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EDU TUTOR: PERSONALIZED LEARNING WITH GENERATIVE AI AND LMS INTEGRATION.

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Abstract: Generative Artificial Intelligence (GAI) has emerged as a disruptive force in personalized

learning, offering unprecedented potential to meet the diverse needs of individual learners. Over its

developmental trajectory, GAI has evolved from early neural networks like RNNs to advanced

models such as GPT-4, powered by breakthrough technologies like transformers and multimodal

systems, enabling adaptive and dynamic educational applications. This study examines GAI's

practical applications in education, revealing its ability to transform traditional approaches by

generating personalized teaching materials, providing real-time feedback, and enhancing problem-

solving capabilities in specific subject areas. By tailoring learning experiences to individual strengths

and weaknesses, GAI fosters deeper engagement and accelerates the mastery of knowledge and skills.

Looking ahead, the integration of GAI with cutting-edge technologies such as smart classrooms,

virtual reality, and mixed-reality environments is expected to create inclusive, efficient, and

interactive learning ecosystems. By bridging the limitations of traditional education with the potential

of future technologies, GAI is poised to redefine education, making it more personalized,

collaborative, and impactful.

keywords: Generative artificial intelligence, large language model, personalized learning, AI for education,

intelligent tutoring systems

1 Introduction

Personalized learning has emerged as a focal point in modern education, driven by the need to address diverse

learner profiles and optimize educational outcomes (Bernacki et al., 2021). Traditional one-size-fits-all teaching

methods often fall short in accommodating individual differences, prompting researchers and educators to explore

innovative solutions. In this context, the integration of advanced technologies, particularly network and information

technologies, has opened new avenues for creating adaptive and learner-centric educational environments (Jiang, Li,

Zhou, et al., 2024). These developments mark a significant shift in how education is designed and delivered, laying

the groundwork for transformative approaches to personalized learning(Kaswan et al., 2024; Park et al., 2024).

Enter the era of network and information technology advancements, which have revolutionized personalized

learning. Technology-supported personalized learning now aims to intellectualize educational strategies, paths,

content, and environments, offering unparalleled convenience and efficiency. These advancements transcend time and

space constraints, providing immediate, adaptive support to students (Shemshack et al., 2021). A quintessential

example is the Intelligent Tutoring System (ITS), meticulously designed to cater to students' unique learning levels

and progress. For instance, AutoTutor aids in comprehending complex concepts in Newtonian physics, enhancing

computer literacy and critical thinking through adaptive natural language dialogue (Graesser et al., 2005). In the realm

of language learning, ITS provides personalized support in subjects like English and Chinese, leveraging speech

recognition and text analysis for skill enhancement (Aleven et al., 2004; Nye et al., 2014).

Such advancements in personalized learning are not confined to traditional methods; instead, they extend

into fields that redefine the educational landscape. With the rapid evolution of artificial intelligence (X. Li et al., 2025a;

Xu et al., 2024) and data analytics (Duan et al., 2024; Sun & Wu, 2023; Zhang et al., 2023), educational technologies

now possess the capability to process vast amounts of data, enabling a deeper understanding of students' needs. This

paves the way for more sophisticated systems that go beyond static learning experiences, offering dynamic, real-time

adjustments to educational delivery. Among these developments, the fusion of generative artificial intelligence (GAI)

and adaptive education stands out as a transformative force in the pursuit of personalized and scalable learning

solutions (Jiang, 2024).

The deep integration of GAI and adaptive education has become a key focus in educational research and

practice. It plays a vital role in various domains, including learning strategies, learning paths, learning materials, and

learning environments. GAI facilitates the development of new instructional models that combine human and machine

interactions, providing innovative approaches to achieve the goal of digitized education (Liu et al., 2024). These

models encompass instructional methods and techniques, instructional planning and assistance, material generation,

and environmental architecture (R. Li et al., 2024; X. Li et al., 2025b).

