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SPECIAL INTERESTS

Cognitive load theory and educational technology

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Abstract

Cognitive load theory provides instructional recommendations based on our knowledge of human cognition. Evolutionary psychology is used to assume that knowledge should be divided into biologically primary information that we have specifically evolved to acquire and biologically secondary information that we have not specifically evolved to acquire. Primary knowledge frequently consists of generic-cognitive skills that are important to human survival and cannot be taught because they are acquired unconsciously while secondary knowledge is usually domain-specific in nature and requires explicit instruction in education and training contexts. Secondary knowledge is first processed by a limited capacity, limited duration working memory before being permanently stored in long-term memory from where unlimited amounts of information can be transferred back to working memory to govern action appropriate for the environment. The theory uses this cognitive architecture to design instructional procedures largely relevant to complex information that requires a reduction in working memory load. Many of those instructional procedures can be most readily used with the assistance of educational technology.

Keywords Cognitive load theory · Human cognitive architecture · Evolutionary psychology · Instructional design

The success or otherwise of educational technology is affected by the characteristics of human cognitive architecture. Technology-based instruction used without reference to the instructional design principles that flow from human cognition is likely to be random in its effectiveness. Cognitive load theory (Sweller et al. 2011, 2019), as an instructional design theory based on our rapidly expanding knowledge of human cognition, is well-suited to provide guidance suggesting which educational technologies are likely to be effective and how they should be used. This paper summarises the theory and applies it to learning that occurs with the assistance of educational technology.

I will begin by describing relevant aspects of human cognitive architecture and its evolutionary psychology base. The purpose of specifying the cognitive and evolutionary psychology base is to identify those aspects of human cognition and evolutionary psychology that are relevant to instructional design. That base then is used to indicate

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general instructional implications, followed by a discussion of several of the specific cognitive load theory effects. The cognitive load effects, all derived from randomised, controlled trials, can be used to partially validate the theory, assuming that a theory that can generate applications is tied to reality. Of course, the major function of the cognitive load effects is to provide specific instructional design guidelines. Most of those effects are directly relevant to technology-based education.

Evolutionary psychology and human cognitive architecture

Evolutionary psychology can be used to indicate those aspects of human cognitive architecture that are relevant to instructional design issues. By doing so, our viewpoints on what we teach, how we teach it, and even why we teach it can be transformed.

Categories of information

Based on Geary's evolutionary educational psychology (Geary 2002; Geary and Berch 2016), we can divide information into two categories, biologically (or evolutionary) primary and secondary information ("information" is termed "knowledge" when it is held in long-term memory and "skills" when knowledge is translated into appropriate action). We have evolved to process and acquire primary information over many generations and can do so easily, automatically and without conscious effort even when the amount of information processed is voluminous. We do not need to teach learners how to process primary information nor do we need to teach them how to acquire it and store it as knowledge. Not only do we not need to teach primary knowledge, we cannot teach it simply because it is acquired automatically, frequently very early in life. Examples of the acquisition of primary knowledge are learning to listen to and speak our native language, learning to plan, learning to self-regulate our cognitive processes, or acquiring general problem-solving strategies such as means-ends analysis (Newell and Simon 1972). All of these skills are acquired automatically without explicit tuition. It also should be noted that they are probably modular with limited relations between them because they may have evolved during different evolutionary epochs.

In contrast, secondary knowledge is much more difficult to acquire despite in most cases incorporating far less information than primary knowledge. Rather than being acquired automatically, it requires conscious effort on the part of the learner and is assisted by explicit instruction. The biologically secondary system is used to acquire knowledge that our culture has deemed important but that we have not specifically evolved to acquire. Secondary knowledge requires explicit guidance while learners must consciously and actively attend to its acquisition. In the absence of these conditions, few people are likely to acquire secondary knowledge and the resultant skills. Examples of secondary knowledge are learning to read and write, learning a second language as an adult, and mathematics. Indeed, since education and training institutions were established precisely because their curricula are rarely acquired without their existence, virtually all topics taught in schools and other training institutions provide examples of secondary knowledge.

