The Advancement of Personalized Learning Potentially Accelerated by Generative AI

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Abstract

The rapid development of Generative AI (GAI) has sparked revolutionary changes across various aspects of education. Personalized learning, a focal point and challenge in educational research, has also been influenced by the development of GAI. To explore GAI's extensive impact on personalized learning, this study investigates its potential to enhance various facets of personalized learning through a thorough analysis of existing research. The research comprehensively examines GAI's influence on personalized learning by analyzing its application across different methodologies and contexts, including learning strategies, paths, materials, environments, and specific analyses within the teaching and learning processes. Through this in-depth investigation, we find that GAI demonstrates exceptional capabilities in providing adaptive learning experiences tailored to individual preferences and needs. Utilizing different forms of GAI across various subjects yields superior learning outcomes. The article concludes by summarizing scenarios where GAI is applicable in educational processes and discussing strategies for leveraging GAI to enhance personalized learning, aiming to guide educators and learners in effectively utilizing GAI to achieve superior learning objectives.

***K*eywords** Generative AI · large language model · personalized learning · educational technology

1 Introduction

Two millennia ago, Confucius introduced the revolutionary concept of "teaching students according to their aptitude,"[1] laying the groundwork for individualized teaching. This transformative idea re-emerged in John Dewey's groundbreaking research and practice, advocating for the recognition of individual differences and charting a course for flexible, personalized education in his visionary "School of Tomorrow." This philosophy propelled the early 20th century's new education movement, leading to significant shifts from traditional, one-size-fits-all teaching approaches to methods that emphasize personalized learning strategies, cooperative learning, and activities tailored to students' interests and needs. Despite these advances, the large-scale implementation of personalized learning has historically faced formidable challenges due to technological limitations.

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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[2]. 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[3]. 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[4, 5].

However, traditional ITSs often demand extensive expert input for content and course structure creation, limiting their scalability and personalization. To address these limitations, researchers have delved into the 'inner loop' of ITS, focusing on specific instructional guidance like feedback and evaluations[6]. Despite advancements in big data, computing, and algorithms, constructing efficient inner loops remains costly and inefficient[7, 8]. Conversely, the 'outer loop' is more adaptable, encompassing learner profile analysis and task decision-making. Yet, long-standing technical challenges have hindered accurate analysis and decision-making in this domain.

This is where Generative AI (GAI) comes in. The advent of GAI, particularly large language models like ChatGPT, has dramatically accelerated the progress of personalized learning. But how exactly does GAI propel personalized learning forward at such a remarkable pace? There is still no comprehensive summary of its contributions. So, this paper aims to bridge that gap by thoroughly exploring the origins, various models, and applications of GAI in personalized learning.

We categorize these applications into Learning Strategies, Paths, Teaching Materials, and Learning Environments[9]. Furthermore, we examine the transformative impact of GAI on teaching and learning practices.

The subsequent sections are organized as follows: Section 2 provides an overview of GAI's historical development and current models. Section 3 discusses GAI technologies in personalized learning. Section 4 analyzes the profound changes GAI has brought to teaching and learning, and Section 5 contemplates the future of personalized learning with GAI, delving into methodologies and findings from extensive research.

2 Generative AI: A Milestones in the Evolution of Machine Intelligence

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.

Generative AI is rapidly evolving, becoming more efficient and cost-effective, and in some cases, surpassing human creativity. Its influence spans industries from social media to sales, transforming processes once solely reliant on human creativity. This could significantly reduce the marginal cost of creative and knowledge work, leading to gains in labor productivity and economic value. GAI has the potential to impact billions of workers, enhancing their efficiency and creativity by at least 10%, generating trillions of dollars in economic value.

The evolution of RNN networks dates back to 1982 with the Hopfield network proposed by Hopfield [10], a type of recurrent neural network. Later, Michael Jordan proposed the Jordan network in 1986 [11], which was further innovated by Jeff Elman to create the Elman network [12], known as the RNN network today. To address issues in long sequence training, Sepp Hochreiter and Jürgen Schmidhuber proposed the LSTM network in 1997 [13]. 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. As shown in Fig.1. This journey has seen rapid growth in model parameters and training data, with the introduction of Reinforcement Learning from Human Feedback (RLHF) adding another stage to this development. The field of GAI will continue to experience rapid iterations and advancements.

