Modeling Curiosity in Virtual Companions to Improve Human Learners’ Learning Experience

Qiong Wu, Chunyan Miao and Cyril Leung
Joint NTU-UBC Research Centre of Excellence in Active Living for the Elderly
Nanyang Technological University
Singapore 639798
Email: wuqi0005@e.ntu.edu.sg, ascymiao@ntu.edu.sg, cleung@ece.ubc.ca

Abstract—
A key design aspect for virtual learning companions is their believability. A lot of attention has been paid to emotion modeling which is at the core of believability. However, most of the existing emotion models neglect the epistemology-based emotions, which are knowledge-related emotions that affect the human learning process. Studies have shown that curiosity is an important epistemology-based emotion that positively influences social learning. Hence, modeling curiosity in learning companions may improve human learners’ learning experience in a virtual environment. However, existing curiosity models assume simplified cognitive processes and fail to capture multiple sources of curiosity stimuli. In this paper, we propose a novel model of curiosity for learning companions to capture salient curiosity stimuli through a psychologically inspired approach. Our model is built based on Berlyne’s theory and considers three most salient appraisal variables in a virtual learning environment, including novelty, surprise, and uncertainty. The model is built on plan-based knowledge representations augmented with planning. Two internal processes are modeled for learning companions to demonstrate curiosity: curiosity appraisal and learning. The proposed model of curiosity is implemented in a learning companion and evaluated through user studies. The evaluation results show that the learning companion’s curiosity significantly improves human learners’ learning experience from multiple aspects.

Keywords—Curiosity, Epistemology-based emotion, Learning Companion, Virtual Learning Environment

I. INTRODUCTION
Teaching and learning are highly social activities [1]. With the goal to bring a social context into virtual learning environments, a growing interest has been shown in designing learning companions (agents) that adopt a peer metaphor to simulate peer interactions. To benefit from peer-mediated learning, an important design factor is that learning companions must be believable so that human learners will suspend disbelief in a virtual learning environment [2]. At the center of believability is a learning companion’s ability to demonstrate emotion. Plenty of attention has been paid to emotion modeling for learning companions [3], and many studies have shown that the affective features of virtual learning companions can positively influence human learners’ learning experience in a virtual environment [4].

Most of the existing emotion models, however, focus on the basic emotions (e.g., happy, sad) [5] and overlook the family of epistemology-based emotions (e.g., interest, anxiety) [6]. Epistemology-based emotions involve reactions to an individual’s state of knowledge and affect the human learning process. An important epistemology-based emotion is curiosity, which is a motivational emotion that drives knowledge acquisition in a learning context [7], [8], [9]. Curiosity also influences and intervenes several other epistemology-based emotions such as interest, boredom and anxiety [8], [10], [11]. Educational studies have shown that a peer learner’s curiosity can reveal contradictions and weakness in a learner’s knowledge structure, which may in turn induce the other learner’s curiosity [12]. Hence, it motivates us to model curiosity for learning companions, which may enhance human learner’s learning experience in a virtual environment. Modeling curiosity in a learning companion allows the agent to discover knowledge gaps and formulate questions. These questions add new ingredients into the interactions provided by the learning companion, which may help human learners notice the weakness in their knowledge structure and motivate them to actively explore in the virtual learning environment.

To simulate human-like curiosity for learning companions, it is desirable to build a computational model of curiosity through a psychologically inspired approach. In this work, we propose a computational model of curiosity based on Berlyne’s theory in the psychology of curiosity [10]. Berlyne proposes that curiosity can be externally stimulated by stimuli in the environment. He identifies a family of appraisal variables that characterize the properties of curiosity stimuli and influences the human curiosity appraisal process. Based on this theory, we model three key appraisal variables that are most salient in a virtual learning environment, including novelty, surprise, and uncertainty. The appraisal variables reflect knowledge gaps between the agent and the environment, which form the agent’s motivation for learn-
Our computational model of curiosity is built based on plan-based representations augmented with decision-theoretic planning techniques, which is a popular approach for modeling agent behaviors in virtual environments [14]. On top of the basic planning process, we propose two internal processes for modeling curiosity: curiosity appraisal and learning. The curiosity appraisal process evaluates the agent’s environment based on the appraisal variables and looks for knowledge gaps. The learning process quenches the agent’s curiosity as it closes the knowledge gaps through improving the incomplete plans. The proposed model of curiosity is implemented in a learning companion that resides in Virtual Singapura, which is a 3D virtual world for learning plant transport systems.

