Review of Cognitive Energy Flow Model Concept for Virtual Student

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Abstract: Data analysis in Virtual Learning Environment deepens the understanding of cognition processes in real student's brain. The challenge is the evaluation of the quality of e-learning courses before the large-scale implementation. With this aim, we formulate the concept for a computer model for Virtual Student's evolution. We combine knowledge elements explored from learners behavior data and cognitive theories. We assume that some of the brains energy flow expenses in learning and memorization are due to energy extraction for applying existing skills, analysis of accumulated knowledge, and adaptation of newly available information. We argue that the proposed Virtual Student model can perform cognitive energy flow modeling by extracting energy from the environmental learning objects and losing the power in a tedious learning process. The research shows that Cognitive Energy Flow model can be computerized to produce synthetic data to improve e-learning courses and predict real student's behavior.

1 INTRODUCTION

Intelligent Agents introduced a breakthrough in computer science because of autonomy, ubiquity, human centric orientation and, what is essential, human-like behavior. Among the number of different agents categories, Learning Agents are more advanced because they have the human-similar ability to learn from experienced interaction with the host learning system. Since 1950th, intelligent agents used to use almost in all of the computer systems with the aim to get the system objects information, to rethink and provide local feedback or public actions. Usually, intelligent agents follow some road-map: (1) Perception, (2) Cognition, and (3) Actuation. These are functional properties of almost all the independent autonomous agents.

In the current research, we propose to invent new features shrinking the gap between improved intelligent agent namely Virtual Student (VS) and real on-line learner behavioral properties. We reflect the concept of improved Learning Agent Model with the following additional properties: (1) emotional states, (2) ability to forget the learned facts, (3) need for rest, and (4) agent's energy flow. Concerning that, we propose the improved learning agent model based on the agent's energy flow modeling is the crucial point of our interest in a proposal of a new Learning Agent model.

We aim to create the preliminary model as a concept that would further help to computerize and simplify real learners' behavior classification problems. We assume to apply traditional predictive analytics methods on outcomes of Virtual Student operation where either (1) usage of Machine Learning Methods are not cost-efficient or (2) the environment has new - not approved learning courses and learners have not produced any data yet.

Such, the Virtual Student's cognitive energy flow model-based approach improves computerized agent model to be applicable for Predictive Analytics (PA) methods applied to real learners without uneconomical Machine Learning (ML) operations. This statement is the current research question.

The research organized as follows: Section 2 - the reflexion of related theories, methods, and approaches. In Section 3, that is the most important in the research we propose the concept of the Virtual Student's Cognitive Energy Flow Model. In Section 4 we provide a discussion of results and conclude the paper.

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2 RELATED WORK

The large-scale picture on human-like Cognition appliances in a Computer-intelligence success like Artificial Intelligence (AI), Machine Learning (ML), or particularly in VLEs has the roots based on some historical conclusions expressed in learning theories.

2.1 Theories of Cognitive Development

Undoubtedly, any learning process aims to gain knowledge results. Mainly, the learning process is cognitive because the learner develops itself regardless of supervised or unsupervised learning style. The most influential theories of Cognitive Development categorized as: (1) Piaget's theory, (2) Sociocultural theories, (3) Core-knowledge theories, and (4) Information-processing theories. The last - Information-processing theories are well adaptable and known in a computer applications domain.

About 1920, Piaget developed the first "*Cognitive theory*" mapped on child cognitive development. At that time, Piaget's the revolutionary idea was to consider a child as a scientist providing experiments on their (Piaget and Campbell, 1976).

Three of Piaget's main essential processing categories (Piaget, 2005) are: (1) construct own learner knowledge from experimenting on the world, (2) learn many things on their own without the intervention of helpers, and (3) to stay intrinsically motivated to learn and do not require rewards to incentivize learning.