3 Applying Generative AI in Personalized Learning Approaches

The deep integration of GAI (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. These models encompass

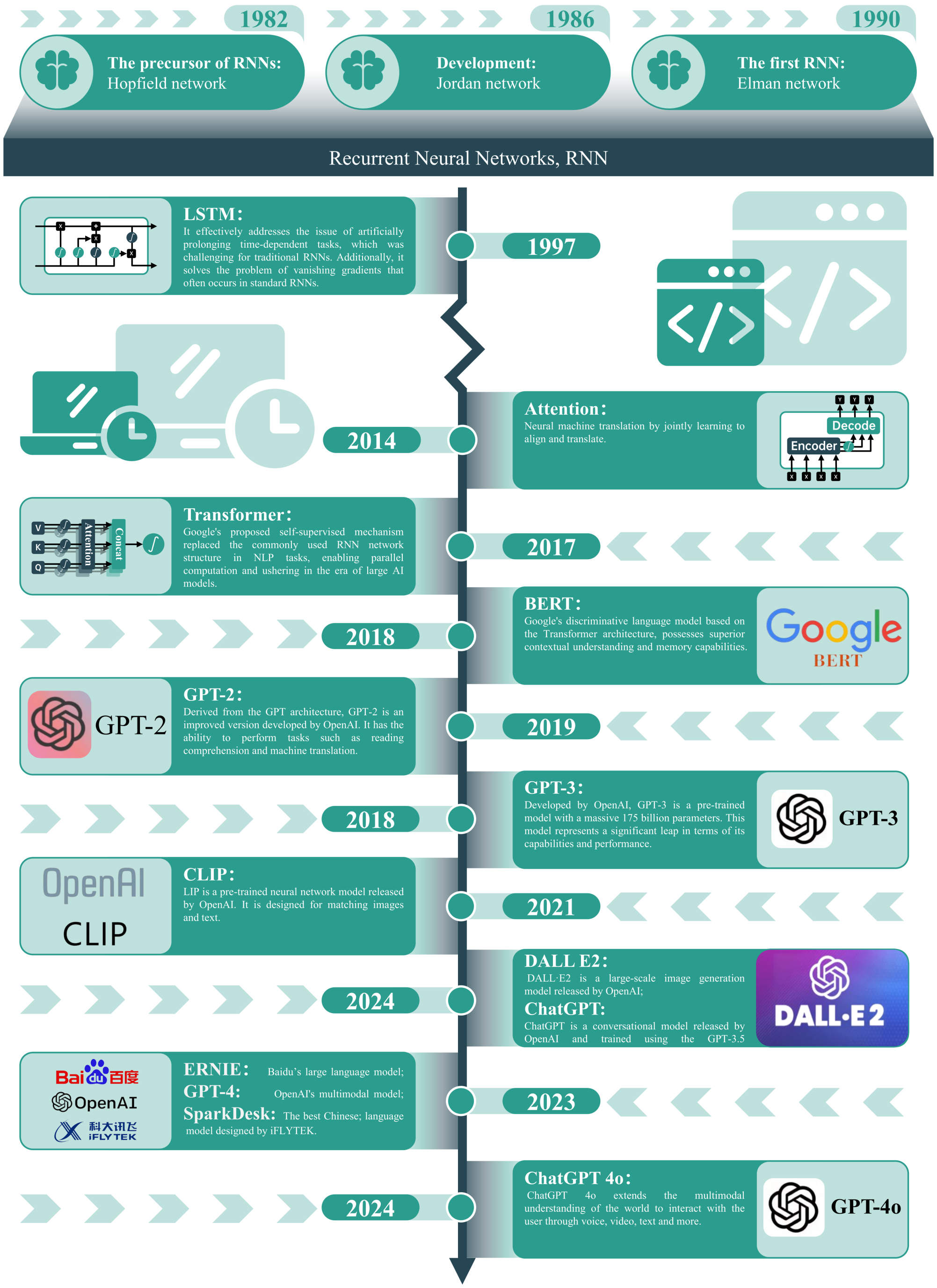

Figure 1: Key milestones in the development of large-scale models

instructional methods and techniques, instructional planning and assistance, material generation, and environmental architecture.