Major contributions of this paper include: Firstly, we propose a novel computational model of curiosity for learning companions based on human psychology, which captures curiosity stimuli originated from not only novelty, but also surprise and uncertainty. This model adopts plan-based knowledge representations and simulates two internal processes for learning companions: curiosity appraisal and learning. Secondly, the model is implemented in a learning companion that resides in Virtual Singapura. Through user studies, it is shown that an agent’s curiosity significantly improves human learners’ learning experience for multiple aspects, including learning gains, self-efficacy, and interest. Also, the study results show that human learners perceive the persona of a curious learning companion more favorably.

Remaining of the paper is organized as follows: In Section II, we introduce the proposed model of curiosity for learning companions. In Section III, we illustrate how the model is implemented in a learning companion. Section IV evaluates the performance of the curious learning companion in Virtual Singapura through user studies. The paper is concluded in Section V.

II. THE CURIOSITY MODEL

In this section, we introduce the proposed computational model of curiosity for learning companions.

A. Theoretical Foundation

In psychology, a major surge of study on curiosity began in 1960s. Berlyne [10]’s drive theory belongs to one of the main stream theories which has a long lasting impact till date. Yet, this theory has not been explored in modeling curiosity for artificial agents. According to Berlyne [10], curiosity can be externally stimulated by stimuli with certain properties. He identified a family of appraisal variables (e.g., novelty, uncertainty) that characterize these properties and govern the curiosity appraisal process.

Based on Berlyne [10]’s theory, we model three most salient appraisal variables in a virtual learning environment, including novelty, surprise, and uncertainty. All three variables inherently reflect certain knowledge gaps of the agent and form its motivation to learn [13]. Intuitively, if an agent is able to appraise world events at the same knowledge level with the human learner, then the appraisal variables discovered by the agent also reflects knowledge gaps of the human learner. Hence, a curious learning companion should assume two abilities: curiosity appraisal and learning. Curiosity appraisal enables the agent to appraise world events and discover knowledge gaps, which simulates a similar curiosity arousal process as is in human beings. Learning enables the agent to absorb knowledge when the human learner learns, in order to maintain a same knowledge level with the human learner. On the other hand, learning is also the process that quenches the agent’s curiosity through closing knowledge gaps.

Motivated as above, we propose a computational model of curiosity for learning companions by modeling both curiosity appraisal and learning. Next, we will first introduce the knowledge representation for learning companions. Then we present the modeling of the curiosity appraisal process for discovering appraisal variables that lead to the agent’s curiosity. After that, we discuss the modeling of the learning process for quenching the agent’s curiosity.

B. Knowledge Representation

A virtual learning environment consists of four major components, denoted by \( V=\langle W, G, L, C \rangle \), where
- \( W \) is the virtual world,
- \( G \) is the learning goal,
- \( L \) is the human learner,
- \( C \) is the virtual learning companion.

In \( V \), \( L \) is the main performer who acts on \( W \) to complete \( G \). \( C \) does not directly act on \( W \) to achieve \( G \) but provides peer-like interactions to facilitate \( L \) achieving \( G \).

