Research on Cognitive Load Theory and Its Design Implications for E-Learning

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This introduction to the special issue provides a context for the contributing articles. for readers who are not familiar with cognitive load theory (CLT), it provides a very brief description of assumptions regarding memory systems and learning processes, different types of cognitive load (intrinsic, extraneous, and germane), and design implications. Whereas traditional CLT research focused on instructional methods to decrease extraneous cognitive load that is not directly relevant for learning, contributions to this special issue represent wider perspectives that reflect new developments in CLT. These articles have been organized into three categories: (a) methods to decrease intrinsic cognitive load, and deal with high-element interactivity materials, (b) methods to increase germane cognitive load that is directly relevant for learning, and (c) methods to deal with differences in learner's individual levels of expertise and expertise development. To conclude, design implications for (adaptive) e-learning are discussed.

☐ In the last decade, cognitive load theory (CLT) has become an established theory in the field of learning and instruction (for overviews, see Kirschner, 2002; Paas, Renkl, & Sweller, 2003, 2004). Recently, more and more applications of CLT have begun to appear in the emerging field of e-learning. At the 2004 Annual Meeting of the American Educational Research Association (AERA) in San Diego, three symposia were organized around this topic: (a) *CLT as a Framework Integrating Studies on Multimedia Presentation, Levels of Expertise, and Task Complexity* (chaired by Paul Ayres); (c) *Scaffolds and Aids for Effective Learning with Multimedia and the Web* (chaired by Jan Plass, Roxana Moreno, and Roland Brünken), and (c) *Cognitive Measurements to Advance the Design of Optimal Learning Environments* (chaired by Richard Mayer). The papers presented in San Diego are examples of the kinds of research currently conducted around the globe on CLT and the design of e-learning. Therefore, making this research available to a broader public in a special journal issue was a logical next step. We are grateful that *Educational Technology Research and Development* accepted our proposal to do just that.

The main goal of this introduction is to provide background information on CLT and to place the contributing articles into context. We will first give a very brief description of the assumptions of the theory, regarding memory systems and learning processes, different types of cognitive load, and design implications. Secondly, for each of the contributing articles we will discuss the main research questions, findings, and conclusions, and indicate how they offer new insights into instructional procedures for the design of e-learning. The articles are organized into three categories that focus on instructional methods that: (a) help learners deal with the intrinsic complexity of instructional materials, (b) stimulate learners to invest mental effort in genuine learning, and (c) enable the assessment of differences in learners' expertise levels in order to adapt instruction to individual needs. In the third and final section of the introduction, some general conclusions are formulated from the contributions.

CLT

CLT (Sweller, 2004) assumes a working memory with a very limited capacity when dealing with novel information, as well as an effectively unlimited long-term memory holding cognitive schemas that vary in their degree of complexity and automation. Working memory capacity is about seven elements for storing information and two to four elements for processing information (Miller, 1956), whereas long-term memory is not subject to the same limitations. Human expertise comes from knowledge stored in cognitive schemas, *not* from an ability to engage in reasoning with many new elements yet to be organized in long-term memory. It is through the—often conscious and mindful—construction of increasing numbers of ever more complex schemas, and through the automation of some of those schemas, that expertise develops.

Schemata are used to organize and store knowledge, and heavily reduce working memory load, because even a highly complex schema can be dealt with as *one* element when brought into working memory. When dealing with knowledge that is tightly organized in schemas, the capacity of working memory is greatly extended. Working memory is limited in capacity when dealing with novel, unorganized information because it becomes increasingly difficult to find an appropriate form of organization when dealing with a large amount of information. That problem does not arise when dealing with knowledge from long-term memory that is already organized in schemas.

Schemata may become automated if they are repeatedly and successfully applied. As is the case for schema construction, automation can free working memory capacity for other activities because an automated schema directly steers behavior, without the need to be consciously processed in working memory. From an instructional design perspective, well-designed training programs should encourage not only schema construction but also schema automation for those aspects of a task that are consistent across problem situations (van Merriënboer, Kirschner, & Kester, 2003).

