

# Empowering Personalized Learning with Generative Artificial Intelligence: Mechanisms, Challenges and Pathways

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**Abstract** The rapid development of artificial intelligence technology has propelled the automated, humanized, and personalized learning services to become a core topic in the transformation of education. Generative artificial intelligence (GenAI), represented by large language models (LLMs), has provided opportunities for reshaping the methods for setting personalized learning objectives, learning patterns, construction of learning resources, and evaluation systems. However, it still faces significant limitations in understanding the differences in individual static characteristics, dynamic learning processes, and students' literacy goals, as well as in actively differentiating and adapting to these differences. The study has clarified the technical strategies and application services of GenAI-empowered personalized learning, and analyzed the challenges in areas such as the lag in theoretical foundations and lack of practical guidance, weak autonomy and controllability of key technologies, insufficient understanding of the learning process, lack of mechanisms for enhancing higher-order literacy, and deficiencies in safety and ethical regulations. It has proposed implementation paths around interdisciplinary theoretical innovation, development of LLMs, enhancement of personalized basic services, improvement of higher-order literacy, optimization of long-term evidence-based effects, and establishment of a safety and ethical value regulation system, aiming to promote the realization of safe, efficient, and sustainable personalized learning.

**Keywords** personalized learning, generative artificial intelligence (GenAI), learning patterns, application mechanisms

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## 1 Introduction

In the wave of comprehensively deepening educational reform, reducing the burden and increasing efficiency have become an important driving force for the development of high-quality education in the new era. To realize this objective, the key lies in how to improve the quality of large-scale education while also catering to the individual developmental needs of students. The rapid development of artificial intelligence (AI) technology has provided new possibilities for solving this challenge, especially its data-driven diagnostic approach to differential needs has given rise to the diversity of personalized cultivation models, promoting the automatic humanization of personalized learning services to become the core content of educational reform in the era of AI. Faced with learners who have different preferences, intelligent machines can track and record the entire learning process, diagnose the unique needs of learners, and then provide them with targeted teaching guidance. Personalized learning provides learners with a more efficient and enjoyable interactive experience, increasing their opportunities to receive high-quality education (Maghsudi et al., 2021). The essence of achieving efficient personalized learning is the highly precise matching of learners' unique needs with the application of intelligent technology. As educational reforms continue deepening and the needs of learners become increasingly complex, society has raised higher demands for the precision, adaptability, and customization of intelligent technology in the application of personalized learning. In recent years, generative artificial intelligence (GenAI) technology, represented by large language models (LLMs), has been rapidly evolving. The introduction of ChatGPT, in particular, has sparked human contemplation of the potential applications of GenAI in the field of personalized learning. Thanks to its powerful content generation capabilities, GenAI makes the interaction

between educational entities and intelligent technology more natural and flexible, and the content of interaction more diverse and creative, continuously pushing learning toward a more intelligent and precise direction. Against this backdrop, leveraging GenAI technology to pay close attention to the dynamic and static differences among individual learners and exploring the theoretical and practical applications of personalized learning have become a core topic in the construction of educational informatization.

GenAI-empowered personalized learning (GenAI-PL) primarily achieves personalized human-machine learning interaction based on core technologies such as model fine-tuning and prompt engineering. During the interaction process, the intelligent machine will diagnose the learners' need based on personal and process data, and generate customized learning content. Additionally, GenAI can use past interaction data for self-learning and iterative optimization to provide learners with more accurate and personalized content recommendations. With GenAI's capabilities in multimodal data processing and interdisciplinary knowledge integration, GenAI-PL goes beyond just recommending learning resources, it also involves the cognitive, emotional, and social experiences of learners. Despite this, the process of GenAI-empowered personalization still faces some challenges. For instance, the fine-tuning of models or the embedding of personalized prompts needs to follow certain teaching principles, which requires educators to intervene manually based on the current state of learners, making full automation difficult to achieve. Additionally, the iterative tuning process in GenAI-PL may lead to resource waste in terms of data and computational power, affecting the feasibility and operability of GenAI-PL. Additionally, as GenAI deeply integrates with educational scenarios, it also faces a series of risks such as algorithmic bias, excessive dependence on the subject, and the lack of ethical standards (Yang, 2024), which result in a significant gap between the application of GenAI and the needs of personalized learning. Therefore, this study clarifies the theoretical foundations and application mechanisms of GenAI-PL, proposes technical strategies and application services for efficient personalized learning, and systematically reviews the main challenges and corresponding strategies of GenAI-PL, in order to provide theoretical guidance for the specific practice of GenAI in empowering personalized learning.

## 2 Theoretical Foundations and Implementation Mechanisms for GenAI-PL

### 2.1 | Connotation of GenAI-PL

Personalized learning is about designing suitable

learning plans for students based on their individual characteristics and preferences, and optimizing learning strategies in real time according to the varying needs of students. In this process, it is necessary to closely follow the students' zone of proximal development, dynamically adjust learning objectives, methods, and content based on their learning processes and behavioral feedback. By establishing appropriate learning scaffolds, true "teaching students according to their aptitude" can be achieved. Personalized learning is an educational philosophy based on "humanistic" theory, placing the learner at the core of educational teaching to tailor learning methods and pathways. It has transformed the way learners interact with machines and plays a key role in enhancing learning interaction and engagement. Personalized learning, empowered by GenAI technology, is an adaptive learning approach that is based on educational large models, supported by individual and process data of learners, centered around differentiated learning through human-computer interaction, and led by highly customized content generation .

GenAI-PL has the following three core characteristics: (1) generating highly customized learning content. Based on the educational philosophy of teaching students according to their aptitude, GenAI can dynamically generate learning resources of varying depths according to the learners' interests, abilities, goals, and needs. (2) Providing contextualized and immersive learning experiences. GenAI enhances the authenticity and engagement of learning interactions by generating educational resources related to real-life or virtual scenarios, effectively facilitating the transfer and application of knowledge. (3) Supporting real-time adaptive learning assessments. By conducting a comprehensive analysis of individual and process data of learners, GenAI enables real-time assessment and feedback on learning progress, and provides data-driven decision support for the following steps in learning. To achieve efficient and reliable personalized learning empowered by GenAI, it is not only necessary to have advanced and appropriate theories to provide guidance, but also to have a thorough understanding of the adaptability technologies in human-computer interaction to offer support.

### 2.2 | Theoretical Foundations of GenAI-PL

GenAI-PL transforms the traditional human-computer interaction model, where students initiate requests and machines respond passively, into a model based on multi-round dialogues that enable deep-level negotiation and cognitive collision between humans and machines. In this process, GenAI needs to deeply explore the patterns of education and teaching in specific scenarios, cognition, behavior, and emotional

changes of students, and generate adaptive content by combining data characteristics with the inherent nature of technology. Thus, the implementation of GenAI-PL requires theoretical support from fields such as education, psychology, and AI, which mainly include humanistic theories, constructivist learning theories, multiple intelligences theory, embodied cognition theory, and distributed cognition theory.

### 2.2.1 Humanistic Theory

Humanistic theory emphasizes the importance of personalized learning, advocating that education should be centered on the comprehensive development of learners (Romig & Cleland, 1972), valuing their individual uniqueness, emotional needs, self-actualization, and overall development. Through the conversational interaction between students and GenAI, along with the fine-grained analysis of students' learning requests, GenAI can better understand the personalized needs of learners, push appropriate personalized learning resources during the learning process, and enhance comprehensive learning experiences that include cognition, emotion, and social aspects.

### 2.2.2 Constructivist Learning Theory

Constructivist learning theory reveals that learning is essentially a dynamic process in which learners actively construct their own knowledge systems (Packer & Goicoechea, 2000). Learning requires shared knowledge construction and collaboration, and the design of personalized learning paths should fully support and stimulate this intrinsic motivation (Bada & Olusegun, 2015). GenAI, by achieving multi-dimensional linkage among individuals, behaviors, and mitigation, can create learning situations related to real life, encouraging learners to explore solutions. At the same time, GenAI provides highly customized learning content for learners, supporting their independent thinking and knowledge construction.

### 2.2.3 Multiple Intelligences Theory

Multiple intelligences theory posits that the diversity in individual combinations of intelligences should be respected and encouraged, and personalized learning strategies should value and actively cultivate this uniqueness (Gardner & Hatch, 1989). GenAI can analyze the dimensions of learners' intelligences to provide learning resources and tasks that align with their personal strengths. By designing cross-intelligence learning activities, it can achieve a balanced development of learners' multiple intelligences, thereby enhancing overall learning outcomes.