1) Virtual World: The virtual world is described by six components \( W=\langle O, F, A, S, K, E \rangle \), where
- \( O=\{o_1, o_2, \ldots, o_n\} \) is a set of objects,
- \( F=\{f_1, f_2, \ldots, f_m\} \) is a set of facts,
- \( S=\{s_1, s_2, \ldots, s_l\} \) is a set of world states,
- \( A=\{a_1, a_2, \ldots, a_p\} \) is a set of actions that can be performed by \( L \) in \( W \),
- \( K=\{k_1, k_2, \ldots, k_q\} \) is a set of knowledge points,
- \( E=\{evt_s, evt_k\} \) denotes two types of events, where
  - \( evt_s \) happens when \( L \) perform an action \( a \) on \( W \), leading to environmental changes.
  - \( evt_k \) happens when \( L \) detects a knowledge point \( k \).

In \( W \), each learning concept is visualized as an object \( o \) and each fact \( f \) is a proposition describing an object. The object described by a fact \( f \) is denoted by \( obj(f) \). For example, the concept ‘car’ can be embodied by a car object \( ocar \) in virtual environments and a fact about the car can be \( f \) at the garage. Here, \( obj(f \text{ at the garage})=ocar \). The current state \( s_i \subseteq F \) contains all the true facts and \( s_{i+1} \) is the updated state of \( s_i \).
Each action \( a \in A \) has precondition \( \text{pre}(a) \subseteq F \). \( a \) is applicable when \( \text{pre}(a) \subseteq s_i \). The effect of an action \( \text{eff}(a) \) is composed of two sets of facts: \( \text{add}(a) \subseteq F \) and \( \text{del}(a) \subseteq F \). When \( a \) is applied, the facts in \( \text{add}(a) \) are added to the world state and the facts in \( \text{del}(a) \) are removed from the world state, i.e., \( s_{i+1} = s_i \cup \text{add}(a) \setminus \text{del}(a) \). The object that action \( a \) is performed on is denoted by \( \text{obj}(a) \). For example, the action \( a: \text{drive} \) is performed on \( a: \text{car} \), i.e., \( \text{obj}(a: \text{drive}) = \text{car} \). A precondition of \( a: \text{drive} \) is \( f: \text{key} \) is available and an effect of \( a: \text{drive} \) is \( f: \text{car} \) not at the garage.

It can be inferred that the effect of certain actions can form the precondition of other actions. In the virtual learning environment, the learning goal \( G \) is achieved by the correct execution of a sequence of actions. For example, to achieve goal \( G \) of learning \( L \) environment, the learning goal \( G \) is performed on is denoted by \( \text{obj}(a) \). For example, the action \( a: \text{drive} \) is performed on \( a: \text{car} \), i.e., \( \text{obj}(a: \text{drive}) = \text{car} \). A precondition of \( a: \text{drive} \) is \( f: \text{key} \) is available and an effect of \( a: \text{drive} \) is \( f: \text{car} \) not at the garage.

There are two types of events in \( W \): \( \text{evt}_s \) and \( \text{evt}_t \). \( \text{evt}_s \) happens when the world state changes. For example, the garage becomes empty because someone drives the car away. \( \text{evt}_t \) happens when a new knowledge point is discovered. For example, a neighbor informs that the main road is closed.

2) Virtual Learning Companion: The virtual learning companion consists of five major components, denoted by \( C = \{ B, P, \mathcal{P}, \mathcal{AP}, \mathcal{LP} \} \), where

- \( B \subseteq K \) is the agent’s knowledge base,
- \( P = \{ p_1, p_2, \ldots, p_j \} \) is a set of agent’s plans given \( B \),
- \( \mathcal{P} \) is the agent’s planning process,
- \( \mathcal{AP} \) is the agent’s curiosity appraisal process,
- \( \mathcal{LP} \) is the agent’s learning process.