Although cognitive schemas are stored in and retrieved from long-term memory, novel information must be processed in working memory. The ease with which information may be processed in working memory is a prime concern of CLT. Working memory load may be affected by the intrinsic nature of the learning tasks themselves (intrinsic cognitive load), the manner in which the tasks are presented (extraneous cognitive load), or the amount of cognitive resources that learners willingly invest in schema construction and automation (germane cognitive load).

Intrinsic cognitive load is determined by the interaction between the nature of the materials being learned and the level of expertise of the learner. It primarily depends on the number of elements that must be simultaneously processed in working memory, which, in turn, depends on the extent of element interactivity of the material or task that must be learned. Materials with high element interactivity are difficult to understand—and the only way to foster understanding is to develop cognitive schemas that incorporate the interacting elements. It follows that a large number of interacting elements for one person may be a single element for another more experienced person, who already has a schema that incorporates the elements. Thus, element interactivity can be determined only by counting the number of interacting elements with which people at a particular level of expertise are likely to deal.

In contrast, *extraneous cognitive load* is associated with processes that are not directly necessary for learning and can be altered by instructional interventions. Extraneous cognitive load may be caused by using weak problem-solving methods (e.g., working backward from a goal using means-ends analysis), integrating information sources that are distributed in place or time, searching for information that is needed to complete a learning task in instructional materials, and so forth. Because working memory can be divided into partially independent visual and auditory working components (Penney, 1989), overloading either the visual or the auditory subprocessor of working memory may also increase extraneous load. For example, if multiple sources of information that are required for understanding are all presented in visual form (e.g., a written text and a diagram), they are more likely to overload the visual processor than if the written material is presented in spoken form, thus enabling some of the cognitive load to be shifted to the auditory processor.

To conclude, *germane cognitive load* is associated with processes that are directly relevant to learning, such as schema construction and automation. For instance, variability of problem situations encourages learners to construct cognitive schemas, because it increases the probability that similar features can be identified, and that relevant features can be distinguished from irrelevant ones. High variability requires the thoughtful engagement of the learners and increases cognitive load because they invest more effort in genuine learning. It yields better schema construction and transfer of learning, indicated by a better ability to solve problems that were not solved before. Under some circumstances, it may be necessary to increase learners' motivation, and encourage them to employ learning processes that yield germane cognitive load. After all, instructional manipulations to improve learning through diminishing extraneous cognitive load and freeing up cogni-

Table 1 □ Traditional effects studied by CLT and why they reduce extraneous cognitive load (reported by Sweller, van Merriënboer, & Paas, 1998).

Effect	*Description*	*Extraneous Load*
Goal-Free effect	Replace conventional problems with goal-free problems, which provide learners with a nonspecific goal	Reduces extraneous cognitive load caused by relating a current problem state to a goal state and attempting to reduce differences between them; focuses learner's attention on problem states and available operators
Worked Example effect	Replace conventional problems with worked examples that must be carefully studied	Reduces extraneous cognitive load caused by weak-method problem solving; focuses learner's attention on problem states and useful solution steps
Completion Problem effect	Replace conventional problems with completion problems, provides a partial solution that must be completed by the learners	Reduces extraneous cognitive load because giving part of the solution reduces the size of the problem space; focuses attention on problem states and useful solution steps
Split Attention effect	Replace multiple sources of information (frequently pictures and accompanying text) with a single, integrated source of information	Reduces extraneous cognitive load because there is no need to mentally integrate the information sources
Modality effect	Replace a written explanatory text and another source of visual information such as a diagram (unimodal) with a spoken explanatory text and a visual source of information (multimodal)	Reduces extraneous cognitive load because the multimodal presentation uses both the visual and auditory processor of working memory
Redundancy effect	Replace multiple sources of information that are self-contained (i.e., they can be understood on their own) with one source of information	Reduces extraneous cognitive load caused by unnecessarily processing of redundant information

tive resources will only be effective if students are motivated and actually invest mental effort in learning processes that use the freed resources.

