Managing Cognitive Load in Adaptive ICT-Based Learning

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ABSTRACT

The history of technological innovations in education has many examples of failed high expectations. To avoid becoming another one, current multimedia ICT tools need to be designed in accordance with how the human mind works. There are well established characteristics of its architecture that should be taken into account when evaluating, selecting, and using educational technology. This paper starts with a review of the most important features of human cognitive architecture and their implications for ICT-based learning. Expertise reversal effect relates to the interactions between levels of learner prior knowledge and effectiveness of different instructional techniques and procedures. Designs and techniques that are effective with low-knowledge learners can lose their effectiveness and even have negative consequences for more proficient learners. The paper describes recent empirical findings associated with the expertise reversal effect in multimedia and hypermedia learning environments, their interpretation within a cognitive load framework, and implications for the design of learner-tailored multimedia.

Keywords: Cognitive Load, Working Memory, Cognitive Architecture, Expertise Reversal Effect, Adaptive Learning Environments

1. INTRODUCTION

The design of effective ICT-based learning environments should take into account how the human mind works and what are its cognitive limitations. Most cognitive processes in learning occur consciously and involve information from the learner knowledge base. These attributes (consciousness and knowledge base) are associated with two major components of our cognitive architecture, *working memory* (a conscious information processor) and *long-term memory* (a store of knowledge). Their essential characteristics have been well established and become important issues in recent theoretical frameworks for learning and instruction.

Mental resources we use when learning and performing different tasks are limited by the capacity and duration of working memory that represents a major factor influencing the effectiveness and efficiency of learning. If more than a few chunks of information are processed simultaneously, working memory may become overloaded and inhibit learning.

On the other hand, our long-term memory is not limited in capacity and duration and considerably influences the operation of working memory. It allows us to handle many interacting elements of information in terms of larger units (chunks) in working memory thus reducing cognitive load and making high-level cognitive activities possible. Available knowledge structures and associated learner cognitive characteristics may significantly change the effectiveness of various instructional methods. Therefore, in order to be efficient, ICT-based learning formats and methods need to be tailored to cognitive characteristics of learners.

2. CHALLANGES

Most ICT-based learning materials continue to be designed in a fixed way with novice learners as assumed intended audience. However, recent studies of the expertise reversal effect (see [1, 2] for recent overviews) have indicated that designs and techniques that are effective with novices can lose their effectiveness and even have negative consequences when used with more experienced learners. The major ICT design implication of these studies is that information presentation and design techniques need to change as learners acquire more expertise in a domain.

Tailoring instruction to individual learners is a very complex problem due to multiple learner characteristics, technical, organizational and other issues. The existing developmental projects in e-learning are focused mostly on technical issues of tailoring content to learner preferences, interests, choices, history of previous on-line behavior etc. and are not based on fundamental cognitive characteristics of learners.

This paper discusses theory- and research-based cognitive principles and guidelines for managing cognitive load in ICT-based learning environments by adapting them to levels of learner prior knowledge and skills. The suggested approaches and techniques are based on contemporary knowledge of human cognitive architecture and extensive empirical studies.

The paper reviews empirical studies of the expertise reversal effect in ICT-based learning environments and their implications for the design of learner-tailored instructional systems. It starts by introducing a general theoretical framework for the described approach followed by the review of cognitively efficient evidence-based instructional techniques, procedures, and different forms of information presentations for learners with different levels of expertise. Finally, the paper suggests procedures and methods for dynamic online tailoring of learning tasks and information presentation formats to levels of learner expertise.

3. THEORETICAL FRAMEWORK

Human Cognitive Architecture

A contemporary model of our cognitive architecture includes two major components: working memory and long-term memory. Their characteristics define how we learn and perform in ICT-based learning environments. Most cognitive processes essentially depend on a knowledge base in long-term memory with effectively unlimited capacity and duration. Organized generic knowledge structures (schemas) allow us to mentally categorize and represent concepts and procedures, and govern our behavior.

Our cognitive system also includes a mechanism that limits the scope of immediate simultaneous changes to the knowledge base. This mechanism is associated with working memory as a conscious processor of information within our focus of attention. Working memory is severely limited in capacity and duration when dealing with novel information [3, 4]. Working memory is believed to have separate limited processing channels for visual and auditory information modalities [5].