Here, each plan \( p \in P \) specifies a sequence of actions believed by \( C \) to achieve the learning goal \( G \). Each \( p \) is the structural representation of knowledge points in \( C \)’s knowledge base \( B \). For example, the partial plan structure in Figure 1 consists of four knowledge points: \( k_1: R(f: \text{key} \text{ is available}, a_i: \text{take key}) = r^{\text{add}}, k_2: R(f: \text{key} \text{ is available}, a_i: \text{drive}) = r^{\text{pre}}, k_3: R(f: \text{car at the garage}, a_i: \text{drive}) = r^{\text{pre}}, \) and \( k_4: R(f: \text{car at the garage}, a_i: \text{drive}) = r^{\text{del}}. \) P can be dynamically formed based on the current knowledge base \( B \). A newly discovered knowledge point \( k \) can be added into \( C \)’s plan structure according to the relationship specified in \( k \). \( C \) performs the planning process \( \mathcal{P} \) based on its current plan structure \( P \) to select an applicable action \( a' \) given the current learning goal \( G \) and the current world state \( s_i \) [15].

The curiosity appraisal process \( \mathcal{AP} \) and the learning process \( \mathcal{LP} \) are triggered by \( \text{evt}_s \) and \( \text{evt}_t \) respectively. \( \text{evt}_s \) triggers \( C \)’s curiosity appraisal process \( \mathcal{AP} \) to look for knowledge gaps by analyzing the differences between \( B \) and \( K \). Based on those knowledge gaps, \( C \) formulates questions to ask \( L \). These questions may bring \( L \)’s attention to the weakness in his/her knowledge structure and motivate him/her to actively explore for answers in the virtual learning environment. If no knowledge gap is discovered, \( C \) performs the planning process \( \mathcal{P} \) to suggest actions for \( L \) to take.

When \( L \) discovers a new knowledge point \( k \) in \( W \), an event \( \text{evt}_t \) happens and triggers \( C \)’s learning process \( \mathcal{LP} \). The agent then adds \( k \) to \( B \) and updates \( P \). Hence, \( C \) learns together with \( L \) and \( C \)’s knowledge level approximates \( L \)’s knowledge level. In this way, \( C \) becomes aware of \( L \)’s learning progress and is able to do planning at the same knowledge level with \( L \).

The detailed modeling for the curiosity appraisal process \( \mathcal{AP} \) and the learning process \( \mathcal{LP} \) will be presented in the following two sections.
by an action, which also reflects a knowledge gap between the agent and the environment, leading to C’s curiosity. If o is surprising to the agent, then \( o \in O^c \).

Uncertainty arises when there is difficulty in selecting a response to a stimulus [10]. For example, a child would feel uncertain about which road to choose for a toy car when insufficient information is provided for two roads. The appraisal of uncertainty involves comparisons among multiple competing responses. Let \( A' = \{ a | \text{pre}(a) \subseteq s_i \} \) denote a set of possible actions that \( C \) believes can be applied in the current state \( s_i \), according to its current plan \( p \) for the learning goal \( G \). If \( |A'| \geq 2 \), then for all \( a \in A' \), \( C \) is uncertain at \( \text{obj}(a) \). This indicates that \( C \) feels uncertain when multiple actions are applicable in one state. It should be noted that we assume each action has unique preconditions. Otherwise, \( L \) may easily get confused on how to act in \( W \). Hence, uncertainty indicates that the precondition of certain actions is not complete and this reveals a knowledge gap between \( B \) and \( K \), which leads to \( C \)'s curiosity. If \( o \) leads to uncertainty, then \( o \in O^c \).

As is defined earlier, \( evt_s \) triggers \( C \)'s curiosity appraisal process \( AP \). Once \( evt_s \) happens, \( C \) performs \( AP \) for discovering stimuli originated from novelty, surprise, and uncertainty. If the set of curiosity arousing objects is not empty, \( C \) will demonstrate curiosity by formulating thought-provoking questions [16] to ask \( L \), which brings \( L \)'s attention to the potential knowledge gaps.

D. Modeling the Learning Process

For the learning companion \( C \), knowledge gaps discovered in the curiosity appraisal process \( AP \) are removed during the learning process \( LP \) by adding new knowledge points in its knowledge base \( B \) and update the plan structure \( P \). Similar processes can be observed in human beings: curiosity arises when knowledge gaps exist between a person and the environment, and is satisfied naturally through learning.