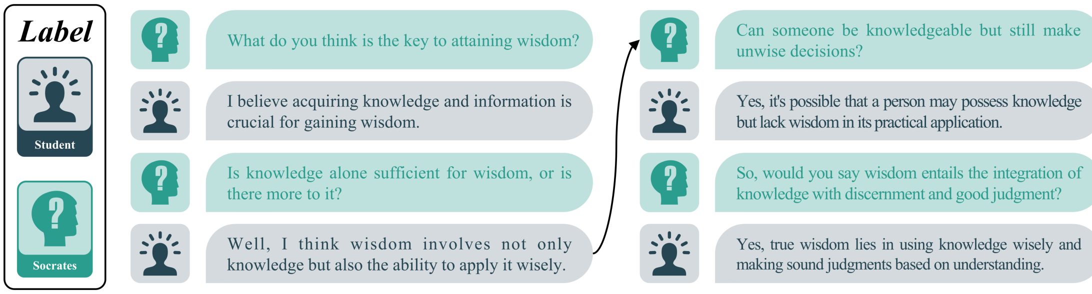

Figure 2: Socratic Q&A generated by ChatGPT

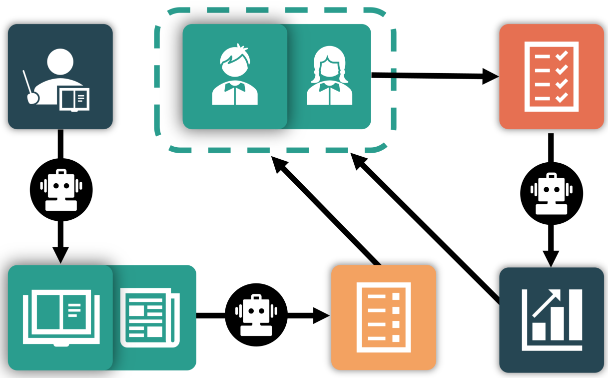

Figure 3: The Lifecycle of Programming Exercises: (1) Teachers create programming exercises and learning materials. (2) Students study the materials and practice the exercises. (3) Students receive feedback

3.1 Assisting in Generating Learning Strategies

Since 1987, the field of education has been exploring how to teach students to learn[14]. From the Latin School Movements[15] to the massive Head Start Program[16], researchers have been dedicated to the exploration and development of learning strategies. Learning strategies can be defined as behaviors that learners aim to influence the way they process information[17]. For example, emphasizing key ideas in an article, summarizing opinions of a lecture, or attempting to articulate newly learned information in one's own words.

The use of question prompts as a learning strategy plays a guiding role throughout the problem-solving process for students[18]. This form of questioning, recognized as an effective scaffolding strategy[19], holds great value in supporting student thinking and is widely employed in high-quality mathematics instruction[20]. The emergence of GAI has brought about significant changes to the research on question prompts, such as Socratic questioning learning. Socratic questioning(Fig.2) is a teaching method that promotes deep learning by guiding students to think and explore[21, 22]. Traditionally, this requires teachers to actively ask questions and interact with students in the classroom. However, GAI can simulate the process of Socratic questioning by automatically generating targeted questions based on students' responses and performance, prompting them to engage in deeper thinking and analysis. This personalized questioning approach can help students actively participate in learning, enhancing their understanding of learning content and critical thinking skills[19]. In a recent study, researchers explored using large language models to generate Socratic-style mathematical question-answering[23, 24]. They emphasized the importance of questions being Focused and Goal-driven, targeting key knowledge in specific domains to help students achieve learning goals[18, 25].

On the other hand, GAI excels in programming education by providing personalized exercises and project tasks based on students' coding proficiency and knowledge levels. It integrates theory with practical application, helping students master programming languages, algorithms, and problem-solving techniques. Acting as a programming tutor, GAI offers real-time suggestions, analyzes code, and provides targeted recommendations for optimization.