Among the criticisms of Piaget's Theory the most strong are: (1) learners' thinking process is affected by social interactions (Vygotsky's Theory), (2) young children have and use much inborn mental machinery for complex abstract thought (Core-Knowledge Theories), (3) thinking is not as consistent as the theory suggests, and (4) thinking is a computational process. The last two criticisms belong to authors of Contemporary Theories. The most relevant example adopted from contemporary theories is the Information Processing approach considering child development as a computer model development. Therefore, we conclude that modern methods of Cognitive Development are pointing again back to the discussions about the Child cognition.

The full theory of intelligence is not yet in existence, although we assume that Master Theory of Cognitive Development should exist in the future (Domingos, 2015), and is applicable in a Human or Artificial World.

2.2 Sense, Perception, Cognition, and Semantics

Overall, Artificial Intelligence (AI) held on a couple of key concepts: Sensing, Perception, Cognition, and Semantic (Sheth et al., 2015). Such processes came into AI systems view to delegate computers to solve human-specific sensing, perception, and thinking problems. Also, we have to consider that a real person does not perceive the real world, the person first interprets what he/she sees and then simulate the next event in their mind. The magic is still, how we learn and get the subconscious to do things effortlessly.

Assuming that Computer-Agent (as a computer program) have Senses to receive various data from the digital learning environment host, the next conscious process in a computational sequence is the Perception: a cyclic process of interpreting data. Perception involves both interpretation and exploration with a firm reliance on background knowledge patterns of the domain of application (Gregory, 1997).

Cognitive computing follows the Perception and aims to develop a coherent, unified, and universal mechanism for understanding problems around the Computer-Agent. Cognition utilizes all the data received from a Perception act. Similarly like in a perception process, cognitive computing context is provided by the existing knowledge base (Modha et al., 2011). Overall, the cognition is the process of gaining knowledge.

Finally, Semantics layer involves mapping observations from various stimuli on Computer-Agent input, such as tactile, speech, or visual signals, to concepts and relationships as humans would interpret and communicate them. Semantics stays out of current research scope.

2.3 Cognitive Learning and Cognitive Engineering

Cognitive Engineering is a method of study using cognitive psychology to design and develop engineering systems aimed to support the cognitive learning processes of users (learners). A person starts with goals and intentions that are psychological variables. Although, Psychological Variables differ from Physical Variables used in engineering systems (Norman, 1987).

In the case of real learner modeling, the computer agent must interpret the learning object physical variables into terms relevant to the psychological goals and must translate the mental intentions into physical actions upon the application algorithms. Overall, the Cognition Engineering challenge is to study and design the process of acquiring knowledge through Agent's thoughts, experiences, and senses. Cognitive Learning involves obtaining knowledge through experience, study, and being taught by Computer-Agents (Brown and Fehige, 2017). At the same time Computer- Agents can be used as Agents that learn.

Learning and Cognition are two almost identical concepts, although cannot occur without each other: Learning requires Cognition, and Cognition involves Learning.

Cognitive Process. Of full value, cognitive process implementation serves goals to complete matching micro-architectures: Senses (Intensity of Sensation), Affection (Weber's Law - quantifying the perception of change in a given stimulus), Attention (Rate, Duration, Degree, Inertia), Perception (Temporal, Qualitative, Quantitative(Simple, Complex)), Association (Law of Association), Memory & Imagination (Cache Operative(a couple of seconds), Middle, Long Term Storage Network), and Action (Emotions & Thoughts). Individual cognitive system requirements can cause simplification of the whole architecture or more detailed research and design of the specific item.

Levels of Cognitive Learning. An ordering of cognitive skills usually are arranged based on Bloom's taxonomy (first edition 1956) contemporary transformed into a new version. The revisited version (Anderson et al., 2001) includes six levels: (1) Remembering, (2) Understanding, (3) Applying, (4) Analyzing, (5) Evaluating, and (6) Creating. Although, we find an applicable reduced version of taxonomy: (1) Memorization, (2) Understanding, (3) Application.

Despite the reduction, the minimized approach includes all the skills above the Application level as the ability to apply the knowledge. For the proposed Virtual Student model, we find three knowledge levels acceptable.

