Quantifying Cognitive Processes in Virtual Learning Simulations

Michael Thornton
Graduate Student, Agricultural & Biosystems Engineering, Iowa State University
Email mpthorn@iastate.edu
Gretchen A. Mosher, PhD
Assistant Professor, Agricultural & Biosystems Engineering, Iowa State University
Email gamosher@iastate.edu

Abstract

Virtual learning simulations have received increasing attention due various proposed educational, instructional, and institutional advantages; with literature focusing largely on perceptions of this technology and empirical comparisons to other instructional methods. Compared to traditional learning environments, virtual learning environments may present methodological advantages in studying learning processes through applying behavioral tracing techniques.

This paper will discuss behavioral indicators of cognitive learning processes used in virtual decision scenarios designed for third year engineering and engineering technology students. Behavioral measures to quantitatively analyze the learning process will be presented. Implications for assessing student learning, instructional strategy selection, and improving higher education quality will be shared from holistic perspective.

Introduction

The emergence and innovation of online and computer-based instruction has drawn considerable attention to how these technologies can further improve teaching and learning in higher education[1]. A particular strength of virtual learning environments is that they may be used to simulate realistic and meaningful problems[2,3,4], facilitating development of situated experiential knowledge[5,6]. In addition to providing learners with simulated experiential learning, computer-based instruction can provide abundant student-generated data that could be used to support teaching and learning[1,7].

The use of this student-generated information to make data-driven instructional decisions has been referred to as "learning analytics"[1]. In *New Horizons 2014*, Johnson et al.[1] (p.38) suggest this student-generated data can be leveraged to "deliver personalized learning, enable adaptive pedagogies and practices, and identify learning issues in time for them to be solved." While researchers strive to understand the cognitive processes that influence learning, individualized instruction is critical to provide a high-quality education to an increasingly diverse educational environment[7].

The intent of this paper is to describe how information acquisition and decision behaviors can support instruction when presenting learners with computer-based decision-making scenarios. A cognitive informatics framework for understanding cognitive processes will be summarized. Next, several cognitive processes proposed to have relatively greater importance in the learning processes will be further examined. Application of behavioral process methods in decision-making will then be reviewed. The paper will conclude with a discussion of potential implications and applications regarding using behavioral processes data to improve teaching and learning.

The Cognitive Informatics Framework of Cognitive Processes

Within the field of psychology, cognitive informatics has been described as the study of the internal information processing mechanisms, essential functions, and cognitive processes of natural intelligence[8,9]. Wang and Wang[8] developed a layered reference model of the brain (LRMB) that suggests all conscious and unconscious mental functions can be separated into one of six overarching layers of cognitive processes. Furthermore, Wang and Wang[8] theorize that the six layers in the LRMB can be further decomposed into 37 elemental cognitive processes (seen in Figure 1).

