

# Behavior-based Cognitive Architecture for Meditative E-Learning

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## Abstract

*E-Learning offers a wide spectrum of learning experiences to the modern information society. As a result, the conventional classroom-based teacher-centered pedagogical learning paradigm has evolved to a learning management system (LMS) based student-centered learning paradigm. An important drawback of this paradigm shift is that the modern e-learning is weakened in providing a pedagogical learning experience with enriched set of measures with cognitive, emotional, behavioral and social factors. This paper proposes a behavior-based cognitive architecture to enrich the e-learning with the pedagogical measures, so that the learner can experience a more concentrated (meditative) and more personalized learning exercise. In addition, the paper discusses the achievements of the cognitive science framework to convince the feasibility of the proposed architecture with respect to the available technologies.*

**Keywords:** E-Learning, Cognitive Science, Cognitive Modeling, Affective Computing, Emotion, Behaviorism, Pedagogy, Psychology, Biofeedback Sensing, Semantic, Ontology, Automata Modeling

## 1. Introduction

### 1.1. The Evolution of Instruction

The success of a generation is solely depends on its previous generation by the instructional guidance they receive. A part of this instructional guidance is inherited in a form of biological encodings, while the other part is available in an assimilable form, which is known as knowledge. A generation's responsibility is to expand the capabilities of this knowledge and finally deliver the

knowledge to relevant descendents in an organized manner.

The ancient form of instruction was demonstration. However later, the humans were able to effectively use their capabilities and perceivables to represent their knowledge in other forms, marking the beginning of information age. The way of instruction came under the scope of pedagogy and it became mission oriented. So, more concepts like society, teacher learner, were emerged and everyone became a part of this massive construction.

With the technological advances, more concepts like computer-based training were developed to fulfill the need of targeting a wider audience and the "one teaching many learning" requirement, and later it became more standardized and specialized through the introduction of the concept of e-Learning. The traditional human-to-human pedagogical perspective is demonstrated as more cognitive, emotional, behavioral and social learning environment [23]. However, in the modern e-Learning, the direct interaction with the human teacher has been removed from the system, thus it is now under the debate of whether it is an actual pedagogical process.

### 1.2. The Learning Landscape

There was a partial effort to understand the human learning from the beginning. However as the introduction of primitive computers in 1950s the intellectual landscape began to change. As a result, the initial idea of understanding human learning was replaced with the idea of machine learning and this has founded the field of artificial intelligence (AI). In AI the learning process is explained as building a large knowledge base. Therefore, the idea was to examine the power of different approaches for knowledge representation. Understanding human learning and decision making was specialized in non-

computer science fields like Psychology, Linguistics and Anthropology.

However, soon it was realized that AI alone cannot be used to understand human level learning or intelligence [19, 28]. Meanwhile, more researches were carried out central to human brain in other fields [1] and as a result in-depth understanding of human level intelligence has been studied under the scope of experimental psychology. Therefore the fields were reorganized into one field in mid 1990s and gave a rebirth to the field of *cognitive science* expanding its scope.

The general definition of cognitive science is explained as an interdisciplinary study of mind and intelligence [31], where Psychology (study of the minds of humans and other animals), Artificial Intelligence, Linguistics (identify grammatical principles that provide the basic structure of human languages), Neuroscience (concerned directly with the nature of the brain), Anthropology (expands the examination of human thinking to consider how thought works in different cultural settings), and Philosophy (abstract and general questions such as the nature of representation and relation of mind and body) are studied.

While cognitive science focuses on human level learning in general, a more specialized field has evolved to model discrete functions of human learning using the power of computer science, which is referred to as *cognitive modeling*. Thus, cognitive modeling is an area of computer science that deals with simulating human problem solving and mental task processes in a computerized model. Such a model can be used to simulate or predict human behavior or performance on tasks similar to the ones modeled. A more appealing definition is given by Chris Forsythe,

*"...the problem was that early models followed logical processes that humans don't always adhere to, and failed to take into account variables that affect human cognition, such as fatigue, emotion, stress, and distraction."* [24]

## 2. Motivation

The e-learning has changed the instruction of learning from the traditional classroom-centered learning experience to a more student-centered learning experience. Most of the time e-learning is described as interactive, where the content is delivered as an interactive multimedia presentation. More research is conducting to improve this interactivity and one camp of researches is trying to enable a more advanced query interface for

multimedia documents under multimedia database systems [29].