Cognitive Cycles. Neuroscientists have independently proposed ideas similar to the cognitive cycle: cascading cycles of recurring brain events. (Fuster, 2002; Baars and Franklin, 2007). Notably, that research results in psychology (Franklin and Graesser, 1997; Anderson et al., 2004) show that cognition in autonomous agents, whether artificial, animal or human, can be thought of as consisting of repeated perception-understanding-action cycles.

Cognitive Cycles Timing. Results from studies in neurosciences determine the length of time taken by each of the phases of the cognitive cycle also, are well known. Some results successfully adopted for specific architectures, for instance: LIDA (Learning Intelligent Distribution Agent) (Madl et al., 2011). We also integrate Cognitive Cycles Timing results to later proposed Virtual Student's model.

2.4 Thoughts on Energy in Learning Process

2.4.1 Mental Energy

The idea of energy associated with mental activity dates far back in human History and cultures. Formulation of Mental Energy (a hard mental effort) in scientific magazines belong to Julian Huxley (Huxley, 1944). The problem complexity relies on the origins of Human Mental Energy correlation to physical, social, and mental health impacting the real learning process. It is a generally recognized truth physical events considering in two ways: from the mechanistic and from the energic standpoint (JUNG, 1969).

2.4.2 Time and Energy

The fundamental principle of causality and a proportional (linearity is not the obligation) connection between time and energy is acceptable for later use to build the Virtual Student Energy Flow model.

2.5 Intelligent Agents

A very simple agent model (Eq. 1) is an abstract concept that can be defined mathematically as an agent function:

$$f : P^* \xrightarrow{decision} A \tag{1}$$

If P^* is a data set of perception on input of model, and A is defined as action on model output, then f is by function defined simple agent.

In general, an agent receives information through its sensors. Decision making is an internal functional facility of Intelligent Agent Model. Such a simplified definition gives insight into concerns about the possible complexity of concise and valuable intelligence of models.

Overall, exist more than one Intelligent Agents classification schemes proposed by Russel (Russell and Norvig, 2003) and Weiss (Weiss, 2013). We follow Russel classification, where group agents divided into five classes based on their degree of perception and capability. Russel evolves five agent groups: (1) simple reflex agents,(2) model-based reflex agents, (3) goal-based agents, (4) utility-based agents, and (5) learning agents. Any other proposed models have variations based on classical concepts of agents architecture, their ability to perceive, control the action reasoning, and to act on sensing networks.

Intelligent Agents can act either as a single instance or in groups: multi-agent systems. In the current paper, we discuss a single instance model.

3 DISCUSSION AND OUTCOMES

The current research question is: The cognitive energy flow model-based approach shows another way to evaluate empty learning course in a digital learning environment where learners have not produced any data yet.

The new approach goal is to create the preliminary model that would help simplify real learners' behavior forecast and classification problems using traditional predictive analytical methods in a digital learning environment.

Based on the essential concepts revealed in the previous section, we propose a new learning agent model named Virtual Student The new model takes into account such quite complicated to explore common human emotional conditions like relaxation, boredom, excitement, and anxiety to explore human emotional conditions.

We specify some crucial principles we follow creating Virtual Student's model: (1) reliable Mental Energy Flow Model for Virtual Student is the primary interest of our research, (2) Virtual Student's Learning Process is a Mental Energy Flow expressed as a consummation of Internal Energy or gain from inherited Learning Objects, (3) every single mental activity is a transition along the learning path rewarded with a specified but finite Energy Portion - Energy Token if the change has a direction to the comfortable emotional condition, (4) if the transition has a direction to the uncomfortable emotional condition, Virtual Student becomes fined by Energy Token Decreasing, (5) Virtual Student initially has enough Energy Tokens to overcome threshold level to join the Learning Course, or to start to explore specific Learning Object, (6) Virtual Student runs based on the principle of causality and a proportional (linearity is not the obligation) relation between time and energy.

On the research roadmap, firstly we draft the Learning Energy flow boundaries for Virtual Student's evolution model. Then, we specify Virtual Student's properties. Finally, we propose the Virtual Student Learning Model concept ready for operational implementation.