### 2.2.4 Embodied Cognition Theory

Embodied cognition theory posits that cognitive processes are not independent of the body and environment but are dependent on the body and its interactions with the environment (Foglia & Wilson, 2013). GenAI can combine technologies such as virtual reality and augmented reality to create immersive learning scenarios, helping learners to better understand knowledge through physical interaction and sensory experiences. GenAI, by understanding the learners' background, task objectives, and emotional states, can generate personalized learning content and pathways that meet the learners' contextual needs.

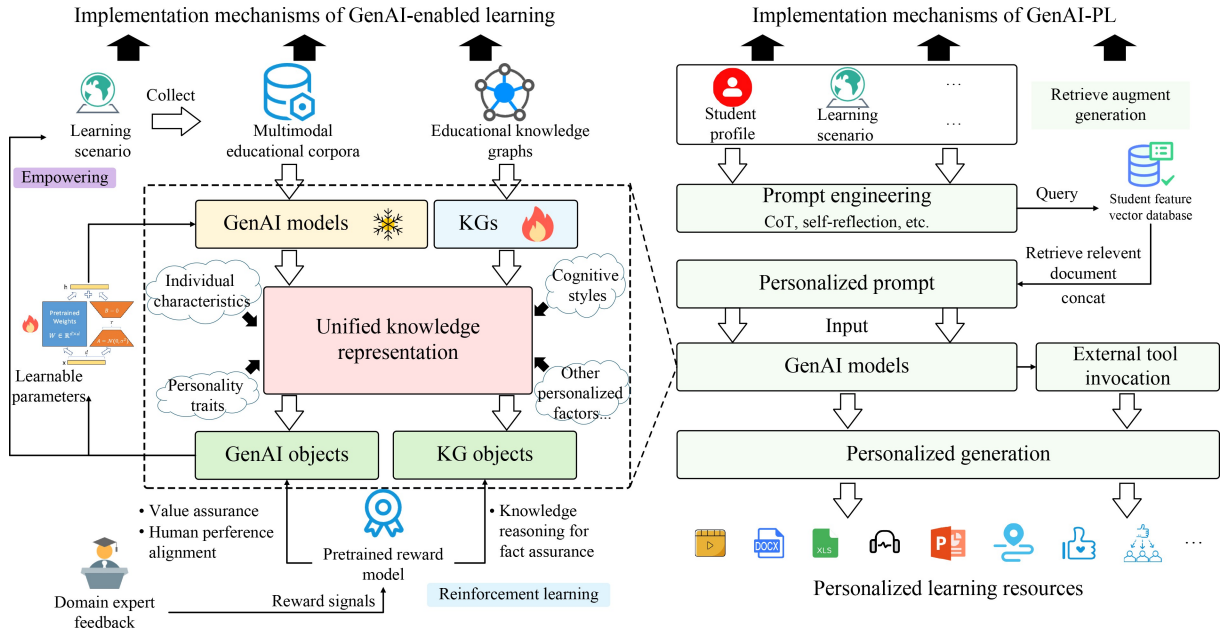
### 2.2.5 Distributed Cognition Theory

Distributed cognition theory emphasizes that cognitive processes are not confined within an individual's mind but are distributed within the individual, between individuals, through media, and within social interactions (Moore & Rocklin, 1998). It is an information processing activity that integrates and exchanges internal representations within the individual's mind and external representations in the environment. GenAI can serve as an advanced cognitive tool to form cognitive synergy with learners. Additionally, GenAI can provide dynamically adaptive learning guidance based on the cognitive needs of learners across different times and locations.

## 2.3 | Implementation Mechanisms of GenAI-Enabled Learning

Understanding the mechanisms by which GenAI supports learning can help grasp the core functions and operational principles of GenAI technology in the field of education, thereby laying the foundation for its in-depth application in the field of personalized learning. The starting point for GenAI in learning scenarios is LLMs with strong general capabilities, which possesses basic abilities such as understanding and generating text, and logical reasoning. This is the cornerstone for fine-tuning GenAI in the field of education. To enable a general GenAI to understand the specific knowledge in the field of education, we need to inject knowledge from the educational domain into it, such as large-scale educational corpora, existing educational knowledge graphs, and expert feedback content (Dan et al., 2023). This ensures that it can generate personalized learning materials based on student characteristics and input prompts, as shown in the left of Figure 1.

First, a large-scale educational corpus collected from real learning scenarios is input into GenAI for low-rank fine-tuning. The purpose is to maintain the



**Figure 1** The implementation mechanism of GenAI in empowering learning. CoT: chain of through; GenAI: generative artificial intelligence; KG: knowledge reasoning; PL: personalized learning.

model’s general generative capabilities while enabling GenAI to learn the linguistic characteristics, terminologies, concepts, and knowledge systems of the educational field, as well as to understand the common expressions, logical relationships, and knowledge structures in education.

Second, by further integrating existing teaching knowledge graphs that cover a variety of content from subject knowledge to teaching methods, training graph neural networks or graph parsers to encode the knowledge graphs as model inputs, GenAI’s teaching reasoning and semantic understanding capabilities are explicitly enhanced. The large model integrated with graph reasoning can not only generate content (GenAI objects) but also demonstrate the logic of knowledge reasoning (KG objects).

Third, an additional reward model is trained to simulate expert feedback on generated content and knowledge reasoning logic, reducing the workload of expert annotation. The reward model scores the value alignment and preference alignment of the content generated by GenAI, as well as the factual reliability of the knowledge reasoning logic (Yildiz Durak, 2023). These scores serve as reward signals to optimize GenAI, which includes two optimization objectives: maximizing generation quality and maximizing reward signals.

Fourth, the well-trained GenAI model is deployed into teaching scenarios, where new teaching data and feedback are continuously collected. The model is further fine-tuned using the newly collected data to continuously improve the accuracy and adaptability of GenAI in empowering learning.

From a technical perspective, GenAI’s empowerment of personalized learning also has a certain degree of appropriateness. Specifically, the core of GenAI lies in simulating human intelligence to understand and adapt to complex and variable environments, which aligns with the customization, flexibility, and adaptability pursued by personalized learning (Chen et al., 2024). A fine-tuned GenAI possesses the reasoning capabilities for personalized learning, often empowering learning through the implementation mechanism shown in the right of Figure 1.

First, GenAI employs prompt engineering techniques to construct template-based specific responses. The prompt templates include features such as user instructions, student personalized information, and teaching background information, combined with the chain-of-thought and self-reflection prompts to enhance the model’s reasoning capabilities.

Second, to enhance the model’s ability to understand the personalized characteristics of different students, GenAI employs the retrieval-augmented generation (RAG) method (Lewis et al., 2020). It retrieves the student’s personalized features from the student feature vector database and concatenates them with the original prompt, customizing a Socratic teaching plan. This plan actively engages students in the cognitive processes essential for truly mastering problem-solving ability (Liu et al., 2025).

Third, GenAI calls upon external tools in areas where it is not proficient to extend its generative and reasoning capabilities, ultimately producing personalized teaching materials.

Thanks to GenAI's powerful reasoning capabilities, scalability, multi-domain adaptability, technological ecosystem, and appropriateness for personalized learning, it is subtly reshaping the methods for setting personalized learning objectives, learning models, the construction of learning resources, and the evaluation system, gradually promoting a revolution in the system of personalized learning (Yu et al., 2024).

## 2.4 | Gap Between Current GenAI and Personalized Learning Requirements

Despite the impressive potential demonstrated by GenAI, it still has significant limitations in deeply understanding the differences in student's literacy objectives, individual static characteristics, and the dynamics of the learning process.

### 2.4.1 Regarding the Satisfaction of Individual Static Differences

Constructivist theory posits that each learner enters the learning context with their own unique prior characteristics, which encompass individual static differences. These are the relatively stable, unchanging personalized traits of learners during the learning process, such as cognitive abilities, prior knowledge and experience, and learning motivation and emotions. However, most existing GenAI systems are trained to be end-to-end based on pattern matching, which tends to capture the commonalities within a group and often struggles to uncover the implicit individual static differences. Specifically, in terms of cognitive ability exploration, current GenAI often relies on superficial behavioral data, which struggles to accurately assess the deep cognitive abilities of learners, and GenAI cannot understand the subtle differences in cognitive styles. In terms of modeling prior knowledge and experience, different students have varied backgrounds, knowledge systems, and levels of understanding, making it difficult for GenAI to accurately identify gaps in learners' knowledge systems and provide adaptive tutoring. In terms of understanding learning motivation and emotions, different learners have different levels of motivation and interest. GenAI cannot understand the true learning motivations behind learners, nor can it comprehend the role of emotions in learning. It is also unable to stimulate students' enthusiasm for learning like a human teacher, let alone to build trust through interaction to inspire students' interest in learning.