Generic-cognitive and domain-specific knowledge and skills

There is another knowledge classification system closely related to the biologically primary and secondary dichotomy that needs to be used when considering the cognitive substrate of instructional design. That system distinguishes between generic-cognitive and domain-specific knowledge and skills (Sweller 2015, 2016; Tricot and Sweller 2014).

Most, though not all biologically primary skills (referred to as "primary skills" below) are generic-cognitive skills. Knowledge and skills that are general and so apply to a wide variety of areas and that refer to cognitive processes are generic-cognitive in nature. The biologically primary skills referred to above such as planning, self-regulating or general problem-solving skills are generic-cognitive. For example, an ability to plan can be assumed to incorporate a wide variety of areas but refers to a specific cognitive procedure.

While not all primary skills are generic-cognitive, it is likely that all generic-cognitive skills are primary. These skills are far too important for us not to have evolved to acquire them. As an example, in order to survive, we must be able to use problem-solving techniques such as means-ends analysis in which we attempt to find problem solving operators that reduce the distance between our current problem state and a goal state. Without this skill, we would have difficulty finding food or shelter. Accordingly, while the problem-solving strategy has been known for decades, as far as I am aware, there is not a single example in the literature of successfully teaching it with the result of improved problem-solving skill. It may be reasonable to speculate that it cannot be taught because everyone automatically acquires this skill as primary knowledge. It may be equally reasonable to speculate that other generic-cognitive skills have exactly the same properties.

In contrast to generic-cognitive knowledge and skills, domain-specific knowledge and skills are specific to a particular domain. We may use means-ends analysis to attempt to solve any novel mathematics problem that we face but if we have learned to solve a particular class of algebra problems such as *a/b = c, solve for a,* by multiplying out the denominator on the left-hand side, then we have acquired a domain-specific skill that is limited to a particular class of algebra problem. Furthermore, the knowledge underlying this skill is biologically secondary. We can learn to solve algebra problems but we have not specifically evolved to solve such problems. They are biologically secondary. Most of the curricular information that is acquired during education is domain-specific, biologically secondary information that unlike generic-cognitive, biologically primary knowledge, will not be acquired unless it is explicitly taught.

Consequences of the distinction between generic-cognitive primary and domain-specific secondary knowledge and skills

Because the distinction between primary and secondary knowledge is relatively new, as is the connection between primary knowledge and generic-cognitive skills on the one hand and secondary knowledge and domain-specific skills on the other hand, they have had minimal impact on either instructional design in general or on the use of educational technology. Nevertheless, our failure to appreciate these distinctions has misled us for generations and to a large extent, continues to do so.

Let us assume that contrary to the above distinctions in the instructional consequences of generic-cognitive, primary and domain-specific, secondary knowledge and skills, that both categories are equivalent in the ease with which they are acquired and the procedures needed to assist in their acquisition. Which knowledge and skills should we emphasise? Both are needed but of course, generic-cognitive, primary skills are far more important than domain-specific, secondary skills. It is surely more important to acquire critical thinking skills (and no, I am unable to define them either), self-regulation or general problem-solving skills than it is to learn about the causes of WW1, or how to multiply out a denominator in an algebraic equation. If we are unable to think clearly or do not know how to solve novel problems, there will be little that we will be able to do with domain-specific knowledge.

This argument has been implicit in much educational discussion and has driven a considerable body of educational research for at least the last 100 years. The issue can be resolved by treating the argument as a testable, scientific hypothesis. If generic-cognitive, primary skills can be taught, then evidence for their effectiveness should be obtainable from far-transfer tasks. Such tasks are required to ensure that any improvements in performance are not due to the acquisition of domain-specific, secondary skills. Generic-cognitive skills presumably apply in a wide diversity of curriculum areas while domain-specific skills are narrow. As far as I am aware, despite decades of effort, there are no substantive, replicated bodies of work using randomised, controlled trials demonstrating superior far transfer performance due to instruction in the use of generic-cognitive procedures. Until such bodies of research are available, we need to look elsewhere for effective instructional procedures. Accordingly, cognitive load theory places its emphasis on the acquisition of domain-specific, secondary knowledge and that emphasis applies to e-learning procedures as well as other forms of instruction. The cognitive architecture discussed next applies to the acquisition of domain-specific, biologically secondary skills rather than generic-cognitive, biologically primary skills.

