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Application of Large Language Models-Based Pedagogical Agents in Classroom Teaching

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Abstract: With The innovative potential of Large Language Models (LLMs) in classroom instruction is becoming increasingly prominent, offering a transformative path for the field of education. The paper focuses on the application of LLM-based pedagogical agents in classroom teaching, aiming to address the limitations of traditional classrooms in providing personalized support and proactive services through their capabilities in multi-modal understanding, natural language generation, and task planning. Centered around an LLM, the pedagogical agents construct a digital brain equipped with reasoning, planning, and interactive abilities, serving multiple roles throughout the entire teaching process—including as a teacher's assistant, a learning companion, and a personal tutor. The paper elaborates on its specific applications: generating intelligent resources and supporting instructional design during lesson preparation, acting as an interactive medium to facilitate teacher-student communication and personalized guidance during class, and serving as a one-on-one tutoring tool for reinforcement and generative assessment after class. Research shows that the pedagogical agent can effectively enhance teaching efficiency, increase student engagement, and promote the practical implementation of the modern educational philosophy of student-centered learning.

Keywords: Pedagogical agents; Classroom teaching; Large language models

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1. Introduction

Rapid advances in artificial intelligence technology are creating new opportunities for educational reform. As the flagship of AI, large language models (LLMs) are reshaping education in revolutionary ways, leveraging their ability to understand multimodal information and generate content to deliver personalized instruction and interactive Q&A. Yet, when deployed in real classrooms, they still suffer from weak autonomous planning and a lack of proactive service, which undermines their effectiveness and limits their support for self-directed learning. At present, LLMs are evolving from mere question-answering engines into intelligent learning companions. Through natural-language understanding and logical reasoning, they are being re-engineered for classroom use. Emerging from this shift are LLM-based pedagogical agents—intelligent tutoring systems that combine an LLM with a curated knowledge base to act simultaneously as teacher, peer, and teaching assistant, fulfilling the full range of instructional and nurturing functions. Pedagogical agents, also termed intelligent tutoring systems, are virtual characters that guide learners within a learning environment [1]. An LLM-based pedagogical agent is a subset of these systems, distinguished by its capacity to engage learners in deep, open-ended dialogue with a virtual character [2]. By overcoming the constraints of traditional classrooms, such agents boost deep learner engagement and open up entirely new pathways for instruction.

2. Building LLM-based pedagogical agents

2.1. Architecture of large-model agents

In contrast to traditional agent technologies, intelligent agents powered by large language models possess the capability to independently reason and utilize tools to progressively achieve assigned objectives. Such agents leverage their inherent strengths in deep comprehension and content generation to perform complex tasks. Without relying extensively on domain-specific data, they can engage in multi-step iterative processes for planning and executing actions, allowing them to quickly adapt to and excel in novel scenarios to fulfill intended operational goals [3].

Guided by user-defined targets, the agent assumes a specific role, autonomously perceives and observes its environment, and utilizes the acquired state information to retrieve historical memory and relevant knowledge. Through reasoning and planning, it breaks down tasks, formulates action strategies, and applies these strategies back to the environment to achieve its goals [4]. Throughout this process, the agent demonstrates continuous learning, evolving in a manner analogous to human growth. Constructing an agent based on a large language model allows full utilization of the model's native capabilities to drive its various functional components.

2.2. LLM-driven pedagogical agents

The large language model is both the technical bedrock and the prime mover of pedagogical agents. Powered by its formidable natural-language processing and contextual understanding, the agent delivers near-human interaction, acting as a teaching assistant for instructors and a personal peer for every learner. With the LLM as its brain, the agent not only sustains high-quality dialogue but also decomposes complex learning tasks into actionable sub-steps, guiding students to master knowledge progressively [5]. Compared with legacy intelligent systems, LLM-based pedagogical agents exhibit two decisive advantages.

First, multi-modal perception: they fuse text, images, speech, and other signals to obtain a holistic view of the learning situation and the user's state, thereby furnishing truly personalized guidance. Second, advanced reasoning and planning: through chain-of-thought prompting and related techniques, they emulate human cognition, autonomously mapping instructional paths, designing solution strategies, and steering learners toward objectives step by step. These capabilities allow the agent to adapt to diverse pedagogical scenarios, provide dynamic, responsive support, and embody the modern ideal of "student-centred" education [6].

