Psychologically Grounded Student Agents for Reliable Classroom Simulation with LLMs

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Practical Work Proposal

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I. Introduction

The integration of Large Language Models (LLMs) in educational simulations offers a transformative method for understanding classroom dynamics, allowing for the creation of dynamic, interactive agents that can realistically mimic the complex behaviors of students and teachers. Recent advancements, such as the **PEERS** (Peer Enhanced Educational Realistic Simulation) [2] and **EduAgent** frameworks [67], highlight the potential of LLM-powered agents to fill these roles within simulated educational environments by deploying autonomous agents that can simulate students learning advanced concepts by asking nuanced questions or a teacher agent experimenting with different pedagogical strategies in real-time. These contributions are foundational in creating controlled settings where educators can explore various teaching strategies to identify potential flaws in their teaching methods, practice timely interventions for specific student concerns, and refine their strategies in a replicable and scalable environment.

However, current LLM-based educational simulations suffer from a significant **"fidelity gap"**, limiting their psychological authenticity in genuinely reflecting the internal cognitive and emotional states that drive human behavior [65]. Educational psychology has long recognized that learners adopt different approaches, often described as **deep, surface, and strategic styles**, each with distinct motivations and behaviors [27], [53], [16]. Further research building up on this show that these styles are not rigid categories but points along a spectrum, with learners fluidly shifting between them based on context and cognitive-emotional states [27], [63], [53]. Cumulative evidence from interdisciplinary studies across psychology, neuroscience, and education consistently point towards the idea that learning is powerfully shaped by the interaction of three main dimensions identified as **affect**, **attention**, and **memory** [63], [26], [20], [12], [7], where affect drives motivation, attention governs information processing, and memory anchors knowledge construction [29], [8], [3], [63]. Beyond these individual explorations, studies have also examined their crucial interplay as research on the link between **affect and attention** has shown how emotional states can direct or impair focus [63], [17], [39], while studies on **attention and memory** have confirmed that focused attention is essential for effective memory encoding [46], [54], [36], [14]. Works also demonstrate how these interactions create compounding effects, particularly for diverse learners, where heightened anxiety (affect) can disrupt attentional control, which in turn compromises working memory, making it exceedingly difficult for a student to follow multi-step instructions or comprehend complex texts [39]. Furthermore, studies focusing on learning disabilities demonstrate that issues regarding attention or memory are often exacerbated by emotional dysregulation, making a unified framework essential to accurately simulate the significant barriers diverse learners face. [26], [36], [59], [62], [42], [55], [38]. This evidence of compounding effects due to interplay reinforces a critical conclusion from cognitive and clinical research: Any model aiming to be psychologically authentic must integrate all three components and simulate their dynamic interplay to reflect how they function interdependently within a natural cognitive system.

A primary issue in the current implementations is the reliance on uniform, static student representations that fail to model the above core cognitive dimensions driving student behavior. [65]. Frameworks like **PEERS** [2] use limited behavioral parameters that model only on-task actions, ignoring off-task behaviors driven by boredom or frustration while even advanced systems like **EduAgent** [67] and **SimClass** [68] struggle to capture the full spectrum of individual differences related to these cognitive aspects, as they are yet unable to simulate how a student with anxiety might freeze up when called upon (affect), how another with attentional deficits might frequently disengage (attention), or how different learning styles impact knowledge retention (memory) [4], [18], [41]. While cognitive architectures like **NEOLAF** and the **Unified Mind Model** [21][22], **ACT-R** [51], **CLARION** [60], **Sigma** [13], and **MalAlgoPy** [58] have hinted at unified systems, there remains a clear gap in models that holistically integrate all three components on a dynamic basis for modeling learning [39], [13], [28], [45]. To address this, we propose a **novel, layered agent architecture** that grounds agent behavior in validated educational psychology by formalizing student archetypes [4], [18], [41], [53], made feasible by advances in persona-based prompting [31], [37], [1] and cognitive digital twins [23], [24]. By implementing specialized cognitive layers for affect, attention and memory, this approach will aim to bridge the fidelity gap where the primary goal will be the development of **authentic psychological diversity**, transforming simulations into powerful training tools to better prepare educators for the unpredictable dynamics of a live classroom, ensuring they are equipped to manage diverse student needs effectively.