Processing limitations of working memory influence significantly the effectiveness of performance, particularly in complex tasks. The learner domain-specific knowledge in long-term memory and associated levels of expertise reduce these limitations and guide high-level cognitive activities.

The available knowledge base is considered as the most important cognitive characteristic that influences learning and cognitive performance. Understanding the key role of long-term memory knowledge base in our cognition is essential to successful management of cognitive load in ICT-based learning.

Cognitive load theory (see [6, 7] for recent general overviews) and closely related cognitive theory of multimedia learning (see [8 9] for recent overviews) consider learning design implications of the above human cognitive architecture. Based on theoretically and empirically established instructional principles, they make specific prescriptions for managing cognitive load in learning and instruction.

These theories define several different types and sources of cognitive load: effective (intrinsic and germane) and ineffective (extraneous) cognitive load. These types of cognitive load are associated with different instructional design methods and techniques. Examples of cognitive load factors that may influence effectiveness of ICT-based learning environments are levels of element interactivity in learning materials, their spatial and temporal configurations, redundant representations of information, etc.

Role of expertise in cognitive processes

The most important factor of our cognitive functioning is how working memory and long-term memory systems interact with each other. Knowledge base in long-term memory allow us to effectively reduce limitations of working memory by encapsulating many elements of information into larger, higher-level units that are treated as elements in working memory. Another way to reduce cognitive load is to practice skills until they can operate under automatic rather than controlled processing [10, 11]. When basic routine procedures occur automatically, the system could avoid an overload and reallocate cognitive resources for higher-level mental processes.

When learners do not have relevant knowledge (or if it not sufficiently automated), they have to deal with many new elements of information that may easily overload working memory. These learners may require considerable external support to build new knowledge structures in a relatively efficient manner. On the other side, more knowledgeable learners may rely on their available domain-specific long-term memory structures for managing cognitive load.

Cognitive studies of expertise demonstrated that prior knowledge is the most important 1earner characteristic that influences learning processes. It has been established that learning procedures and techniques that are beneficial for learners with low levels of prior knowledge may become redundant for more knowledgeable learners. The effect is related to increased cognitive overload for more knowledgeable learners due to processing redundant for these learners instructional components [12, 13].

Knowledge structures in long-term memory perform an organizing and governing role in complex cognitive processes. In the absence of relevant knowledge or sufficient external instructional guidance, we would use mostly random search processes in attempts to handle the task. If no guidance is provided for dealing with new units of information, the task may cause a cognitive overload.

However, if guidance is provided to learners who have sufficient knowledge base for dealing with the same units of information, learners would have to relate and reconcile the related components of available long-term memory base and external information. Such integration processes may impose an additional cognitive load and reduce resources available for learning new knowledge, thus causing an expertise reversal effect.

Presenting knowledgeable learners with detailed external guidance may hinder their learning and performance relative to the levels they could achieve with minimal instructional support. Therefore, as levels of learner expertise in a domain increases, relative effectiveness of learning tasks with different levels of instructional support may reverse.

Although the expertise reversal effect was predicted within the cognitive load theoretical framework as a form of redundancy effect that could occur when some presented information that was beneficial (and non-redundant) for novice learners became redundant for learners with higher levels of knowledge in a task domain [14], the effect was then extended to different presentation modalities and levels of instructional guidance.

The main implication of the expertise reversal effect is the need to tailor instructional techniques and procedures to changing levels of learner expertise in a domain. In order to design adaptive procedures capable of tailoring instruction in real time, it is necessary to have sufficiently rapid online measures of learner knowledge. Such measures should also have a sufficient diagnostic power to detect different levels of expertise.

The idea of rapid diagnostic assessment of expertise is based on evaluating knowledge structures that learners are able to activate rapidly and apply to a briefly presented problem situation [15]. This approach has been successfully used for designing adaptive learning environments in well-defined (mostly, technical) areas. Its usability and applications in poorly defined task domains still remains to be established.

Sources of cognitive load

One major type of cognitive load, an intrinsic cognitive load, is essential for learning and caused by internal complexity of the task relative to the level of learner expertise. Expertise in the language of instruction may also influence the level of intrinsic cognitive load, e.g., simple and routine sentences for native speakers may cause significant cognitive overload for second language learners. Intrinsic cognitive load is required for comprehending a situation and results in modified or new knowledge structures in long-term memory.