Cognitive load theorists argue that intrinsic, extraneous and germane cognitive load are additive (Paas et al., 2003). During instruction, the extent to which extraneous cognitive load presents students with a problem mainly depends on the intrinsic load. If intrinsic load is high, extraneous cognitive load must be lowered; if intrinsic load is low, a high extraneous cognitive load due to inadequate instructional design may not be harmful, because the total cognitive load is within working memory limits. Furthermore, if the sum of intrinsic and extraneous cognitive load leaves additional processing capacity, it is important to invite students to invest germane cognitive load in learning processes, especially with regard to schema construction and automation. Thus, the main instructional principle of CLT is to decrease extraneous cognitive load and to increase germane cognitive load, within the limits of totally available processing capacity (i.e., prevent cognitive overload). In order to do so, the learner's level of expertise must be taken into account, because this determines the intrinsic cognitive load of the learning tasks.

Until five years ago, CLT was primarily used to study instructional methods intended to decrease extraneous cognitive load for novice learners. Some of the major effects that yield better schema construction and higher transfer test performance, and which may be attributed to a decrease in extraneous cognitive load, are briefly summarized in Table 1. But over the last five years, more and more CLT related studies have investigated the effects of instructional manipulations on intrinsic and germane cognitive load, and related those effects to the level of expertise of the learners (van Merriënboer & Sweller, 2005). As a consequence, there has been a greater focus on adapting instructional procedures to meet the needs of the individual learner. As discussed in the next section, the contributions to this special issue clearly reflect the new directions taken by CLT research.

CONTRIBUTIONS TO THE SPECIAL ISSUE

Over the last five years, CLT has undergone important developments that were driven both by theoretical progress and by changes in the field of instructional design. The contributions to this special issue will be organized according to three major developments. First, there is a shift in focus from studying written materials to working on online learning tasks. The cognitive load imposed by such tasks may be too high for novices, and seriously hamper learning. Conventional methods to decrease extraneous cognitive load (cf., Table 1) often fail to lower the total load to an acceptable level. Therefore, sequencing methods are beginning to be studied that diminish intrinsic cognitive load in the early phases of learning. Second, recent studies focus less on short laboratory experiments and more on real courses. This makes it more important than ever to pay attention to student motivation and to apply instructional methods that encourages students to invest freed-up processing resources to schema construction and automation; that is, to learning processes that cause germane cognitive load. And third, instructional methods that work well for novice learners may have no positive or even negative effects when learners acquire more expertise. New methods for the continuous assessment of expertise are needed to develop adaptive e-learning applications. By adapting instruction according to levels of expertise, the difficult task of attempting to predict subsequent levels of expertise prior to the commencement of an instructional sequence is obviated.

Dealing with High-Element-Interactivity Materials: Intrinsic Cognitive Load

Many e-learning applications are built around complex learning tasks, which are characterized by a large number of interacting elements. In conceptual domains, there are many interacting pieces of information that must be processed simultaneously in working memory in order to reach understanding; in skill domains, there are many interacting constituent skills that must be coordinated in working memory in order to reach coherent performance. Even after the removal of all sources of extraneous cognitive load, the element interactivity of such materials may be too high to allow for efficient learning. Thus, it may be helpful not to present all information at once. For example, one might first present information with only a few of the relevant element interactions present, and then increasingly add more of the required interactions; or one might first present a simple version of a task and then present more and more complex versions of this task. Such progressive methods initially alter *intrinsic* cognitive load, because the element interactivity of the materials is artificially reduced in the early phases of the instruction.