However, still most e-Learning systems offer the same content for all the learners without considering the capabilities of understandability and dynamic emotional states of students. This has created a situation where students are less interested to follow an e-Learning lesson compared to traditional classroom based lesson. As a solution some researchers are trying to deliver an adaptive learning content by monitoring the learner's patterns of following a lesson [4] in a LMS. The patterns are identified from the paths the learner is naturally following in an e-learning courseware. Meanwhile another camp of researchers is trying to use basic cognitive factors, such as, eye movements, to understand the learning experience of students [5, 17]. However, still the e-learning is weakened to consider as pedagogy, where learning is demonstrated as more cognitive, emotional, behavioral and social experience [23]. Another interesting approach is proposed by Karunanda [20], where his solution is a Buddhist ontology driven approach to make e-learning more humanize. However, the implementation of this approach is unclear respect to current technological landscape.

In recent years, cognitive science has reported a major step forward with respect to modeling of discrete cognitive functions. In addition, recent research has identified the critical role of emotion in the form of personality and bodily reactions in rational decision making [1]. As a result classical definitions of informatics are gradually changing to its modern definition of cognitive informatics [16,27].

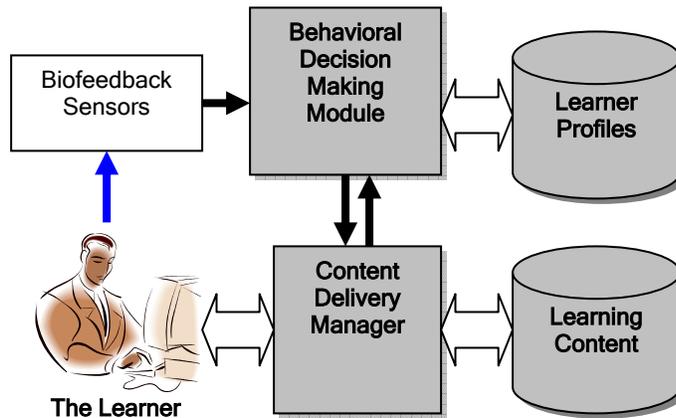
Therefore, considering the feasibility with respect to current technological landscape and weaknesses in current approaches, we have decided to answer the central question of how to make e-learning a pedagogy by introducing a behavior-based cognitive architecture for learning management systems.

## 3. Background and Proposed Approach

The literature has emphasized the importance of using psychological feedback in the form of emotions to construct a good learning environment for e-learning. Our proposed approach is titled behavior-based in the form of emotions, where it counts the biological feedback of the learner to the content he/she is observing, and cognitive decision driven, where the decisions made by the system are more human like rather than artificial. The meditative e-learning can be explained as the presentation is more

personalized and thus the learner is more attracted consciously (concentrated) to the learning he/she is experiencing.

The proposed high-level architecture of the system is depicted in figure 1. The justifications for design-specific decisions are discussed in separate topics and finally a layered architecture of human cognition is proposed.



**Figure 1: The High-level Diagram of Emotion-based Cognitive Architecture for Meditative E-Learning**

The following is a summarized description of the functionality of the system:

The learner interacts with the *learning content* through the *content delivery manager*. While the learner experiencing the learning, the *biofeedback sensors* constantly monitors his/her bodily reactions as in the form of heart rate, blood pressure, galvanic skin response (GSR), etc. These responses are inputted to the *behavioral decision making module*, where it then compares these values against expected reactions of the learner to the learning content and learner’s behavioral profile, and then notifies the content delivery manager to adjust or tune the content for a better learning experience by the learner.

### 3.1. Modeling Human Cognition

The study of the human brain was extensively omitted until the 19<sup>th</sup> century when it was first discovered that human cognitive functions depend on specific areas of the brain [1]. Since then, many technologies were discovered to scan the brain, such as, electroencephalography (EEG), positron emission tomography (PET), magnetic resonance imaging (MRI) and functional MRI (fMRI). As a result, researchers were able to answer the question “how

brains work?” to some extent and were able to describe different biological components of the brain.

Until recently, human brain power has consulted mostly to understand the learning process, fostering the field of Artificial Intelligence. In contrast, the modern cognitive science is trying to replicate human cognition, as it is, as computational models. When modeling human cognition, more knowledge is needed to simulate the functioning of cognitive components those are in biological essence with proper representations for psychological signals. Wang and Wang [26] uses memory-based architecture for model human cognition where memory is divided into 3 components, namely, sensory (and action) memory, short-term memory and long-term memory. The functioning of the brain is explained by willingness-driven, event-driven and time-driven information processing model. The ACT-R/PM is a much more sophisticated cognitive modeling architecture that simulates human learning and reasoning process while representing knowledge as declarative and procedural nature, and involving buffers for perceptual and motor processing [3].

