

Managing cognitive load in ICT-based learning

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ABSTRACT

The paper describes theory- and research-based principles and design guidelines for handling cognitive load in e-learning environments by adapting instructional methods, and presentation formats to levels of learner prior knowledge in a task domain. The suggested approaches and techniques are based on contemporary knowledge of human cognitive architecture, cognitive load theory, and, most importantly, on extensive empirical studies of the instructional consequences of learner prior knowledge (expertise reversal effect) in controlled experimental conditions.

Keywords: Cognitive Load, Working Memory, Learner Knowledge Base, Expertise Reversal Effect, Adaptive Learning Environments

INTRODUCTION

The design of effective ICT-based learning environments should take into account how the human mind works and what are its cognitive limitations. 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.

Thus, the extensive knowledge base reduces working memory limitations by allowing experts to process information more efficiently. Available knowledge structures and associated 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.

CHALLENGES

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 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.

This 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.

THEORETICAL FRAMEWORK

A contemporary model of our cognitive architecture includes two major components: working memory and long-term memory. Working memory provides temporary storage and transformation of verbal and pictorial information that is currently in the focus of our attention (e.g., constructing and updating mental representations of a situation or task). Processing limitations of working memory influence significantly the effectiveness of performance, particularly in complex tasks. Our working memory becomes overloaded if more than a few chunks of information are processed simultaneously ([3], [4]). For a simple example, we all experience this cognitive overload when trying to keep in memory an unfamiliar telephone number or add two four-digit numbers in the absence of a pen and paper.

Long-term-memory represents a large store of organized information with effectively unlimited storage capacity and duration. It contains a huge number of organized knowledge structures (schemas) that effectively determine our capabilities to function successfully in complex environments. Generally, schemas are organized knowledge structures that are used for mentally categorizing and representing concepts and procedures in long-term memory. Most of our cognitive activities are based on available domain- and task-specific knowledge base. We know what to do when buying things at a supermarket, eating at a restaurant, filling in a car at a gas station. We easily understand fiction books we read, however certainly encounter huge problems when reading specialist books in unfamiliar domains. This is because we have massive knowledge base for dealing with our natural and social environment in everyday life which is usually sufficient for understanding fiction

books, but no specific knowledge in many professional domains.

The learner domain-specific knowledge in long-term memory and associated levels of expertise reduce working memory 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 [5], [6] for an overview) and closely related cognitive theory of multimedia learning (see [7], [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 (e.g., intrinsic) 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.

The effective cognitive load is associated with cognitive resources directed towards achieving certain learning objectives. When this type of cognitive load is involved, the learner attends to the learning elements, attempts to establish connections between them and construct a coherent mental representation in working memory. Because this load is essential for comprehending the material and constructing new knowledge, it is vital to maximize its level within limits of working memory capacity. On the other side, the irrelevant extraneous cognitive load represents invested cognitive resources that are not essential for achieving learning goals and are caused by the instructional design features of specific learning tasks.

Major sources of excessive extraneous cognitive load that may inhibit performance and learning with

multimedia applications are spatially and/or temporally split elements of information that need to be integrated for understanding; an excessive step-size and/or rate of information presentations that introduce too many new elements of information into working memory too fast to be organized and comprehended; insufficient user support or guidance for lower prior knowledge learners; excessive redundant support overlapping with available knowledge structures of more experienced learners.

Based on a large number of studies ([10], [11]) within a cognitive load framework, it has been established that learning procedures and techniques that are beneficial for learners with low levels of prior knowledge may become ineffective for more knowledgeable learners, and vice versa (the expertise reversal effect). The effect is related to increased cognitive load for more knowledgeable learners due to processing redundant for these learners instructional components.

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 expertise. Such measures should also have a sufficient diagnostic power to detect different levels of expertise. The idea of rapid diagnostic approach is based on evaluating knowledge structures that learners are able to activate rapidly and apply to a briefly presented problem situation.

EVIDENCE-BASED METHODS

For efficient performance and/or learning, total cognitive load imposed on cognitive system should not exceed limited working memory capacity. When a learning task is characterized by a high degree of element interactivity relative to the learner level of expertise, it may require a heavy intrinsic (effective) cognitive load to comprehend the situation. In this case, an additional extraneous cognitive load caused by an inappropriate design can leave insufficient cognitive resources for efficient performance and/or learning because total cognitive load may exceed the learner working memory capacity. The available cognitive resources may be inadequate for sustaining the required level of total cognitive load. Elimination or reduction of extraneous cognitive

load by improving the design of presentation formats or task procedures may be critical for learning.

There are different sources of cognitive load related to different modes and modalities of ICT-based information presentations (verbal and pictorial representational modes, or 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. Using dual-mode presentations (e.g., auditory explanations of a visual diagram) is an alternative approach to eliminate split attention. Examples of other means for dealing with potential cognitive overload are eliminating redundant components of presentations or segmenting presentations. However, the instructional efficiency of different formats of information presentation depends on levels of learner expertise in specific task domains.