3. Pedagogical agents in classroom practice

3.1. Pre-class: The teacher's lesson-planning assistant

In the pre-class stage, the pedagogical agent powered by LLMs evolves into an intelligent lesson-design hub. Its role is not limited to saving teachers' time but also to systematically enhancing the intellectual depth, creativity, and curricular alignment of lesson planning [7]. The process begins with a Learning Analytics Radar. By integrating historical data from the school's learning management system (LMS), homework platforms, and classroom response systems, the pedagogical agent applies clustering and sequence modeling algorithms to generate knowledge heatmaps at the class level and cognitive trajectories at the individual level [8]. These analytics allow teachers to identify common misconceptions, pinpoint focal areas of student interest, and diagnose differentiated learning needs with precision. Next, the agent initiates the Scenario Generation Module. A teacher may provide a natural-language instructional vision—for example, encourage students to think like economists when reasoning about opportunity cost. Within minutes, the pedagogical agent delivers several fully developed instructional frameworks. Each framework incorporates an introductory narrative, a conflict-based situation, cognitive scaffolds, and emotional anchors, all mapped to disciplinary core competencies to ensure engagement and curricular validity.

From a resource perspective, the agent's multimodal retrieval–generation engine operates on two fronts. On one hand, it conducts semantic searches across open educational resource repositories such as OER Commons, Khan Academy, and the China National Smart Education Platform to retrieve highly relevant videos, simulations, and AR assets. On the other hand, it leverages generative diffusion models to visualise abstract concepts in real time—for instance, rendering mitosis as a rotatable 3D chromatid animation, or transforming trigonometric functions into an interactive unit-circle application [9]. All resources are formatted to SCORM standards and can be embedded into PowerPoint slides or Moodle course packages with a single click.

The pedagogical agent also upgrades traditional test item preparation into a Multidimensional Assessment Workshop. It analyzes existing item banks using knowledge-graph algorithms to identify assessed competencies, Bloom's taxonomy levels, and stylistic features. Based on this analysis, it generates item sets across six cognitive levels—Remember, Understand, Apply, Analyze, Evaluate, and Create. For example, if a teacher requests a cross-cultural STEM project for collaboration between students in two countries, the pedagogical agent employs cross-lingual models to produce a bilingual, project-based task complete with rubrics and exemplar answers aligned with advanced reasoning models such as GPT-4. Finally, a Reflective Risk-Audit Module evaluates the cognitive load of the entire lesson plan. It identifies sections that may exceed working-memory capacity and suggests refinements grounded in cognitive load theory [10]. For instance, it may recommend replacing a verbal explanation in Step 3 with a visual flowchart, thereby reducing cognitive load. In this way, lesson preparation shifts from an individual, search-based process to a co-creative human–AI endeavour, enabling teachers to reinvest the saved time into providing emotional support and conducting pedagogical research.

3.2. In-class: An interactive medium for teachers and students

During classroom instruction, the pedagogical agent functions as a multimodal partner, reshaping instructional rhythm and social interaction through real-time sensing and generation. Technologically, the agent operates within an edge cloud collaborative framework, integrating IoT-enabled devices such as 4K cameras, microphone arrays, interactive whiteboards, and student tablets [11]. Cameras capture micro-expressions and gestures, while microphone arrays localise speech and suppress background noise. These data streams feed into a continuously updated engagement–attention dashboard, refreshed every 30 seconds. Teachers receive discreet feedback through wearable haptic devices.

Instructional interactions are structured into three tiers of support. The first one is real-time Q&A. When students pose verbal questions, the agent provides structured answer capsules, comprising a concise explanation, analogy, real-life application, and a one-minute extension video. If multiple learners raise similar questions, the agent shifts into a collective micro-instruction mode, projecting a synchronized animation to the main display. The second one is dynamic scenario injection, where teachers can discreetly trigger scenario generation. The agent then creates open-ended problems or ethical dilemmas relevant to the current lesson content. For example, while teaching buoyancy, it may challenge students to design an offshore floating farm based on buoyancy principles, thereby transforming the classroom into a design-thinking studio. The third one is differentiated group facilitation, in collaborative activities, the agent assigns roles such as encourager, sceptic, or summarizer to different groups and participates in discussions by offering prompts, counterexamples, and scaffolding through text or voice. Group interactions are logged and analyzed to generate a collaboration quality report, mapping contribution indices and group social-semantic networks.

Assessment is embedded through stealth analytics. By analyzing response times, keystroke dynamics, and gaze-tracking heatmaps, the agent estimates students' mastery probabilities in real time. When these probabilities fall below a set threshold, personalized remedial exercises are automatically deployed, establishing micro-cycles of error correction. Consequently, the classroom evolves from a one-to-many broadcast into a multi-nodal interactive network, enabling large-scale yet fine-grained personalization and enhancing both precision and inclusivity in teaching.

3.3. Post-class: The student's private tutor

After class, the pedagogical agent assumes the role of a personal tutor and growth coach, providing continuous and adaptive learning support. Its first capability is Error Reverse-Mapping. Students can upload images of their assignments, which the agent processes through OCR combined with symbolic reasoning. It identifies the underlying knowledge gaps and generates a closed-loop training package that includes a micro-lecture video, an interactive simulation, and three variant practice problems. If repeated errors occur, the agent lowers task difficulty and activates a Knowledge Backtracking Module to reinforce prerequisite concepts, thereby creating an adaptive staircase for mastery learning.