### 2.4.2 Regarding the Adaptation to Dynamic Process Differences

Constructivism emphasizes the dynamic process by

which learners autonomously construct their knowledge systems, and the differences in the learning dynamic process reflect the personalized learning trajectories exhibited by learners during the learning process. Existing GenAI operates primarily based on learning from large amounts of data. It analyzes historical data to predict future behaviors, essentially forecasting the unknown based on the known. This "data-driven" approach excels in static, patterned tasks, but struggles to capture the dynamic evolution of the human learning process. The learning process for learners is not a simple linear process, but rather a complex one that involves continuous trial and error, adjustment, reflection, and construction, filled with uncertainty and nonlinear changes. This is the intense collision between the essence of GenAI's data-driven nature and the dynamic evolution of human learning, resulting in a contradiction. The aforementioned contradiction causes the model's understanding of the real learning process to remain on the surface of behavior, making it difficult to reach the intrinsic mechanisms of student learning.

### 2.4.3 Regarding the Supporting Higher-Order Literacy Objectives

Inspired by humanistic theory, GenAI-enabled personalized teaching must be centered on the comprehensive development of learners, with literacy objectives being an indispensable part of it. Learners' literacies, especially non-cognitive literacies such as critical thinking, creativity, cooperation, and communication skills, are comprehensive reflections involving emotional attitudes and values. However, existing GenAI learns from quantifiable data and patterns, and this modeling approach based on statistics and likelihood has obvious limitations in areas such as creativity, bias response, complex problem reasoning, and abstract semantic understanding. These limitations restrict GenAI's ability to understand the differences in literacy objectives. Specifically, in terms of developing higher-order thinking skills, GenAI struggles to capture the complex connotations and dynamics of these literacies, to differentiate between students' surface behaviors and their deep literacies, and to capture the challenges students encounter, the efforts they make, and the shifts in their ways of thinking during the learning process; in terms of value cultivation, different cultural backgrounds have varying understandings and emphases on literacy, and GenAI's training data often includes corpora from different countries and regions, inevitably influenced by specific cultural backgrounds, leading to potential value biases when assessing and nurturing literacies (Adeshola & Adepoju, 2023); in terms of emotional attitude support, since the

cultivation of literacy requires not only cognitive understanding but also emotional identification and support, the majority of GenAI currently do not possess emotional understanding and empathy capabilities (Zhang et al., 2024b), making it difficult to provide personalized support with warmth.

### 3 Technical Solutions and Application Services for GenAI-PL

#### 3.1 | Technical Solutions for GenAI-PL

To better empower personalized learning with GenAI, there are primarily two viable solutions, as shown in Figure 2.

##### 3.1.1 Edge-Based GenAI Solutions for Personalized Learning

First, knowledge distillation is performed using the cloud-side GenAI on a teaching domain dataset to obtain a lightweight edge-side GenAI; second, this GenAI is deployed on a learner’s terminal device, providing basic learning services while ensuring privacy protection. During the service process, local data collection, storage, and preprocessing are conducted; third, through end-to-end automatic incremental training, the model is continuously fine-tuned based on

local learner interaction data, gradually optimizing the distilled model. This allows the model to gradually perceive the learner’s personalized factors, ultimately providing a highly customized learning experience.

##### 3.1.2 Personalized Learning Solution for GenAI Under the Guidance of Pedagogical Theory

This solution incorporates personalized factors into the GenAI through techniques such as prompt engineering, involving both design and implementation phases. During the design phase, experts manually write prompts that integrate personalized factors for processes such as multimodal perception, pattern discovery, learning diagnosis, personalized generation, and feedback reception. These prompts are crafted to ensure they are correctly understood by the GenAI and can stimulate its reasoning capabilities; in the implementation phase, experts also need to consider personalized factors for specific processes, define the logic for prompt invocation, write specific code scripts to link different prompts, and apply prompt enhancement strategies. This ultimately leads to the creation of a comprehensive personalized learning service workflow.

Generally speaking, a complete GenAI-PL solution needs to include the following three core functionalities: multimodal perception, pattern discovery and learning diagnosis based on learning analytics, and

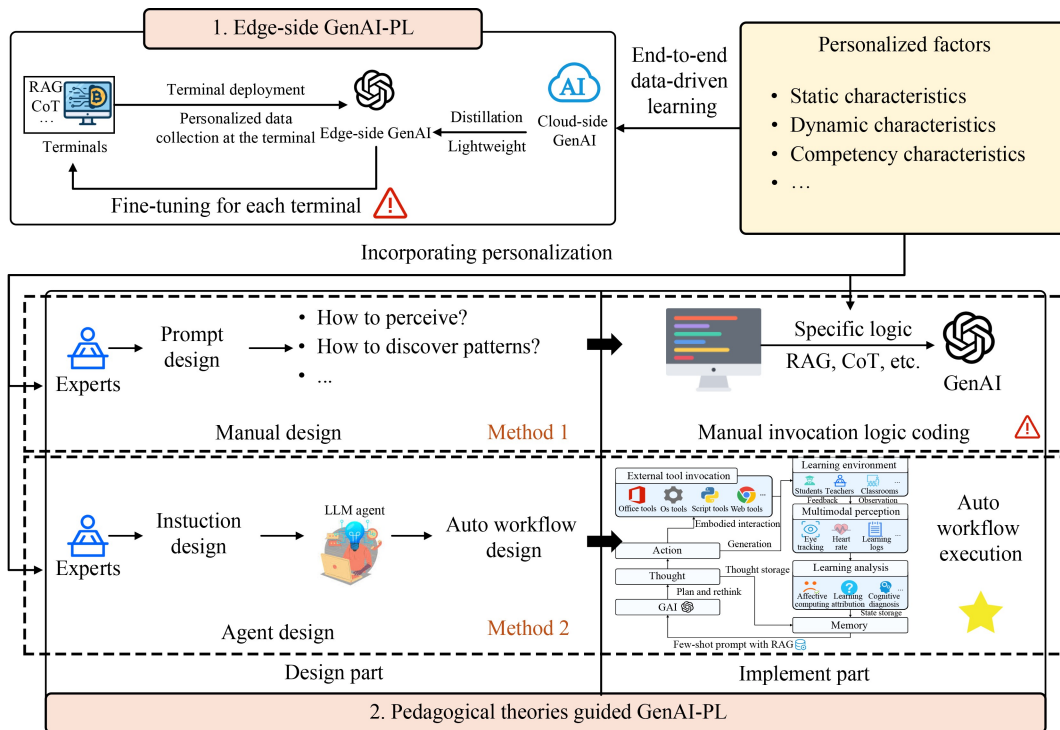


Figure 2 GenAI-driven personalized learning technology solution diagram. CoT: chain of through; GenAI: generative artificial intelligence; PL: personalized learning; RAG: retrieval-augmented generation.

embodied learning.

*Multimodal perception.* Perceptual intelligence refers to the ability of machines to perceive and understand the external world. In personalized learning, it is primarily used to perceive various learning elements and their interrelationships. Beyond traditional classroom observation tools such as cameras and microphones, GenAI can connect with wearable devices to monitor students' physiological signals, such as heart rate, skin conductivity, and brainwaves, and combine these with behavioral data and learning records to explore the student's implicit learning states (Sonlu et al., 2024). Additionally, GenAI can quickly infer the current learners' learning topics and objectives based on teaching context information. By perceiving the learners' locations and times, GenAI can assess the learning environment and the time of learning, providing support for adjusting the learning content, methods, and pace (Song et al., 2023). GenAI can also perceive social data to gather information about students' social media activities and interactions on learning platforms, understanding their learning groups and social relationships. This enables further exploration of the students' role and contributions in group learning, thereby providing support for collaborative learning. For the perceived multidimensional data, first, GenAI performs preprocessing and alignment. This involves cleaning, normalizing, and feature extraction for different modalities of data to ensure uniform data formats, facilitating subsequent processing; second, contrastive learning or self-supervised learning tasks are employed for semantic alignment across different modalities; third, methods such as attention mechanisms, concatenation, or cross-modal mapping are used to integrate features from different modalities, allowing the model to understand the correlations between them. This enables a more comprehensive and in-depth understanding of students' information, providing a more accurate basis for personalized learning.

*Pattern discovery and learning diagnosis based on learning analytics.* Computational intelligence refers to the ability of machines to perform reasoning, learning, and decision-making through algorithms. It is the core driving force behind personalized learning. Faced with the multidimensional and complex student learning data, GenAI maps learning modalities to the learners' characteristic representation and, in the process, uncovers potential patterns and risks in student learning (Le et al., 2024). In pattern discovery, GenAI deeply analyzes various dimensions such as students' learning time, learning paths, resource utilization, and interaction behaviors, along with their interrelationships. Using techniques like explainable knowledge tracing and time-series analysis, GenAI uncovers deep patterns and characteristics in students'

learning modes and knowledge mastery levels (Liu et al., 2021). This enables further exploration of the causal relationships between teaching elements and processes, quantifying their contribution to learning outcomes; in learning diagnosis, GenAI comprehensively evaluates dimensions such as students' knowledge and skill mastery, learning strategies, and more. It utilizes cognitive diagnosis and affective computing models to identify subtle anomalies and diagnose cognitive, behavioral, and emotional factors during the learning process. This leads to the explainable identification and prediction of potential cognitive bottlenecks, psychological crises, burnout, and other risk factors (Huang et al., 2025).