The first contribution to this special issue, "The Impact of Sequencing and Prior Knowledge on Learning Mathematics Through Spreadsheet Applications," by Tracy Clarke, Paul Ayres, and John Sweller, studies one progressive method to alter cognitive load. In their experiment, students with low and high spreadsheet knowledge were taught mathematical skills using a spreadsheet application. One group of students was trained first in using the spreadsheet application and then in applying the mathematical skills with this application; another group of students practiced spreadsheet skills and mathematical skills simultaneously. As expected, for students with low prior spreadsheet knowledge the sequential presentation was superior to the concurrent presentation and yielded higher test performance. But for students with high prior spreadsheet knowledge, there was a tendency toward the reverse effect. It is concluded that sequencing learning tasks from simple to complex is important only if the complex, combined task represents a high level of element interactivity for the target group—as is the case for the low-prior-spreadsheet-knowledge group. However, sequencing learning tasks from simple to complex is not desirable, and may even be detrimental, if the combined task represents a low level of element interactivity for the target group—as is the case for the high-prior-spreadsheet-knowledge group.

Dealing with Learners' Motivation to Learn: Germane Cognitive Load

Recent applications of CLT focus less on short laboratory experiments, where participants may invest effort in learning primarily because they try to please the experimenter or exhibit desirable behaviors, and more on regular courses and educational programs. As a result, students may be less inclined to employ their processing resources, which may make it necessary to encourage them explicitly to invest mental effort in schema construction and automation. As discussed above, increasing the variability of practice is one effective way to provoke students to generalize and discriminate cognitive schemas, which is a schema construction process associated with germane cognitive load. Several other instructional manipulations may stimulate students' effortful schema construction processes, including manipulations that require them to actively *interact* with the learning materials (e.g., letting students organize procedural steps or a chain of events; letting them manipulate pictures or animations) or to *self-explain* these materials (e.g., by having them process annotations).

The second contribution to this special issue, "A Motivational Perspective on the Relation Between Mental Effort and Performance: Optimizing Learners' Involvement in Instructional Conditions," by Fred Paas, Juhani Tuovinen, Jeroen van Merriënboer, and Aubteen Darabi, discusses the relationship between motivation, the investment of mental effort, and performance. The authors of this contribution identify motivation as an important dimension that determines learning success as well as causing the high dropout rate among online learners, especially if e-learning applications are used in a distance education setting. It is, thus, important for CLT researchers to investigate the motivational effects of instructional methods. A motivational perspective is presented on the relationship between mental effort and performance, indicating that lower task involvement is indicated by a lower investment of mental effort combined with a lower performance, and higher task involvement is indicated by an increase in invested mental effort combined with an increase in performance. A procedure is presented to compute and visualize the motivational effects of instructional methods, and this procedure is illustrated by reanalyzing an existing data set. This article clearly illustrates that the effects of CLT-based manipulations are not limited to the purely cognitive domain, and points out that manipulations that affect motivation may be especially important to increase learner's germane cognitive load.

The third contribution, "Cognitive Load and Learning Effects of Having Students Organize Pictures and Words in Multimedia Environments: The Role of Student Interactivity and Feedback," by Roxana Moreno and Fred Valdez, describes the effects of interactivity in learning from unimodal and multimodal presentations in the domain of meteorology. As expected, multimodal presentations with integrated, nonredundant words and pictures are superior to unimodal presentations. But interactivity, which meant that students had to organize the presented chain of events (i.e., *make* meaning instead of *take* meaning), only yielded positive effects on learning when students were asked to evaluate their actions before receiving corrective feedback from the instructional system. Thus, the beneficial effects of interactivity in multimedia learning are less dependent on the behavioral interaction between student and system than on the mental interaction needed to actively involve the learner in the process of understanding—a finding that is fully consistent with the idea that learners should be stimulated to increase their germane cognitive load.