II. Objectives

The primary goal of this research is to develop and validate a psychologically-grounded architecture for creating realistic student agents in educational simulations, focusing on three main objectives:

1) **Develop a Novel Cognitive Agent Architecture**: Create a layered agent system that integrates empirically-derived student archetypes from educational psychology literature with programmatic cognitive processing layers to simulate authentic student behaviors and learning patterns.
2) **Implement Psychologically-Authentic Simulation Components**: Design and validate specialized cognitive processing modules including an **Affective module** to dynamically modulate emotional states based on established psychological theories of student motivation and anxiety, an **Attention module** modeling variations in executive function and attention, such as distractibility and sustained focus [6][56][56], and a **Memory and Decoding module** with memory filtering mechanisms simulating variations in phonological and orthographic processing, such as character-level decoding fidelity and working memory for text [33][43][19].
3) **Demonstrate Superior Simulation Fidelity**: Validate the architecture's effectiveness through comprehensive evaluation including human expert assessment of agent believability, quantitative analysis of behavioral pattern differentiation between agent archetypes, and comparative analysis with existing student modeling approaches in terms of predictive accuracy and educational insight generation.

III. Proposed Implementation

Our implementation strategy consists of four integrated phases designed to create a comprehensive psychologically-grounded educational simulation framework:

a) Phase 1: Literature Review and Archetype Formalization: We begin with a systematic review of educational psychology literature to identify and formalize 3-5 empirically-validated student archetypes, building upon established frameworks such as the Deep/Surface/Strategic learning approaches [4][18][41][53]. Each archetype will be characterized through comprehensive behavioral profiles including learning motivations, communication patterns, cognitive processing preferences, and response tendencies to different pedagogical interventions. This phase will also incorporate findings from student modeling research using Bayesian Knowledge Tracing [32][64][66] and cognitive agent computing models [61] to ensure compatibility with existing educational technologies.

b) Phase 2: Disposition Layer Implementation: For each identified archetype, we will engineer sophisticated "meta-prompts" that serve as the agent's psychological constitution. These prompts will define core motivations, communication styles, and worldviews that establish the baseline parameters for the cognitive modules in the next phase. (e.g., "You are a '*Surface Learner.*' Your primary goal is to pass assessments with minimal effort. You prefer clear, factual information and avoid deep, open-ended discussions that require extensive cognitive processing..."). The meta-prompting approach will draw from recent advances in persona-based LLM control [31][37][1][67] and psychological authenticity research in conversational agents [30][57].

c) Phase 3: Core Cognitive Module Implementation: We will implement three primary programmatic modules that dynamically update a structured "Control Panel" input. This strategy leverages an Instruction fine-tuned LLM that is trained to read this Control Panel and generate behavior that matches the specified cognitive state to simulate core cognitive functions and individual differences. The modules function as follows:

- **Affect Module (*Emotional State Modulator*)**: A state-machine implementation tracking dynamic emotional states (confident, confused, anxious, engaged) based on interaction history and performance outcomes. This module will modify LLM prompt components in real-time to reflect emotional influences on communication style, response length, and cognitive processing approach. Here we update the emotion field of the Control Panel *(e.g., "emotion": "primary": "anxious", "confidence": 0.3)*, which the LLM interprets to modulate its communication style, response length, and cognitive processing approach.
- **Attention Module (*Focus Manager*)**: A dynamic attention modeling system that simulates varying attention spans and distractibility patterns. Drawing from cognitive models of attention and executive function [6][56][56], this module will implement time-decay functions for attention, threshold-based coherence degradation, and attention reset mechanisms triggered by direct engagement or environmental changes. Here we update the focus field of the Control Panel in real-time *(e.g., "focus": "level": 0.4)*, which instructs the LLM to adjust its response coherence and relevance.
- **Memory and Decoding Module (*Memory Filter*)**: A cognitive processing filter that models information processing variations, particularly those reflecting a spectrum of information processing speeds and accuracies [33][43][19]. This system will introduce controlled character-level noise (e.g., b/d reversals, transposition errors) with probability distributions calibrated to diverse reading patterns, affecting information encoding and retrieval accuracy. Here we update the memory field of the Control Panel *(e.g., "memory": "decoding_fidelity": 0.85*), affecting information encoding and retrieval accuracy.