Human cognitive architecture and the acquisition of domain-specific knowledge

A specific cognitive architecture is associated with the acquisition of domain-specific, secondary knowledge that provides a base for cognitive load theory. That architecture is analogous to the information processing system which guides evolution by natural selection. It can be described by five principles that reflect a natural information processing system (Sweller and Sweller 2006). These principles indicate how we acquire novel information, process and store it before retrieving it from storage to govern action that is appropriate for the environment in which we find ourselves.

Acquiring Information

Randomness as genesis principle

This principle deals with novel information that: (a) is obtained from the external environment; (b) is not obtained from another person in spoken or written form and (c) for which we do not have previously acquired knowledge indicating how it should be processed. For example, it is used to determine problem-solving moves for when we do not have a previously learned solution. When solving a novel problem, we may reach problem states that allow multiple possible solution moves that appear equally likely to lead to a solution goal. The only possible way to determine a move is to randomly select one and test it for effectiveness. If it appears to move us closer to the goal, we will retain it and continue. If it does not appear to move us closer to the goal we will discard it and try a different move. The point is that we have no way of determining whether the move is effective until after we have chosen it and tested it for effectiveness either mentally or physically. Its effectiveness cannot be determined prior to it being chosen and so it must be chosen randomly and only then can its effectiveness be determined.

This randomness as genesis principle provides the initial source of all secondary knowledge. It allows us to obtain knowledge through problem solving when we have no alternative source of information. Commonly, there are alternative sources of information and these are discussed next.

The borrowing and reorganising principle

As is the case for the randomness as genesis principle, the borrowing and reorganising principle also deals with novel, secondary information from the external environment for which we do not have previously acquired knowledge. The two principles differ in that the borrowing and reorganising principle relies on information from other people and as a consequence, has different biologically primary characteristics to the randomness as genesis principle that relies on problem solving.

While the randomness as genesis principle provides the initial source of all secondary information, once information is obtained, it can be transmitted to others using the borrowing and reorganising principle. When we obtain information from others, it then is combined with previously stored information before the new information is itself stored. Novel information borrowed from others is rarely stored without being reorganised by previously stored knowledge.

In this manner, the borrowing and reorganising principle provides another source of information that is also the major source of human knowledge. Humans are intensely social. Most of our knowledge is not obtained by random generate and test during problem solving, rather, it is obtained far more easily from others. We listen to what others say and read what they write. Because the vast bulk of our secondary information is obtained from others, this principle is central to the education process and so is central to e-learning. Accordingly, it also needs to be central to any instructional theory such as cognitive load theory. For this reason, cognitive load theory is mainly concerned with how information should be presented to learners during the instructional process. The purpose of instruction is to use this principle to provide needed information to learners.

The borrowing and reorganising principle does not only apply to information obtained during instruction. We also can obtain information from other people under a variety of circumstances including for example, during collaborative learning (Kirschner et al. 2018). One of the advantages of collaboration is that information can be shared among collaborating individuals who otherwise might have difficulty obtaining it. The process of collaboration is underpinned by the borrowing and reorganising principle.

Processing and storing processed information

The narrow limits of change principle

The randomness as genesis and the borrowing and reorganising principles indicate the two ways in which humans can acquire novel, secondary information. The narrow limits of change principle describes the manner in which that information is initially processed by the human cognitive system. Working memory provides the processing engine.

When dealing with novel, secondary information from the external environment, whether obtained via the randomness as genesis principle or the borrowing and reorganising principle, working memory has two notable characteristics. It is very limited in both capacity and duration. We can remember no more than about seven elements of novel, secondary information (Miller 1956) and can process, in the sense of comparing, contrasting or dealing with, no more than 2–4 elements of information (Cowan 2001). In addition, we can hold that information in working memory for no more than about 20 s (Peterson and Peterson 1959).

The narrow limits of change principle reflects these working memory limits. There are severe limits in our ability to process novel, domain-specific, secondary information, the category of information that is overwhelmingly represented in most instructional contexts. Accordingly, instructional procedures that ignore the narrow limits of change principle are unlikely to be effective. The principle is central to cognitive load theory and to instructional design.