Specifically, the strategies for programming education are consistent with those of other subjects. Programming courses and assignments typically progress in complexity, gradually introducing new concepts while ensuring that students are not overwhelmed, thus avoiding cognitive overload[26] and fostering students' proximal development[27]. The

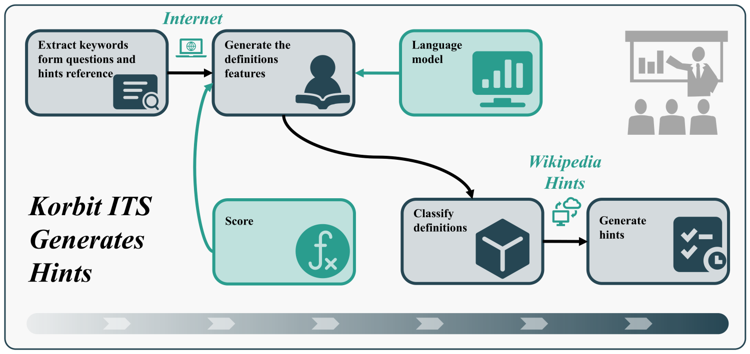

Figure 4: Korbit ITS generates hints

design of programming courses and assignments often aligns with the concept of deliberate practice[28], facilitating mastery through consistent practice[29, 30, 31]. Apart from creating programming assignments, teachers frequently provide feedback to students on their coursework[32, 33, 34]. In recent research, [35]used Codex to formulate more personalized programming learning strategies. Similar to the GPT[36]model, Codex[37]is a large language model developed by OpenAI with a specific focus on comprehending and generating programming languages. Sarsa and colleagues[35]investigated novel methods to create programming exercises that enhance the quality of generated content by introducing concepts in a structured manner. They also incorporated step-by-step explanations, as it aligns with the multi-structural levels of the SOLO taxonomy and is often generated by students when prompted to explain code[38]. This learning strategy makes it easier for students to achieve their learning objectives. This structure is shown in the Fig.3.

3.2 Planning Personalized Learning Path

The learning path is the implementation of learning strategies. It consists of a set of learning activities that help users achieve specific learning goals. Personalizing pathways has become an important task due to differences in users' limitations, backgrounds, and goals[39]. Technology and instructional innovation are redefining education. The core of this integration is e-learning. Nowadays, using electronic learning systems such as Intelligent Tutoring Systems (ITS) has become commonplace[40]. These systems aim to provide educational resources to users[41]. They have several advantages compared to traditional learning methods, where the teacher plays a major role and controls the classroom. The main advantages include availability[42], cost reduction [43], improved collaboration[42], enhanced flexibility (students can learn at their convenience), etc[44]. With the emergence of GAI, there have been new methods for learning pathway generation.

In ITS, prompts are a common form of instructional guidance or planning. Generative models have greatly improved the personalization and accuracy of prompts. In [45], learning guidance and planning are carried out in the Korbit ITS using three steps: keyword recognition, determining sentence spans, and generating prompts through embedded language model technology (Fig.4). Additionally, during the generation step, the model incorporates explanations based on Wikipedia to help students better understand and remember concepts effectively. Empirical research has shown that personalized prompt generation significantly improves students' performance, while explanations based on Wikipedia provide valuable learning feedback.

On the other hand, research has found that structuring learning experiences in the form of interactive "narratives" or "stories" told by the learning environment can enhance learner engagement[46, 47]. Making the learning approach more interactive and aligning learning path presentation with typical narrative structures can expedite students' achievement of learning goals[48]. In[48], an AI-based approach was proposed to automatically generate learning content and integrate it into the appropriate positions within the learning path (Fig.5). In other words, the interactive narrative sequences that conform to general narrative expectations are constructed by intertwining the learning path with the automatically generated learning content referred to as narrative fragments. The method proposed in this study constructs this interactive narrative in a domain-agnostic manner[48]. It can generate narrative fragments for learning resources in any format, unlike many AI-based learning environments that accept only specific formats of learning sources. Though narrative fragments can be created manually, they would cost a large amount of time and effort. Additionally, AI-based learning content generation methods can achieve adaptive learning by dynamically generating content based on learner-driven variations. Ultimately, the model built using GPT-2[23] has shown excellent results in empirical research.

