Instructional Design for Advanced Learners: Establishing Connections Between the Theoretical Frameworks of Cognitive Load and Deliberate Practice

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Cognitive load theory (CLT) has been successful in identifying instructional formats that are more effective and efficient than conventional problem solving in the initial, novice phase of skill acquisition. However, recent findings regarding the "expertise reversal effect" have begun to stimulate cognitive load theorists to broaden their horizon to the question of how instructional design should be altered as a learner's knowledge increases. To answer this question, it is important to understand how expertise is acquired and what fosters its development. Expert performance research, and, in particular, the theoretical framework of deliberate practice have given us a better understanding of the principles and activities that are essential in order to excel in a domain. This article explores how these activities and principles can be used to design instructional formats based on CLT for higher levels of skills mastery. The value of these formats for e-learning environments in which learning tasks can be adaptively selected on the basis of online assessments of the learner's level of expertise is discussed.

☐ Nowadays, most researchers agree that, ideally, instruction for complex skill learning should center on authentic tasks, should be adaptive to the individual learner's needs and capacity, and should support and motivate learners in acquiring the ability to plan, monitor, and evaluate their own learning process. Modern e-learning tools allow the incorporation of sophisticated online assessments of the level of learner expertise, and are, therefore, very helpful in the delivery of this kind of instruction. However, the challenge for instructional designers is to develop instruction that suits the above demands, and that is not only effective, but also as efficient as possible. To be able to do so, insight into the mechanisms that underlie or mediate the acquisition of particular complex skills at different levels of expertise is required.

In investigating the acquisition of complex skills, the lines of research on cognitive load theory (CLT; Sweller, 1988) and expert performance (Ericsson, 2002) have very different foci. Research on expert performance investigates the history of skill acquisition of highly skilled professionals in order to identify the mechanisms that underlie their superior achievements, without the aim of translating these very specific mechanisms into general instruction for complex skills in educational settings. In contrast, CLT research has mainly focused on developing effective and efficient instructional strategies to support initial skill acquisition in educational settings.

Complementary to CLT's almost exclusive focus on the initial learning phase, the recently found "expertise reversal effect" (Kalyuga, Ayres, Chandler, & Sweller, 2003; Kalyuga, Chandler, & Sweller, 1998), indicating that most CLT effects become less effective as a function of increasing expertise, can be considered a strong indication for the need of CLT research to broaden its scope toward providing instructional design recommendations *beyond* the initial phase of skill acquisition. From both a theoretical and a practical point of view, the basic tenet of CLT, to take the limitations of human cognitive architecture into account when designing instruction, does not seem to put any obstacles in the way of fulfilling this need. However, we argue that in order to successfully develop design guidelines for instruction beyond the initial phase, CLT research should take into account the mechanisms that underlie the superior achievement of experts who have been identified in expert performance research, especially because this research, although it has not aimed to provide general instructional guidelines, has provided valuable insights about the interaction between human cognitive architecture and developing expertise.

CLT AND THE EXPERTISE REVERSAL EFFECT

CLT (Paas, Renkl, & Sweller, 2003) holds that instructional design should explicitly consider the human cognitive architecture and its limitations in order to be effective. According to CLT, cognitive architecture consists of a general-purpose working memory that has a limited capacity of about seven chunks of information when just holding information, and not more than two or three chunks when processing information, and a long-term memory that has a virtually unlimited capacity, and holds information stored in schemas. Schemas can reduce working memory load, because once they have been acquired and automated, they can be handled in working memory with very little conscious effort. In addition, no matter how extensive a schema is, it will be treated as one chunk of information, thereby increasing the amount of information that can be held and processed in working memory without requiring more conscious effort. This ensures that there is enough cognitive capacity available to solve very complex problems. However, when schemas have not yet been acquired, all information elements (chunks) of the problem have to be kept in working memory as separate items, which might lead to a high or excessive demand on working memory capacity. Consequently, there would not be enough capacity left for the formation of a problem schema, and learning would be hampered.

CLT is concerned with instructional techniques for managing working memory load in order to facilitate the changes in long-term memory associated with schema construction and automation. These techniques aim at minimizing extraneous, ineffective cognitive load (i.e., not requiring complex reasoning processes with many interacting unknown chunks of information), and increasing germane, effective cognitive load that facilitates domain-specific knowledge acquisition. CLT research on instructional formats that take these principles into account has identified the following effects: the "goal-free effect," the "worked example effect," the "split-attention effect," the "redundancy effect," the "modality effect," the "completion effect," the "variability effect," and the "imagination effect" (see Sweller, 2004; Sweller, van Merriënboer, & Paas, 1998).