2 Development Trajectory

Humans have excelled in analytical abilities, but machines now surpass them in many domains, analyzing

large datasets for diverse applications like fraud detection and personalized content recommendations. This falls under

"Analytical AI," traditionally known as AI. However, human intelligence extends to creativity, which machines were

once unable to replicate. The advent of 'Generative AI' marks a significant shift, with machines now generating novel

and aesthetically pleasing creations, surpassing mere analysis. Figure 1 shows the key milestones in the development

of large-scale models discussed in this study.

Fig. 1 Key milestones in the development of large-scale models。 These large-scale models have undergone rapid

development in recent years and have formed large language models represented by GPT-4o

Generative AI is rapidly evolving, becoming more efficient and cost-effective, and sometimes surpassing

human creativity (Zhuang, Mao, et al., 2024; Zhuang, Wu, et al., 2024). Its influence spans industries from social

media to sales, transforming processes once reliant on human creativity (Chen et al., 2024). This could significantly

reduce the marginal cost of creative and knowledge work, leading to gains in productivity and economic value. GAI

has the potential to impact billions of workers, enhancing their efficiency and creativity by 10%, generating trillions

in economic value.

The evolution of Recurrent Neural Network (RNN) dates back to 1982 with the Hopfield network proposed

by Hopfield (Hopfield, 1982), a type of recurrent neural network. Later, Michael Jordan proposed the Jordan network

in 1986 (Jordan, 1997), which was further innovated by Jeff Elman to create the Elman network (Elman, 1990), known

as the RNN network today. To address issues in long sequence training, Sepp Hochreiter and Jürgen Schmidhuber

proposed the Long Short-Term Memory (LSTM) network in 1997 (Hochreiter & Schmidhuber, 1997). Furthermore,

Graph Neural Network (GNN) (Scarselli et al., 2008; Yin et al., 2022) is removed to facilitate better processing of

graph structured data (S. Li et al., 2024; Meng et al., 2024). In 2014, the Google team introduced the Attention

mechanism, first used in the seq2seq model. In 2017, they proposed the Transformer model, introducing Multi-Head

Self Attention and positional coding. In 2018, the Google team proposed the Bert pre-training model for natural

language processing tasks. In 2019, OpenAI introduced the GPT-2 model, which has since iterated to GPT-4. This

journey has seen rapid growth in model parameters and training data, with Reinforcement Learning from Human

Feedback adding a new stage to this development. The field of GAI will continue to undergo rapid iterations and

advancements.

3 Development Trajectory

3.1 Generating Subject Teaching Materials

Teaching materials form the cornerstone of a seamless learning journey, encompassing a range of resources

utilized for educational and instructional purposes. These resources include, but are not limited to, books, textbooks,

teaching aids, slides, laboratory equipment, and multimedia materials. The primary objective of teaching materials is

to impart essential knowledge, concepts, skills, and understanding, thereby facilitating student learning and

development. Given the unique characteristics of each academic discipline, teaching materials exhibit significant

variation across different subjects. In fields like mathematics and science, where materials are abundant and complex,

the integration of machine assistance is imperative to reduce workload. The specific supported methods are shown in

Fig. 2.

Fig. 2 GPT subject teaching materials generation

In an experimental study, Bezirhan and Von Davier explored the application of OpenAI's advanced language

model, GPT-3, in the automatic generation of reading materials (Bezirhan & von Davier, 2023). The study entailed a

comparative evaluation of the quality of texts generated by GPT-3 against original reading materials, supplemented

by minor edits from human editors. This domain poses considerable challenges and has garnered attention, with

numerous cutting-edge studies focusing on automated content generation in educational materials. Consequently, this

has become a focal point of current research and a challenging area of study. Many investigations are specifically

focused on this aspect. To be more specific:

⚫ Mathematics: Teaching materials in mathematics cover knowledge in areas such as numbers and operations,

algebra, geometry, probability, and statistics. These materials help students develop logical thinking, problem-

solving, and reasoning abilities;