*Embodied learning.* Embodied intelligence refers to the intelligence generated through the physical form of the body and its dynamic interaction with the environment. This is one of the most prominent advantages of GenAI compared to traditional AI technologies. In the personalized learning process, GenAI constructs a responsive and adaptive learning ecosystem, continuously offering learners a simulated environment that aligns with their learning goals. It provides multisensory stimuli and allows learners to explore freely, choosing their own learning path based on their interests. In the dynamic learning process, GenAI analyzes learners' behaviors and provides instant feedback to guide their learning (Wang et al., 2024), enabling more personalized teaching.

The rapid development of large model distillation and lightweighting technologies has enabled deployment on edge devices (Huang et al., 2024; Jin & Wu, 2024; Kundu et al., 2024; Qin et al., 2024; Sreenivas et al., 2024). However, in practical personalized learning, there are hardly any strategies based on such methods (Latif et al., 2023; Sander et al., 2025). Because each GenAI needs to be independently optimized and fine-tuned in consideration of the personalized needs of learners. That is to say, on one hand, this approach prevents cross-learner sharing and requires significant computational resources for each student, leading to high computational costs and the risk of overfitting to local training data; on the other hand, the existing personalized learning solution guided by educational theory involves a complex workflow, requiring experts to manually write high-quality prompts, develop meticulously structured code, and conduct rigorous system testing. Most of the work (Bany Abdelnabi et al., 2025; Ng & Fung, 2024; Park et al., 2024) requires pre-setting prompts, or manually resetting prompts at specific learning stages, or integrating them into the system to construct prompts through code invocation. For example, Wang et al. (2024) presents ChatPRCS, a personalized English reading comprehension system that manually designs different prompt patterns based on students' cognitive levels to generate tailored

questions and evaluations using ChatGPT. However, prior work not only creates high barriers to entry and difficulty but also incurs substantial labor and testing costs. Both solutions have significant limitations, making them difficult to implement in practical use. GenAI-based intelligent agents possess unique capabilities in personalized planning, environmental adaptability, and interactive learning. These capabilities allow them to overcome the limitations of the aforementioned solutions while still meeting the needs of personalized learning. For example, Gao et al. (2025) introduces Agent4Edu, a personalized learning simulator that leverages LLM-powered generative agents to simulate learners' response data and detailed problem-solving behaviors for intelligent education systems. In addition, Swan et al. (2025) develops a tool named Math Agents which translates difficult math concepts into understandable formats, making them easier for students to grasp. Many other studies have mentioned the potential of using agents in personalization in future work (Chen et al., 2023; Li et al., 2024; Zhang et al., 2024a). Therefore, the technology of GenAI-based intelligent agents has inspired another personalized learning solution guided by educational theory and holds great promise for transforming education by tailoring educational experiences to individual needs, as shown in the bottom subfigure of Figure 2.

An intelligent agent can generate automatic workflows through instruction input. A workflow is a series of steps and rules defined to accomplish a specific task. In this context, the intelligent agent interacts with various elements of the teaching environment, dynamically planning its own path, thought processes, and action execution steps. Experts only need to define the tasks for the intelligent agent based on personalized factors. The agent will automatically carry out the iterative optimization process of planning, generation, perception, analysis, memory, learning, and re-generation according to the workflow until the task is completed. This approach offers better ecological benefits and practical feasibility.

The agent effectively addresses the shortcomings of GenAI in empowering personalized learning and has the following characteristics: In terms of perceptual intelligence, due to the enhanced level of human-computer interaction, the agent can more deeply perceive the personalized characteristics of students during interactions and provide a more comprehensive insight into the various elements of learning; in terms of computational intelligence, on one hand, because memory units centrally store dynamic contents such as the agent's work plans, action execution status, learners' status, and workflow evolution, the agent possesses stronger dynamic feature perception and contextual computational reasoning

capabilities. This temporal modeling approach provides more in-depth and comprehensive evidence for pattern discovery. On the other hand, the agent's deeper insight into learners enables it to have a stronger ability to integrate learning analysis results and to be better at learning diagnosis from multidimensional learning state changes. The agent's embodied intelligence is supported by workflows, allowing for more autonomous and flexible exploration and learning abilities with just task instructions as input. Under the premise of being ecologically friendly and having relatively simple processes, it can adapt more dynamically and robustly to learners' feedback, providing better support for personalized student learning.

### 3.2 | Application Services of GenAI for Personalized Learning

Based on the core intelligences of GenAI in perception, computation, and embodiment, it primarily supports the realization of personalized learning through four key application services.

#### 3.2.1 Supporting Precise Data Mining and Performance Evaluation

GenAI, with its powerful natural language processing and deep learning capabilities, can perceive and process educational data from various channels and forms. This goes beyond just academic performance, encompassing multidimensional data such as learners' behaviors, interaction logs, and more. Based on this, GenAI performs personalized analysis of learners' learning processes and outcomes across multiple dimensions, enabling both teachers and students to gain timely and accurate insights into personalized learning effectiveness. For example, by mining behavior data such as click-through rates and interaction frequencies on online learning platforms, GenAI can predict learners' interests and preferences, as well as forecast their future learning trends or potential learning risks. Compared to traditional personalized learning assessments, GenAI can incorporate multidimensional indicators such as emotions and social factors, enabling a comprehensive evaluation of students' competencies. Specifically, emotional analysis techniques can be used to assess learners' emotional changes and social interaction levels. Additionally, by analyzing learners' response patterns and logical reasoning processes, GenAI can evaluate students' innovative thinking abilities.

#### 3.2.2 Supporting Cognitive/Non-Cognitive Diagnosis and Content Generation

Based on the comprehensive learning data collected and its powerful computational intelligence, GenAI can

break through the limitations of traditional education's single learning model. It is capable of accurately identifying learners' personalized characteristics and diagnosing their unique needs. This personalized learning diagnosis no longer focuses solely on learners' cognitive needs; it may also involve diagnosing non-cognitive needs, such as learners' emotional states and learning motivations (Binhammad et al., 2024). Through comprehensive diagnosis of learners' unique needs, GenAI can generate adaptive learning content or learning paths tailored to the educational context and recommend them to learners. For example, GenAI can diagnose learners' emotional burnout state during the learning process and generate suggestions or resources that help alleviate their negative emotions. Additionally, GenAI can flexibly integrate interdisciplinary knowledge and resources, encouraging learners to approach problems from multiple perspectives and solve them in a holistic manner, thus expanding their knowledge horizons.

### 3.2.3 Supporting Interactive Problem-Solving and Real-Time Feedback

This is also a core aspect of GenAI's application in personalized learning. For specific problems encountered by learners during the learning process, GenAI can provide immediate and targeted solutions. This real-time personalized feedback helps learners optimize their learning strategies (Chiu, 2024). At the same time, GenAI does not just provide direct answers; it can guide learners by asking reflective questions or expanding on the problem, encouraging them to understand the issue from multiple perspectives and stimulating deeper critical thinking. This guided problem-solving approach enables students not only to receive immediate feedback but also to cultivate stronger independent thinking and problem-solving skills. More importantly, GenAI can further clarify feedback through an interactive feedback loop. If a student fails to understand a particular piece of feedback, GenAI can rephrase the explanation or provide examples in different ways to ensure better understanding.

### 3.2.4 Supporting Enhanced Learning Experiences and Creativity Cultivation

GenAI's embodied intelligence can support personalized learning systems in generating virtual learning scenarios based on learners' needs. This goes beyond offering static learning content; by utilizing technologies such as virtual reality and the metaverse, it creates immersive learning environments for learners, enhancing both the sense of immersion and the enjoyment of the learning experience. At the same time,

by generating diverse learning materials such as videos, images, and audio, GenAI can help learners understand complex concepts from multiple dimensions, enriching their sensory experiences (Rusmiyanto et al., 2023). Additionally, GenAI can guide learners to explore multiple possibilities for solutions by generating novel questions or ideas. In this way, learners can access a wealth of creative resources in a short amount of time, thereby stimulating their own creative thinking.