In recent years, most of these CLT effects have been found to facilitate learning for novices, but to become less effective or even dysfunctional as a function of increasing expertise, which is known as the "expertise reversal effect" (Kalyuga et al., 2003). As an example, the "split-attention effect" occurs when learners have to divide their attention over two (or more) information sources that cannot be understood in isolation, such as mutually referring text and diagram, and therefore, physically integrating the text and diagram is beneficial for learning. But with increasing expertise, a learner might be able to understand the information sources in isolation, and when this is the case, the integrated format will lead to a "redundancy effect," which hampers learning (e.g., Chandler & Sweller, 1991).

However, the expertise reversal effect has been found in studies that use the same instructional materials for students of very low and somewhat higher levels of expertise. Therefore, the conclusion that some of the instructional *formats* based on CLT do not work for more experienced learners (Kalyuga et al., 2003) may be premature. It is still possible that CLT-based formats (e.g., worked examples) can benefit learners at higher levels of expertise, by taking into account their prior knowledge. Nonetheless, the findings regarding the expertise reversal effect have caused increased attention by CLT researchers to the fact that the learner's level of expertise is an important factor mediating the relation between cognitive architecture, information structures, and learning outcomes. Consequently, researchers have started to explore how to design effective and efficient instruction for learning beyond the initial levels of mastery, and, therefore, need to understand what it means to acquire expertise, and what fosters its development.

EXPERT PERFORMANCE RESEARCH

Research on expert-novice differences (Chi, Glaser, & Farr, 1988) has shown that experts excel mainly in their domain of expertise, are faster than novices at performing skills, perform their tasks (almost) error free, have superior short-term and long-term memory, and have deeper and more principled problem representations than novices, who tend to build superficial representations of a problem. As Ericsson and Lehmann (1996) noted, this research on expert-novice differences has taken a knowledge-based approach to expertise, which equates expertise with having acquired a lot of knowledge during many years of experience in a domain. However, there is evidence (see Ericsson & Lehmann) that experts by this definition often do not show superior performance on relevant tasks as compared to less-experienced individuals.

Expert performance research is concerned with identifying the mechanisms that have enabled individuals to attain expert performance, that is, "consistently superior performance on a specified set of representative tasks for a domain" (Ericsson & Lehmann, 1996, p. 277). It uses techniques such as collecting retrospective verbal protocols, diaries, and interview data to study small groups of people differing in their current (high) levels of performance under normal conditions (e.g., Ericsson, Krampe, & Tesch-Römer, 1993), as well as process-tracing methods such as eye tracking, reaction time tasks, recall tasks, and verbal reports to study expert performance under experimentally varied conditions (Ericsson & Lehmann).

Expert performance research has shown that it is not the amount of experience in a domain that is relevant for acquiring expert performance, but rather the amount of deliberate effort to improve performance. As Ericsson et al. (1993) argued, expertise and expert performance are acquired by extensive engagement in relevant practice activities, and individual differences in performance are for a large part accounted for by differences in the amount of relevant practice. Relevant practice activities for improving performance are referred to as *deliberate* practice, and typically—in domains such as sports, typing, chess and music—these activities are initially designed by the teacher or coach to help students to improve specific aspects of their performance. Deliberate practice activities are at an appropriate, challenging level of difficulty, and enable successive refinement by allowing for repetition, giving room to make and correct errors, and providing informative feedback to the learner (Ericsson et al., 1993; Ericsson & Lehmann, 1996). Given that deliberate practice requires students to stretch themselves to a higher level of performance, it requires full concentration and is effortful to maintain for extended periods. Students do not engage in deliberate practice because it is inherently enjoyable, but because it helps them improve their performance. That is why deliberate practice activities are often scheduled for a fixed period during the day (at which body and mind are best capable of the effort), and this daily period is of limited duration (Ericsson et al., 1993).

A few other important findings from expert performance research should be mentioned here. The first is that for domain-relevant tasks, expert performers are able to acquire cognitive mechanisms and physiological adaptations that circumvent or change limits constraining the performance of novices. For example, working memory limitations are expanded by the acquisition of long-term working memory (Ericsson & Kintsch, 1995), reasoning is improved by knowledge encapsulation (Rikers, Schmidt, & Boshuizen, 2002), and rapid responses are attained by anticipation and many other qualitative changes (Ericsson, 2002, 2003; Ericsson & Lehmann, 1996). A second finding is that—in contrast to assumptions by theories of skill acquisition (e.g., Fitts & Posner, 1967)—the most important aspects of expert performance are not fully automated and the expert performer retains control over them. Ericsson (2002; Ericsson & Lehmann, 1996) proposed that maintaining high levels of conscious monitoring and control is essential for further improvement of a skill through deliberate practice. Finally, teachers and coaches are helping future expert performers to become independent learners, and design and monitor their own training activities (Glaser, 1996; Zimmerman, 2002), which is critical to the ultimate goal for expert performers, namely to make a major creative contribution to their domain of expertise (Ericsson & Lehmann, 1996).