\( evt_k \) triggers \( LP \) if the perceived knowledge point \( k \) is not in \( B \). \( C \) updates \( P \) based on the relationship described by \( k \): if a knowledge point gives information about the precondition of an action, i.e., \( R(f, a) = r^{pre} \), then \( \text{pre}(a) \leftarrow \text{pre}(a) \cup f \). If a knowledge point gives information about the effect of an action, i.e., \( R(f, a) = r^{add} \), then \( \text{add}(a) \leftarrow \text{add}(a) \cup f \); or \( R(f, a) = r^{del} \), then \( \text{del}(a) \leftarrow \text{del}(a) \cup f \). In this way, the former discovered knowledge gaps are closed, which quenches \( C \)'s curiosity. \( C \) removes the objects (of the fact and action) described by \( k \) from the curious object set \( O^c \).

III. IMPLEMENTATION IN A LEARNING COMPANION

The proposed model of curiosity has been implemented in a virtual learning companion. Figure 2 presents an overview of the agent architecture. We can see that the learner acts in the virtual world and the agent listens to two types of events in the environment: \( evt_s \) and \( evt_k \). \( evt_s \) may trigger two processes: (1) curiosity appraisal procedure to discover curiosity stimuli and formulate questions, and (2) the agent’s planning process to suggest actions for the learner. \( evt_k \) occurs when a knowledge point is discovered, which triggers the agent’s learning procedure to update the current plan structure and to satisfy curiosity.

In the virtual learning environment, learning concepts are visualized as virtual objects, the states of which are changed through actions. For example, the concept water is visualized as a water molecule object in the virtual world, and the location of water changes from ground to root if the action trigger osmosis is applied on the water molecule object. Learning goals can be achieved by following a correct plan of actions. For example, to complete the goal carry water into root, the correct plan is \( a_1 \): collect water molecules, \( a_2 \): collect partially permeable membrane, \( a_3 \): adjust water ratio, and \( a_4 \): trigger osmosis. The virtual learning environment provides knowledge points that can be learnt by human learners to form plans. For example, an important knowledge point that is required to form the plan for the task bring water into root is partially permeable membrane is required for osmosis. In a virtual learning environment, a knowledge point can be acquired from other knowledgeable non-player characters.

\( evt_s \) happens when the world state changes due to the learner’s actions. This will trigger the agent’s curiosity appraisal process to discover curiosity stimuli in the environment. When the agent’s curiosity arises, it will demonstrate curious behaviors by asking thought-provoking questions to the learner and encourage the learner to actively look for answers. For example, when surprise arises upon the failure of the action trigger osmosis, the companion will show curiosity by telling the user that “It surprises me! I’m wondering why osmosis failed.” Another example is shown in Figure 3a.

If no curiosity stimuli is discovered, the agent selects the next applicable action according to its current plan. The agent shares its plan with the learner through dialogs. For example, when the agent select the next action osmosis, it will inform the learner saying that “Hey, my plan is to get into the osmosis hole now.” Another example is shown in Figure 3b.
Once the learner acquires a new knowledge point, \( evt_k \) triggers the agent’s learning process to add the new knowledge point into its knowledge base, which contributes to forming better plans. For example, when the Sage informs that osmosis happens when water ratio in ground is larger than that in the root. The agent will incorporate \( f: \text{water ratio ground} > \text{root} \) into \( Pre(a_4; \text{osmosis}) \).