The information store principle

Once processed by working memory, novel, domain-specific, secondary information can be stored in long-term memory, as reflected in the information store principle. This principle assumes that through learning, useful information is stored in long-term memory for later use. The main function of learning is to store that newly acquired information. If it is not stored, learning has not occurred. Accordingly, the main function of instruction is to ensure learners have stored novel information.

While it has always been self-evident that we store information in long-term memory, our realisation concerning the nature of that information and its function in human cognition have only become evident more recently. Long-term memory is not simply a passive repository of largely unrelated, individual, rote-learned facts. Rather, it is a central, possibly the central structure of human cognition. Evidence for its surprising role initially came from the work of De Groot (1965); (see also De Groot and Gobet 1996). De Groot was concerned with the factors that allow chess masters and grand-masters to consistently defeat chess hobby players. Chess is a game of problem solving so the issue was why are expert chess players better at solving chess problems than less able chess players? De Groot found no evidence that expert chess players considered a greater breadth of moves at each choice-point or searched in depth for a better series of moves than less able players. The only difference he could find was in memory of chess-board positions taken from real games. Masters or grand-masters shown a board configuration taken from a real game for 5 s could then reproduce that configuration from memory with over 80% accuracy while hobby players could only reproduce less than 30% of the pieces accurately. Chase and Simon (1973) replicated this result and in addition found little difference between more and less expert players using random configurations, with both only able to remember the location of very few of the pieces.

How should we interpret these results? Based on De Groot's and Chase and Simon's findings, acquired skill in problem solving does not derive from some undescribed, learnable, general problem-solving strategies. Rather, it is due to the acquisition over a long period of time of an enormous store of domain-specific knowledge. Expert chess players have learned to recognise a very large range of board configurations and have learned the best move associated with each configuration. It is that knowledge, acquired over many years and stored in long-term memory that permits them to defeat hobby players (Ericsson and Charness 1994). Similar results to these have been obtained in a variety of educationally relevant domains (Chiesi et al. 1979; Egan and Schwartz 1979; Jeffries et al. 1981; Sweller and Cooper 1985). The information store principle assumes that expert skill derives from a large knowledge base of domain-specific information stored in long-term memory.

Using stored information to generate action

The environmental organising and linking principle

This principle provides the ultimate justification for the preceding principles. On receiving appropriate environmental signals, relevant information previously stored in long-term memory can be transferred to working memory to generate action appropriate to that environment. The characteristics of working memory when dealing with previously processed information that has been stored in long-term memory are very different to its characteristics when dealing with novel information from the environment. As may be recalled from the discussion of the narrow limits of change principle, working memory has severe capacity and duration limits when processing novel information. In contrast, when dealing with stored information from long-term memory, there are no known capacity or duration limits to working memory. Seemingly unlimited amounts of information can be transferred from long-term to working memory and held in working memory for seemingly unlimited periods of time. Because of the vastly different characteristics of working memory when dealing with novel or familiar information, Ericsson and Kintsch (1995) have used the term "long-term working memory" to describe the structure and function of working memory when dealing with familiar as opposed to unfamiliar information.

It is a truism to say that education transforms us. This cognitive architecture in general and the environmental organising and linking principle in particular, explain how. Through the transformation of working memory from a limited capacity and duration to an effectively unlimited capacity and duration structure, we are able to engage in cognitive activities that in the absence of this transformation, would leave us deprived of the facility to act. The very act of transforming squiggles into meaningful (hopefully!) text that readers of this article are engaged in provides an obvious example of this function. Indeed, we might expect that if De Groot's (1965) experiment was repeated using text rather than chess board configurations with competent readers of English compared to people with less knowledge of written English, analogous results to those obtained by De Groot should be obtained. Indeed, as indicated in the previous section on the information store principle, analogous results to those of De Groot have been obtained in a variety of educationally relevant areas.

This cognitive architecture is universal and applies to all instructional systems including technology assisted systems such as e-learning. The next question is how should we organise instruction to accord with this architecture or indeed, use this architecture to leverage and facilitate learning?