The fourth contribution, "Enabling, Facilitating, and Inhibiting Effects of Animations in Multimedia Learning: Why Reduction of Cognitive Load Can Have Negative Results on Learning," by Wolfgang Schnotz and Thorsten Rasch, is also concerned with the issue of interactivity, which is defined in their study as manipulating figures. In learning about time zones and the rotation of the earth, pictures that can be manipulated by the learners have an *enabling* function for students with high prior knowledge; that is, they allow for cognitive processing that would otherwise be impossible, and yield higher learning outcomes than pictures that allow only for simulation. For students with low prior knowledge, pictures that provide a visual simulation have a *facilitating* function; that is, they reduce load and allow for cognitive processing that would otherwise require a high investment of effort. However, this facilitating effect does not lead to higher learning outcomes because learners with low prior knowledge are not encouraged to perform relevant cognitive processes on their own (e.g., running a mental simulation). This suggests that the instructional methods that generate germane cognitive load are different for low and high expertise learners, and that relevant learning processes should be not only facilitated, but also explicitly evoked.

The fifth contribution, "The Function of Annotations in the Comprehension of Scientific Texts: Cognitive Load Effects and the Impact of Verbal Ability," by Erik Wallen, Jan Plass, and Roland Brüncken, investigates annotations rather than interactivity as a way to affect germane cognitive load. Three types of annotations in scientific texts (dealing with (a) selection, (b) organization, and (c) integration) were studied with regard to their effects on factual recall, comprehension, and mental model construction. It was found that different types of annotations facilitate different learning outcomes, consistent with Mayer's (2001) cognitive theory of multimedia learning. Furthermore, especially for low-verbal-ability learners, the use of multiple annotations instead of single annotations results in a high cognitive load and low performance on tests for higher-level processing. In summary, it seems that annotations may stimulate learners to engage in learning processes that yield a germane cognitive load, but for the design of the annotations, both the desired learning outcomes and the level of expertise of the learners should be carefully taken into account.

Dealing with Expertise Development: Toward Adaptive E-learning

As indicated above, the same learning materials may have high element interactivity for low-expertise learners but low element interactivity for high-expertise learners. This explains why instructional methods that work well for novice learners may have no, or even adverse, effects when learners acquire more expertise—a phenomenon that is often called the "expertise reversal effect" (see Kalyuga, Ayres, Chandler, & Sweller, 2003). For instance, students with low expertise in a domain learn more from studying worked examples than from solving the equivalent problems in the domain, but the reverse is true for students with a relatively high level of expertise. This suggests that a good instructional strategy for teaching problem solving starts with the presentation of worked examples and smoothly proceeds to independent problem solving if learners acquire more expertise. The continuous, real-time assessment of a learner's expertise level may be indispensable in adapting instructional methods to individual needs, and in replacing preplanned instruction with a more effective form of adaptive e-learning.

The sixth contribution to this special issue, "Instructional Design for Advanced Learners: Establishing Connections Between the Theoretical Frameworks of Cognitive Load and Deliberate Practice," by Tamara van Gog, Anders Ericsson, Remy Rikers, and Fred Paas, discusses the relationship between CLT and expertise research. Identification of the expertise reversal effect stimulated cognitive load researchers to study how instructional methods should be altered as a learner's expertise increases, making it more important than ever to understand how expertise is acquired and what fosters its development. Expert performance research provides an understanding of the principles and activities that are important in order to excel in a domain. In particular, the principles of "deliberate practice"—which refers to the extensive engagement in relevant practice activities that are often initially designed by a teacher or coach to improve specific aspects of learner performance—can be used to design instructional formats based on CLT for higher levels of expertise. In order to develop adaptive forms of instruction and e-learning, it is necessary to describe optimal instructional methods for different levels of expertise, to design smooth transitions between those instructional methods, and to devise handy methods to measure expertise.