Therefore, it is vital to provide all the necessary resources to accommodate this load without exceeding limits of working memory capacity. For example, to manage intrinsic cognitive load, the learning goal could be divided into a series of sub-goals that require less processing resources, instructional tasks could be segmented into smaller units.

Alternatively, some of the essential interactions between elements of information could be excluded from consideration in order to artificially reduce structural complexity of the task on initial stages of learning followed by the fully interactive materials later [16]. If intrinsic load is at low levels and much cognitive capacity remains unused, it could be increased, for example, by setting more challenging learning goals that require more complex cognitive activities with higher levels of element interactivity.

In contrast to essential, extraneous cognitive load is an irrelevant form of load associated with a waist of cognitive resources due a poor presentation design, inappropriate selection and sequencing of learning tasks, or inadequate instructional support. For example, separating related sources of information in space and/or time; duplicating the same information simultaneously in different modalities; or using unguided problem-solving or exploratory activities with novice learners.

The expertise reversal effect is associated with two types of situations that cause extraneous cognitive load: 1) insufficient external guidance does not compensate for limited knowledge of novice learners; 2) expert learner knowledge base overlaps with provided external guidance thus forcing learners to waste limited resources on co-referring internal and external representations of the same information.

It should also be noted that the difference between extraneous and intrinsic cognitive load is relative to levels of learner expertise: some components of cognitive load that are essential for novice learners could become extraneous (irrelevant) for relatively more experienced learners, and vice versa.

4. EVIDENCE-BASED METHODS

Dealing with split-attention and redundancy

Different sources of cognitive load are related to different modes and modalities of ICT-based information presentations (verbal and pictorial representational modes; auditory and visual information modalities). When learners process text and visuals that could not be understood in isolation, the integration of verbal and pictorial representations is required. When text and pictures are not appropriately located or synchronized in time, integrating these referring representations may increase cognitive load and inhibit learning.

Instructional design techniques dealing with such split attention situations may enhance learning. Physically integrated or embedded formats were demonstrated to be an effective alternative to "split-source" instructions (split-attention effect [17, 18].

Using dual-mode presentations (e.g., auditory explanations of a visual diagram) is an alternative approach to eliminate split attention.). Integration of the verbal auditory and pictorial visual information may not overload working memory if its capacity is effectively expanded by using a dual-mode presentation (modality effect; e.g., [19. 20]). For example, it was demonstrated that an animation depicting the operation of a bicycle tire pump with simultaneous audio text produced better learning results than the audio text only without an animation or the animation only without audio text [21]. Comparisons between simultaneous and sequential presentations of the related audio and visual information demonstrated that dual-mode instructions were superior only when presented in the simultaneous form (the temporal contiguity or split-attention effect) [22, 23].

Examples of other means for dealing with potential cognitive overload are eliminating redundant components of presentations. If different sources of information are intelligible in isolation, elimination rather than integration of a redundant source could be preferable (redundancy effect; e.g., [24, 25]). However, whether information is redundant depends on the level of expertise of the learner: what is essential for novices could be redundant for more knowledgeable learners.

When onscreen text is embedded into a diagram or narrated when the diagram is presented, it is not possible to avoid processing the redundant information and integrating it with available knowledge structures in long-term memory. These processes consume cognitive resources that become unavailable for constructing higher levels of knowledge. Eliminating redundant verbal or pictorial information could be the best design decision when dealing with more experienced learners. Thus, the effectiveness of different instructional formats may depend on levels of domain-specific expertise of the intended learners (in accordance with the expertise reversal effect).

Therefore, the relation between the split-attention and redundancy effects may reverse as learner gains more expertise [14, 26]. While novice learners may learn best from textual explanations embedded into a diagram or narrated over the diagram, for more experienced learners, diagram-alone materials could generate higher levels of performance and be easier to process. Textual explanations that are essential for novices may become redundant for experts. Thus, the instructional efficiency of different formats of information presentation depends on levels of learner expertise in specific task domains.

