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INTEGRATION OF GENERATIVE AI INTO PERSONALIZED EDUCATIONAL PLATFORMS TO IMPROVE LEARNING EFFECTIVENESS

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Abstract
This article examines the theoretical, technological, and practical aspects of integrating generative artificial intelligence (GenAI) into personalized educational platforms. Based on an analysis of current research on intelligent learning systems and large-scale language models, the potential of generative technologies for improving learning effectiveness through adaptive delivery of materials, automatic content generation, personalized feedback, and support for metacognitive strategies is assessed.

Keywords: Generative artificial intelligence, large language models, personalized learning, intelligent learning systems, adaptive educational platforms, automatic content generation.

Introduction

Scientific Novelty. An integrative approach to the use of generative AI in personalized learning has been developed. It combines learning process adaptation, content quality control, and risk assessment, demonstrating how AI can improve learning effectiveness while maintaining pedagogical appropriateness and data security.

Personalized learning is one of the most noticeable trends in modern pedagogy, designed to take into account the individual characteristics of students: their pace, interests, learning style, and prior knowledge. Such approaches have already proven their effectiveness in intelligent learning systems (Intelligent Tutoring Systems , ITS). However, the emergence of generative artificial intelligence (GenAI), especially large language models (LLM), is opening a new chapter in the development of personalized learning.

Generative AI can create educational content (texts, assignments, explanations) in real time, as well as engage in dialogue with students, answer questions, facilitate reflection, and motivate them to continue learning. These capabilities are particularly attractive for educational platforms in the United States, where the implementation of AI in universities and schools is actively developing. For example, in the California State University system (California) State OpenAI launched a specialized version of ChatGPT to integrate generative tools into the learning process for students and teachers [1]. Furthermore, initiatives to train teachers and students in the responsible use of AI are already emerging in American schools, such as in Arlington Public Schools , where a “Year of Generative AI Research” has been declared, and teachers are being trained to work with such technologies [2]. Mandatory AI literacy is also being discussed in higher education: for example, Ohio State The University stated that all students will receive “AI Fluency ” training as part of their programs to be prepared to use AI in their professional lives [3].

On the other hand, academic research in the US has documented both positive and problematic aspects of GenAI . For example, in a recent study, STEM students described using LLM (e.g., ChatGPT) primarily to save time: they input problems into the AI to derive solutions, sometimes bypassing their own thought processes [4]. This raises the question of whether GenAI truly helps develop deep problem-solving skills or serves as a "cheat," facilitating but deepening dependencies.

Furthermore, there are significant practical and ethical challenges. A systematic review by scholars highlights numerous issues: low model transparency, the risk of hallucinations, privacy concerns, insufficient system replicability , and the lack of clear ethical standards [5]. In educational design, it is important not only to integrate GenAI into a platform but also to consider how to do so in a pedagogically meaningful way: ensuring human oversight (" human-in-the-loop "), verifying automatically generated content, and designing learning situations so that GenAI enhances, rather than replaces, thinking.

Thus, the key challenge of this paper is how to integrate generative AI into personalized education platforms in the US so that it facilitates genuine learning rather than simply speeding up the process of completing tasks.

In recent years, there has been a rapid growth in research activity focused on integrating generative AI (especially large-scale language models, LLMs) into educational systems and personalized platforms. Below is an overview of key research areas:

1. Systematic reviews of GenAI applications in higher education. In a review by TechTrends (Pedagogical Applications of Generative AI in Higher Education ") analyzes publications from the first two years after the launch of ChatGPT . The authors identified new thematic trends: creative thinking, learning autonomy, critical thinking, and prompt literacy . literacy) [6] . Researchers conducted a review of international studies on ChatGPT in higher education and identified seven thematic clusters: assessment, written assignments, ethics, perception, etc. [7].

2. Integration of LLM with knowledge tracking systems (Knowledge Tracing , KT). A Systematic Study Review of Knowledge Tracing and Large Language Models in Education : Opportunities , Issues , and Future Research » examines synergies between knowledge models Tracing and LLM: LLMs can strengthen KT models via in-context learning , potentially solving the problem of " cold start " and complementing the predictive capabilities [8] . In the work " How to Build an Adaptive AI Tutor for Any Course Using Knowledge Graph-Enhanced Retrieval-Augmented Generation (KG-RAG)" Knowledge architecture is proposed Graph-Enhanced Retrieval-Augmented Generation (KG-RAG), which combines knowledge from ontologies (knowledge graphs) with the RAG approach, enables LLM to provide context-based, accurate answers and strongly supports educational scenarios. A trial (n = 76) demonstrated significant effectiveness: an increase in grades of approximately 35% [9].