Meanwhile, most of the models are trying to inhibit the hierarchical nature of the human brain by organizing functional components into layers. The advantages of such an incremental architecture are emphasized by Brooks [19]. Most researchers describes human cognition using 3 layers, namely, sensory, perception and cognition, where sensation is described as the resulting neural excitation when visual, auditory and haptic sensory systems constantly stimulated by a stream of events from the environment. The transformation of continuous sensory stream into discrete percepts of visual, audio and haptics is called perception. The cognition refers to the process involved in knowing, understanding, remembering, judging and thinking. In addition, a semantic gap is generated when there is a lack of transformation methodology for conversion of low-level sensations into percepts and subsequently into concepts [14]. The ACT-R/PM architecture also having two layers of functionality, namely, cognition layer and perceptual/motor layer [15], where it assumes that a low-level sensory layer is exist to transform the sensory streams to percepts.

### 3.2. Modeling Emotion in Cognitive Architecture

Cognitive science has initially ignored the study of emotion. However, soon it has been realized that the emotions are an inherent part of rational decision making. Therefore more research has been

conducted to model emotions in the cognitive architecture [6, 12].

Most cognitive scientists are agreed upon two categories of emotions, one concerning judgments about a person's general state or personality, and the other one as bodily reaction, such as, anger, fear or happiness, those are goal driven [1]. When modeling behaviorism, Chittaro and Serra [9] propose a method based on personality and probabilistic automata. In this method, the personality is described using a Five-Factor Model (FFM), where personality traits are summarized in five continuous dimensions (openness, conscientiousness, extraversion, agreeableness, and neuroticism), whose values range from 0 to 100. In contrast, Bécheiraz and Thalmann [22] use emotions, as in the form of bodily reactions, and perceptual states of humans to determine a possible behavior. When representing emotions in this nature, a threshold and intensity is used to quantify the relative measures of emotions.

The emotions of the form of bodily reactions are generated as a result of biological functions of a body. Therefore there is always a change of biological measurements of a body when emotions are generated. These biological changes are visible as sudden changes in the face, as well as some advanced psychological signals, such as, changes in heart-rate or blood pressure. A number of researches have been conducted to determine the emotional state of a human based on psychological signals of humans and positive results have been reported when using the psychological signals, such as, skin conductivity, blood volume pressure, respiration and electromyogram on the messeter [7].

Meanwhile, another camp of researchers is studying the emotional quality of multimedia information [10]. This relationship is also very much important when calculating the expected emotional appraisal of a learner who is exposed to an emotional multimedia presentation.

### **3.3. Semantic Gaps in Cognitive Architectures**

The goal of machine learning is finding a rule set that efficiently characterizes a concept, while cognitive modeling tries to understand human learning [28]. Literature suggests many different forms of knowledge representation methods to fulfill the requirement of efficiently characterizing a concept, such as, rules and facts, scripts, plans, themes [8]. In contrast, the ACT-R uses chunking and goal-oriented learning mechanism, and a memory system consisting of declarative and procedural components to simulate human learning [3].

As discussed in a previous section, the higher layers of the human cognition assume that information is available as percepts rather than streams of sensation. In addition, the relationships (connections) between knowledge items (concepts) are also determined by the higher-layers. The resulting network of conceptual construction is referred to as a semantic network of knowledge (more importantly, an ontology). Next, the cognitive memory system provides the persistence (retention) for the network of knowledge. According to Wang and Wang [26] the functional model or semantic organization of long-term memory is hierarchical neural clusters.

The multimedia database community also influenced by the idea to organize information of a multimedia stream (e.g. video) in a semantic way, so that users can issue queries and get answers about various properties of the presentation [29, 11]. However, some authoring enabled systems already implementing such models to organize multimedia information in a semantic nature, for instance, JSFL DOM [18] and SCORM [30].

Sometimes, there is a need to narrow-down the knowledge based on the context or availability of resources. For instance, when someone wants to explain about a computer for a person who doesn't know about electronics, then the first person have to narrow-down his explanation only to non-electronic descriptions. Yang et. al [13] proposes a better mechanism to construct a self-adaptive schema mechanism for multimedia databases. The study is much more important to e-learning discipline as well when a self-adaptive learning content has to be delivered based on capabilities of understanding of learners.