## 4 Key Challenges Related to GenAI-PL

### 4.1 | Educational Theories Lag behind and Lack of Practical Guidance

Personalized learning empowered by GenAI not only needs to reflect teaching philosophies such as "learner-centered," "teaching students according to their aptitude," and "instruction based on learning," but also must focus on the comprehensive development of students' core competencies. Although traditional educational theories such as humanism and constructivism provide a theoretical foundation for GenAI-powered personalized learning, the ever-evolving developments in AI, which lead to pervasive environments, diverse subjects, and dynamic processes, present significant challenges in the applicability of existing educational theories for guiding personalized learning practices in the AI era. These challenges are primarily reflected in the following three aspects:

#### 4.1.1 Lack of an Innovative Foundational Theory Focused on Human-Machine Collaborative Enhancement

Personalized learning content generation based on GenAI primarily relies on contextual deep collaboration and interaction between humans and machines. In this process, the human-machine relationships and interaction methods are quite complex. From the perspective of technological phenomenology, the relationships between humans and machines includes four types: embodiment relation, hermeneutic relation, alterity relation, and background relation (Ihde, 1974). In the process of personalized learning empowered by GenAI, there may be overlaps among the four types of relationships mentioned above, ultimately aiming to achieve human-centered human-machine collaborative symbiosis. This involves mutual learning and promotion between humans and machines. However, there is currently no innovative theory to support the explanation of the intrinsic mechanisms and pathways of this process.

#### 4.1.2 Lack of Innovative Application Models Focused on the Cultivation of Core Competencies

Due to the influence of performance-oriented practices in traditional education, current personalized learning practices still tend to emphasize knowledge transmission while neglecting the development of core competencies. The cultivation of core competencies in the new era requires the establishment of new, feasible models for the application of GenAI technology in learning, assessment, and management. These models must integrate the concept of competency development into all aspects of personalized learning, including the construction of learning contexts, content integration, and learning path design. However, there is still a lack of theoretical guidance in this area, making it difficult to truly innovate and transform traditional personalized learning models.

#### 4.1.3 Lack of a Systematic Evidence-Based Framework Focused on Optimizing Practical Outcomes

To achieve deep empowerment for learners' short-term goals and long-term planning, the application of GenAI technology needs to leverage scientific data and evidence support. It should continuously iterate and optimize based on the practical outcomes of personalized learning, while also providing theoretical insights and experience for further personalized learning practices. However, due to issues such as the difficulty of integrating the full process of GenAI-PL data and the lack of a scientific evaluation system, a major challenge lies in how to establish a data-driven, systematic evidence-based framework for diverse scenarios in personalized learning practice.

### 4.2 | Weak Autonomy and Control of Educational Large Models

To improve the accuracy and adaptability of GenAI-powered personalized learning, it is urgent to develop specialized large models driven by data and knowledge tailored for specific learning services. These models need to integrate domain-specific expertise with learners' characteristics to support personalized learning services. The main challenges in this process are as follows.

In terms of knowledge learning, the education field is often multidimensional and interdisciplinary, with high dynamism and complexity. Currently, GenAI lacks the ability for deep interdisciplinary reasoning when integrating knowledge from different disciplines (Sajja et al., 2024), which leads to difficulties in the integration and updating of knowledge in the educational field. For example, GenAI may not be able to achieve deep interdisciplinary understanding in areas

such as the integration of physics and mathematics or the connection between history and sociology. Additionally, learners' knowledge systems are complex and personalized, making it a persistent challenge in personalized learning to incorporate learners' complex prior knowledge into the pre-trained models of GenAI.

In terms of model training, there is still a lack of high-quality annotated data specific to the personalized learning domain, leading to suboptimal model performance and wasted computational resources. This is likely due to the difficulty of collecting large amounts of multimodal data in personalized learning processes. Annotating such data requires specialized knowledge and educational experience, making the annotation process complex and costly.

In terms of content generation, limitations in the support of domain-specific knowledge and high-quality training data for large models can result in the phenomenon known as hallucination, where the model generates content that deviates from facts or does not align with real-world needs. The hallucination problem is a key factor currently limiting the practical deployment of generative AI technologies. It arises from the low inference ability of GenAI, which leads to the generation of seemingly plausible but false or incorrect content. This can cause learners to receive incorrect information, affecting learning outcomes and potentially leading to cognitive biases, thereby restricting the widespread application of GenAI in personalized learning.

### 4.3 | Insufficient Understanding and Adaptation to Learning Processes and Learners

A deep understanding of and adapting of the learning process and individual learners' characteristics is key to enabling GenAI to effectively empower personalized learning. Currently, the challenges in this process are primarily reflected in the following two aspects.

In terms of understanding of and adapting to individual learners' characteristics, GenAI faces difficulties in deeply and comprehensively mining learners' personalized traits and needs for dynamic adaptation. Current systems primarily rely on learners' historical data and behavior patterns, and there are shortcomings in responding to changes in learners' needs in real-time. Learners' needs are often not obvious and are not static. For example, a learner's interests or long-term development plans may not be directly manifested in the short term, nor can they be easily reflected through simple interaction data. Additionally, due to the lack of comprehensive exploration of learners' contextual information, there is a risk of bias in the interpretation of personalized traits based on multimodal data such as learners' behavior

and text (Xu et al., 2023a). This can lead to the generation of learning paths that do not truly align with the students' actual needs. Moreover, large models trained on general learning data may perform well for specific groups, but they struggle to adapt to each individual learner. At the same time, excessive optimization of individual learners' characteristics could lead to a situation where the system, while providing personalized services, overlooks the common needs of the learner group as a whole, resulting in biased or one-sided learning recommendations. Therefore, finding the right balance between personalization and universality is a major challenge in enabling personalized learning with GenAI.

In terms of understanding of and adapting to the learning process, the process involves complex multidimensional features such as cognition, emotion, and social factors. Some of these features may be implicit and difficult to capture through traditional behavioral data mining or simple semantic analysis. As a result, GenAI may fail to fully capture and understand the changes in learners' multidimensional states at different stages of their learning journey. In the interpretation of learning processes, the ambiguity of learners' behavior semantics and the dynamism of learning processes both constrain the precise understanding and in-depth modeling of learning processes. Existing research has pointed out that learners' behavioral data often have multiple interpretations (Heikkinen et al., 2023), and current data mining methods are often unable to interpret the true intentions behind these behaviors, making it difficult to accurately determine the learners' actual cognitive states. Moreover, existing personalized learning systems, which are typically based on general models, lack sensitivity to cultural backgrounds and course characteristics in specific scenarios, making it difficult to achieve a deep understanding of learning contexts and provide adaptive support. Additionally, learners' needs and task statuses are in constant real-time flux. One of the current challenges during the learning process is how to dynamically uncover and understand their cognitive, emotional, and social states, and to achieve bidirectional adaptation between these dimensions.

#### 4.4 | Missing Mechanisms for Enhancing Students' Higher-Order Literacy

In personalized learning environments, although GenAI has made significant breakthroughs in cultivating learners' basic skills, it still has limitations in enhancing higher-order literacy, which are mainly reflected in the following three aspects:

GenAI-PL lacks support for learners' social

interactions. Current personalized learning systems focus more on content generation and recommendations for individual learners, making it difficult to support the construction of social scenarios such as team collaboration, and thus failing to promote abilities in collaboration and interpersonal interaction. The learner-centered paradigm originates from social constructivism theory, which posits that learning occurs through social interaction, rather than allowing learners to study at their own pace in isolation (Laak & Aru, 2024). Consequently, establishing a mechanism for cultivating social abilities such as communication and teamwork has become a major challenge for GenAI-PL.

The design of GenAI-PL pays insufficient attention to learners' higher-order abilities, making it difficult to protect and enhance their metacognition, self-regulated learning, and creative thinking. There is a lack of mechanisms to guide students in deep thinking and creative exploration. Studies have shown that even the most complex personalized learning systems struggle to support the enhancement of learners' self-regulated learning abilities (Molenaar, 2022). Although the application of GenAI in personalized learning can improve learning performance, this does not necessarily translate to an improvement in learners' higher-order skills, and may even lead to cognitive laziness due to over-reliance on the system, severely hindering the enhancement of learners' metacognition (Cukurova, 2025). Furthermore, current personalized learning systems tend to focus more on the completion of short-term learning tasks, with relatively weak support for students' long-term developmental goals, making it difficult to effectively cultivate students' sustained learning abilities and habits for lifelong learning.

GenAI's adaptability in terms of emotional, attitudinal, and value-based objectives is insufficient. Currently, GenAI's content generation relies more on the single goal of knowledge transmission, neglecting the personalized needs of learners in terms of emotions, attitudes, and values (Sung et al., 2025). Although personalized learning systems enhance the acquisition of subject knowledge and skills, they still have limitations in recognizing and understanding learners' deep emotional needs and attitudinal changes. Moreover, the content generated by GenAI may be more based on the mainstream values in the training data, making it difficult to apply to individual learners with diverse cultural backgrounds and values. Existing personalized assessment and feedback systems also focus more on students' knowledge mastery, lacking comprehensive assessments that incorporate their emotions, attitudes, and values.