ESTABLISHING CONNECTIONS BETWEEN THE TWO FRAMEWORKS AND SUGGESTIONS FOR NEW RESEARCH IN EDUCATION

On the long road from beginner to expert performer, there are many fundamental changes in the structure of the mechanisms mediating performance as well as in the conditions of learning and practice. Although the designed instruction of beginners and the self-guided deliberate practice of expert performers may have very little in common, we will in this section explore how methods and insights from the study of expert performers might allow instructional designers to extend and supplement the methods of CLT to increased levels of skill and expertise. First we will discuss methods for identifying and describing acquired cognitive structures and mechanisms, such as schemas, which are necessary if we want to make predictions about how instructional methods might aid advanced learners. We will then examine how the insights from deliberate practice by expert performers can be adapted and incorporated into the instruction and training of less advanced students.

Identifying Cognitive Structures and Skilled Mechanisms of Advanced Learners

Whether it is possible to extend CLT-based instructional strategies that are effective for novices to more skilled learners depends on several issues that have received relatively little attention by researchers. First, it must be possible to study and describe advanced performers' problem solving, and their use of explicit schemas.

If a learner's knowledge base changes, and this change influences future learning, we need a way to accurately judge the content of this knowledge base to be able to design effective instruction. Although CLT research relies heavily on assumptions about schema construction, it has predominantly evaluated the effectiveness of instructional intervention using the combined measures of transfer test performance and mental effort. Although it is valid to conclude that an instructional format that results in higher transfer performance with a lower investment of mental effort is more efficient, this does not provide insight into the mechanisms that underlie this enhanced performance. CLT assumes that schema acquisition was successful based on the higher performance measures, but these measures say very little about the content of such a schema, how it is used when solving transfer problems, and whether errors in performance occur because of a lack of understanding or from computational errors for example (see also van Gog, Paas, & van Merriënboer, 2004). More importantly, whereas this assumption works fine for the initial phase of skill acquisition, when no appropriate schemas for the specific problems are present, it will fail when designing instruction for more advanced students, because according to CLT, schemas largely determine the cognitive load. Another assumption that is hardly tested is that a given instructional design will elicit the same specific learner activities for all learners (Gerjets & Scheiter, 2003). So, to make predictions about the cognitive load imposed by different designs on learners who have passed the initial phase of skill acquisition, existing schemas and their organization, as well as learners' processing strategies, will have to be taken into account. Techniques that are very often used in expert performance research might be of use here, such as analysis of concurrent or retrospective verbal protocols (Ericsson & Simon, 1993), and other process-tracing methods such as eye tracking (e.g., Charness, Reingold, Pomplun, & Stampe, 2001). Using these methods to explain differences in performance not only during transfer tests, but also during practice might help researchers pinpoint the mechanisms that underlie schema acquisition.

Another interesting approach to identify schema content would be to try to design experiments that aim at directly comparing the problem representations established in long-term memory by different instructional formats. For example, learners could be asked to reproduce from memory the solution path of either the worked example they just studied or the conventional problem they just solved. If the worked example group has indeed acquired a better problem schema, they should perform better on this task than the problem-solving group. Similarly, the assumption that completion problems (worked examples with blanks that learners have to fill in) force learners to pay more attention than studying complete worked examples (e.g., Paas, 1992), could be tested by removing the completion problem or worked example after a given study time and asking learners to reproduce it. The combination of these memory reproduction tasks and concurrent verbal protocols during study might provide more direct evidence on what and how students learn from different instructional formats.

Designing Instruction and Training Based on the Characteristics of Deliberate Practice

The specific nature of deliberate practice depends on the structure and the amount of previously acquired skill, and will differ greatly across individuals. We will therefore limit the discussion of applying the characteristics of deliberate practice to instruction, to the ideal of instruction for complex skill learning sketched in the introduction: adaptive, individualized instruction, based on authentic tasks, that gradually allows learners to take control over the process—an approach for which adaptive e-learning environments are well-suited. A first step to applying these ideas would be to try and identify aspects of skilled performance on representative tasks in a given domain, together with performance criteria associated with different levels of expertise. Tasks could be developed, or existing tasks should be identified that improve performance on these aspects (i.e., deliberate practice tasks). However, as Ericsson et al. (1993) emphasized, it is important that activities to improve specific aspects of a skill are carried out in the context of the entire skill.