⚫ Science: Teaching materials in science encompass knowledge in fields such as physics, chemistry, biology, and

other natural sciences. They explore natural phenomena, scientific principles, and experimental methods,

fostering students' observation, experimentation, and reasoning abilities;

Mathematics: In the field of mathematics, a study conducted by Frieder et al. indicates that ChatGPT's

mathematical abilities are inferior to those of graduate students in mathematics departments (Frieder et al., 2023). It

has been observed that its accuracy in solving mathematical word problems (MWP) varies with task complexity

(Shakarian et al., 2023). In the process of learning mathematics, combining assessment research and the findings

summarized in by Wardat et al., it can be identified that generative models can produce various types of mathematical

instructional materials, including (Wardat et al., 2023):

(i) Personalized hints for mathematical solutions

(ii) Practice exercises for mathematical problems

(iii) Step-by-step analysis of mathematical problem-solving processes

These three types of content can respectively serve the processes of teaching, assessing, and learning.

However, like all GPT models, including ChatGPT, there is a possibility of misconceptions when solving problems.

This is because these models are trained on large corpora containing both correct and incorrect information.

Additionally, GPT models lack reasoning and comprehension abilities, which can lead to errors or misunderstandings.

Science: In the field of scientific disciplines, existing research primarily focuses on the use of generative

models for teaching assistance or experiments in physics and chemistry.

⚫ In the domain of physics, Küchemann et al. developed physics curriculum tasks using GPT3.5 and compared

the performance of GAI in physics task generation against that of using traditional textbooks (Küchemann et al.,

2023). The experimental results showed that participants achieved high task correctness using tasks generated

by ChatGPT, surpassing average scores on conceptual tests. This finding suggests that ChatGPT can help address

potential conceptual difficulties that future physics teachers may encounter and reduce the likelihood of

converting them into assessment tasks.

⚫ In the field of chemistry, Tsai et al. proposed a solution to construct virtual models for chemical engineering

using ChatGPT, enhancing students' understanding through interactive activities (Tsai et al., 2023). Bran et al.

combined the reasoning ability of LLM with chemical expert knowledge to create the ChemCrow tool, which

provides various warnings based on user input during the chemical experimentation process and checks for

dangerous molecules before synthesis plans, serving as a valuable assistant in chemical laboratories across

various domains (Bran et al., 2023).

In addition, GAI, particularly in the form of ChatGPT's 'instructional responses,' has been increasingly

utilized in language learning, demonstrating notable efficacy across the four fundamental language skills: listening,

speaking, reading, and writing. In the realm of listening, ChatGPT is adept at creating text and audio materials that

are instrumental in enhancing listening comprehension skills, tailored to the user's proficiency level. Moving to

speaking, the technology employs natural language processing to analyze users' speech, providing feedback on

pronunciation and grammar, thereby refining their spoken language proficiency. Regarding reading, ChatGPT

contributes by offering reading materials that align with the user's ability and interests, coupled with specific strategies

and techniques to bolster reading skills. In the context of writing, the system effectively checks users' compositions

for grammatical correctness, suggesting vocabulary enhancements and stylistic improvements to elevate the quality

of written language (Liao et al., 2023). Through these applications, GAI technology, exemplified by ChatGPT's

responses, offers support in language learning. It aids learners in honing skills across listening, speaking, reading, and

writing, showcasing the multifaceted capabilities of GAI in education.

3.2 Creating Efficient Learning Environment

Generally speaking, intelligent learning environments are considered effective, efficient, and engaging

(Merrill, 2012), with learners at their core (Fig.3). These environments aim to provide self-directed, self-motivated,

and personalized services, allowing learners to participate at their own pace and access personalized content based on

their individual differences (Kim et al., 2013). Hwang highlighted potential criteria for such environments, including

context-awareness, instant and adaptive support, and adaptability to learner interfaces and subject matter (Hwang,

2014). Intelligent learning environments enable access to resources and interactions anytime, anywhere, providing

instructional guidance and support tools when needed (Z.-T. Zhu et al., 2016). They support learners' and educators'

planning and innovative approaches, embodying effectiveness, efficiency, engagement, flexibility, adaptability, and

reflectiveness (Spector, 2014).