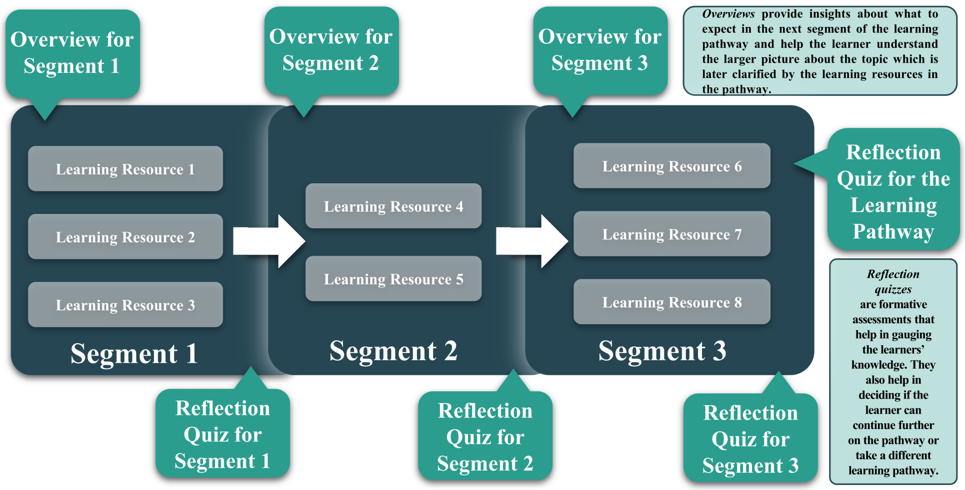

Figure 5: Learning Pathway showing different segments and addition of narrative fragments

3.3 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 both abundant and complex, the integration of machine assistance is imperative to reduce the human workload. The specific supported methods are shown in the Fig.6.

In an experimental study, Bezirhan and Von Davier[49] explored the application of OpenAI's advanced language model, GPT-3, in the automatic generation of reading materials. 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 considerable 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 cutting-edge 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. [50] indicates that ChatGPT's mathematical abilities are inferior to those of graduate students in mathematics departments. It has been observed that its accuracy in solving mathematical word problems (MWP) varies with task complexity[51]. In the process of learning mathematics, combining assessment research and the findings summarized in by Wardat et al. [52], it can be identified that generative models can produce various types of mathematical instructional materials, including:

(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 text corpora that contain both correct and incorrect information. Additionally, GPT models lack human-like reasoning and comprehension abilities, which can sometimes lead to errors or misunderstandings.

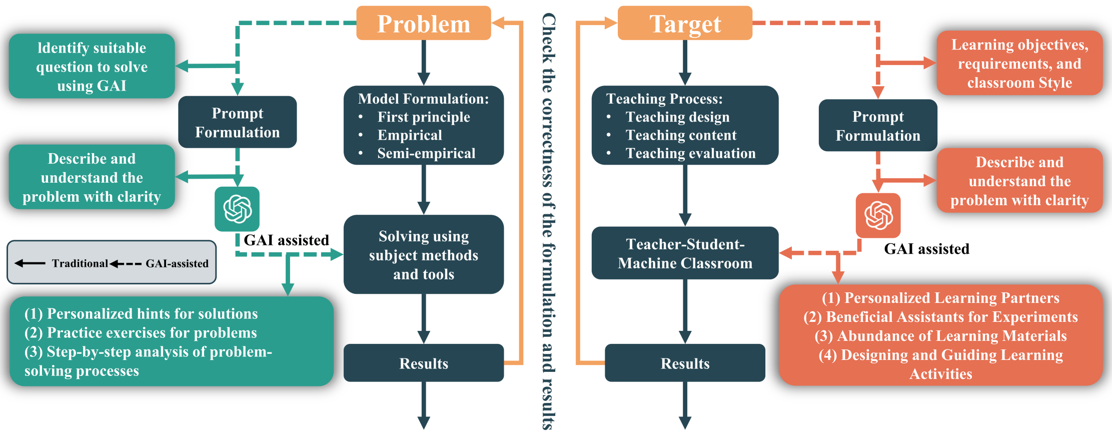

Figure 6: GPT subject teaching materials generation

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. [53] developed physics curriculum tasks using GPT3.5 and compared the performance of GAI in physics task generation against that of using traditional textbooks. 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. [54] proposed a solution to construct virtual models for chemical engineering using ChatGPT, enhancing students' understanding through interactive activities. Bran et al. [55] 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.