Instructional design

Cognitive load theory assumes the major aim of instruction is to facilitate the transfer of domain-specific, biologically secondary information, initially into working memory from the external environment, and then from working memory to long-term memory where it can be stored. Lastly, once information is stored in long-term memory, it can be transferred back to working memory to govern action appropriate to the environment. All of these transfers are biologically primary and so do not need to be taught. The relevant biologically primary processes are incorporated in the five principles outlined above that delineate the characteristics of the cognitive system that need to be considered when designing instruction. While the principles are driven by biologically primary knowledge in the sense that we do not have to be taught how to: randomly generate and test; borrow information from others; process that information in working memory; store it in long-term memory; or use it under appropriate environmental conditions, the combined function of these principles is to allow us to acquire, process, store and appropriately use biologically secondary information.

There are instructional conclusions that flow from this cognitive architecture along with many specific prescriptions. The instructional conclusions and prescriptions are associated with the concept of element interactivity that links human cognitive architecture to instructional design (Sweller 2010).

Element interactivity

Element interactivity is a measure of informational complexity that is central to cognitive load theory. The theory is concerned with instructional designs that reduce unnecessary informational complexity and so reduce working memory load when acquiring new knowledge. If the purpose of the theory is to reduce informational complexity, techniques for determining informational complexity are required.

The nature of the human cognitive system as described above renders the measurement of informational complexity difficult. We cannot simply consider the characteristics of the information. We must simultaneously consider both the characteristics of the information and the knowledge held by learners in long-term memory. As indicated above under the information store principle and the environmental organising and linking principle, information that is impossibly complex for one person may be trivially simple for someone else, depending on knowledge held in long-term memory. For the readers of this paper, the following squiggles, "the cat sat on the mat" represent a single, trivial element of information that can be easily processed and reproduced if required. We can readily deal with this information in a variety of ways because of the large amount of relevant information held in long-term memory. That information can be treated as a single element when transferred back to working memory. In contrast, for someone who cannot read the English alphabet, the information is impossibly complex because of the enormous number of elements of information that must be processed simultaneously. Complexity only can be determined by simultaneously determining both the nature of the information and the knowledge held in the long-term memory of the person processing that knowledge.

The concept of element interactivity resolves this problem by estimating the number of elements that a particular individual must process simultaneously in working memory. The following factors are relevant when estimating element interactivity.

1. Some elements can be processed individually without reference to other elements. For example, when learning a second language, we can learn the translation of the word "dog" independently of the translation of the word "cat". The two elements do not interact and so do not need to be processed simultaneously in working memory. Element interactivity is low. If element interactivity is low, a task may be easy if there are few elements, or difficult if there are many, but the difficulty will not be due to an excessive

working memory load since the elements can be processed independently of each other. A difficult, low element interactivity task will have a low cognitive load despite its difficulty.

2. Other elements interact and so unlike the above example, must be processed simultaneously in working memory. When learning to solve the problem, $(a+b)/c=d$, solve for a, we must process all of the elements simultaneously in working memory because they interact. Element interactivity is high for anyone first learning algebra with each of the symbols constituting a single element that must be processed simultaneously with all of the other symbols. Furthermore, each time a change is made in the equation, the elements of the new equation must not only be processed simultaneously, to understand the change the new set of elements must be compared with the previous set. To learn how to solve a problem such as this, an enormous number of elements will need to be processed rendering this high element interactivity task very difficult.
3. For anyone familiar with introductory algebra, the above problem is very low in element interactivity and so very simple. All of the interacting elements are incorporated into a single element held in long-term memory.
4. Currently, the only method we have of determining the element interactivity of a task is by estimating the knowledge base of the learners under consideration and counting the number of elements. This process cannot yield precise measures. For instructional design purposes, a lack of precise measures is not critical if we are comparing competing instructional procedures that vary sufficiently substantially in element interactivity for us to be confident the difference is real. Small differences in element interactivity should not be used to prescribe differences in instructional design.

Intrinsic and extraneous cognitive load

Differences in element interactivity can be attributed to either differences in intrinsic or extraneous cognitive load. Intrinsic cognitive load is determined by the intrinsic properties of the information being processed. It can be altered only by either changing the subject matter that must be assimilated or by changing the knowledge base of the learner. Differences in learning the nouns of a foreign language or learning to solve an algebra problem are due to differences in intrinsic cognitive load.