3.1 Virtual Student Learning Energy Centered Ecosystem

3.1.1 Learning Energy Network

Here, we invent the isolated learning network with boundaries for Virtual Student operations when sensing, and declare rules for reasoning (perception, cognition) and acting. Learning network bounds energy consumption or production. In other words - the amount of internal energy U in the ecosystem is constant. Equation (2) formalize this assumption. Each component in the ecosystem holds their energy denoted as E_i. Under such a restriction the only way to keep U constant and simultaneously provide energy flow is the process of energy redistribution among system components. We follow the simple principle: no energy - no action. Therefore, to operate, the model system energy should be greater than zero: $U > 0$.

$$U = \sum_i E_i = Const. \tag{2}$$

We specify three top class energy-related objects for the ecosystem and their properties:

- System Energy Depot - E^D,
- Virtual Student's Energy Buffer - E^{VS},
- Learning Object Energy Storage - E^{LO}.

In the model, learning network Enthalpy we specify as:

$$U = \sum_i E_i^D + \sum_j E_j^{VS} + \sum_k E_k^{LO} \tag{3}$$

3.1.2 Initial Energy Flow Considerations

Invented Initial Energy Depot holds a certain amount of energy distributed among other components on system simulation start. For our experiment, we use one System Energy Depot, one Virtual Student's instance, and a specified number of Learning Object with various but specified learning related energy value. As follows, for one Virtual Student Equation (3) transforms into:

$$U = E^D + E^{VS} + \sum_k E_k^{LO} \tag{4}$$

Equation (4) depicted in Fig. 1 applying directions of possible energy flow. Firstly, at the learning process initialization, each Learning Object ($LO_1 \ldots LO_k$) receives specific initial energy portion ($E_1^{LO} \ldots E_k^{LO}$). Next, Virtual Student's Energy Buffer (VS) receives their initial amount of energy sufficient

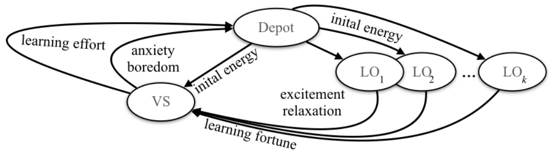

Figure 1: Energy Flow Model for Virtual Student's Ecosystem: System Energy Depot (Depot), Virtual Student's Energy Buffer (VS), and k Energy Storages for Learning Objects ($LO_1 \dots LO_k$).

to start the simulation based on some algorithmic considerations.

3.1.3 Energy Flow Control Algorithm

After the Virtual Student's simulation start, their instance sequentially interacts with Learning Objects imitating all the phases of the cognition process. In the case of success, indicated as the corresponding flag in the algorithm, Virtual Student receives energy portion from the Learning Object it communicated. Learning fortune path transfers energy tokens as rewards from Learning Objects to Virtual Student. A decision regarding learning fortune rewards amount depends on the Virtual Student: (1) Virtual Student's self-assessment score, (2) Virtual Student's assessment by Learning Object requirements gathered from submission, (3) Virtual Student's emotional conditions after the task finishing, and (4) on time spent for learning. Learning fortune path is active only at favorable emotional conditions like excitement or relaxation. Similarly, indications of negative emotions (anxiety, boredom) lead to energy tokens loss from Virtual Student's Energy Buffer. As mentioned before, the ecosystem model assures energy is returning to system depot. Also, we argue that Virtual Student's energy reduction is a consequence of effort in a conventional learning process. Thinking on ecosystem model parameters, we consider that real average learner can hold approximately two or three learning tasks in their attention at the same time, or one complex task. Task complexity metrics in the ecosystem the point of interest. Here, we identify learning objects as tasks.

3.1.4 Initial Energy Flow Conditions

In the beginning, sufficient initial energy amount E^{VS} can be assigned to Virtual Student. If energy assigned to Learning Object $E_i^{LO} > E^{VS}$, we say that this is border condition not to start a learning process directed to specific Learning Object. If all the Learning Objects in a system have energy level bigger than specific Virtual Student's energy, learning cannot start at all. Such simple rules allow modeling various initial learners' conditions.

