be high (Sweller, 2010). In addition to instructional procedures that alter extraneous cognitive load, the intrinsic properties of information determine intrinsic cognitive load. Some information, because of its nature, requires learners to assimilate multiple, interacting elements that can result in a high intrinsic working memory load. An addition of extraneous and intrinsic cognitive load provides the total working memory load. Most cognitive load effects are due to reductions in extraneous cognitive load because this cognitive load is directly caused by inappropriate instructional procedures that usually can be changed. Other cognitive load effects are obtained by optimizing intrinsic cognitive load.

The worked example effect, discussed above, is probably the best known of the cognitive load effects obtained by reducing extraneous cognitive load. Studying worked examples is superior to solving the equivalent problems because the number of interacting elements that must be simultaneously processed when solving a problem with an unknown solution is greater than the number that must be processed when studying a worked example in which the solution is provided, resulting in a reduced working memory load when studying the solution.

There are many other cognitive load effects and only a few will be discussed here. The split-attention effect (Sweller et al., 2011) is another frequently studied extraneous cognitive load effect. If a problem solution or any other instruction is presented in a manner that requires learners to split their attention between multiple sources of information that need to be mentally integrated in order for the instruction to be understood, then the number of interacting elements that need to be processed in working memory is greater than if the multiple elements are physically integrated, obviating the need for mental integration. As another example, the redundancy effect (Sweller et al., 2011) occurs if additional, unnecessary elements are added encouraging learners to simultaneously process both the necessary and unnecessary elements. More elements will need to be processed in working memory than if the unnecessary elements are eliminated, leading to the redundancy effect.

While extraneous cognitive load needs to be reduced, intrinsic cognitive load needs to be optimized. The variability effect provides an example of increasing intrinsic cognitive load in order to improve learning (Paas & van Merrienboer, 1994; Sweller et al., 2011). If the variability of worked examples is increased, then students must not only learn how to solve a particular class of problems, they also need to learn how to distinguish between problems and learn how to classify them into solution categories. Element interactivity is increased but increased by providing information that is important. While intrinsic cognitive load is increased, so long as learners have sufficient working memory resources to process the additional elements, learning will be facilitated. That result was obtained by Paas and van Merrienboer (1994). In contrast, if learners do not have sufficient resources to process additional, intrinsically important elements, learning will be reduced by the inclusion of those elements. It may be important to omit important interacting elements if they overload working memory. Learning may be facilitated by first omitting important elements before including them later, as demonstrated by the isolated elements effect (Sweller et al., 2011). As can be seen, intrinsic cognitive load needs to be optimized rather than reduced. Under the variability effect, intrinsic cognitive load is increased while it is decreased under the isolated elements effect.

Element interactivity, through its effects on working memory, has consequences for all other cognitive load effects and so can be classed as an effect in its own right. The element interactivity effect can be seen clearly in recent work on relations between the generation and worked example effects (Chen, Kalyuga, & Sweller, 2015). The generation effect occurs when providing learners with instructional guidance results in worse test performance than having them generate responses themselves, a reverse result to that obtained by the worked example effect. The contrasting results are determined by levels of element interactivity. Instructional guidance only is beneficial under conditions of a heavy, intrinsic working memory load. Guidance is likely to have negative effects due to redundancy when working memory load is light. Accordingly, the generation effect is obtained when element interactivity and intrinsic working memory load is low, while the worked example effect is obtained when they are high.

The expertise reversal effect (Kalyuga, Ayres, Chandler, & Sweller, 2003) is a variant of the element interactivity effect. This effect occurs when the relative advantage of an instructional procedure is eliminated or reversed by increases in expertise. For example, studying high element interactivity worked examples may be superior to solving the equivalent problems for novices but with increases in expertise, the effect reduces and can be reversed (Kalyuga, Chandler, Tuovinen, & Sweller, 2001). Increases in expertise result in decreases in element interactivity due to the environmental organizing and linking principle. Information that is treated as individual elements by novices and so imposes a heavy working memory load, may be treated as a single element by more expert learners resulting in a light working memory load. Element interactivity decreases with increases in expertise resulting in a reversal of effects caused by high element interactivity and its attendant high working memory load. In summary, element interactivity can be altered either by altering the nature of the materials or the expertise of learners. In either case, high element interactivity information requires instructional guidance while low element interactivity information does not require guidance.

Cognitive load theory has been used to generate many other instructional effects. In all cases, the effects are caused by either a reduction of extraneous cognitive load or the optimization of intrinsic cognitive load. In this way, the central role of working memory in human cognition has been used to generate a large range of instructional applications.

Conclusions

The cognitive architecture outlined above suggests that the knowledge acquired in academic contexts consists of biologically secondary, domain-specific rather than generic–cognitive information. It may be the only information that can be taught (Sweller, 2015). Generic–cognitive knowledge may be far too important for us not to have evolved to acquire it automatically and without instruction. At this point, there seems to be no body of literature based on randomized, controlled experiments unequivocally demonstrating effective, teachable generic–cognitive skills despite many decades of work. The best we seem able to do is demonstrate that learners may need to be told to use previously acquired, generic–cognitive knowledge in specific domains (Youssef-Shalala et al., 2014).

In contrast to the paucity of literature demonstrating effective teaching of generic–cognitive knowledge, there is a large literature indicating techniques for teaching domain-specific knowledge. That literature emphasizes the critical importance of the well-known characteristics of human cognition when devising instructional procedures. The constraints of working memory when acquiring novel, biologically secondary information and the elimination of those constraints when dealing with familiar information stored in long-term memory are central to this work. Without this critical knowledge of human cognition, instructional design is blind.

Conflict of Interest Statement

The author declares that he has no conflict of interest.

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