With the advent of GAI, learning environments can become more intelligent, enabling discussions,

interactions, tutoring, and other teaching activities anytime, anywhere. They can generate targeted learning tasks

(Küchemann et al., 2023), provide intelligent assistance for experiments (Bran et al., 2023), help solve problems step

by step through Socratic questioning (Shridhar et al., 2022), and explore root causes for unresolved problems (Sarsa

et al., 2022). GAI enriches teaching methods and establishes a more efficient learning environment. Additionally, it

can enhance learning objectives by combining Bloom's taxonomy and GAI to formulate instructional objectives

(Sridhar et al., 2023). Research on intelligent educational materials has contributed to smart learning environments.

Traditional materials may not effectively convey complex information (Ericson, 2019). Augmenting textbooks with

automated annotations and relevant videos (Barria-Pineda et al., 2022), transforming e-books into interactive editions

(Sovrano et al., 2023), generating guiding questions (Van Campenhout et al., 2020), and quizzes (Dijkstra et al., 2022)

promote active learning and faster feedback. An immersive and interactive learning environment can enhance learning

performance. GAI in constructing metaverse scenarios can help engineers rapidly create complex structures (Castelli

& Manzoni, 2022). GAI can enhance users' understanding of tasks and environments, facilitating a more immersive

experience (Huang et al., 2023). Combining GAI with mixed reality technology can maximize its generation

capabilities, although its use in education is not yet widespread, its potential can be further explored.

Fig. 3 Smart Learning Environment in the GAI Era

4 Case Analyse

In the realm of utilizing GAI to enhance personalized learning, our research indicates that GAI primarily

serves as a scaffolding tool in education. This role is evident in programming education, where GAI assists in coding

exercises and code explanations (Sarsa et al., 2022), and in mathematics learning through Socratic questioning

techniques (Shridhar et al., 2022). Such instructional scaffolding extends beyond computer-based support, resembling

one-on-one or peer scaffolding. It offers tailored assistance for each student’s specific needs, exhibiting peer-like

characteristics (Kekang, 2017). The efficacy of artificial intelligence in education (Wang et al., 2023) has been further

substantiated by Wang et al. Their comprehensive research encompasses adaptive learning systems, intelligent

teaching systems, learning analytics, and educational data mining. Through GAI, learning content can be tailored to

the backgrounds and abilities of learners, offering a customized learning experience. However, it is crucial to

acknowledge that GAI is not a universal solution. It operates within a specific utility range and, while offering support

in certain educational domains, may not be effective or could introduce challenges in others. For instance, GAI is

particularly suited for scenarios such as:

⚫ G1. (Sarsa et al., 2022) GAI excels in programming learning by generating reasonable and novel exercises,

adjusting processes based on context for easy corrections. Its code explanations cover 90% of the content, with

67.2% accuracy, and errors are minor and easily correctable.

⚫ G2. (Wang et al., 2023; Wardat et al., 2023) GAI can deconstruct and solve mathematical and physics problems

into smaller components, generating progressive solutions. However, its accuracy is limited to simpler problems

and drops significantly with complexity.

⚫ G3. (Küchemann et al., 2023; Schroeder et al., 2022) GAI-generated courseware effectively integrates textbook

content and exercises, allowing students to learn while doing. It assists teachers in creating instructional materials

with task correctness, appropriate difficulty, and quality comparable to those made by teachers.

⚫ G4. (Bran et al., 2023; Tsai et al., 2023) GAI performs well in chemistry, solving reasoning tasks from simple

drug discovery to complex molecule synthesis. It assists in chemistry engineering courses by helping students

build models quickly, enhancing understanding and identifying errors.