**IV. CASE STUDY IN VIRTUAL SINGAPURA**

The curious learning companion was implemented in Virtual Singapura (VS),\(^1\) a 3D virtual learning environment designed to teach plant transport systems. The study was conducted in the underground scene, where learners will shrink their avatars to ant size and jump into an ant hole to access the underground world (Figure 3). The goal for the human learners is to collect necessary materials (water and mineral salts) and figure out how to send them into the root of the plant in order to save Uncle Ben’s dying banana tree. Through this game, learners will learn the key concepts in plant transport systems, such as osmosis, diffusion, and active transport. The virtual world of VS and the virtual learning companion are implemented with Torque 3D engine.

To our best knowledge, there are no available curious learning companions in the literature to compare with. Hence, we built two versions of learning companions to evaluate the performance of a curious learning companion:

- **Basic learning companion (BLC)**: a reactive agent that offers basic companionship by following the learner and watch out world events for the learner. For example, if an osmosis door is perceived, the basic learning companion says “Look! There is an osmosis door in front of us!”.

- **Curious learning companion (CLC)**: an agent with the proposed model of curiosity, which offers not only basic companionship but also learning and curiosity appraisal ability to direct learners’ attention to knowledge gaps.

We followed Kim’s methodology for evaluating pedagogical agents [1] and studied the impact of a CLC on four aspects: learning, agent persona, self-efficacy, and interest. Our general hypotheses are:

- \( H_1 \): A CLC can lead to better learning gains than a BLC.
- \( H_2 \): Learners will perceive the persona of a CLC more favorably than that of a BLC.
- \( H_3 \): Learners who play with a CLC will achieve higher self-efficacy than those who play with a BLC.
- \( H_4 \): Learners will feel more interested in learning the plant transport systems with a CLC than with a BLC.

\(^1\)http://virtualsingapura.com/game/project/

**A. Experiment Procedure**

31 graduate students in a local university voluntarily participated in the study. The participants included 21 male and 10 female. The average age of the participants was 27.52 (S=2.85). The participants were randomly divided into an experimental group and a control group. In the experimental group, 16 participants played VS with the CLC. In the control group, 15 participants played VS with the BLC.

The study includes one session of 50 minutes, which is divided into three parts: pre-test (10 min), game-playing (30 min), and post-test (10 min). Before playing the game, the participants were given a set of pre-test questions regarding the plant transport systems to evaluate the participants’ prior knowledge. The maximum total score of the pre-test was worth 9 points. After receiving a brief introduction to the game, the participants were allowed to play in VS till they finished all the tasks. Then, they took a post-test, in which they answered a set of post-test questions on the plant transport systems, to evaluate their learning gains. The maximum total score of the post-test was also 9 points. After that, they filled out a questionnaire with 23
questions, which was designed to evaluate their subjective feelings on the agent persona, self-efficacy, and interest. The questionnaires were adapted from Kim’s scales [1] to ensure the validity. Each item was scaled from 1 (Strongly disagree) to 5 (Strongly agree). Log files were collected, recording the relevant student interface actions.

B. Experimental Results

This section presents the results obtained from the study.

1) Learning Gains: Learning gains was objectively measured by the score difference between the pre-test and post-test. F-test and One-tailed T-test were conducted with the two groups. Table I shows that the F-test result supports equal variance of the two groups (p=0.82>0.05) and the one-tailed T-test reveals a significant main effect of the two learning companions on learning gains (p=0.0016<0.05). Hence, the results support the hypothesis H1 that the CLC can lead to better learning gains than the BLC.

Table I: Results for Learning Gains

<table>
<thead>
<tr>
<th>Group</th>
<th>Control</th>
<th>Experimental</th>
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</thead>
<tbody>
<tr>
<td>Mean</td>
<td>2.4</td>
<td>5.25</td>
</tr>
<tr>
<td>STD</td>
<td>2.36</td>
<td>2.41</td>
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<tr>
<td>F</td>
<td>p=0.82</td>
<td></td>
</tr>
<tr>
<td>T (one-tailed)</td>
<td></td>
<td>p=0.0016</td>
</tr>
</tbody>
</table>

2) Agent Persona: Agent persona was assessed with the Agent Persona Instrument (API) [4]. According to API, agent persona includes four sub-measures: facilitating learning, credible, human like, and engaging. Hence, H2 is decomposed into four sub-hypotheses:

H2a : A CLC can better facilitate learning than a BLC.
H2b : A CLC is more credible than a BLC.
H2c : A CLC is more human-like than a BLC.
H2d : A CLC is more engaging than a BLC.