In the seventh research contribution, "Rapid Dynamic Assessment of Expertise to Improve the Efficiency of Adaptive E-learning," Slava Kalyuga and John Sweller propose a "rapid assessment test" to measure the quality of learners' schemas that guide their problem solving in the domain of algebra. A rapid assessment of expertise was achieved by asking students to indicate their *first* step toward solution of a task, and to rate their associated mental effort invested. For students with a low level of expertise, their first step will include fewer mathematical operations than for students with a higher level of expertise. Moreover, mental effort ratings yield important additional information: Two persons may attain the same performance levels, with one person needing to work laboriously through an effortful process to arrive at the correct answer, and the other reaching the same answer with a minimum amount of effort. Expertise is higher for the person who performs the task with minimum effort than for the person who exerts substantial effort. The study compared two groups in a controlled experiment. In the adaptive e-learning group, instructional methods were dynamically adapted to learners' individual levels of expertise; in the control group, participants received the same instruction as their yoked counterparts. Highest gains in algebraic skills, from pretest to posttest, were found for the adaptive e-learning group; thus, there is evidence that adaptive e-learning is superior to nonadaptive learning.

The final contribution to the special issue, by Gary Morrison and Gary Anglin, contains a critical discussion of each individual article, and points out important directions for future research.

DISCUSSION

This introduction to the special issue started with a brief review of CLT. The theory posits that cognitive schemas organize and store human knowledge and heavily reduce working memory load. However, novel information must be processed in working memory in order to construct the schemas, after which they may become automated if they are repeatedly and successfully applied. The ease with which information may be processed in working memory is a prime concern of CLT. Working memory load may be affected by the element interactivity of the learning tasks themselves (intrinsic cognitive load), the manner in which the tasks are presented (extraneous cognitive load), or the amount of cognitive resources that learners willingly invest in schema construction and automation (germane cognitive load). Intrinsic, extraneous, and germane cognitive load are additive. For a long time, CLT focused on the development of instructional methods to decrease extraneous load. But more and more recent research deals with manipulations of intrinsic and germane load, as well as interactions between instructional methods and the level of expertise of the learner.

The articles in this special issue represent some of the new directions taken by cognitive load researchers, but it is also notable that many of the established findings of CLT have been incorporated into the researchers' experimental designs. Six of the seven articles are empirical (van Gog et al. being the only exception), and each uses various cognitive load effects to enhance their instructional materials. For example, three studies used worked examples to lower cognitive load, and three studies, which featured words and pictures or diagrams, were specifically designed to avoid the split-attention effect. In addition, four articles used a self-rating measure of cognitive load as a standard tool, two of which (Kalyuga et al. and Paas et al.) have developed new applications of the subjective measure. Five articles also use some form of expertise differentiation to allow for expert-novice differences to be studied. It can be seen from these examples that previous CLT effects have become building blocks for new research.

The contributions were organized in three categories, which nicely correspond to three new lines of CLT research. A first category of studies develops methods that help learners to deal with the high intrinsic complexity of learning tasks; if this complexity is too high even after extraneous cognitive load has been minimized, it may be necessary to decrease the intrinsic cognitive load through simplification of the learning tasks in the early phases of learning. A second category of studies develops methods that encourage learners to invest effort in learning; that is, to increase germane cognitive load. These methods try to increase learner motivation and, especially, task involvement by letting them manipulate and interact with learning materials. The third category of studies develops dynamic instructional methods to adapt instruction to learners' individual needs; they continuously measure learners' levels of expertise on the basis of performance and cognitive load, and dynamically adapt instruction to the needs of individual learners.

The three new research directions discussed in this issue signify the growing practicability of CLT, which is evolving from a theory for instructional message design, with a strong focus on presentation formats, to a full-fledged instructional design model. The presentation of methods for sequencing complex tasks and study materials, methods for encouraging students to invest germane load in learning, and methods for student assessment and the development of adaptive forms of instruction suggests that CLT is becoming more and more useful for the design of large courses and e-learning programs that are characterized by a high level of interactivity. In addition to an increased practicability, the new research lines also contribute to theoretical progress. This set of articles incorporated a paradigm of controlled experimental designs, which has been critical to the development of CLT. This rigor is too often missing in educational research, but is badly needed to develop sound instructional theories capable of making a real difference to educational practice. □

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