⚫ G5. (Shridhar et al., 2022; Zhao et al., 2023) GAI's chain of thinking approach supports education similarly to

Socratic questioning strategies. While Socratic questioning enhances learning, effectiveness increases with

previous knowledge or intermediate solution information.

⚫ G6. (Sridhar et al., 2023) GAI-generated learning objectives are reasonable, correctly expressed with action verbs,

and align with Bloom's taxonomy, appropriately distinguishing between lower-level concepts and higher-level

projects.

⚫ G7. (Bitzenbauer, 2023) Teachers can use GAI to support critical thinking by guiding students through text

generation, analysis, and revision. Students generate text with GAI, analyze and evaluate it, exchange texts to

see different responses, modify them using other sources, and share findings in class discussions.

GAI is not suitable and may cause new problems:

⚫ B1. (Wardat et al., 2023) Users sometimes deceive GAI to produce incorrect or biased answers, which is

problematic in complex scenarios like mathematics, where phenomena like illusion effects can hinder learning.

⚫ B2. (Wardat et al., 2023) GAI can solve mathematical problems but lacks deep understanding, limiting its ability

to provide tailored feedback and effective solutions, and may struggle with specific student questions.

⚫ B3. (Sridhar et al., 2023) Errors in GAI-generated learning objectives can accumulate, creating larger issues

throughout the learning process and potentially increasing teacher burdens instead of alleviating them.

⚫ B4. (Küchemann et al., 2023) GAI faces challenges in answering specific questions due to data limitations, lack

of background knowledge, and insufficient reasoning and logical capabilities, even if these questions are simple

for humans.

As shown in table 1, these issues predominantly involve technical and ethical aspects. Therefore,

technological advancements and improvement of ethical policies are pivotal factors for the future utilization of GAI

to accelerate personalized learning development.

Table 1 GAI Case Analyse

Educational Problems

Help from GAI

Additional issues caused by GAI

Programming Problem Generation(G1)

Excellent

-

Program Analysis(G1)

Excellent

-

Simple Mathematics (Physics) Problem-Solving(G2)

Excellent

-

Complex Problem-Solving(B1; B2)

Bad

Hallucination phenomenon

Specific Problem-Solving(B4)

Bad

Hallucination phenomenon;Prejudice

Chemical Problem-Solving(G4)

Excellent

-

Generation of textbooks and teaching activities(G3)

good

Still requires manual evaluation

Step-by-Step Teaching(G5)

normal

-

Critical Thinking Cultivation(G7)

normal

-

Generation of Learning Objectives(G6; B3)

good

Easy to accumulate problems; Prejudice

5 Discussion

The impact of GAI's development in the field of education is rapidly expanding, and significant changes are

anticipated in the future of personalized learning. Particularly in the realm of personalized education, more effective

learning assistance, engaging educational environments, tailored learning materials, and pathways will shape future

development (Wei et al., 2024).

5.1 GAI Facilitates New Developments in Interactive Personalized Learning

The rise of GAI has transformed the traditional teacher-student model into a trinary "teacher-machine-

student" structure, shifting education towards a student-centered and demand-driven paradigm (Z. Zhu & Dai, 2023).

This structure relieves teachers of repetitive tasks, allowing them to focus on fostering student autonomy and creativity,

thereby improving learning outcomes and knowledge transfer (Huang et al., 2023). GAI supports curriculum design,

classroom instruction, learning assessment, and administrative tasks. For instance, in a middle school science class on

plant photosynthesis, GAI can generate course objectives, content, teaching steps, and hands-on experiment designs

like "starch synthesis test from green leaves" and "oxygen production in green plants." It can also create question lists,

course-related multimedia, virtual discussion groups, learning evaluation tests, and student progress reports.

Additionally, GAI serves as a virtual tutor, particularly in language learning, simulating real-life scenarios to help

students enhance their skills. Advances in virtual reality and multimodal processing further enhance GAI's role in

education, offering immersive learning experiences that boost understanding, memory retention, creativity, and

problem-solving abilities. GAI also develops interdisciplinary learning resources and guidance, helping students grasp

connections and applications across different subjects.