Table II presents the evaluation results for agent persona. In complementary to the objective measurement for learning using learning gains, “facilitating learning” measures learning subjectively. Table II shows that the F-test result supports equal variance of the two groups (p=0.87>0.05) for facilitating learning. The one-tailed T-test reveals a significant main effect of the two learning companions on facilitating learning (p=4.5*10^-6<0.05). Hence, the results support H2a that the CLC can better facilitate learning than the BLC.

From the perspective of credibility, the F-test result supports equal variance of the two groups (p=0.81>0.05). The one-tailed T-test reveals a significant main effect of the two learning companions on their perceived credibility (p=0.0005<0.05). Hence, the results support H2b that the CLC is perceived to be more credible than the BLC.

From the perspective of being human-like, the F-test result supports equal variance of the two groups (p=0.54>0.05). The one-tailed T-test reveals that there is a significant main effect of the two learning companions on participants’ perception of whether the learning companions are human-like (p=0.03<0.05). Hence, the results support H2c that the CLC is perceived to be more human-like than the BLC.

From the perspective of being engaging, the F-test result supports equal variance of the two groups (p=0.20>0.05). The one-tailed T-test reveals a significant main effect of the two learning companions on participants’ perception of whether the agents are engaging (p=0.001<0.05). Hence, the results support H2d that the CLC is more engaging than the BLC.

3) Self-efficacy: Self-efficacy is defined as an individual’s belief in his/her competency of performing a particular task [17]. In this study, self-efficacy refers to the learners’ belief about their competency in the knowledge of plant transport systems. The results for self-efficacy are presented in Table III. The F-test result supports equal variance of the two groups (p=0.09>0.05). The one-tailed T-test reveals a significant main effect of the two learning companions on participants’ self-efficacy (p=0.02<0.05). Hence, the results support H3 that learners who play with the CLC can achieve higher self-efficacy than those who play with the BLC.

4) Interest: Interest is defined as a disposition organized through experience which impels an individual to seek out particular objects, activities, or goals for attention or acquisition [18]. In this study, interest refers to learners’ disposition towards learning the topic of plant transport

Table II: Results for Agent Persona

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<th></th>
<th>Facilitating Learning</th>
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<tr>
<td>F</td>
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<tr>
<td>T (one-tailed)</td>
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<td>p=4.5*10^-6</td>
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<td>T (one-tailed)</td>
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<td>0.72</td>
<td></td>
</tr>
<tr>
<td>F</td>
<td>p=0.20</td>
<td></td>
<td></td>
</tr>
<tr>
<td>T (one-tailed)</td>
<td></td>
<td>p=0.001</td>
<td></td>
</tr>
</tbody>
</table>
systems. The results for interest are presented in Table IV. The F-test result supports equal variance of the two groups (p=0.38; p<0.05). The one-tailed T-test reveals that there is a significant main effect of the two learning companions on participants’ interest (p=0.005; p<0.05). Hence, the results support H4 that learners feel more interested in learning the plant transport systems with the CLC than with the BLC.