Selection rules and variables. For any learner, the current level of performance and areas of improvement should be identified, and this assessment can be based on the performance criteria for aspects of skilled performance on representative tasks. This provides the first input for selection rules for assigning deliberate practice tasks. Because the same level of performance can be attained by different individuals, but with different mediating processes and at very different costs, those rules should be composed from task and learner variables. In addition to task performance, variables such as mental effort, time on task, and strategies should be considered in the selection of practice tasks. Recently, Camp, Paas, Rikers, and van Merriënboer (2001) investigated the use of a combined measure of performance and mental effort (i.e., efficiency) as a basis for dynamic task selection in the domain of air traffic control (see also Kalyuga & Sweller, 2005; Salden, Paas, Broers, & van Merriënboer, 2004). However, it should be determined if CLT efficiency measures can be applied for the selection of deliberate practice activities, because deliberate practice requires the investment of a high level of effort. On the other hand, a high level of effort does not necessarily imply engagement in deliberate practice. Comparable to the concept of germane cognitive load, in deliberate practice the increased concentration and effort has a special function, namely to allow students to attain a higher level and to improve the targeted aspect of performance.

More generally, we see the need for studying how detailed assessments of student performance can guide the selection of appropriate practice activities. A good starting point might be to investigate the actual training practices as well as decision processes and deliberations of master teachers and coaches who have experience in selecting deliberate practice activities (e.g., in domains such as sports, typing, chess and music; see Ericsson, 2002). However, it is likely that rules used by teachers and coaches would not be sufficiently explicit to allow simple translation into selection rules that can be used in instructional design. We believe that the issue of selecting appropriate training activities for more advanced students will provide a very fruitful area of research where analysis of measurable aspects of performance and assessment of mediating cognitive mechanisms will lead to the discovery of valid rules for selection of training tasks.

Format and scheduling of activities. In spite of the evidence for the expertise reversal effect (Kalyuga et al., 2003), there is some suggestion that instructional format based on CLT may be effective when adapted to advanced levels of expertise. In particular, some recent formats that aim at enhancing germane cognitive load might qualify as deliberate practice activities for students at certain levels of expertise, such as instructing students to self-explain (Renkl, 2002), or to imagine or anticipate on next steps (Cooper, Tindall-Ford, Chandler, & Sweller, 2001). These formats encourage students to generate rich responses and thus learn from errors and difficulties, and feedback in the form of the right explanation or steps gives students the opportunity to diagnose and learn from their errors. Important for both the concept of germane cognitive load and deliberate practice is that it will have positive effects on performance only if learners are motivated to put in the effort. Motivation is thus a mediating variable, and can be an important constraint on effectiveness. Monitoring learner motivation, or the interaction between a particular format, motivation, and effectiveness, might provide important information on how to schedule different types of activities (see also Paas, Tuovinen, van Merriënboer, & Darabi, 2005).

Ericsson et al. (1993) have shown that deliberate practice activities are usually of limited duration (2–4 hr) and are often scheduled for a fixed time during the day, because they require such high amounts of effort. A very interesting question is whether this is more efficient, that is, whether the improvements in performance are equal to or higher than those attained with traditional forms of instruction, even though the time spent per day is limited. Zhu and Simon's (1987) findings are interesting in this respect. They compared a traditional 3-year mathematics curriculum to a redesigned curriculum based on carefully chosen sequences of worked-out examples and problems. They found that most of the students in the new curriculum were able to complete the entire curriculum in 2 years and were at least as successful as students learning by conventional methods.

However, as indicated before, there are probably other principles that come into play at higher levels of expertise or task complexity. Highly interesting in this respect are recent efforts to study the microstructure of practice activities of expert performers by process-tracing methods, such as "think aloud" and detailed observation (Deakin & Cobley, 2003; for reviews, see Ericsson, 2002, 2003). In addition, longitudinal research should be used to identify those principles, as well as provide answers to the questions raised here. Such research can also provide more detailed information on how learners use the informative feedback provided by deliberate practice, how they use the opportunity for repetition (i.e., how many times), and how they go about correcting errors if they make any.

Learner control. If students are to continue improving their performance after the end of formal education, they have to be prepared to shape their own learning processes, that is, diagnose their needs for improvement, seek out their own activities, and plan, monitor, and evaluate this entire process (see Zimmerman, 2002). The most common method to prepare students for increased independence in domains of expertise is to gradually reduce the teacher-controlled selection of tasks, and thus force the learner to develop skill in the selection of tasks in parallel with development of other aspects of expertise (Glaser, 1996).