Second, the pedagogical agent advances generative feedback into a personalized growth narrative. Synthesizing data from assignments, classroom participation, and assessment records, it composes a learning story that includes affective acknowledgement, cognitive diagnosis, strategic recommendation, and metacognitive prompting [12]. Each narrative is written in the second person and accompanied by an AI-generated digital badge to encourage motivation and self-recognition.

Third, the agent maintains a Metacognitive Dashboard that generates weekly "learning ECGs" for each student, visualizing trends in effort, strategies, and achievement. These dashboards promote adaptive self-regulation by attributing performance to controllable factors, while parents receive only anonymized "growth digests" to safeguard privacy. Finally, the Community Connector function matches students with complementary learning trajectories and recommends peer activities such as paired study sessions or online collaborative whiteboard challenges. In doing so, post-class support evolves from static answer provision into a three-dimensional ecosystem of data-driven insight, emotional companionship, and peer synergy, substantially extending the educational value chain.

4. Application challenges and countermeasure suggestions

4.1. Application challenges

Although large language model-based pedagogical agents demonstrate significant application potential in classroom teaching, their practical promotion faces multifaceted challenges that require systematic responses at technological, ethical, and educational practice levels.

At the technological level, pedagogical agents still exhibit notable limitations. A primary issue is their tendency to produce hallucinations, generating plausible yet incorrect or fabricated knowledge, which poses a direct risk to instructional accuracy [13]. Moreover, the outputs of these models are somewhat uncontrollable and may not always align with teaching objectives and value requirements. Additionally, current large language models remain limited in supporting complex logical reasoning and training creative thinking, focusing more on pattern matching and information reorganization rather than fostering deeper cognitive abilities. Ethical and security risks also cannot be overlooked. When processing educational data, pedagogical agents may involve issues of student privacy leakage; the algorithms themselves might also contain biases inherent in the training data, thereby affecting educational fairness. Greater concern is that over-reliance on these agents by students could inhibit the development of independent thinking and critical engagement with knowledge, leading to intellectual inertia, which contradicts the educational goal of cultivating higher-order thinking skills. Furthermore, both teachers and students face challenges in adapting to new roles. Teachers need to transition from traditional knowledge transmitters to designers of learning processes, guides, and managers of AI-assisted teaching tools, requiring mastery of human-machine collaborative teaching strategies. Students, too, must develop new learning habits and enhance their ability to discern and critically evaluate machine-generated content.

4.2. Countermeasure suggestions

To address the above challenges, it is necessary to systematically design countermeasures across three dimensions: technology, application mechanisms, and personnel training. At the technological level, it is advisable to adopt a hybrid architecture of a large language model and an education-specific vertical model. By incorporating educational knowledge bases and teaching rule constraints, domain adaptability can be enhanced, and factual errors reduced. Simultaneously, multi-layer filtering and fact-checking mechanisms should be established to verify the reliability of generated content and impose educational safety and ethical constraints on outputs. At the application mechanism level, a teacher-machine-student tripartite collaborative teaching model must be clearly defined, emphasizing that the teacher always maintains a leading role, and the pedagogical agent should be used under teacher supervision. Clear application norms and ethical guidelines should be formulated, including boundaries for data usage, limits on the agent’s involvement in teaching, and principles for accountability, to ensure the standardization and safety of the teaching process. At the training level, focused efforts should be made to strengthen teachers’ professional development support. Through smart education literacy training, prompt engineering workshops, and case-based teaching, teachers’ ability to appropriately design, deploy, and evaluate agent behaviors should be enhanced, enabling them to effectively harness the technology to better serve teaching objectives.

In conclusion, the healthy development and effective application of pedagogical agents require not only continuous technological improvements but also the establishment of a matching educational application framework and teacher development system. Through multi-faceted collaborative efforts, pedagogical agents can ultimately be promoted as a beneficial force in building a high-quality, personalized education system.

5. Conclusion

This paper has systematically examined the value and practical pathways of LLM-based pedagogical agents in classroom instruction. Research shows that, by deeply integrating the reasoning, generative, and multimodal capacities of large language models, the agent can span the entire “pre-class – in-class – post-class” workflow, offering holistic support to teachers and students alike. Before class, it helps instructors prepare efficiently and generate exercises; during class, it fosters real-time interaction and personalized guidance; after class, it acts as a private tutor for precision consolidation and motivational assessment. The agent not only mitigates the chronic problem of insufficient resources for differentiated instruction but also significantly broadens and deepens human-machine collaboration in education. As large-model technology continues to evolve and application scenarios expand, pedagogical agents are expected to make further advances in emotion recognition, interdisciplinary integration, and adaptive learning, ultimately becoming a core force driving the modernization and transformation of education.

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