Extraneous cognitive load is determined by instructional procedures. Some instructional procedures unnecessarily increase element interactivity and so increase extraneous cognitive load. The vast majority of the cognitive load effects are due to changes in extraneous cognitive load.

Cognitive load effects

A cognitive load effect is demonstrated when an instructional design based on cognitive load theory is compared with a more conventional design using a randomised, controlled trial. If the cognitive load theory-based procedure results in better test performance than the more conventional procedure, a cognitive load effect has been demonstrated.

There are many cognitive load effects. A complete current list may be obtained in Sweller et al. (2019). Only some of the cognitive load effects more relevant to technology-assisted instruction will be discussed here. They are summarised in Table 1.

Table 1 Summary of some of the instructional effects generated by cognitive load theory

Instructional Effect	Description
Worked example	Studying worked examples is superior to solving the equivalent problems
Split-attention	If multiple sources of information need to be considered simultaneously, physically integrating them is superior to requiring learners to split their attention between them
Modality	If a diagram and text need to be considered simultaneously and the text is simple and short, presenting the text in spoken rather than written form is superior
Transient	High element interactivity information should be presented in permanent rather than transient form or presented in smaller chunks
Redundancy	Eliminating unnecessary information results in superior learning
Expertise reversal and element interactivity	With increases in expertise and decreases in element interactivity, information that is essential for novices becomes redundant for more expert learners, decreasing learning
Working memory depletion	Working memory use depletes working memory resources that recover after rest

Worked example effect

This effect is probably the best known of the cognitive load effects (Cooper and Sweller 1987; Glogger-Frey et al. 2015; Renkl 2013, 2014). It occurs when learners provided with problems to solve perform more poorly on subsequent test problems than learners provided the same problems along with worked examples of the solutions. From a theoretical perspective, it is assumed that the worked examples provide learners with the domain-specific, biologically secondary information that needs to be stored in long-term memory for subsequent use. Worked examples reduce extraneous working memory load by reducing element interactivity. When solving a problem, learners need to search through a variety of possible moves at each choice point, determine whether each possibility is effective in moving closer to the goal and choose the best of the range of possibilities before repeating the process from the new problem state. A worked example eliminates all of the interacting elements associated with this process by indicating exactly which moves are appropriate at each choice point thus reducing element interactivity and extraneous cognitive load. Based on these results, novice learners should be provided with explicit guidance when learning (Kirschner et al. 2006; Sweller et al. 2007). Instructional procedures, including technology-based instruction, that require novice learners to engage in problem-solving search are likely to be deficient. Educational technology systems centred around problem-solving activity for novice learners rather than providing examples of successful problem-solving for learners to study are unlikely to optimise learning.

Assuming the above explanation for the worked example effect is valid, we would expect there to be many conditions that will compromise the expected result. The effect assumes that studying a particular worked example reduces working memory load compared to solving the equivalent problem. Based on cognitive load theory, some worked examples can be assumed not to have this effect. A failure to obtain the worked example effect has led to several additional cognitive load effects, such as the split-attention effect, discussed next.

Split-attention effect

Some worked examples require learners to split their attention between multiple sources of information that cannot be understood in isolation and so need to be mentally integrated to increase intelligibility. If the same information is physically integrated by for example, placing text at appropriate places on a diagram rather than next to or under a diagram, element interactivity due to extraneous cognitive load is decreased and learning facilitated (Tarmizi and Sweller 1988).

It needs to be noted that the logical relations between the multiple sources of information are critical to this effect. It only will be obtained if the sources of information refer to each other and cannot be understood unless they are processed simultaneously in working memory. If they are intelligible in isolation, the redundancy effect (see below) rather than the split-attention effect is relevant.

With respect to technology-based learning, presenting split-source information on separate screen pages because it is convenient to do so is probably the most common source of split-attention. Sometimes, split-attention is unavoidable due to insufficient screen size. Nevertheless, if at all possible, it should be avoided.