For highly skilled performers, a high level of learner control is possible, because analyses show that they are capable of monitoring their performance, so they can diagnose and modify the mediating cognitive mechanisms in response to inferior achievement and design their own training activities to improve their weaknesses (Ericsson, 2002). Therefore, it is likely that with acquiring increasingly complex cognitive mechanisms, individuals will also acquire mechanisms for monitoring and assessing their performance, and become able to use general feedback and their expected and observed performance outcomes to help them diagnose and make appropriate adjustments in the mechanisms controlling their performance.

This raises both an interesting question for further research, and a major challenge for instructional design. The question is on if it is possible to facilitate student development of the skill to diagnose their own needs for improvement; in other words, to teach them how to identify appropriate training activities. For example, a specific type of process-oriented worked example (van Gog et al., 2004) that shows explicitly how teachers and advanced learners select tasks by monitoring the processes mediating the task performance, might benefit the acquisition of this skill. A major challenge, but also a major benefit for instruction for more skilled performers would be to develop a collection of authentic training tasks that can qualify as deliberate practice activities and support self-regulated learning, generation of feedback, and repeated practice of corrected performance.

GENERAL DISCUSSION

Researchers studying CLT and expert performance have focused on the beginning and the ultimate goal of the acquisition of skilled performance, respectively. As instructional designers working within the CLT framework extend their work toward increasingly skilled students, we see great promise in developing connections to the framework of expert performance research. In this article, we have indicated a number of interesting relations between both frameworks; their implications for instructional design research are summarized in Table 1.

Skilled and expert performers have acquired a wide range of complex cognitive mechanisms that mediate their superior performance and allow them to circumvent the processing limits that constrain novices. These mechanisms also allow developing performers to monitor and gradually refine their performance during deliberate practice. A fundamental question is if and how instructional interventions might facilitate this learning process and whether the duration of this training can be shortened by designing training activities according to CLT, as Rikers, van Gerven, and Schmidt (2004) suggested. Another highly relevant question emerging from the expert performance perspective concerns the motivational factors that support skilled performers to focus their lives on attaining high levels of performance and spending thousands of hours in deliberate practice (Ericsson, 2002). Might a better understanding of these motivational factors help instructional designers to facilitate the engagement of less skilled students in deliberate training activities?

One of the exciting challenges of developing instruction for advanced learners is that their learning will involve the modification of skills and information that have been previously organized in long-term memory. In this article we sketched the opportunities for instructional designers to use process-tracing methods to assess individuals' organization of these preexisting structures and to develop instructional methods to fit to the attributes of the individual advanced learner. Once this can be realized for a given domain, there is great promise for instruction in the development of a collection of suitable training tasks. E-learning tools would have considerable benefits in storing such a collection of tasks in a database, in allowing online assessment of level of expertise based on a number of variables, and in translating this assessment into selection rules for retrieving tasks. Current tech-

Table 1 □ Suggestions for instructional design research.

Memory or Cognitive Structures ID research should identify the actual effects on memory structures of different instructional formats for learners at different levels of expertise, instead of deriving assumptions about these structures from subsequent task performance.
Improving Learning or Performance ID research should identify what instructional formats are capable of increasing germane cognitive load, or may constitute deliberate practice, for learners of different levels of expertise. This requires the identification of aspects of skilled performance on representative tasks in a domain and the associated performance criteria at different levels of expertise.
Adaptive Training Design ID research should identify what the relevant aspects of performance (i.e., a more fine-grained performance measure) and other relevant variables are in a domain, and investigate how these variables can be assessed and used in subsequent task selection to make instruction adaptive to the needs for improvement of individual learners.
Effort or Motivation ID research should focus more on the relationship between motivation, investment of mental effort, and effectiveness of differ ent instructional formats.
Self-regulation or Control ID research should identify at what point in their development learners become capable of self-assessment and self-selection and what the relevant mechanisms are that support these skills, and investigate whether these skills can be trained.

nological developments increasingly allow the development of tools that incorporate these functionalities (Shute & Towle, 2003). However, when it comes to instruction aimed at improving performance instead of knowledge, we still have a long way to go, because the domain should allow the use of e-learning tools without devaluating task authenticity, and those tools should allow for gradually increasing learner control in assessment and selection. The questions raised in this article show that establishing connections between the theoretical frameworks of CLT and expert performance research provides fertile grounds for future research on instructional design. Eventually, integrating those theoretical perspectives and their empirical findings could be attempted. □

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