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[56]. Through these diverse applications, GAI technology, exemplified by ChatGPT's instructional responses, offers comprehensive support in language learning. It effectively aids learners in honing their skills across listening, speaking, reading, and writing, showcasing the multifaceted capabilities of GAI in educational environments.

3.4 Creating Efficient Learning Environment

Generally speaking, intelligent learning environments are considered effective, efficient, and engaging [57], with learners at their core (Fig. 7). 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 [58]. Hwang [59] highlighted potential criteria for such environments, including context-awareness, instant and adaptive support, and adaptability to learner interfaces and subject matter. Intelligent learning environments enable access to resources and interactions anytime, anywhere, providing instructional guidance and support tools when needed [60]. They support learners' and educators' planning and innovative approaches, embodying effectiveness, efficiency, engagement, flexibility, adaptability, and reflectiveness [61].

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 [53], provide intelligent assistance for experiments [55], help solve problems step by step through Socratic questioning [62], and explore root causes for unresolved problems [35]. 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 [63]. Research on intelligent educational materials has contributed to smart learning environments. Traditional materials may not effectively convey complex information [64]. Augmenting textbooks with automated annotations and relevant videos [65], transforming e-books into interactive editions [66], generating guiding questions [67], and quizzes [68] 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 [69]. GAI can enhance users' understanding of tasks and environments, facilitating a more immersive experience [70]. 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.

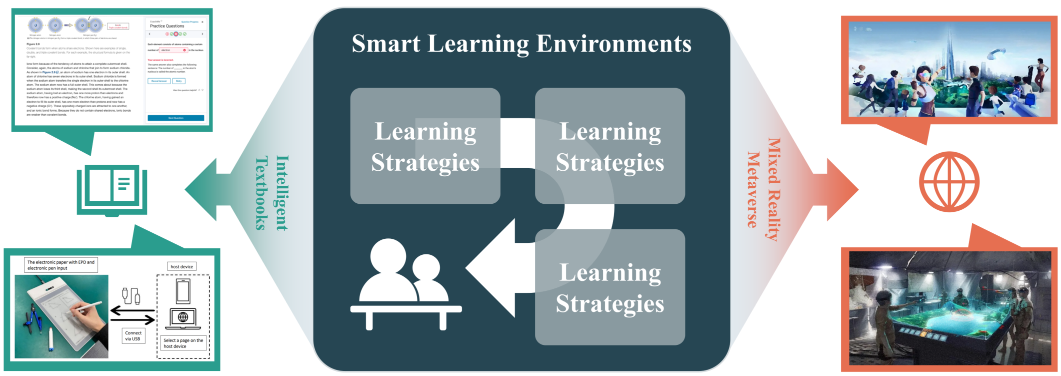

Figure 7: Smart Learning Environment in the GAI Era

4 How does Generative AI transform teaching and learning

4.1 Assistance for Teaching

GAI has the potential to assist in the teaching process, ease teacher workload and improve teaching efficiency. To ensure the effective integration of GAI into pedagogical practice, it is crucial to recognize the capabilities of AI and comprehend the roles of teachers in this process. Therefore, the analysis will be conducted from both technical and teachers' perspectives. Below we discuss how GAI may offer teachers opportunities for improved planning, implementation, and assessment in their teaching, and the roles of teachers in these processes.

4.1.1 Planning, implementation and assessment

GAI integration in educational planning aids teachers in creating instructional materials and fostering interactive teaching practices. GAI generates personalized content and resources, such as GPT-4's learning objectives for AI courses [63] and a Human-NLP system for reading quiz questions [71]. Applications include adaptive courseware [72], personalized practice problems [35], and ChatGPT-assisted lesson planning [73]. ChatGPT helps teachers with instructional goals and strategies, enhancing classroom discussions with examples and scenarios. Markel et al. developed 'GPTeach' for teacher training, allowing practice with simulated students [74]. GAI enables teachers to craft high-quality pedagogical plans and curate resources, dynamically refining plans based on simulated student responses.