Modality effect

The modality effect occurs using information with the same logical relations as the split-attention effect. For the effect to occur, multiple sources of information must refer to each other and be unintelligible unless they are considered in conjunction. If split-attention is unavoidable due to screen size as indicated above, rather than attempting to eliminate it by for example, physically integrating diagrams and text, it may be possible to eliminate the effect by presenting written information in spoken form. Using visual information for one source such as a diagram, and auditory information for the other source such as text, can increase available working memory and so enhance learning (Tindall-Ford et al. 1997). Working memory capacity can be increased by using dual-modality rather than single-modality instruction (Baddeley 1999) that in turn, facilitates learning.

Dual-modality presentations require e-learning systems and so the modality effect is particularly relevant to e-learning. In the absence of a live presentation, an e-learning system with its ability to present spoken as well as written information is a requirement for dual-modality presentations.

Transient information effect

The modality effect only is obtainable if the auditory information is sufficiently simple to allow it to be processed in working memory (Leahy and Sweller 2011; Wong et al. 2012). Lengthy, complex, information may require learners to cycle between various aspects before it can be assimilated. If that information is transient as is the case when it is spoken, returning to it while processing current information may be difficult or impossible due to working memory characteristics. Holding current information in working memory while searching for other, relevant information may be overwhelming resulting in reduced learning. Relating current and previous information may be easier when it is in permanent, written form. Similar concerns apply when using video animations rather than still diagrams or pictures.

The transient information effect occurs when lengthy, complex, transient information is learned better using permanent rather than transient information. Frequently, it is possible to rectify these issues associated with transience by dividing the information into smaller chunks as well as by using permanent information.

This issue can be particularly important when using educational technology. Converting permanent, written information into transient spoken information or permanent diagrams into transient animations can be easy using educational technology. When that information is lengthy and complex, the effect can be negative and the impulse to convert permanent into transient information should be resisted.

Redundancy effect

The advantage of using integrated diagrams and text under split-attention conditions is often erroneously assumed to apply to all uses of diagrams and text. In fact, the logical relations between the two sources of information are critical. As indicated above, for the split-attention effect, both sources are essential to understanding the materials. A statement such as "Angle ABC = Angle XYZ" is unintelligible without a diagram. To understand such geometry instruction, both the text and diagram must be attended to and integrated. Omitting either will leave the instruction unintelligible. In contrast, diagrams and text are very often provided under conditions where both the text and diagram are intelligible without reference to each other. For example, text may simply re-state the information in a diagram using language. Under those circumstances, either the text or the diagram (usually the text) should be eliminated due to redundancy. The effect occurs when redundant information interferes with learning compared to non-redundant information (Kalyuga et al. 2004).

It should be noted that a broad definition of redundancy is used. While most commonly it refers to a source of information that repeats other information in a different form such as text in spoken and written form during a presentation, it can also refer to any unnecessary information such as, for example, background noise or even music. All are redundant and interfere with learning.

Redundancy can pose a major problem in technology mediated instruction. The temptation to include possibly interesting but redundant information on a screen can be overwhelming. We have all seen instructional materials that are so "busy" that they render the real information being presented almost unintelligible. Processing redundant, unnecessary information using our limited working memory may provide a major reason for a lack of effectiveness of educational technology.

Expertise reversal and element interactivity effects

Most cognitive load effects including all of the above effects assume that learners are novices just commencing a course of study on a particular topic. Working memory load is higher for novices than for more expert learners and cognitive load theory is concerned with information that imposes a high working memory load. As indicated above, with increasing expertise, element interactivity decreases and decreases in element interactivity have instructional consequences. These instructional consequences lead to the expertise reversal effect (Kalyuga et al. 2003) which is a particular example of the element interactivity effect (Chen et al. 2017).

With increasing expertise and its resultant decrease in element interactivity and intrinsic cognitive load, the advantage of cognitive load generated instructional procedures decreases. With further increases in expertise, differences between instructional conditions may disappear or even reverse. These changes are referred to as the expertise reversal effect. Examples of it can be seen with respect to the worked example effect. For novices on a topic, studying problem solutions can be a very effective way of learning compared to solving the same problems. With increases in expertise, problem solving becomes increasingly effective and studying worked examples becomes increasingly ineffective. Once a problem solution is understood, additional practice may allow increasing levels of competence but those increases are best obtained by solving problems rather than studying worked examples (Chen et al. 2015, 2016a, b; Kalyuga et al. 2001). Studying worked examples for a more expert learner provides an example of the redundancy effect and decreases learning compared to solving problems. A similar trajectory can be found for all cognitive load effects. With changes in expertise, changes in instructional procedures are needed.