5.2 Efficient and Personalized Learning Guidance Assistant

With further technological breakthroughs, GAI will inspire student-centered motivation and potential,

forming a human-machine collaborative learning community. This will construct an open, free, connected, and shared

intelligent learning system, enabling higher levels of personalized learning (Jiang, Li, Wei, et al., 2024). GAI allows

students to quickly access generated learning materials based on their specific needs, providing targeted assistance in

pre-class preparation, in-class learning, and post-class review, thus increasing enthusiasm for learning. GAI deeply

analyzes learning objectives, searches relevant information, generates multiple learning topics, and evaluates the

difficulty of each topic based on students' knowledge and abilities, helping them make informed decisions (Z. Zhu &

Dai, 2023). It customizes learning materials based on context and styles, generating text-based materials or multi-

modal resources like images, videos, and audio. GAI can recommend appropriate learning paths, tasks, and provide

customized scaffolds, helping students practice and reinforce their knowledge through exercises, prompts, feedback,

and task scheduling. GAI also offers guidance in academic planning, career counseling, and psychological support

(Huang et al., 2023). However, students must critically evaluate the reliability and biases of GAI-provided information,

identify flaws, and engage in decision-making to optimize outputs. They should also avoid over-reliance on this

technology, which may hinder educational goals and development.

5.3 Driving New Developments in Paperless Classrooms

On October 20, 2014, the American magazine Time published an article titled "The Paperless Classroom is

Coming," (Schere, 2014) with the subtitle "The national shift to computers in the classroom is happening fast, with

paper, textbooks, and pencils replaced by tablets, headphones, and keyboards." Intel provided an instructional video

with a thought-provoking title: "Bridging Our Future." It aims to bridge today's classrooms with ongoing engineering

projects, paving the way for students to step into the future. Students have different interests and individual strengths.

Over a long period, there have been expectations for educators to develop appropriate textbooks catering to students

with various levels of foundational knowledge mastery. The idea is to write a textbook for each student that truly

meets their interest and satisfies their needs, which is almost an impossible task in the past. The concept of intelligent

textbooks has been proposed at an early stage and has undergone extensive research. However, before the emergence

of GAI, the intelligence reached by these studies seemed insufficient and limited. Now, with the exceptional aid of

GAI, intelligent textbooks may truly become intelligent. Through GAI, textbooks can be equipped with an outstanding

textbook expert - an intelligent mentor who can respond to any questions students may have about the material.

Students will be able to utilize a proficient evaluator who can assess their comprehension of particular knowledge or

skills and pinpoint areas that need enhancement. Moreover, they will benefit from a visionary planner who uses their

learning content and test results to help chart a personalized learning path, enabling them to achieve efficient and

personalized learning.

6 Conclusion

GAI has revolutionized personalized learning, tailoring educational experiences to individual needs.

Intelligent learning companions use machine learning to understand learners' strengths and weaknesses, offering

personalized recommendations and assessments. This customization enhances understanding and mastery of subjects.

GAI also creates immersive learning environments, promoting active participation and deeper comprehension. It

designs adaptive lesson plans, providing tailored tasks based on learners' expertise levels for optimal challenge and

support. These concepts are encompassed in In-Context Learning and Chain-of-Thought Prompting (Zhao et al., 2023).

In-context learning requires understanding context to meet students' needs. Chain-of-thought prompting helps students

incrementally acquire knowledge, as seen in Socratic questioning (Shridhar et al., 2022). Teaching assistants (Bran et

al., 2023) combine contextual understanding with chain-of-thought prompts. Future developments like VR integration

and smart classrooms highlight the need for an intelligent core capable of understanding context and providing step-

by-step guidance. This technology, emulating human thinking, marks a significant advancement in education's

personalized learning effectiveness.

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