3. Specific applications of LLM tutors in subject teaching. The work “Beyond Answers: Large Language Model-Powered Tutoring System in Physics Education for Deep Learning and Precise Understanding” was developed Physics-STAR system based on LLM, for tutoring V

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physics . An experiment with high school students showed that their system increased the accuracy of answers to complex conceptual problems and improved the solution efficiency by ~5.95% [10]. In the article " Generative AI alone May not be enough : Evaluating AI Support for Learning Mathematical Proof conducted a study of LLM- Tutor , a chatbot and assistant that provides feedback on proofs in mathematics. The experimental group (148 students) improved their homework performance, although the impact on exams was less significant. A risk of overreliance on the chatbot was also identified for students with low self-efficacy [11].

4. Critical Thinking and Metacognitive Effects. In an article in the journal " Smart" Learning Environments presents a systematic review of research on LLM in teaching English as a foreign language (EFL). The authors found that the use of GenAI tools can promote critical thinking: students formulate arguments, synthesize information, and reflect on their conclusions [12]. The risks of oversimplifying thought processes are also discussed: some educators fear that students may rely on AI without engaging in independent reflection.

5. Ethical and research challenges. A recently published systematic review for postgraduate Research shows that the use of GenAI accelerates research, but raises questions about integrity, originality, and accountability [13]. Another empirical study shows that teaching strategies are transformed: teachers report increased productivity, but also the need for new teaching methods and verification of generated content [14]. Ethical concerns (academic integrity, plagiarism, misrepresented or distorted materials) regularly surface in the literature.

Integrating generative AI into personalized educational platforms requires a multi-layered architectural approach that ensures consistency across data, pedagogical decisions, and quality control mechanisms. Current thinking on such an architecture is based on a combination of traditional components of intelligent learning systems and new generative AI modules.

First layer (Learner Model) captures the learner's dynamic knowledge profile, problem-solving strategies, errors, behavior, and metacognitive parameters. Generative models can access this layer through specially adapted representations (features) . abstractions), reducing the risk of personal data leakage.

Second layer (Content Layer) includes learning objects annotated with metadata: learning objectives, cognitive complexity, and topic connections. Generative AI uses this metadata to generate content units (explanations, questions, solutions) aligned with the learning trajectory.

Third layer (Generative Layer) provides generation of training materials, answers, and recommendations. Retrieval - Augmented is often used to improve accuracy. Generation (RAG) or hybrid approaches with knowledge graphs.

The fourth layer (Pedagogical The Engine performs adaptation: it selects the next learning step, adjusts the difficulty level, and provides differentiated feedback. Integrating LLM into this layer enables the formation of flexible, context-sensitive explanations, but requires strict constraints to maintain pedagogical appropriateness.

Fifth layer (Validation & Safety) Layer) is responsible for content verification, factual correctness, error filtering, and monitoring compliance with ethical standards. Scientific literature emphasizes the need to implement automated verification (confidence) . scores , rule - based validators) and human supervision (human - in - the - loop).

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Finally, Interaction The layer defines the interaction interface. It should ensure transparency of AI decisions, support for reflection, and tools for assessing confidence in one's own knowledge.

Table 1 - Main components of the generative AI integration architecture

Architecture layer	Functions	Features of integrating generative AI
Learner Model	Storing student data, predicting knowledge	Data abstraction for secure access; profile-based generation
Content Layer	Learning Object Storage, Metadata, and Relationships	Using content metadata for conditional generation (prompt conditioning)
Generative Layer	Creation of texts, explanations, tasks, examples	RAG, knowledge graphs, style and complexity control
Pedagogical Engine	Selecting the next step of training, adaptation	Hybrid Algorithms: Rules + LLM-Based Recommendations
Validation & Safety Layer	Validation, error filtering, ethics	Fact-checking, filters , evaluation authenticity , human-in-the-loop
Interaction Layer	User interface, dialog, visualization	Explainability, transparency of decisions, support for reflection

The implementation of generative AI in personalized educational systems has already demonstrated positive results in a number of pilot projects and controlled studies. The most significant effects are observed in three areas: improved feedback quality, improved learning trajectories, and reduced cognitive load for students.

First, using LLM to generate customized explanations in STEM subjects can improve understanding of complex concepts. Experiments in which students received adaptive explanations based on analysis of their errors showed increases in mastery scores. learning and reducing the number of repeated attempts when solving problems.