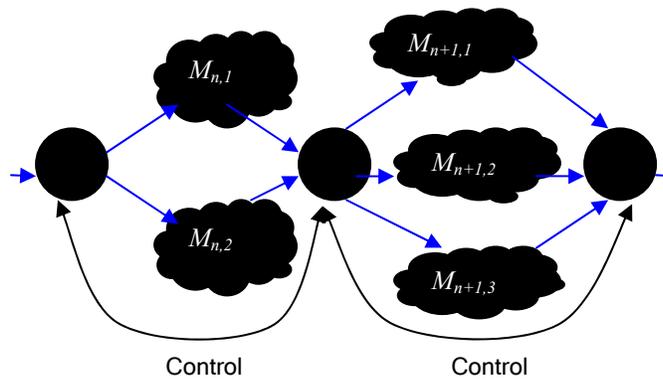
### **3.4. Modeling Behaviorism**

After the 19<sup>th</sup> century, the experimental psychology has developed and it gradually dominated by behaviorism, a view that virtually denies the existence of mind. According to behaviorists such as J.B. Watson, psychology should restrict itself to examining the relation between observable stimuli and observable behavioral responses. Talking of consciousness and mental representations was banished from respectable scientific discussion. Especially in North America, behaviorism dominated the psychological scene through the 1950s. However, later the intellectual landscape changed giving birth to more disciplines like AI until the evolution of cognitive science to its modern appearance [2].

Cognitive scientists use different approaches to model behaviorism. In ACT-R, the behaviorism may

be described as the activation of production rules and attentional responses to its buffers. In contrast, scientists who are active with cognitive agents (robots) are flavored to model behaviorism using finite-state machines (FSMs). Bécheiraz and Thalmann, [22] proposes a method to compose possible behaviors using FSMs, whose selection is determined by perceptual and emotional state of an agent. The Chittaro and Serra [9] uses personality and probabilistic automata to model behaviorism.

In contrast, we are proposing a hybrid-model, using the concept of FSM, probabilistic automata [21], ACT-R activation and timed-automata [25] to model behaviorism with self-adaptive capabilities. The complete description of this model is beyond the scope of this paper. Figure 2 depicts a possible instance of the model.



**Figure 2: A hybrid automata model for behavioral modeling (Cognitive Automata)**

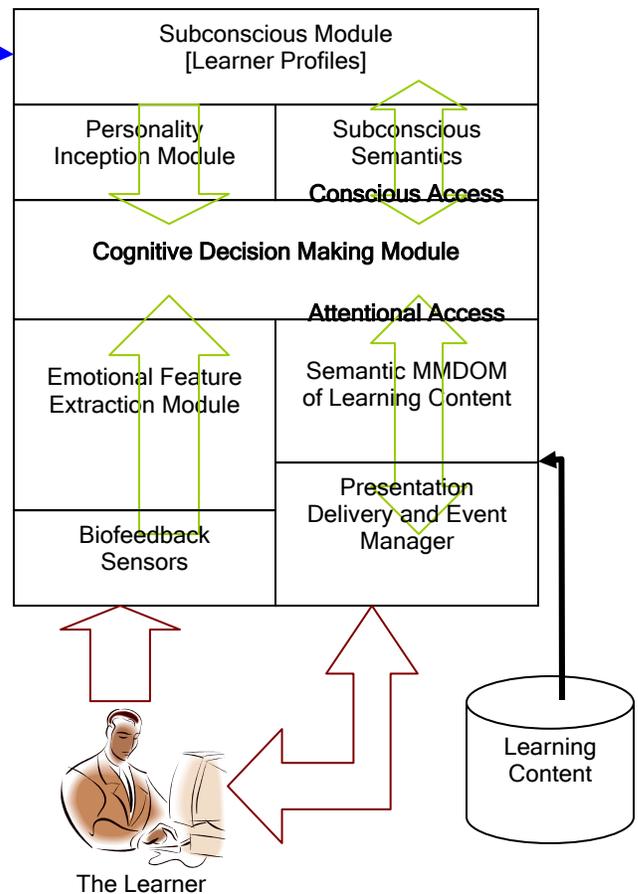
The proposed automata model is expandable along the clouds and also scalable as introduction of more decisional paths to the model. The circles represent major decisional points, where external stimuli are considered and actions are executed. The possible transitions are decided by the previous state, knowledge availability, emotional appraisal and personality.