3.1.5 Optimal Energy Flow Conditions

Energy awareness is a central interest point of energy flow control algorithm. That is to say, a Virtual Student with a capability of estimating its energy flow in the cognitive learning process can determine the potential points for energy optimization. Such an approach requires both (1) sensing data and (2) computational schemes based on the learning model.

3.1.6 Final Energy Flow Conditions

During the model runtime, energy control algorithm follows the energy balance principle. As we stated above, final conditions lead to process termination based on energy comparing rules.

3.2 Virtual Student Properties

We invent the following groups of static and dynamic properties that characterize Virtual Student: (1) need the rest property, (2) ability to forget the learned facts, (3) emotional states, and (4) cycling through motivational sequences. The cycling through motivational sequences depending on real student's emotions is crucial for the Virtual Student model proposal and later discussed in details.

Need for the Rest property involves relatively slow action modeling daily workout process. Just as the human need rest and recuperation the Virtual Student must re-stock on vital energy from system depot. Such an approach allows simulating long-term inactivity gaps like housekeeping, sleeping, and vacations. "Need the Rest" property simulation results lead to the opportunity to study memorization and forgetting depending on Virtual Student's idleness and leisure. We suggest that current property activation would improve the Virtual Student's conformity to a real one.

Albeit forgetting is a human-like property, we use **Forgetting property** to add a new research vector. Forgetting curve, adopted from Murre follows the Exponential Distribution, whereas Memorization modeled as the Poisson Arrival Process (Murre et al., 2013) and is useful for Virtual Student's memory model. For Virtual Student model, we apply three-tier memory architecture: sensory, short-term, and long-term memory. We also accept The 24-hour point of upward jump in Ebbinghaus' forgetting curve (Murre and Dros, 2015).

Also, in the further development of memory process control algorithm, we propose to include the module for memorization processes' volume control

- an option for the Virtual Student to practice the memory and become smarter. For further references let's name the memorization processes' volume control module as MVC.

Emotional States. With this property, we understand real learners' emotional conditions playing a specific role in the learning modeling confidence. In the next section, we discuss, specify, and utilize four emotional categories classified as follows: very pessimistic, skeptical, confident, and very confident. Considering correlation to Virtual Student's energy model, we elaborated the Emotional States factors. Positive emotions incentivize learners subconsciously growing their energy, although negative sentiment - lead to stuck, depression, energy loss to learn.

Motivational Sequences. To form Virtual Student emotionally motivated interactions with ecosystem layers and components required for cognitive learning process modeling, we adopt a commonly occurring Apter's *Motivational Sequence model* (Apter, 1989). Fig. 2 depicts adopted Motivational Sequence model mapped to the timeline. Virtual Student's attempts to catch and hold certain pleasant states like excitement or relaxation are alternating with unpleasant ones like flat, tiresome states.

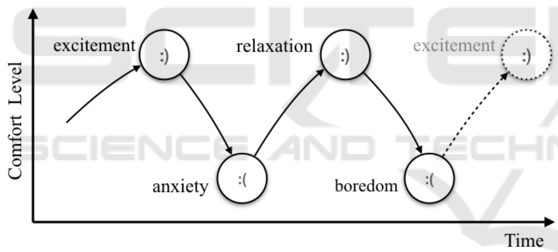

Figure 2: Van der Molen Motivational Cycling model transformed into Motivational Sequence model by mapping to timeline.

In the amended Motivational Sequences model (Fig. 2), we define the excitement state as the initial one, therefore indicating Virtual Student's addiction to learning. We argue that a tendency to begin to learn at the emotional excitement phase correlates with the real learners' motivation keen to learn. By standing anxiety as the next position in the sequence, we realize that in reality, human behavior follows the same path: positive emotions and negative emotions are in the constant cycling process. Therefore, we simplify the Motivational Sequences model avoiding the direct transition to any other state except categorized as emotionally opposite.