#### 4.5 | Lack of Security, Ethical, and Value Guidelines

In the process of using GenAI to enhance personalized

learning, there are still deficiencies in safety measures and ethical standards, which may give rise to a range of potential risks and issues.

From the perspective of data privacy, personalized learning requires the collection of a vast array of multidimensional data on learners' cognition, behavior, and emotions. This process may lead to concerns about loss of agency, privacy leakage, and computational opacity. In previous research, Xu et al. (2023b) used federated learning to address privacy issues in personalized learning. By training models on local devices and only sharing model parameters, they reduced reliance on personal data, thus protecting learners' privacy. However, there is still an inevitable risk of information leakage when models are synchronized between different devices.

From the aspect of content generation and values, GenAI relies on training with large-scale data, and the system's learning and generation outcomes may be influenced by biases inherent in the training data, such as culture, gender, and race, leading to unfair treatment of certain groups. Moreover, contents generated by general large models may lack targeted personalization of learning objectives and educational values, and may not respect and adapt to multicultural backgrounds and societal needs. Unregulated output from general large models could also lead to serious consequences such as cognitive imbalance, technophobia, and social disorder.

From the perspective of human agency, while GenAI serves as a creative knowledge production tool and effectively supports educational activities, there is a risk that technology and education may become

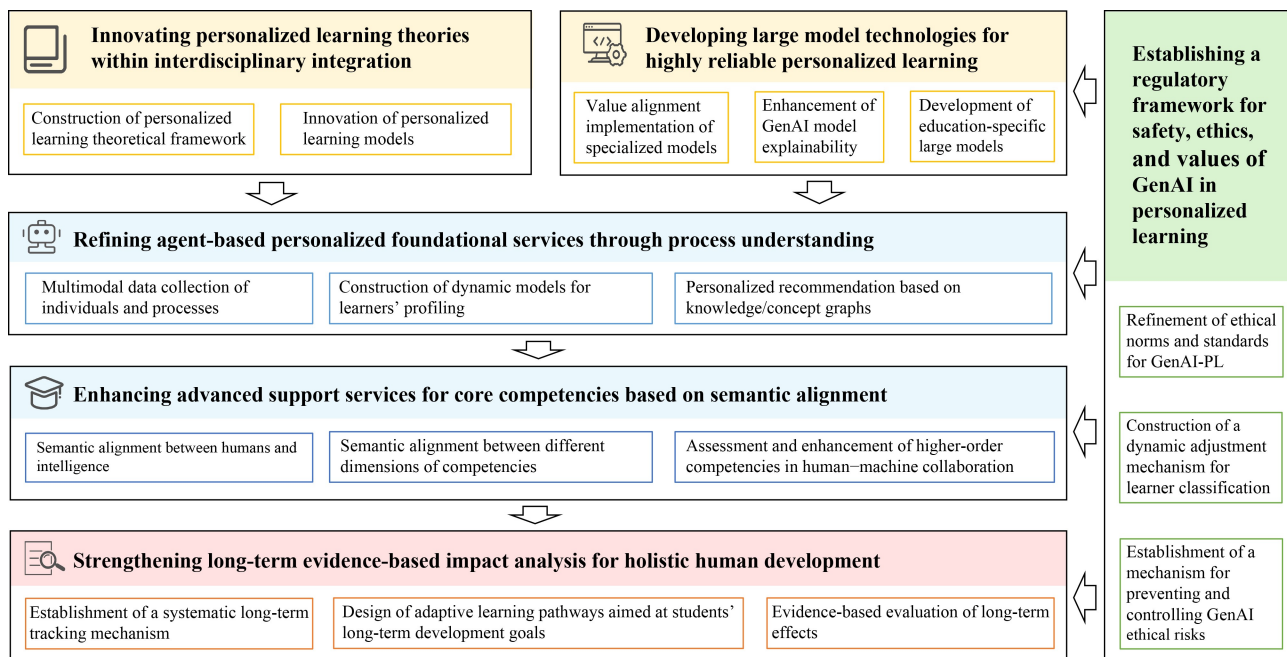
alienated. GenAI might be used merely as a tool to increase educational efficiency, neglecting the ethical values and humanistic significance of education. Additionally, learners may become overly reliant on the learning paths and contents recommended by GenAI, which could strongly impact the essence and primary position of human beings. Therefore, how to take the promotion of "human's all-round development" as the fundamental starting point, to establish and embed correct moral values to create a safer and more appropriate AI system, and to achieve a healthy and benevolent deep human-AI collaboration is a significant challenge for education in the near future.

## 5 Pathways for Empowering Personalized Learning with GenAI

In response to the aforementioned challenges, this study proposes a realization path for GenAI-PL that encompasses innovation in learning theory, development of LLMs, enhancement of personalized foundations and advanced services, optimization of long-term evidence-based effects, and the establishment of a safety, ethics, and value regulation framework. The specifics are illustrated in Figure 3.

### 5.1 | Innovating Personalized Learning Theories Within Interdisciplinary Integration

In response to the challenge that personalized learning



**Figure 3** The implementation pathways of GenAI-PL. GenAI: generative artificial intelligence; PL: personalized learning.

theory is lagging and lacks practical guidance, there is an urgent need to innovate and apply interdisciplinary theories in practice.

First, it is necessary to construct a personalized learning theoretical framework based on interdisciplinary theories such as education, psychology, and AI, deeply integrating and applying advanced learning theories that emphasize adaptability, personalization, and appeal. On one hand, the core roles of various disciplinary theories in personalized learning need to be accurately grasped; educational theory can support learner-centered and differentiated instruction, psychological theory can help understand the psychological states and behavioral characteristics of learners at different stages, and AI theory can support real-time perception and dynamic adaptation in the personalized learning process. On the other hand, the construction of the theoretical framework needs to consider factors such as differentiated learning objectives, adaptive scenario understanding, and dynamic path adjustment, while emphasizing the importance of increasing learner engagement and overall learning experience in the personalized learning process.

Second, attention must be paid to the design of operable personalized learning models guided by interdisciplinary theories. This requires a bottom-up deepening of the teaching practice community's recognition and emphasis on the concept of GenAI-empowered personalized education, promoting the mutual advancement of interdisciplinary theories and personalized learning practices, and integrating them throughout the learning process in resource recommendation, path design, and problem feedback. For instance, leveraging cognitive science in LLM-based personalized learning systems enhances the precision of behavioral analysis and improves the adaptability of individualized learning pathways. At the same time, innovative theories can be applied in small-scale personalized learning prototypes and application tests to enhance the operability of personalized learning models. Furthermore, practical data from personalized learning can be used to iteratively optimize the theoretical framework, making it more adaptable.

## 5.2 | Developing Large Model Technologies for Highly Reliable Personalized Learning

The architecture of LLMs that is independent of specific domains, along with their natural language processing capabilities, provides opportunities to address the limitations of personalized learning. LLMs based on prompt engineering can offer more personalized tutoring for learners (Jeon & Lee, 2023). To achieve more efficient and reliable personalized learning, it is necessary to focus on the dynamic differences of

learners while ensuring the robustness and trustworthiness of large models. That is to say, more autonomous and controllable LLMs are needed to explore which can dynamically adapt to different learning contexts and self-optimize based on learners' feedback.

From a practical standpoint, first and foremost, it is essential to prioritize the alignment of values for domain-specific models in personalized learning, establishing an efficient and secure system for the collection, storage, and sharing of large-scale personalized learning data. This enhances the reliability and autonomy of the computing power, algorithms, and data within independently developed personalized learning systems. Second, it is crucial to strengthen the interpretability of GenAI models, making the process of personalized content generation and decision logic more transparent, which facilitates learners' understanding of the rationality behind the decision-making process.

Additionally, it is necessary to enhance the adaptability of large models to differentiated learning scenarios and processes. This can be achieved by leading with educational general-purpose large models and exploring the development of education-specific vertical large models based on personalized education sub-scenarios and learner groups. Data augmentation techniques can be utilized, with a clear content generation target framework as guidance, to continuously enhance the adaptability of large models to learners' literacy objectives through reinforcement learning methods. This ensures that the contents generated by large models aligns with the target framework to reduce the issue of hallucination and provides references for the self-optimization of large model technology through technology effect feedback guided by the target framework.

## 5.3 | Refining Agent-Based Personalized Foundational Services through Process Understanding

To address the challenge of GenAI's insufficient understanding of the learning process and learners, highly adaptive personalized learning support can be provided based on intelligent agents. Intelligent agents refer to machines that continuously accumulate knowledge from past experiences and can change their behavior based on changes in knowledge, possessing characteristics of high intelligence and autonomous learning.