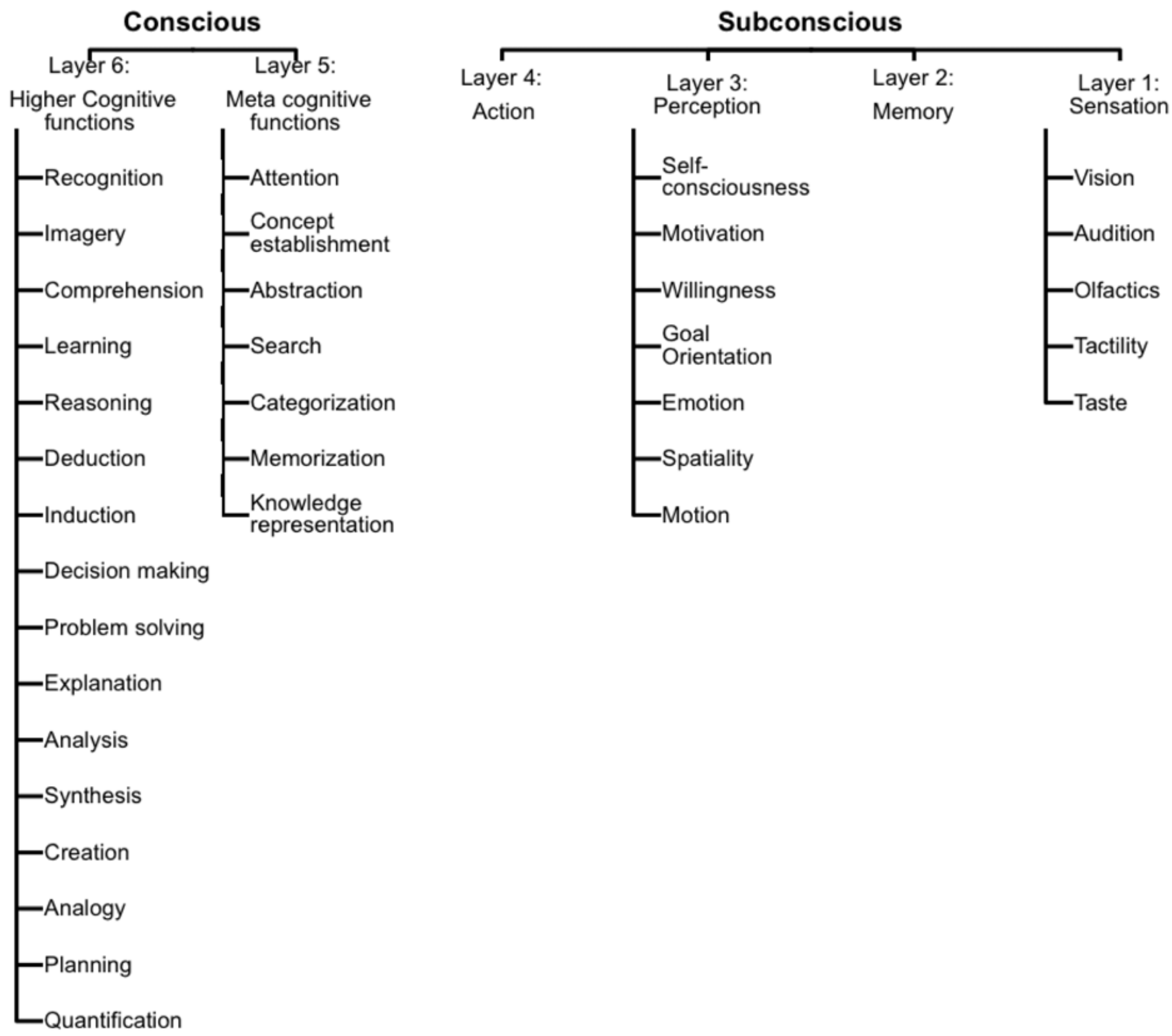

Figure 1. Layered Reference Model of the Brain cognitive processes (source: own, based on Wang et al.[8])

The subconscious operating system consists of four major cognitive processes types: sensation, memory, perception, and action. These processes are believed to be relatively fixed, and do not tend to change drastically after birth. The first layer of the LRMB model is the sensation layer, which is responsible for acquiring input-information from the external environment through an individual's senses. The second layer of the LRMB model is the memory layer, with is responsible for retaining information of both the external and internal environment. It is within the memory layer which -term memory can be transferred into long-term memory when information is recoded[10,11] and can be accommodated or assimilated into an individual's cognitive structures. The perception layer of the LRMB regulates internal search of abstract information and memories. The perception layer also plays a sort a sensory role to internal environmental factors including self-esteem, efficacy, and motivation. The action layer of the LMB is responsible for subconscious cognitive processes that are responsible for output-oriented activities. Some of the activities which are guided by action layer cognitive processes can be conceptualized as the physical movements one engages in but that do not require conscious effort in order to execute the movements[8,9].

Conscious intelligent applications are thought to be malleable, programmable, and which can accommodate increasing quantities of information based on factors such as motivation, or an individual's goal orientation[8,9]. The cognitive layers classified as conscious intelligent applications in the LRMB include the meta-cognitive process layer and the higher cognitive functions layer[8,9].

Key processes in learning: Motivation, self-efficacy, and cognitive-load

In their review of research published in *Contemporary Educational Psychology*, Mitchell and McConnell[7] (p.138) identified motivation-related articles as the most frequently studied topic, followed by topics such as self-efficacy, and cognitive load.

Current achievement orientation model of motivation has been shown to play a key role in influencing students' cognitive processes[12]. The fundamental proposition of the achievement orientation model is that the particular achievement motives that guide student behavior, largely determine the depth of cognitive processing a student applies within various learning scenarios[12]. Achievement orientations have typically been classified as either mastery oriented or performance oriented, where the former assigns greater importance to develop new skills, knowledge, and abilities; while the latter assigns greater weight to comparative performance and meeting normative learning goals[12,13]. The mastery orientation has been shown to correlate with a tendency to engage in deep cognitive processes during learning, which in turn positively correlates with high academic achievement[12]; however there is little evidence that suggests a negative relationship exists between a performance orientation and engaging in deep processing.