Four alternating model states represent cycling through comfort levels: excitement, anxiety, relaxation, boredom mapped to the timeline. The comfort cycling model mapping to energy-based model follows a simple idea: if the emotional state classified as negative, Virtual Student does not receive the energy and starts to lose one proportional to the time spent in such a condition. By replacing a single emotional Comfort Level vector (Fig. 2) with two Learning Energy vectors beginning at the point of "*Passivity*" we invent the Energy Fluctuation model (Fig. 3). The farther from middle ("*Passivity*") level resides the emotional state, the more energy we associate with such a condition.

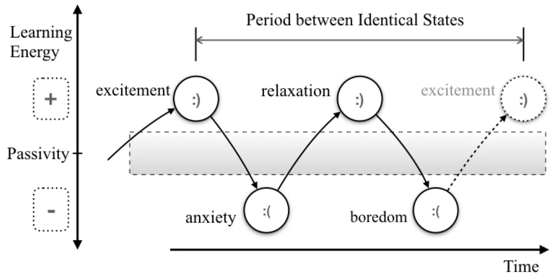

Figure 3: Four alternating model states represent emotional cycling: a) adopted to timeline model, b) proposed Energy Fluctuation model as a function of emotional cycling in time.

In the figure, the shaded area considered as low energy region or "No Flow!" zone. Such an area indicates Virtual Student being close to shut-off or dropout in reality.

Alternating Emotional states represent emotional cycling process having an impact on Energy Fluctuation in the Virtual Student Learning Model. Following diagram (Fig. 4) depicts one of the possible scenarios of possible strategic trends in Virtual Student's Energy Fluctuation model. Learning Energy gaining in the next simulation step denoted as a "FUTURE." Also, we invent the "*Comfort Zone*" bounding Energy Flow gulf for Virtual Student.

Overall, comparing of classified emotional states is the beginning point to start to compare simulations' outcomes and real learners' classification results. A computerized model can apply such consequences in a blended learning process for comparing real and virtual students operating in one shared virtual learning environment.

3.3 Virtual Student Learning Model

From Franklin's results (Franklin and Graesser, 1997), we take into consideration the existence of universal cognitive cycling paradigm: cognition in autonomous agents is subject independent - whether artificial, animal or human. This cycling paradigm is the crucial concept point to follow.

At first, we find that Stringer's Action Spiral model (Nasrollahi, 2015; Stringer, 2013) stated the

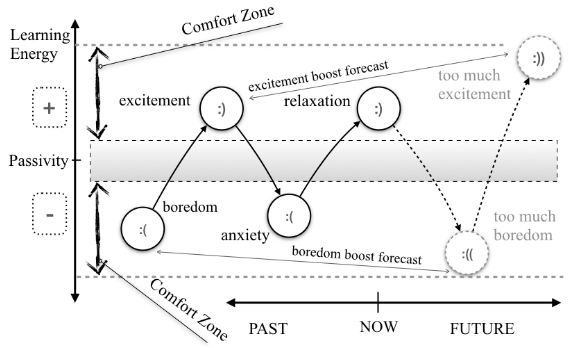

Figure 4: Energy Fluctuation model. Scenario: Suspicious Energy boosting in both directions leaving a Comfort Zone moving towards extreme threshold levels: hidden subburning (too much boredom) and overexpectations (too much excitement).

existence of look-think-act cycles in cognitive learning correlate with similar results proposed by Anderson (Anderson et al., 2004). Next, we conclude that Anderson uses nouns: perception-understanding-action, although Stringer applies verbs: look-think-act to describe the same paradigm.

In our conceptual Virtual Student model, we apply both emotions related and look-think-act cycles (Fig. 5).

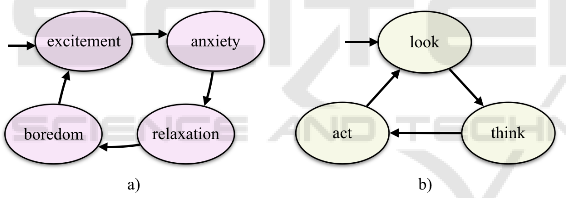

Figure 5: Virtual Student Learning model Components: subplot a) - Motivational Cycling (MC) model, and subplot b) - Stringer's Action Spiral (SAS) model.