Table IV: Results for Interest

<table>
<thead>
<tr>
<th>Group</th>
<th>Control</th>
<th>Experimental</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>2.63</td>
<td>3.21</td>
</tr>
<tr>
<td>STD</td>
<td>0.52</td>
<td>0.66</td>
</tr>
<tr>
<td>F</td>
<td></td>
<td>p=0.38</td>
</tr>
<tr>
<td>T (one-tailed)</td>
<td></td>
<td>p=0.005</td>
</tr>
</tbody>
</table>

C. Discussion

The mean scores of the control group and experimental group for the seven aspects are shown in Figure 4. The results confirm that the CLC can help learners achieve more learning gains (H1), better facilitate learning (H2a), be more credible (H2b), be more human-like (H2c), be more engaging (H2d), better improve learner’s self-efficacy (H3), and make learners feel more interested (H4) than the BLC. The CLC achieves better results probability because the agent is driven by curiosity to learn, which follows a similar learning process as the learner. Hence, the CLC provides hints that are aware of both the environmental context and learners’ learning progress. Whereas, the BLC does not actually “learn” with the learners, which can only provide hints that are environmental context aware but not learning progress aware.

Another possible reason is that a CLC may stimulate learners’ curiosity through questions it poses. By presenting the gaps of knowledge with thought-provoking questions, the learners can become motivated to find answers and actively inquire into the subject in order to resolve their curiosity. In this way, inquiry-based learning [19] is established and learners learn in a question-driven and open-ended context.

From our observations, the CLC better facilitates learners who are less active in asking themselves questions and looking for answers. In this case, the CLC acts more like a leader and learners follow the leader to complete tasks. In the case with learners who take more initiative in questioning and answering, learners take the role as leaders and the CLC acts like a follower who looks out for information probably missed by the learners.

As for the improvement on learners’ perception of agent’s persona, the reason might be that curiosity itself is a type of epidemiology-based emotion and emotion is at the core of agent’s believability. Hence, agent with curiosity, especially in a learning context, will be perceived to be more human-like and believable.

D. Related Works

In our previous works, we have modeled curiosity for virtual learning companions to detect potentially interesting learning topics for users [20]. We adopted Fuzzy Cognitive Maps for knowledge representation and inference in the virtual learning companions. However, the agent requires a user to manually input his/her current learnt knowledge through drawing concept maps on a virtual blackboard. The agent detects knowledge gaps through comparing between the user’s concept maps with the expert concept maps. From our previous studies, we found that prompting users to draw concept maps during the game playing process may sometimes be very interruptive and affect the game playing experience. The model proposed in this paper avoid this issue because the agent automatically learns a student model without requiring users to manually input their knowledge.

We have also modeled curiosity-related emotions for virtual peer learners in an earlier work [11]. The virtual peer learners were implemented in a reinforcement learning framework and try to maximize positive rewards during its learning process. Simulation results showed that curious virtual peer learners can demonstrate human-like learning patterns in virtual learning environments. However, the virtual peer learners do not provide interactions with users.

Curiosity has also been modeled in various other domains. For example, in machine learning frameworks, curiosity has been modeled as self-regulation rules to enhance the learning ability of extreme learning machines [21]. For autonomous development robotics, curiosity has been proposed as algorithmic principles to focus learning on novel and irregular noises [22]. In the domain of artificial creativity, computational models of curiosity have been proposed as an intrinsic evaluation of novelty [23]. A survey on computational curiosity is available in [9].
V. CONCLUSION

In this paper, we proposed a computational model of curiosity for learning companions to improve human learners’ learning experience in virtual environments. The model is built based on human psychology and follows Berlyne’s theory. Three most salient appraisal variables in virtual learning environments are captured in the model, including novelty, surprise, and uncertainty. This model adopts plan-based knowledge representations and employs decision-theoretic planning techniques. Two internal processes are modeled to simulate curiosity: curiosity appraisal and learning. The curiosity appraisal process looks for knowledge gaps based on the appraisal variables to stimulate the agent’s curiosity, whereas the learning process quenches the agent’s curiosity through closing knowledge gaps. The model was implemented in a virtual learning companion and was carefully studied in Virtual Singapura with human users. Evaluation results showed that the learning companion’s curiosity significantly improves human learners’ learning experience from several aspects, including learning gains, self-efficacy, and interest. Also, the experimental results supported that human learners perceive a curious learning companion’s persona more favorably.

VI. ACKNOWLEDGMENTS

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REFERENCES