Managing cognitive load in interactive visualizations

Sophisticated ICT-based learning environments include various forms of interactivity and respond dynamically to learner actions. They involve multiple representations, linked information networks, and high levels of learner control. Such environments are expected to promote active construction and acquisition of new knowledge. High levels of cognitive load in interactive learning environments could be caused by a large number of variables involved in corresponding cognitive processes; by uncertainty and non-linear relationships between these variables; and by temporary delays. In many situations, learners have to carry the burden of deciding when to use additional instructional support (if available) and what forms of support to request. While more advanced learners could handle such burden, it may go beyond cognitive resources available to less experienced learners.

The cognitive load framework could be effectively applied to different forms of dynamic visualizations such as instructional animations, simulations, and games. For example, continuous animations may be too cognitively demanding for novice learners due to a high degree of transitivity. Less knowledgeable learners may benefit more from a set of equivalent static diagrams.

The effects of static diagrams and computer animations on learner mental models of a mechanical system were studies in [27]. No evidence was obtained that animated diagrams led to superior understanding compared to static diagrams. Comprehension of diagrams was enhanced by asking students to predict the behavior of the machine from static diagrams and by providing them with a verbal description of the dynamic processes. Predicting motion from static diagrams presumably engaged students' spatial visualization and mental animation processes.

However, animations still could be relatively more beneficial for more experiences learners who have acquired a sufficient knowledge base for dealing with issues of transitivity and limited working memory capacity. Optimal forms of tailoring visual dynamic representations to levels of learner expertise require selecting appropriate levels of visual dynamics.

The interaction between levels of learner expertise and effectiveness of animated and static procedural examples in the task domain of transforming graphs of linear and quadratic equations in mathematics was investigated in [28]. The results demonstrated that less knowledgeable learners performed significantly better after studying static examples. Learners with higher levels of prior knowledge showed better results after studying animated instructions.

As levels of learner expertise increased, the performance of the animated instruction group improved more than performance of the static group. Knowledge structures of more experienced learners may help them to handle the transitivity of animations, but processing details in static graphics may require redundant activities for these learners. Static graphics may be less beneficial for more experienced learners because their available dynamic knowledge structures would need to be integrated and reconciled with redundant for them details displayed in graphics. Additional cognitive resources may be required for such processes, increasing working memory demands and reducing relative learning effects.

Interactive simulations may provide appropriate environments for exploring hypotheses and receiving immediate feedback, thus enhancing the development of critical thinking and problem-solving skills. However, high levels of working memory load could be responsible for instructional failures of many simulations.

Many instructional simulations and games represent purely exploratory learning environments with limited guidance for learners. From cognitive load perspective, random search procedures that novice learners have to use in such environments may impose excessive levels of cognitive load and interfere with meaningful learning. Optimizing levels of instructional guidance represent an essential means for managing cognitive load and enhancing learning outcomes in such environments.

Two different modes of visual representations in a gas law simulation for middle-school chemistry students were compared in [29]. Essential gas characteristics were presented either in symbolic form only (words ‘temperature’, ‘pressure’, and ‘volume’ with corresponding numerical values) or by adding iconic information to the symbolic representations (e.g., burners for temperature, weighs for pressure). While low prior knowledge learners benefited more from added iconic representations than from symbolic formats only, high prior knowledge learners benefited more from symbolic only representations. Iconic representations were redundant for these learners.

An important feature of animations, as well as static images, is their fidelity level that characterizes the degree of realism or resemblance to the real world. High fidelity levels with many non-essential details that may distract learner attention may not always be instructionally effective. For example, it was demonstrated that schematic low-fidelity illustrations were retained better than analogical high-fidelity illustrations [30].

5. TOWARDS ADAPTIVE ICT-BASED LEARNING

A major instructional implication of the expertise reversal effect is the need to tailor dynamically instructional techniques and procedures, levels of instructional guidance to current levels of learner expertise. In ICT-based instructional systems, the levels of expertise may change noticeably as learners develop more experience in a specific task domain. Therefore, the tailoring process needs to be dynamic, i.e. consider learner levels of expertise in real time as they gradually change during the learning sessions. As levels of learner expertise increase, relatively less-guided exploratory, problem-solving, or game-base environments could effectively assist in learning advanced knowledge and skills in specific task domains.

Personalized adaptive environments may provide learner-centered experiences that are specifically tailored to individual learners or groups. A possible adaptive methodology could be based on empirically established interactions between levels of learner expertise and instructional methods (the expertise reversal effect), and on real-time monitoring of expertise using rapid diagnostic methods. For example, completion tasks and faded worked examples could be used for providing appropriate levels of instructional support that are optimal for learners with different levels of expertise. As learners acquire more experience in a domain, reduced levels of guidance and more independent exploratory-based forms of learning could become more effective.