First, intelligent agents act as a bridge between learners and systems, capable of capturing learners' behavioral and emotional data in real-time, dynamically adjusting generated content according to learners' needs, and providing timely learning suggestions,

answering questions, and offering emotional encouragement. Second, in personalized learning based on intelligent agents, due to the dynamic complexity of the learning process, relying solely on static learner profiles is insufficient to provide precise learning support. A comprehensive and in-depth understanding of the learning process can provide a more accurate data foundation for learning agents, enabling them to generate content that is more scientific and personalized.

Specifically, by comprehensively collecting learners' individual and process-oriented multimodal data, and applying data analysis methods guided by educational psychology theories (such as cognitive diagnosis and knowledge tracing), combined with complex network analysis and dynamic system modeling, a dynamic model of learner profiles can be constructed. Utilizing GenAI technology to accurately pinpoint learners' personalized needs, and integrating with subject knowledge graphs and causal graphs, enriches the relationship mining and logical reasoning capabilities between knowledge concepts, and models the event chains and causal relationships of teaching and learning events. This enables situational awareness and process analysis, intelligently pushing the required learning resources and personalized learning paths to learners. In the design process of intelligent agents, reinforcement learning and adaptive learning strategies should be integrated, along with situational awareness computing, to enhance their responsiveness to changes in the learning process. It is important to focus on the alignment of course content, learning activity design, and personalized learning contexts, and to emphasize the joint participation of learners, teachers, and developers in the design and optimization of personalized agent services.

#### 5.4 | Enhancing Advanced Support Services for Core Competencies Based on Semantic Alignment

The cultivation of learners' higher-order core competencies can be achieved through an efficient human-computer collaborative mechanism, which primarily relies on multi-level interaction and feedback mechanisms between educational entities and intelligent agents. Specifically, educational entities set cooperative goals through guidance inputs to the intelligent agents and initiate preliminary collaboration through semantic alignment and task instruction transmission. As interactions deepen, intelligent agents gradually adjust their response patterns through deep learning and reasoning mechanisms, and optimize in real time based on feedback from educational entities. To better achieve semantic alignment in human-computer collaboration, higher-order core

competencies need to be transformed into reward signals through coding frameworks or vector embeddings, making implicit features explicit representations, and encouraging intelligent agents to maximize cumulative rewards, thereby guiding the model to learn behaviors that align with human expectations.

When GenAI is deeply involved in students' learning processes, there is a call for accurate assessment of students' capability enhancement in specific dimensions, which necessitates the establishment of a new continuous monitoring system and a multidimensional evaluation system for student capabilities. Specifically, a fine-grained capability monitoring mechanism based on learning behavior data needs to be established. Temporal modeling techniques can be used to analyze students' learning trajectories, interaction behaviors, and output content, quantifying students' capability changes across different dimensions. At the same time, interpretable assessment models need to be designed to ensure transparency and fairness in the assessment process, and to provide feedback to students and teachers to guide subsequent learning and teaching. In the co-learning process of GenAI and students, it is necessary to conduct a comprehensive assessment not only on the enhancement of students' knowledge and skills but also on the dimensions of processes and methods, as well as emotions, attitudes, and values. Semantic alignment between dimensions can be incorporated into the capability monitoring and assessment system during the learning process. For the cultivation of students' higher-order core competencies, indicators such as students' thinking patterns in collaboration with GenAI, the proposal of innovative solutions, and the depth of critical analysis can be used to measure the enhancement of students' higher-order thinking abilities.

Additionally, existing research supports the notion that learner agency and self-regulation should be focal points in the design of personalized learning systems (Brod et al., 2023). When constructing evaluation metrics, it is also necessary to dynamically monitor potential declines in abilities such as independent thinking, metacognitive laziness, knowledge transfer, and case analysis during learner collaboration with GenAI, and to incorporate these considerations into a multidimensional evaluation system (Fan et al., 2025). For instance, a metacognitive semantic graph can be established, and a semantic embedding and matching mechanism between metacognitive goal frameworks and learner behaviors can be constructed to uncover patterns of metacognitive laziness or decline, thereby achieving dynamic monitoring of metacognitive abilities and their trends of decline.

### 5.5 | Strengthening Long-Term Evidence-Based Impact Analysis for Holistic Human Development

The comprehensive development of individuals is not only about learners' acquisition of knowledge and mastery of skills in the cognitive dimension but also includes emotional regulation, social abilities, creativity, and other aspects of growth, which are the core objectives of personalized learning. To achieve the all-around development of students, GenAI-PL should not be based solely on the improvement of short-term learning outcomes but should be based on the planning and continuous optimization of learners' long-term learning paths. In other words, to verify the real application effects of GenAI in personalized learning, it is necessary to pay attention not only to the short-term performance such as learners' performance improvement and engagement but also to observe the long-term performance of learners in aspects such as social abilities.

On one hand, a systematic, long-term data tracking mechanism can be established for learners, comprehensively recording multidimensional data such as learning performance, emotions, and metacognition during the learning process. Based on the results of long-term data tracking, GenAI can be used to plan and design learning paths and adaptive adjustment strategies aimed at students' long-term development goals, guiding students to achieve continuous progress in an effectively motivated personalized learning system.

On the other hand, in the practice of personalized learning, an evidence-based approach can be adopted for long-term personalized learning practices, which takes into account both the short-term effectiveness and long-term goal development of learners. By combining quantitative and qualitative assessment methods, the strategies and technologies generated by GenAI during the learning process can be continuously evaluated and verified to ensure they truly enhance learning outcomes. Specifically, long-term data tracking results can be used to quantitatively assess the short-term effects and long-term goals of learners, and their implicit experiences can be understood through interviews, observations, and learner feedback, which is also of great importance for enhancing the robustness of GenAI in the application of personalized learning.

### 5.6 | Establishing a Regulatory Framework for Safety, Ethics, and Values of GenAI in Personalized Learning

To address the safety and ethical challenges in the process of empowering personalized learning with

GenAI, it is necessary to establish a systematic set of rules and frameworks. This ensures that the application of technology is safe, adheres to ethical principles, and has a clear educational value orientation. This is the foundation for ensuring the secure implementation of GenAI technology in the field of personalized learning.

Specifically, first, it is necessary to refine the ethical standards and norms for GenAI-PL, establish a review and supervision system for the ethical implications of GenAI in education, and track and adjust the ethical impacts of new GenAI technologies in real-time to ensure synchronicity between ethical norms and technological development. In the human-computer interaction process oriented toward personalized learning, it is necessary to carefully design ethical guidelines for data mining, clarify the standards for the collection, storage, and use of learner data, and establish mechanisms for data encryption and anonymization to minimize the possibility of data breaches. For example, when learners use tools like ChatGPT or Grammarly, the AI may store user-inputted text and use it for algorithm training, potentially leading to privacy breaches. To mitigate this risk, user data can be processed locally, and users should be allowed to delete their data records at any time to reduce the risk of data leakage.

Second, in the design of personalized learning systems, it is important to avoid oversimplified and stereotypical categorization of learners. Instead, multi-dimensional learning analytics models should be introduced, along with dynamic adjustment mechanisms for learner classification to prevent a chain reaction of injustice or bias. Specifically, learners can be allowed to automatically remove or adjust their labels after completing certain tasks or demonstrating improved performance. Meanwhile, the classification mechanism can be made transparent to users, allowing them to provide additional information (such as self-assessments) to influence system decisions (Murtaza et al., 2022). Centered around the value orientation of the comprehensive development of students, the value and behavioral norms of GenAI systems should be continuously assessed and optimized through educational practices to align with human values.

Third, it is necessary to establish a comprehensive ethical risk prevention and control system for GenAI. The government should take the lead in formulating guidelines for the research and design of generative AI, intervening from the front end of technology development to ensure the safety and controllability of AI technology research and development. At the same time, it is possible to categorize the ethical risks associated with GenAI in empowering personalized learning, and to develop targeted contingency plans, as well as to develop risk warning systems that are in line with the ethics of personalized learning.

## 6 Conclusions

In the era of AI, GenAI technology, represented by LLMs, has become a core topic in empowering personalized learning. Generative AI, through fine-grained data analysis and personalized content generation, endows the entire process of personalized learning with unprecedented flexibility and adaptability. However, there are still significant shortcomings in understanding the higher-order literacy differences among learners, individual static differences, and dynamic process differences in personalized learning. This study mainly reveals the theoretical basis and application mechanisms of GenAI-PL, analyzes the technical strategies and application services for efficient personalized learning, systematically sorts out the main challenges and coping strategies for GenAI-empowered personalized learning, and aims to build an efficient, innovative, and sustainable personalized learning model under the empowerment of GenAI.