### 3.5. The Model of Behavior-based Cognitive Decision Driven Architecture for Meditated Adaptive E-Learning

So far we have discussed possible cognitive models for the brain, cognitive components, the critical role of emotions and modeling of emotions in cognitive architecture, the semantic gap, and human decision making process under behaviorism. No one has yet proposed a complete architecture or a model to describe the complete cognitive process of

humans. However, we were able to develop a possible cognitive architecture, more flavored towards our proposed objective of developing behavior-based cognitive architecture for meditative adaptive e-learning, and the model is depicted in figure 3.

The lowest level of the model is the sensory layer. The sensory layer is comprised of two components, one component for sensing psychological signals of the learner, and other components as an interface between learner and the system when delivering the learning content. The module immediately follows the emotional sensory layer is the emotional feature extraction module, where perception of emotion is extracted. However, there is no need to insert a perceptual layer onto the sensory layer of content delivery, since the content is already exist as discrete percepts. However, semantic gap is exist and is handled by a semantic network of learning content. An external persistence mechanism provides a long-term memory for learning content.



**Figure 3: The Model of Behavior-based Cognitive Architecture for Meditative E-Learning**

The most advanced layer is cognitive layer where it is the one which decides what learning content to be delivered. However, these decisions are influenced (form of strengthening or weakening) by emotional state of the learner and the personality. The subconscious module keeps track of personality measurements of each learner as well as general goals and believes, and there is a feedback to these measurements through the subconscious semantics.

#### 4. Implementation

The system is implemented assuming the model we have proposed under the section 3.5 and implementation specific details we discussed under the other sections.

##### Biofeedback Sensors

Biofeedback sensors are attached to the learner’s outer-shell (body) to constantly monitor the learner’s bodily reactions (biofeedback) to the external stimuli. The potential signals are of the form EMG, SCR, heart rate and respiration waveforms. These signals are then presented to the emotional feature extraction module.

##### Emotional Feature Extraction Module

The main function of this module is recognizing the emotional state of the learner from the signals coming from biofeedback sensors. The methodology and algorithms used in this process is beyond the scope of this paper (refer [7]). The output of this module is the current emotional appraisal and it’s implemented as a class containing information about the name and attribute (threshold and intensity) pairs of emotions.

E.g.

Emotion Name: anger  
 Emotion Intensity: 0.6  
 Effective Threshold: 0.2

Emotion Name: distress  
 Emotion Intensity: 0.7  
 Effective Threshold: 0.1

##### Personality Inception Module

Personality is the total sum of all the behavioral and mental characteristics by means of which an individual is recognized as being unique.

The responsibility of this module is to calculate the personality appraisal of the learner from the information available at the subconscious module and present it to the cognitive decision making module. The personality appraisal is based on the five factor model (FFM) giving a value between 0 and 100 for each factor, openness (open-minded close-minded), conscientiousness, extraversion (extravert introvert), agreeableness, and neuroticism.

##### Cognitive Decision Making Module

This is implemented using the cognitive automata modeling methodology we proposed under the section 3.4.

##### Semantic Multimedia Document Object Model (MMDOM) of Learning Content

An event driven MMDOM data structure is used to organize the learning content. The MMDOM is a hierarchical structure where learning objects are organized respect to time and their semantic nature (see figure 4). An external repository provides the persistency for learning content. The delivery of the content is decided by the Cognitive Decision Making Module; however the learner also can explicitly interact with the content up to some extent by events (mouse clicks, key presses).