This approach to dynamic tailoring of instruction to learner characteristics assumes a system-controlled format: a computer program or instructor dynamically select an instructional method that is most appropriate for the current level of learner expertise. An alternative format could be realizes as a learner-controlled approach to the individualization of instruction.

Despite expected advantages of learner control (e.g., positive learner attitudes and a sense of control) research findings have been inconclusive and more often negative rather than positive in relation to learning outcomes [31, 32, 33]. Learners may not be able to select appropriate learning strategies on their own and require assistance in effective use of provided control facilities.

According to cognitive load theory, the level of learner expertise is a defining factor: students could have control over the content and instructional sequences when they have sufficient knowledge of the task domain; otherwise they may require appropriate assistance. One form of such assistance is providing advisement to learners for making their own decisions [34]. Providing guidance and advisement to learners as they proceed through the instructional program may combine advantages of both learner control and system control. Using this information, learners can make effective decisions themselves.

An advanced form of the advisement approach is an adaptive guidance strategy: providing learners with information on the current level of their knowledge, what to study or practice to achieve mastery, how to sequence learning tasks for gradual transition from basic to more complex strategies, and how to allocate cognitive resources [35, 36]. Advisement and adaptive guidance approaches are based on providing individualized prescriptive information in the form of recommended learning materials and tasks based on past performance.

Existing adaptive ICT-based learning environments are mostly based on external characteristics of learner behavior rather than on real cognitive characteristics. Learner levels of prior knowledge or expertise should be made the primary factors in adaptive instructional systems, complemented with relevant secondary factors (e.g., navigational patterns, learning styles, and preferences). Individualized adaptive instruction should be based on detailed diagnostic assessment of learner knowledge structures that could appropriately direct instructional interventions. Different variable levels of learner control and adaptive guidance approach should be implemented in these environments as means of enhancing their adaptive capabilities.

Students that have significant prior knowledge in a domain may be allowed control of the instructional content. These students could be able to use their prior knowledge to determine an appropriate instructional sequence. Low-ability and low-knowledge learners need to be provided with more guidance and default paths through the knowledge base. Pace control should be provided when students could benefit from additional time to integrate new information with their available knowledge base.

Complex learning environments should assist learners in making effective use of the control they are provided. Adaptive guidance could be used to monitor and assess learner progress and provide learners with diagnostic information and individual recommendations on future learning activities. As learners acquire basic lower-level knowledge and skills, adaptive guidance should tailor subsequent learning tasks and activities to focus attention on more advanced knowledge and skills. A continuously available instructional support is important even when adaptive advice is provided to learners.

6. CONCLUSION

The expertise reversal effect has been observed in many studies in ICT-based multimedia learning environments. They may provide a valuable guidance for instructional designers, particularly for the design of learner-adapted ICT-based instruction. For example, it has been demonstrated that a minimal instructional guidance would allow more knowledgeable learners to take advantage of their knowledge base in the most efficient way. Instructional guidance should be provided at the appropriate time, while unnecessary support removed as a learner progresses to more advanced levels of proficiency in a specific domain. Adaptive learning environments that dynamically tailor levels of instructional support to changing individual levels of learner expertise in a domain have the best potential for optimizing cognitive load.

The quality of adaptive environments depends on the accuracy of information about levels of learner knowledge and skills. Using traditional tests and tracing user interactions with the system cold be imprecise and incomplete. Applying modern artificial intelligence approaches and using fine-grained production rule-based learner models in intelligent tutoring systems allowed a significant increase in the precision of adaptive methodologies [37]. However, implementations of such approaches require complex computational modeling and, therefore, have been limited to several well defined and relatively simple domains.

A rapid diagnosis-based approach may offer appropriate tools that combine high levels of diagnostic precision with simplicity of implementation in learner-tailored instructional procedures. The development of adaptive learning environments in different domains would also require rapid diagnostic instruments for measuring levels of learner expertise in poorly defined task areas. Also, achieving higher levels of expertise is associated with flexible performance in new situations. Extending the described approaches and techniques to developing adaptive forms of expertise represents an important direction for future research.

7. REFERENCES

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