E-learning can be a particularly useful technique for dealing with the expertise reversal effect. Based on the effect, instructional procedures should change with changing levels of expertise. By assessing levels of expertise, the use of e-learning can allow commensurate changes in instructional procedures resulting in more efficient learning (Kalyuga and Sweller 2004, 2005). Altering instructional procedures depending on levels of expertise is likely to be difficult or impossible in the absence of e-learning.

Working memory depletion effect

This effect is new and currently only has limited data in support (Chen et al. 2018). Cognitive load theory has assumed that for any given individual, working memory characteristics are fixed and only can be altered by changes in long-term memory via the information store and environmental organising and linking principles. In fact, there may be another way in which working memory capacity can be altered. After concentrated cognitive effort, working memory capacity may be depleted and require rest before recovery. Chen et al. (2018) demonstrated increases in working memory capacity after rest compared to after cognitive effort. They also demonstrated that this change could be used to explain the spacing effect.

The spacing effect occurs when identical instruction is spaced over a longer period with rest periods between learning episodes than a shorter period with the same learning episodes massed together without spacing. The effect is obtained when spaced practice results in superior test performance compared to massed practice. There are many explanations of the spacing effect but working memory depletion may provide a plausible candidate. Chen et al. (2018), in two experiments, demonstrated the conventional spacing effect and in addition found that working memory capacity was greater after spaced than after massed practice. That finding suggests that by incorporating working memory depletion effects, cognitive load theory may be used to explain the spacing effect.

Under e-learning conditions, progression should be structured as far as possible to permit learners to progress at their own pace, assuming that they will naturally space learning episodes appropriately. As far as I am aware, at this point there are no data with respect to the assumption that learners will naturally space learning episodes appropriately.

The large range of cognitive load theory effects has a dual purpose. The main purpose is to generate novel instructional procedures. A secondary purpose is to provide validation for the underlying theory. To this point, the theory has had a degree of success in these two aims but it needs to be noted that the theory is under constant development as new data become available. Most commonly, a failure by the theory to predict an instructional outcome results in further theoretical development and novel instructional effects. Two examples from the above instructional effects can be used to demonstrate this process. The split-attention effect was found when success in using worked examples for algebra that did not use split-attention was followed by failure to obtain the worked example effect in geometry and physics that conventionally used a split-attention format. Without that failure, the split-attention effect may not have been discovered. Similarly, the spacing effect has been known since the 1800s but was assumed not to be a cognitive load effect. The hypothesis that working memory capacity might not be constant but rather, may deplete with use and recover with rest, allowed the spacing effect to be incorporated as a cognitive load theory effect.

Conclusions

Cognitive load theory places a heavy emphasis on our increasingly detailed knowledge of human cognition. In particular, it is unique amongst instructional theories in its emphasis on evolutionary psychology and the consequences of evolution for human cognitive architecture. That emphasis allows us to prescribe which categories of knowledge are likely to be amenable to instruction and which are likely to be impervious to instructional manipulations. The use of human cognitive architecture and evolutionary psychology has resulted in an ever-increasing list of cognitive load effects indicating appropriate instructional procedures. Those experimental effects and the resultant instructional procedures provide the ultimate validation of the theory. The experimental effects also have a critical role in expanding the theory. Ultimately, the theory is dependent on the data that underlies each effect and those data, especially data indicating the limits of particular effects, interacting with the basic theory, provide a dynamic tension that allows the theory to continually develop while retaining its initial, core principles.

Cognitive load theory is directly applicable to technology-assisted learning. Many of the instructional procedures generated by the theory are difficult to use without the assistance of educational technology. In addition, other instructional procedures that instructional technology enables such as the presentation of some transient information are incompatible with human cognitive architecture and may need modification. Accordingly, the theory can provide a guide to appropriate uses of technology-assisted learning.

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