During implementation, GAI assists teachers in providing immediate, tailored feedback. Large language models offer feedback on writing tasks [75], and in programming education, they provide feedback on syntax errors with a validation mechanism [76]. Machine-learning approaches in ITS automate feedback generation, improving students' success rates with personalized hints and explanations [45]. Teachers supplement AI feedback by providing sub-step feedback, refining system feedback, and offering emotional support [77, 78]. Emotional support from teachers fills gaps in AI's ability to provide a human touch, facilitating social interaction and contextualizing learning experiences [79].

GAI aids in automating evaluations and providing insights for assessment improvement. GPT-3 has been used for automated essay scoring with reliable accuracy on TOEFL11 essays [80], and to simplify math word problems, improving readability [81]. Assessments benchmarked against GPT identified strengths and weaknesses in engineering education, offering recommendations for future assessment design [82]. Teachers must supervise GAI output and design comprehensive assessments, verifying AI-generated evaluations [83] and monitoring GAI performance [84]. Diversified assessment methods, including formative and summative assessments, group projects, hands-on activities, and oral presentations, are necessary for comprehensive evaluation of students' abilities [85]. Collaborative research is needed to further explore the roles of teachers and GAI in assessment.

4.1.2 Complementary relationships between teachers and GAI in education

The relationship between GAI and teachers in adaptive learning environments emphasizes hybrid intelligence, shifting from AI replacing teachers to augmenting their capabilities. The most effective adaptive learning combines AI and human facilitators [86, 87, 88]. Holstein et al. [86] identify four key areas where AI and teachers can enhance adaptability: goal, perceptual, action, and decision augmentation. Jeon and Lee [87] explore role division between teachers and GPT to maximize teaching effectiveness, showing potential for collaboration in curriculum planning, teaching implementation, and evaluation. Bai et al. [89] note the evolving role of teachers in AIED, focusing on guiding learning, assessing performance, and offering personalized support.

AIED tools enable teachers to better understand students' needs and progress by analyzing data, leading to more personalized teaching plans. These tools also assist in classroom management and supervision, allowing real-time monitoring of student engagement and automating grading to reduce workload and improve efficiency.

However, caution is needed to avoid over-reliance on algorithms, which might overlook human factors or misuse data. Teachers must ensure AIED tools enhance their role in promoting student learning and development. Despite progress, empirical studies on the collaboration between teachers and GAI in adaptive learning are limited, requiring further research to optimize this synergy.

4.2 Assistance for Learning

From learners' perspective, GAI holds the potential to offer multifaceted assistance to the learning process. The diverse range of applications provided by GAI can be roughly categorized into three kinds according to the type of content they provide, including direct solutions, hints and instructional cues, and heuristic dialogues.

4.2.1 Provide learners with direct solutions

Generative AI assists learners by providing solutions to various problems, including math, coding, and essay writing. Wardat et al. [52] found that ChatGPT proficiently executes mathematical operations, manipulates algebraic expressions, and solves complex calculus problems. Poesia et al. [90] enhanced code generation reliability using large pre-trained language models. This capability allows learners to quickly access learning resources and potential solutions to their problems. A study [91] explored Quillbot's impact on students' writing skills, finding it effectively helped students preprocess text and reduce plagiarism. The study, conducted in three stages—planning, implementation, and evaluation—showed improved paraphrasing skills among English education majors. However, the accuracy of GAI-generated solutions can vary with problem complexity and context, necessitating double-checking by learners [52, 90]. As GAI advances, more reliable solutions are expected to enhance learner support across various scenarios.