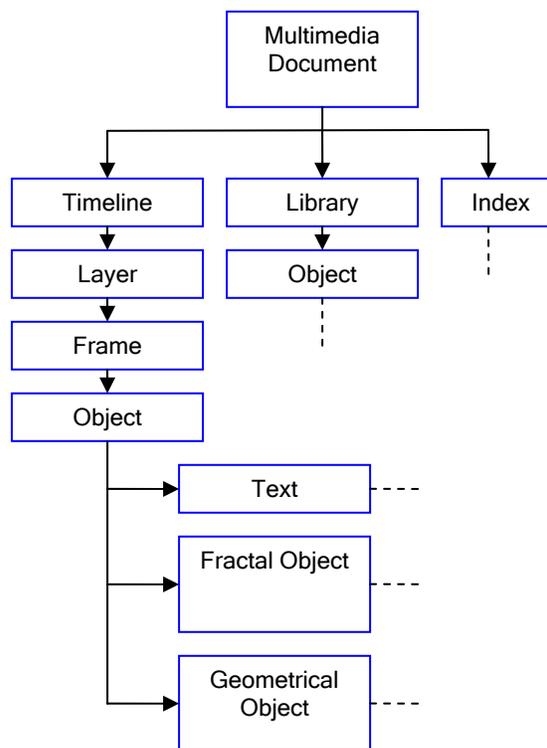
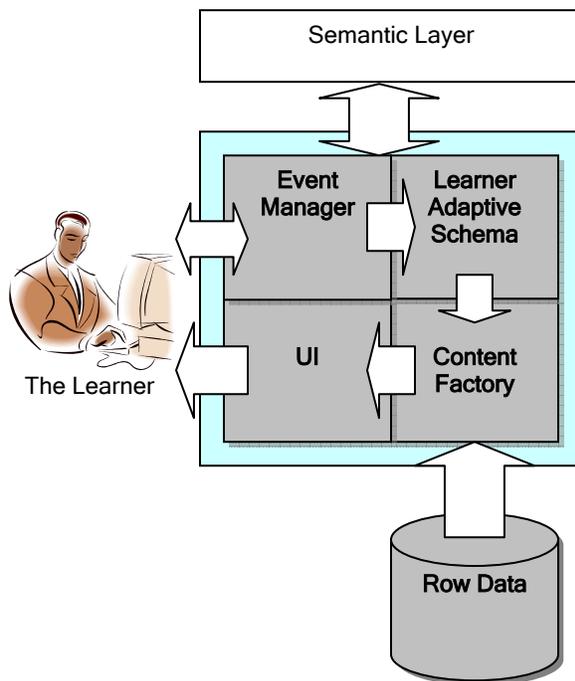


Figure 4: The Semantics of MMDOM

## Presentation Delivery and Event Manager

At the Presentation Delivery Module (see figure 5), raw binary data are integrated to the learner adaptive semantic schema constructed at the Semantic MMDOM Module and rendered to the learner. In addition, the events generated by the learner are also captured and reported to the Semantic MMDOM Module.



**Figure 5: The Presentation Delivery and Event Manager**

## Subconscious Semantics and Subconscious Module

This also a long-term memory about learners' profiles, where it contains learner specific information to identify the learner from psychological appraisal, the patterns of learning and goals.

## 5. Discussion and Conclusions

The objective of this paper was two fold. First, it examined the current technological landscape with respect to modeling human cognition and behaviorism, and then it extended its discussion for implementation specific details of developing a more pedagogical learning environment for e-learning.

The cognitive model we proposed may be not a complete model when describing human cognition. The idea was to construct a compatible architecture compromising both our objective and generally agreed architectures. To get an idea about a general agreed cognitive model of humans, we have studied the architectures considered in other fields as well, such as, autonomous animation development, robotics, artificial intelligence and multimedia database systems.

When implementing the system, the author assumes that the psychological experiments which led to positive hypothetical conclusions are stable enough despite the context. This may be evidence when emotional appraisal of a learner has to be extracted from psychological signals in the form of biological feedbacks [7]. According to the results of the research the accuracy they reported is not less than 75% for most instances, however it varies with the type of emotion they are considering. In addition, the categories of sensors we expect to use are relatively cheap compared to using brain waves or other advanced biological feedbacks.

In this research we assumed that the cognitive decisions are only dependent on knowledge factors, emotional appraisal and personality of the learner. And the decisions are non-deterministic (probabilistic and timed). Even though the complete architecture is not discussed here, someone can argue that decisions are also dependant on some other factors, such as, experience, context. However, the idea was to develop a minimal architecture that considers at least emotional feedbacks when deciding possible behaviors, in addition to knowledge.

Considering the above feasibilities with respect to technologies and architectures, we can expect that the system will soon get realized and deployed. So that we can increase the attraction for e-learning and more knowledge can be delivered to our succeeding generations effectively.

## 6. Future Work

This study is only a preliminary attempt of a more advanced solution. More work has to be done in order to perfect the architecture and functionality of the system. We have considered only a subset of available psychological feedback signals for constructing a relationship with learning and behaviorism. However literature suggests that many other alternatives are available. Therefore this work can be extended finding most appropriate feedback sensing methodologies and their relationships to learning.

As we have discussed under the discussion, one can think of more factors for effective cognitive decision making. Here we have used dynamic automata modeling for deciding decisions; however it may be inefficient under the non-deterministic manner. So one can think for improving the model or propose a more efficient solution for the problem.

The knowledge representation of the subconscious layer is not yet clear. Sometimes it may be need to store more information than we assumed here.

In addition, the outcome of this solution can be extended for more application domains. One important domain is enabling learning environments for disabled. Other domains are cognitive robotics, virtual reality and autonomous systems.

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