Just as students' achievement orientation has been proposed to influence cognitive processing, students' beliefs regarding their ability to succeed in a particular domain similarly affects the likelihood of engaging in effortful information processing[12]. These self-perceptions regarding one's capability to successfully perform are frequently referred to as "self-efficacy"[14]. Similar to one's achievement orientation, low self-efficacy does not negatively correlate with deep processing, however there is a positive relationship between both a mastery orientation and deep processing[12].

	Alternative 1 (A_1)	Alternative 2 (A_2)	Alternative *n* (A_n)
Dimension 1 (D_1)	V(1,1)	V(2,1)	V(n,1)
Dimension 2 (D_2)	V(1,2)	V(2,2)	V(n,2)
Dimension *m* (D_m)	V(1,m)	V(2,m)	V(n,m)

Figure 2. Example IDM (source: own, based on: Keren, et al., 2011)

In order to support a positive learning environment, the instructor must first understand the long and short-term memory systems within human cognitive architecture[10,11]. Cognitive load theory is based on a model of human cognitive architecture that is characterized by unlimited cognitive storage capacity in long-term memory but is constrained by the capacity in the working-memory[11,15]. In order to avoid cognitive overload during learning, cognitive processing required to interpret information must not exceed the learners' working-memory capacity[10,15].

Behavioral Process Method

The behavioral process method, sometimes referred to as the "process tracing technique"[16], is a research methodology used to study the information acquisition behaviors in the decision-making process[17]. Information acquisition data gathered using this method is used to make inferences regarding decision strategies likely utilized in the scenario[16,18]. This method was developed to capture the dynamic and sequential information acquisition data not reliably captured through direct survey techniques[19].

The foundational element of the behavioral process method is the representation of a decision scenario within the construct of an information-display-matrix (IDM)[16,20]. The matrix structure of the IDM consists of various decision alternatives (A_i) and alternative dimensions (D_i), as presented in figure 2. The information available in V_{nm} represents the field of data that holds information regarding dimension (D_m) of alternative (A_n).

Contemporary process tracing research has applied IDM process tracing to computer-based instruction, where researchers can automate the data collection and storage processes. In order for a participant to access the information within a cell, he/she must use a computer mouse, cursor, or touch screen to actively select the cell[16,20]. Once a cell is selected, the information within that cell is displayed for the participant. Aschemann-Witzel and Hamm[20] note the behavioral process approach has historically been most frequently applied to studying consumer choice scenarios; where participants must choose a product by evaluating the various alternatives on provided dimensions.

Keren et al.[18] introduced the dimension search index, seen in equation 1, as a measure of how frequently information bins within a particular dimension has been reviewed relative to those reviewed in other dimensions.

$$D_1SI = \frac{N_j}{\frac{1}{(n-1)} \times \sum_{i=1, i\neq D_1}^{n} Ni} \tag{1}$$

Where,

Nj represents the number of times information bins in the D_1 dimension are visited,
Ni represents the number of times information bins other than dimension *i* are visited,
n represents the number of dimensions in the decision matrix (n=3).

Implications & Applications for Teaching and Learning

Keren et al.[21] applied their dimension search index to evaluate program outcomes of an undergraduate safety curriculum. The researchers tracked the information acquisition patterns students demonstrated when presented with a safety-related decision making scenario. The results indicated a significant shift in the students' cognitive processes towards higher safety awareness following the implementation of the safety curriculum. This study may provide the basis for even further applications of the decision making-based methodology in education. Detecting changes in cognitive processes resulting from a particular curriculum provides educators with greater information that can be used to make more informed pedagogical decisions.

While observing changes in student cognitive processes has been applied to evaluate educational program, application of the behavioral process method may also have applications for enhancing student learning. If student information acquisition patterns can be used to evaluate an entire curriculum, this same method might be used in identifying changes in cognitive processes resulting from an individual course or unit. Further, if course content could be embedded within a decision-making scenario, student cognitive processes could be tracked while learning occurs. Rather than providing instructors with lagging indicators of changes in student cognitive processes, these changes could potentially be tracked and used to provide real-time feedback or even adapt and personalize the content presentation based on concurrent indicators of learning.

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