d) Phase 4: Validation and Integration: The complete architecture will undergo comprehensive validation through multiple evaluation methodologies: human expert blind rating of agent believability and archetype consistency, quantitative analysis of behavioral differentiation between agent types, and integration testing within educational simulation environments. We will also explore the proposed "Committee of Agents" alternative architecture as an ablation study, implementing student agents as coordinating processes managing multiple trait-specific sub-agents to compare monolithic versus composable persona approaches.

*A. **Core Cognitive Module Architecture***

This section details the design of the three core cognitive modules that form the foundation of our psychologically-grounded student agents. Each module is designed to be a programmable "wrapper" that shapes the LLM's generative process, with parameters derived from formalized student archetypes.

*1) **The Affective Module** (Emotional State Modulator):*

Theoretical Grounding: This module is grounded in **Pekrun's Control-Value Theory of Achievement Emotions** [47] [48], which links emotions to an individual's perceived control over and valuation of a task. It also incorporates **Appraisal Theory** [52][44], suggesting that emotions arise from our interpretation of events. This framework allows us to model how a "Deep Learner" might react to a challenge with curiosity, while a "Surface Learner" might react with anxiety, based on their underlying motivations [15][25].
Operational Definition: The module will be a state-machine where states are key achievement emotions (e.g., Confident, Anxious, Engaged, Bored). State transitions are governed by:

- **Control Appraisal:** An internal variable representing perceived self-efficacy, which changes based on performance outcomes and feedback.
- **Value Appraisal:** A parameter derived from the agent's archetype that defines the intrinsic or extrinsic value of a task.
- **Affective Influence:** The current emotional state will dynamically modify the LLM's meta-prompt in real-time. An 'Anxious' state may add instructions for shorter, more hesitant responses, while an 'Engaged' state may prompt for more proactive and detailed contributions.

<u>*Evaluation Metrics:*</u>

- **Emotional Valence in Language:** Sentiment analysis of the agent's generated text to track emotional shifts.
- **Behavioral Indicators:** Measurement of behaviors such as help-seeking frequency, response length, and proactive questioning.
- **Human Expert Ratings:** Educators will evaluate the authenticity of the agent's emotional and motivational trajectory.

<u>*Testable Hypotheses:*</u>

- $\boldsymbol{H_1}$ **:** An agent whose 'Control Appraisal' is systematically lowered through negative feedback will transition to negative emotional states (e.g., frustration, anxiety) and exhibit a corresponding increase in negative-valence language.
- $\boldsymbol{H_2}$ **:** Agents equipped with the Affective Module will be perceived by human raters as demonstrating more believable and differentiated student personalities than agents defined only by a static dispositional prompt.

2) ***The Attention Module*** *(Focus Manager):*

<u>*Theoretical Grounding:*</u> This module is grounded in hierarchical models of attention that differentiate between sustained attention (maintaining focus over time) and selective attention (filtering distractions) [10][50]. It also draws from cognitive models of executive function, such as **Baddeley's model of working memory** [5], which includes a central executive responsible for attentional control, and **Load Theory of Attention** [34] which posits that the ability to ignore distractions depends on the perceptual load of the current task. These concepts are quite central to understanding various underlying conditions that affect Attention, such as ADHD [9]. Our model operationalizes these concepts to simulate how an agent's focus can decay, be captured by competing stimuli, or be reset by direct engagement.
<u>*Operational Definition:*</u> The module will be a state-based system governed by the following parameters:

- **Attention Span:** A numerical value representing the number of conversational turns an agent can maintain focus on a single topic before a potential "attention lapse." This will be implemented as a timer that resets upon re-engagement.
- **Distractibility Threshold:** A value that determines the likelihood of an external or internal stimulus (e.g., an off-topic comment, a complex thought) shifting the agent's focus.
- **Cognitive Load:** A variable that increases with task complexity. As cognitive load approaches its maximum, the probability of an attention lapse increases, simulating mental fatigue.