Secondly, adaptive platforms that use generative AI to dynamically adjust task difficulty have been shown to improve learning efficiency. Such systems can automatically determine a student's "zone of proximal development" and adjust the level of cognitive load.

Third, a number of empirical studies have shown that generative AI can speed up the process of generating drafts, projects, and essays, thereby freeing up time for deeper analytical work. However, research also highlights the need for pedagogical validation mechanisms to prevent students from replacing their own reasoning with automated generation.

Table 2 - Examples of practical use of generative AI and observed effects

Example of application	Task type	Observed results	Restrictions
Generating Personalized Explanations in STEM	Error analysis and adaptive explanations	Improved depth of understanding; reduced number of retry attempts	Possible inaccuracies in explanations without validation
Automatic adaptation of task difficulty	Customizing the task level to the student's profile	Increased speed of learning; increased motivation	A precise learner is required model
Essay and project writing support	Drafting, reformulating	Saving time and improving the quality of final texts	The risk of over-reliance on AI
Generating training questions	Formation of various tasks	Increasing the coverage of topics and forms of control	The need to filter irrelevant tasks
Conversational learning assistants	Explanation, asking questions	Improving metacognitive strategies and reflection	Possible "hallucinations", need for supervision

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The integration of generative AI into personalized educational platforms is accompanied by a range of risks affecting both the quality of education and the legal obligations of educational institutions. First and foremost, the risk of cognitive dependence is significant: students may rely on automated response generation, reducing their own engagement in problem solving and weakening the development of critical thinking. This requires the implementation of pedagogically sound restrictions and mechanisms for reflective interaction.

Another issue concerns data privacy. Generative models can use sensitive information about students, including their academic profiles, behavioral patterns, and activity history. A breach of privacy could lead to legal consequences, particularly under FERPA and other regulations governing the processing of educational data.

Another significant challenge is model hallucination: the generation of unreliable or unverifiable information. In the educational process, this can lead to students developing false knowledge if the system is not equipped with layers of verification and interpretation.

Furthermore, there is a risk of bias and discrimination, as models can inherit structural biases from the training data. This is especially critical in adaptive systems that make decisions about task difficulty or recommendations that influence the learning trajectory.

Practical risks include operational instability, dependence on external APIs, and high computing costs, which may limit the scalability of systems. Therefore, implementing secure integration requires technical, pedagogical, and legal measures to ensure the transparency, auditability , and controllability of generative AI.

Table 3 - Main risk groups when using generative AI in educational platforms

Risk category	**Description**	**Potential consequences**	**Mitigation mechanisms**
Ethical	AI dependence, weakening critical thinking, data biases	Declining quality of education, discriminatory recommendations	Human-in-the-loop , AI transparency, regular auditing
Legal	Breach of Privacy (FERPA), Improper Handling of Personal Data	Institutional liability, data leaks	Differential privacy, data minimization, local models
Cognitive	Hallucinations and AI errors	Formation of false knowledge, disorientation of students	Fact-checking , validation layers, limitations on auto-generation of solutions
Pedagogical	Incorrect difficulty adaptation, "overtraining" on hints	Distortion of the educational trajectory	Teacher monitoring, hybrid adaptation rules
Practical	High computing resources, API dependence	Limited scalability, service instability	Caching, local inference solutions, fault-tolerant architectures

Effective integration of generative AI into personalized educational platforms requires a combination of technical, pedagogical, and organizational strategies. A hybrid approach is recommended, in which generative models complement, but do not replace, traditional

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adaptation mechanisms. This involves combining rules based on pedagogical logic with the LLM capabilities for generating explanations and variable content.
Secondly, it is necessary to implement a multi-level validation system, including automated fact checking, error filtering, and human involvement in the decision-making cycle. This architecture reduces the risk of inaccurate answers and ensures the pedagogical correctness of the created materials.
Ensuring transparency and explainability is an important component. Students should understand why the system makes certain recommendations, and instructors should have access to tools for analyzing AI decisions. This fosters trust and reduces the risk of uncritical use of the system.
It is also recommended to develop AI policies at the educational institution level, covering issues of data privacy, academic integrity, and acceptable use cases. Such policies should comply with legal regulations and reflect the specifics of the educational context.
Finally, an important component of implementation is the professional development of teachers so they can effectively use generative AI, correctly interpret its results, and integrate it into instructional design. Teacher training is seen as a key factor in sustainable and safe implementation.
Thus, the integration of generative AI into personalized educational platforms has significant potential to improve learning effectiveness, provided that careful design, quality control, and ethical standards are observed.

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