The general guidelines for minimizing extraneous cognitive load in ICT-based learning environments include providing learners with direct access to required knowledge base, avoiding diversion of learner cognitive resources on redundant and/or irrelevant cognitive activities, managing step-size and rate of information presentation, and eliminating spatial and temporal split of related sources of information.

In the most general form, the main instructional implication of cognitive load theory could be expressed as the need to avoid anything that gets in the way of learning. Some specific design implications in respect to ICT-based learning include (see also [7], [9] for more details):

- enrich on-screen text with visual representations;
- present visualizations and corresponding textual explanations simultaneously rather than successively to avoid temporal split-attention;

- present related sources of information close to one another on screen (e.g., embed the text into the graphic, avoid covering or separating information that must be mentally integrated for learning, design space for guidance or feedback close to problem statements);
- avoid irrelevant graphics, stories, interesting but irrelevant details, irrelevant sounds and music, nonessential words and lengthy text;
- use visual representations explained by audio narration rather than on-screen text;
- use animated visualizations with brief audio narrations rather than on-screen textual explanations;
- present static or animated visualizations with narration-only instead of duplicating the narration with onscreen text.

When designing an instructional guidance on how to use the hardware that involves material with high levels of element interactivity, a self-contained instruction that does not require the use of the computer or other hardware could be superior to instructional formats that involve continual interactions with the hardware.

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. However, animations could be relatively more beneficial for more experienced 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.

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 thus interfering with meaningful learning. Optimizing levels of instructional guidance represent an essential means for managing cognitive load and enhancing learning outcomes in such environments.

TOWARD 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. 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

the 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 learning could be involved.

Preliminary studies have indicated that using rapid dynamic performance indicators in adaptive methodologies is a viable approach to the problem of tailoring e-learning environments to levels of learner task-specific expertise. The rapid diagnostic methods were used for optimizing levels of instructional guidance and cognitive load in several adaptive learning environments in algebra and kinematics [11]. All these environments used a similar adaptive procedure. At the beginning of a session, each learner was allocated to an appropriate level of guidance according to the outcome of the initial rapid diagnostic test. Depending on the outcomes of the rapid diagnostic probes during instruction, the learner was allowed to proceed to the next stage of the session or was required to repeat the same stage and then take the rapid test again. At each subsequent stage of the tutoring session, a lower level of instructional guidance was provided to learners, and a higher level of the rapid diagnostic tasks was used at the end of the stage. Important advantages of this approach to learner-adapted learning environments are its transparency and relative simplicity.

In some of the studies, the allocation of learners to appropriate stages of instructional guidance was based on levels of task-specific expertise as measured by the rapid online first-step or rapid verification tests. In other studies, the rapid measures of task-specific expertise were combined with measures of cognitive load based on subjective ratings of task difficulty. Since expertise is associated not only with higher levels of performance but also with lower cognitive effort, combining both measures was expected to produce a better indicator of learner task-specific expertise.

Critical levels of efficiency were defined for each class of tasks as criteria for achieving proficiency in

this task domain. Appropriately defined cognitive efficiency indicators were used for the initial selection of optimal levels of instructional guidance, as well as for continuous monitoring of learner progress and tailoring instruction to changing levels of task-specific expertise. With both approaches, results indicated that learner-adapted conditions resulted in significantly better knowledge gains than non-adapted conditions. However, there were no significant differences found between the two adaptation procedures when they were used in the same study and could be meaningfully compared.

Thus, dynamically adapting task selection procedures and levels of instructional guidance to levels of learner task-specific expertise using rapid diagnostic methods enhanced learning outcomes and supported previous results ([12]. [13]). Despite differences in performance assessment methods, definitions of instructional efficiency, and task selection algorithms, learner-adapted conditions were superior to non-adapted formats in all these studies.

Incorporating learner control approaches into adaptive instruction represents alternative ways of dynamic tailoring of instruction to levels of learner expertise. Shared-responsibility, advisory, and adaptive guidance models could be effectively used in adaptive multimedia learning environments. For example, a shared control model demonstrated higher learning outcomes than a fully system-controlled condition [14]. The shared control model effectively combined system- and learner-controlled environments by first selecting a subset of tasks based on learner performance and cognitive load indicators, and then presenting this subset to the learner who made the final decision.

The quality of adaptive environments depends on the accuracy of information about levels of learner knowledge and skills in specific task domains. Using traditional multiple-choice tests and tracing user interactions with the system may not produce sufficient levels of diagnostic precision. Applying modern artificial intelligence approaches and developing sophisticated fine-grained production rule-based learner models allowed a significant increase in the precision of adaptive methodologies [15].

However, implementing these methodologies requires complex computational modeling

procedures. Therefore, their application has been limited to several well defined and relatively simple for modeling domains (e.g., programming and mathematics). On the other hand, the models that are used in most adaptive hypermedia and web-based environments are based on several discrete coarse-grained levels of learner expertise. An important advantage of the suggested rapid diagnosis-based approach to the design of learner-adapted environments is combining high levels of diagnostic precision with simplicity of implementation.

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.

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