# Cognitive Issues in Tailoring Multimedia Learning Technology to the Human Mind

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## INTRODUCTION

In order to design effective and efficient multimedia applications, major characteristics of human cognition and its processing limitations should be taken into account. A general cognitive system that underlies human performance and learning is referred to as our cognitive architecture. Major features of this architecture will be described first. When technology is not tailored to these features, its users may experience cognitive overload. Major potential sources of cognitive load during multimedia learning and how we can measure levels of this load will be presented next. Some recently developed methods for managing cognitive overload when designing multimedia applications and building adaptive multimedia systems will be described in the last two sections, which will be followed by the conclusion.

# HUMAN COGNITIVE ARCHITECTURE

Existing theoretical models of human cognition and empirical evidence indicate several major characteristics that underline operation of this system in learning and performance (see Sweller, 2003; van Merriënboer & Sweller, 2005, for more detailed descriptions of these features). First of all, our cognitive system is knowledge-based. It includes a large store of organized information with effectively unlimited storage capacity and duration. This store of knowledge is called long-term memory (LTM). It contains a vast base of organized domain-specific knowledge structures that allow us to treat multiple elements of information as a single higher-level chunk. Such structures allow us to rapidly classify problem situations and retrieve appropriate procedures for handling these situations instead of employing inefficient search-based strategies.

Another key feature of our cognitive system is the mechanism that significantly limits the scope of immediate changes to this information store, thus preventing possibility of major disruptions. The concept of working memory (WM) is a currently accepted implementation of this mechanism. The essential common attribute of most existing models of WM (e.g., Baddeley, 1986; Cowan, 2001) is its severe limitations in capacity and duration when dealing with novel information. Working memory not only temporarily stores and transforms information that is in the focus of our attention, but also constructs and updates mental representations of a current situation or task. If more than a few novel elements of information are processed simultaneously in WM, its capacity may become overloaded. According to cognitive load theory, processing limitations of working memory and associated cognitive load represent a major factor influencing the effectiveness of learning (Sweller, van Merrienboer, & Paas, 1998).

WM capacity is distributed over partly independent auditory and visual modules. For example, Baddeley's (1986) model includes the phonological loop that processes auditory information (verbal or written material in an auditory form), and the visuospatial sketchpad that deals with visual information such as diagrams and pictures. Therefore, limited WM capacity could be effectively expanded by using more than one sensory modality, and instructional materials with dual-mode presentation (e.g., a visual diagram accompanied by an auditory text) can be more efficient than equivalent single modality formats. The amount of information that can be processed using both auditory and visual channels might exceed the processing capacity of a single channel.

The next two important features of our cognitive architecture define the means by which we are able to acquire a huge knowledge base in LTM, considering very restrictive conditions of slow and incremental changes to this base. Firstly, most of this information is actively reconstructed or reorganized (within WM) information borrowed from other stores, that is, from knowledge bases of other people delivered through variety of media. Secondly, if such external stores of information are not available (including the cases when the information is truly new), the system has a default general problem-solving mechanism for the generation of new information, a random search followed by tests of effectiveness.

Even though WM is limited in duration and capacity, our cognitive system is capable of organizing complex situations or tasks, appropriately directing our attention, and coordinating different cognitive activities. Knowledge structures in LTM are performing this organizing and governing (executive) role, and there are effectively no limitations on the amount of the organized information in LTM that can be used for this purpose within WM. In the presence of the relevant knowledge base in LTM, WM can effectively handle an unlimited amount of information, organize very complex environments, and govern very rich cognitive activities. In the absence of such knowledge structures, the system has to employ search-and-test procedures that require significant WM resources. Organized knowledge structures held in LTM allow us to reduce WM limitations and eliminate WM overload by encapsulating many elements of information into larger, higher-level units that could be treated as elements in WM. Similar cognitive-load-reduction effects could also be achieved by practicing skills until they can operate under automatic rather than controlled processing.

# SOURCES OF COGNITIVE LOAD

Establishing connections between essential elements of information in WM and integrating them with available knowledge structures in LTM represents a major source of WM load called an intrinsic cognitive load. The level of this load is determined by the degree of interactivity between individual elements relative to the specific level of learner expertise. What constitutes an element is determined by the knowledge the user holds in LTM knowledge base. When task elements need to be processed simultaneously (even if the number of elements is relatively small), the material is high in element interactivity and can impose a high intrinsic cognitive load. Intrinsic load is essential for comprehending a situation or performing a task, and all the necessary resources should be provided to accommodate this load without exceeding limits of WM capacity.

In contrast, extraneous cognitive load is associated with carrying out activities irrelevant to task performance or learning. This load is caused by design-related factors rather than by the task complexity for the user. For example, when related textual, graphical, or audio elements are divided in space or not synchronized in time, their integration might require otherwise unnecessary search and match processes. Segments of text may need to be held in WM until corresponding components of a diagram are located, attended, and processed. Similarly, images may need to be active in WM until related textual fragments are found and processed. The required resources might significantly increase demands on WM. A significant extraneous cognitive load could also be imposed by searching for solution steps in the absence of suitable knowledge base.

Our learning and performance alter significantly with the development of expertise in a specific domain. In the absence of relevant prior knowledge, novices are dealing with many novel elements of information that may easily overload WM. Without considerable external support, they may experience significant extraneous cognitive load. On the other hand, if detailed support is provided for more experienced learners, the process of reconciling the related components of their available LTM knowledge base and externally provided guidance would likely require WM resources and also impose extraneous cognitive load. Consequently, less capacity could be available for new knowledge acquisition and performance improvement, resulting in a phenomenon that has been referred to as the expertise reversal effect (see Kalyuga, 2005, 2006, for recent overviews).

Thus, major sources of extraneous cognitive load are: split attention situations when related elements of information are artificially separated in space or not synchronized in time; insufficient external user support that does not compensate for lacking knowledge, thus forcing users to search for solutions; overlaps of user knowledge base with redundant external guidance that require learners to co-refer different representations of the same information; and introducing too many new elements of information into WM or introducing them too quickly for successful integration with available LTM knowledge structures.

The intrinsic and extraneous cognitive load result in the total cognitive load that should not exceed lim4 more pages are available in the full version of this document, which may be purchased using the "Add to Cart" button on the publisher's webpage: <u>www.igi-</u> global.com/chapter/cognitive-issues-tailoring-multimedia-learning/17404

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