4.2.2 Offer instructional cues and hints to learners

Another approach for GAI to assist learners is by offering instructional cues and hints. Constructivism emphasizes learners' active role in constructing knowledge through hands-on experience or problem-solving. Providing hints and scaffoldings can aid learners without harming their initiative. Pankiewicz and Baker [92] used GPT-3.5 to generate personalized hints for programming assignments, which were positively received by students and improved their task-solving abilities. An experiment with a Chatbot-Assisted Classroom Debate (CaIcD) involved students using a chatbot named Argumate to support their viewpoints and present opposing perspectives. This helped students anticipate counterarguments and prepare effective rebuttals, leading to more organized and substantial arguments and higher motivation [93]. However, students showed a lower success rate initially when switched to more complex tasks without GPT-generated hints, indicating potential reliance on GAI [92]. A study [94] found AI applications beneficial for supporting metacognitive, cognitive, and behavioral regulation aspects in online education but less effective for motivational regulation. Abdelghani et al. [95] used GPT-3 to generate pedagogical cues to stimulate children's curiosity, enhancing their question-asking abilities. Other examples of GAI-generated scaffoldings include code explanations [35] and reading quizzes [71]. Learners can leverage GAI-provided cues and scaffoldings to improve their learning experience.

4.2.3 Facilitate Heuristic Dialogues for Learning

Generative AI can leverage the “Socratic Method" to facilitate learning through discussions, Q&A sessions, and debates. This method fosters critical thinking by engaging students in a dialectical process of questioning and inquiry, helping them independently analyze, evaluate, and understand complex concepts. Recent work has used GAI to implement Socratic questioning strategies. Shridhar et al. [62] explored using large language models (LMs) to generate sequential questions for solving math word problems. They found that LMs could produce effective questions that improved problem-solving performance in simple tasks, but the efficiency decreased with task difficulty, potentially hindering performance in more complex tasks. Another study introduced a dataset of Socratic conversations to help novice programmers fix bugs and test the Socratic debugging abilities of GPT-based models [96]. The study found that human experts outperformed GPT-based models in generating Socratic questions for debugging and noted the risk of repetitive and irrelevant questions from GPT, which could mislead learners. Besides problem-solving, Socratic questioning can also involve eliciting clarification, evidence, and implications. Future research should explore more ways to integrate GAI with the Socratic method to support learners in various contexts.

5 Discussion and conclusion

5.1 Practical Case Discussion

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[35], and in mathematics learning through Socratic questioning techniques[62]. 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[97]. The efficacy of artificial intelligence in education has been further substantiated by Wang et al[98]. 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. [35] GAI excels in programming learning by generating reasonable and novel exercises, adjusting processes based on context for easy corrections. Its code explanations cover 90
- G2. [52, 99] 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. [53, 72] 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. [54, 55] 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. [62, 100] GAI’s chain of thinking approach supports education similarly to Socratic questioning strategies. While general Socratic questioning enhances learning, effectiveness increases significantly with previous knowledge or intermediate solution information.
- G6. [63] 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. [101] 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. [52] 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. [52] 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.

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

B3. [63] 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. [53] 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 the table 1, these existing issues predominantly involve technical and ethical aspects. Therefore, technological advancements and the improvement of ethical policies are pivotal factors for the future utilization of GAI to accelerate personalized learning development.

5.2 Discussions on the Future of Personalized Education in the Development of GAI

The impact of GAI's development in the field of education is rapidly expanding, and significant changes are expected in the future of personalized learning. Especially in the realm of personalized education, more efficient learning assistance, engaging learning environments, personalized learning materials, and pathways will become the direction for future development.

5.2.1 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 [102]. This structure relieves teachers of repetitive tasks, allowing them to focus on fostering student autonomy and creativity, thereby improving learning outcomes and knowledge transfer [103]. 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.

5.2.2 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. 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[102]. 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[103]. However, students must critically evaluate the reliability and value bias of information provided by GAI, identify flaws or errors, and engage in decision-making control to correct and optimize outputs. They should also be cautious of developing over-reliance on this technology, which could hinder educational goals and holistic development.

5.2.3 Driving New Developments in Paperless Classrooms

On October 20, 2014, the American magazine Time published an article titled “The Paperless Classroom is Coming,"[2] 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.

5.3 Conclusion of Personalized Learning in the Development of GAI

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[100]. In-context learning requires understanding context to meet students’ needs. Chain-of-thought prompting helps students incrementally acquire knowledge, as seen in Socratic questioning[62]. Teaching assistants[55] 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.

ETHICS STATEMENT

No ethics agreement was required for this project as the authors have only worked with previously published material.

CONFLICT OF INTEREST STATEMENT

The authors have no conflicts of interest to declare.

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