Finally, by adding operation control logic, we combine both motivational cycling and cognition cycles approaches into one coherent system presenting the concept of Virtual Student Learning Model (Fig.6).

For simplicity, the Virtual Learning Environment on the proposed model depicted as a single simple Learning Object (LO). The bi-directed line represents Virtual Student's communication with LO. Virtual Student's requests for available data and retrieves the next information portion proportional to the attention quantity. Computerized VS model measures such an effort and the time applied to the Learning Object. The Learning Object's response comes along with LO's specific METADATA set.

We suggest a real e-learning environment (VLE) modification by implementing VS related METADATA in specific LO's model. A METADATA should include at least ENERGY-Specific credentials. We propose to apply to use Energy Tokens. Also, METADATA represents a set of specific Learning Object parameters like size, complexity, expected learning effort, average forgetting parameters, and virtual learning path constraints to control the cognitive process.

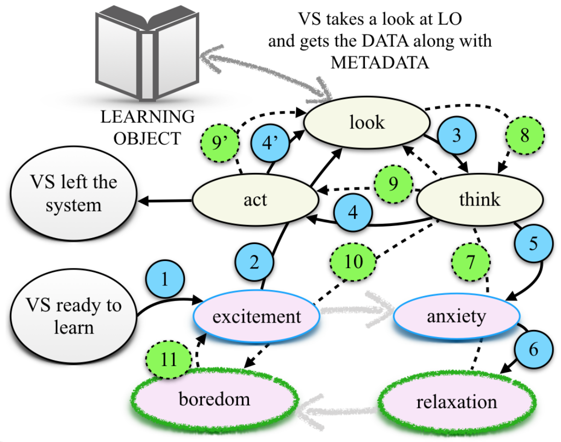

Figure 6: Interaction of Virtual Student Learning model Components with Learning Object in a Spatial Design.

Also, Fig. 6 depicts the Virtual Student Learning model in dynamics. Each transition on the scheme denoted as a colored circle object with a sequence number inside. Blue colored transitions, and corresponding solid directed arcs reveal a path for the first stage of learning process switching from positive excitement state to harmful one - anxiety. The route goes via cognitive learning cycling (transitions 2, 3, 4, 4'). Transition 5 means a decision at a "think" state to get stuck. Next, after some arbitrary time spent in state "anxiety," follows transition 6 returning Virtual Student to a comfortable emotional level - "relaxation." Green circles and dotted lines specify the third phase in motivational sequences model leading to switching to the next uncomfortable - boredom state. Finally, without discussions of reasons, Virtual Student returns to the "excited" state. Either route goes through a decision-making component implemented in the look-act-think module.

The main system algorithm controls the learning process interacting with every module with the aim to supervise ecosystem energy flow. On a condition of insufficient enough energy, what is the worst scenario, Virtual Student is dropped out of the course. In the case of acceptable quality of interaction with learning objects, the mission completed.

4 CONCLUSION AND FUTURE DIRECTIONS

Summarizing research results regarding energy aspects of the discussed model, we conclude: (1) Learning Energy redistribution flow among the system objects can be observed and controlled by the main system algorithm, (2) Learning Energy Ecosystem model's Energy Quantity is constant for every simulation run, (3) proposed Learning Energy Ecosystem for Virtual Student evolution has clear operating conditions to simulate the learning process based on the energy balance principles, (4) proposed Virtual Student will produce more synthetic data ready for validation of correlation with real user behavior data.

For future works, we consider the following concept point: cognition for every autonomous agent is subject independent. To approve such a concept we consider: (1) tudy Virtual Student model computer implementation depending on model Verification results on the model validation stages, (2) translate the conceptual model to operational one and verify it by implementation into real Virtual Learning Environment, (3) build the computerized model, (4) apply the proposed model in a blended learning process for comparing both real and virtual students operating in one shared virtual learning environment.

Further research by applying validation to the proposed model with an implementation in the Virtual Learning Environment might clarify the aspect of Virtual Student's potential.

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