<u>*Evaluation Metrics:*</u>

- **Time-on-Task:** Percentage of conversational turns where the agent's output is semantically relevant to the ongoing topic.
- **Frequency of Off-Topic Utterances:** A count of instances where the agent's output deviates from the established topic.
- **Human Expert Ratings:** Blind evaluators will rate the believability of an agent's attentional patterns.

<u>*Testable Hypotheses:*</u>

- $\boldsymbol{H_3}$ **:** Agents with a lower 'Attention Span' parameter will exhibit a statistically significant higher frequency of off-topic utterances compared to agents with higher attention spans.
- $\boldsymbol{H_4}$ **:** Agents with a lower 'Distractibility Threshold' will show greater performance degradation in simulated environments with high levels of external distractions.

3) ***The Memory and Decoding Module*** *(Memory Filter):*

<u>*Theoretical Grounding:*</u> The module is based on the **Dual-Route Cascade Model of Reading** [11][35], which explains how individuals decode familiar and unfamiliar words. Deficiencies in phonological (sound-based) and orthographic (visual-based) processing, which are often implicated in dyslexia, will be modeled [40]. Furthermore, it incorporates principles from **Verbal Efficiency Theory** [49], which posits that effortful decoding consumes finite working memory resources needed for comprehension.
<u>*Operational Definition:*</u> This module acts as a filter that pre-processes text input to the LLM. It is defined by:

- **Phonological Noise Parameter:** A probability distribution that introduces controlled, character-level errors into the agent's "internal reading" of text (e.g., b/d reversals, transposition errors) to simulate decoding difficulties.
- **Working Memory Buffer:** A fixed-size buffer representing the agent's capacity to hold information. Effortful decoding, as dictated by the noise parameter, will consume space in this buffer, reducing the resources available for higher-level comprehension.

Evaluation Metrics:

- **Reading Comprehension Accuracy:** Agent performance on simulated comprehension tasks.
- **Error Analysis:** Classification of agent errors into phonological, orthographic, or semantic categories.
- **Information Recall Fidelity:** The accuracy with which an agent can recall facts presented in a passage, testing the integrity of its working memory.

Testable Hypotheses:

- $\boldsymbol{H_5}$ **:** Agents with a high 'Phonological Noise' parameter will make significantly more phonologically-based errors than agents with a low parameter.
- $\boldsymbol{H_6}$ **:** A reduction in the 'Working Memory Buffer' size will be negatively correlated with an agent's ability to answer questions about long passages of text.

IV. Expected Milestones

The project is envisioned as a four-month intensive research program with clearly defined deliverables and evaluation checkpoints:

- **Month 1: Foundation and Architecture**
  Complete a systematic review of educational psychology to formalize student archetypes, followed by the design of the complete Cognitive Twin architecture and development of initial meta-prompts.
  Deliverables: Comprehensive literature analysis, formal archetype specifications, and a complete architectural design with an initial meta-prompt library.
- **Month 2: Implementation and Preliminary Validation**
  Develop and implement the three core cognitive processing modules (Affect, Attention, Memory and Decoding). Integrate all system components and conduct preliminary validation studies, including agent behavior consistency testing.
  Deliverables: A functional, integrated system with documented performance characteristics and preliminary validation results.
- **Month 3: Comprehensive Evaluation and Alternative Architecture Exploration**
  Conduct full validation study including human expert evaluation, behavioral differentiation analysis, and Committee of Agents implementation as a comparative study.
  Deliverables: Complete validation results and architectural comparison analysis.
- **Month 4: Analysis, Documentation, and Dissemination**
  Analyze all collected data, optimize system parameters based on evaluation results, and prepare comprehensive documentation, including academic paper preparation for submission to relevant conferences (AIED, EDM, or similar venues).
  Deliverables: Final thesis document and prepared academic publication.

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