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## References

- Adeshola, I., & Adepoju, A. P. (2023). The opportunities and challenges of ChatGPT in education. *Interactive Learning Environments*, 32(10), 6159–6172.
- Bada, S. O., & Olusegun, S. (2015). Constructivism learning theory: A paradigm for teaching and learning. *Journal of Research & Method in Education*, 5(6), 66–70.
- Bany Abdelnabi, A. A., Soykan, B., Bhatti, D., & Rabadi, G. (2025). Usefulness of large language models (LLMs) for student feedback on H&P during clerkship: Artificial intelligence for personalized learning. *ACM Transactions on Computing for Healthcare*. (in press).
- Binhammad, M. H. Y., Othman, A., Abuljadayel, L., Al Mheiri, H., Alkaabi, M., & Almarri, M. (2024). Investigating how generative AI can create personalized learning materials tailored to individual student needs. *Creative Education*, 15(7), 1499–1523.
- Brod, G., Kucirkova, N., Shepherd, J., Jolles, D., & Molenaar, I. (2023). Agency in educational technology: Interdisciplinary perspectives and implications for learning design. *Educational Psychology Review*, 35(1), 25.
- Chen, J., Liu, Z., Huang, X., Wu, C., Liu, Q., Jiang, G., Pu, Y., Lei, Y., Chen X., Wang, X., & et al. (2024). When large language models meet personalization: Perspectives of challenges and opportunities. *World Wide Web*, 27(4), 42.
- Chen, W., Su, Y., Zuo, J., Yang, C., Yuan, C., Chan, C.-M., Yu, H., Lu, Y., Hung, Y.-H., Qian, C., & et al. (2023). Agentverse: Facilitating multi-agent collaboration and exploring emergent behaviors. *arXiv Preprint*, arXiv:2308.10848.
- Chiu, T. K. (2024). Future research recommendations for transforming higher education with generative AI. *Computers and Education: Artificial Intelligence*, 6, 100197.
- Cukurova, M. (2025). The interplay of learning, analytics and artificial intelligence in education: A vision for hybrid intelligence. *British Journal of Educational Technology*, 56(2), 469–488.
- Dan, Y., Lei, Z., Gu, Y., Li, Y., Yin, J., Lin, J., Ye, L., Tie, Z., Zhou, Y., Wang, Y., & et al. (2023). EduChat: A large-scale language model-based Chatbot system for intelligent education. *arXiv Preprint*, arXiv:2308.02773.
- Fan, Y., Tang, L., Le, H., Shen, K., Tan, S., Zhao, Y., Shen, Y., Li, X., & Gašević, D. (2025). Beware of metacognitive laziness: Effects of generative artificial intelligence on learning motivation, processes, and performance. *British Journal of Educational Technology*, 56(2), 489–530.
- Foglia, L., & Wilson, R. A. (2013). Embodied cognition. *Wiley Interdisciplinary Reviews: Cognitive Science*, 4(3), 319–325.
- Gao, W., Liu, Q., Yue, L., Yao, F., Lv, R., Zhang, Z., Wang, H., & Huang, Z. (2025). Agent4Edu: Generating learner response data by generative agents for intelligent education systems. *arXiv Preprint*, arXiv:2501.10332.
- Gardner, H., & Hatch, T. (1989). Educational implications of the theory of multiple intelligences. *Educational Researcher*, 18(8), 4–10.
- Heikkinen, S., Saqr, M., Malmberg, J., & Tedre, M. (2023). Supporting self-regulated learning with learning analytics interventions—A systematic literature review. *Education and Information Technologies*, 28(3), 3059–3088.
- Huang, C., Tu, Y., Wang, Q., Li, M., He, T., & Zhang, D. (2025). How does social support detected automatically in discussion forums relate to online learning burnout? The moderating

- role of students' self-regulated learning. *Computers & Education*, 227, 105213.
- Huang, Y., Wan, L. J., Ye, H., Jha, M., Wang, J., Li, Y., Zhang, X., & Chen, D. (2024). New solutions on LLM acceleration, optimization, and application. In: *Proceedings of the 61st ACM/IEEE Design Automation Conference*. New York: Association for Computing Machinery, 1–4.
- Ihde, D. (1974). The experience of technology: Human-machine relations. *Cultural Hermeneutics*, 2(3), 267–279.
- Jeon, J., & Lee, S. (2023). Large language models in education: A focus on the complementary relationship between human teachers and ChatGPT. *Education and Information Technologies*, 28(12), 15873–15892.
- Jin, H., & Wu, Y. (2024). CE-CoLLM: Efficient and adaptive large language models through cloud-edge collaboration. *arXiv Preprint*, arXiv:2411.02829.
- Kundu, A., Lim, F., Chew, A., Wynter, L., Chong, P., & Lee, R. D. (2024). Efficiently distilling LLMs for edge applications. *arXiv Preprint*, arXiv:2404.01353.
- Laak, K. J., & Aru, J. (2024). AI and personalized learning: Bridging the gap with modern educational goals. *arXiv Preprint*, arXiv:2404.02798.
- Latif, E., Fang, L., Ma, P., & Zhai, X. (2023). Knowledge distillation of LLM for education. *arXiv Preprint*, arXiv:2312.15842.
- Le, H. D., Xia, X., & Chen, Z. (2024). Multi-agent causal discovery using large language models. *arXiv Preprint*, arXiv:2407.15073.
- Lewis, P., Perez, E., Piktus, A., Petroni, F., Karpukhin, V., Goyal, N., Küttler, H., Lewis, M., Yih, W., Rocktäschel, T., & et al. (2020). Retrieval-augmented generation for knowledge-intensive NLP tasks. *arXiv Preprint*, arXiv:2005.11401.
- Li, Y., Zhang, R., & Liu, J. (2024). An enhanced prompt-based LLM reasoning scheme via knowledge graph-integrated collaboration. In: *Proceedings of Artificial Neural Networks and Machine Learning—ICANN 2024*. Cham: Springer, 251–265.
- Liu, J., Huang, Z., Xiao, T., Sha, J., Wu, J., Liu, Q., Wang, S., & Chen, E. (2025). SocraticLM: Exploring socratic personalized teaching with large language models. In: *Proceedings of Neural Information Processing Systems 2025*. (in press).
- Liu, Q., Shen, S., Huang, Z., Chen, E., Zheng, Y., Yin, M., Wang, M., & Chen, E. (2021). A survey of knowledge tracing. *arXiv Preprint*, arXiv:2105.15106.
- Maghsudi, S., Lan, A., Xu, J., & van Der Schaar, M. (2021). Personalized education in the artificial intelligence era: What to expect next. *IEEE Signal Processing Magazine*, 38(3), 37–50.
- Molenaar, I. (2022). The concept of hybrid human-AI regulation: Exemplifying how to support young learners' self-regulated learning. *Computers and Education: Artificial Intelligence*, 3, 100070.
- Moore, J. L., & Rocklin, T. R. (1998). The distribution of distributed cognition: Multiple interpretations and uses. *Educational Psychology Review*, 10, 97–113.
- Murtaza, M., Ahmed, Y., Shamsi, J. A., Sherwani, F., & Usman, M. (2022). AI-based personalized e-learning systems: Issues, challenges, and solutions. *IEEE Access*, 10(18), 81323–81342.
- Ng, C., & Fung, Y. (2024). Educational personalized learning path planning with large language models. *arXiv Preprint*, arXiv:2407.11773.
- Packer, M. J., & Goicoechea, J. (2000). Sociocultural and constructivist theories of learning: Ontology, not just epistemology. *Educational Psychologist*, 35(4), 227–241.
- Park, M., Kim, S., Lee, S., Kwon, S., & Kim, K. (2024). Empowering personalized learning through a conversation-based tutoring system with student modeling. *arXiv Preprint*, arXiv:2403.14071.
- Qin, R., Liu, D., Xu, C., Yan, Z., Tan, Z., Jia, Z., Nassereldine, A., Li, J., Jiang, M., Abbasi, A., & et al. (2024). Empirical guidelines for deploying llms onto resource-constrained edge devices. *arXiv Preprint*, arXiv:2406.03777.
- Romig, D., & Cleland, C. C. (1972). Educational applications of humanistic psychology. *Journal of School Psychology*, 10(3), 289–298.
- Rusmiyanto, R., Huriati, N., Fitriani, N., Tyas, N. K., Rofi'i, A., & Sari, M. N. (2023). The role of artificial intelligence (AI) in developing English language learner's communication skills. *Journal on Education*, 6(1), 750–757.
- Sajja, R., Sermet, Y., Cikmaz, M., Cwiertny, D., & Demir, I. (2024). Artificial intelligence-enabled intelligent assistant for personalized and adaptive learning in higher education. *Information*, 15(10), 596.
- Sander, J., Cohen, A., Dasari, V. R., Venable, B., & Jalaian, B. (2025). On accelerating edge AI: Optimizing resource-constrained environments. *arXiv Preprint*, arXiv:2501.15014.
- Song, C. H., Wu, J., Washington, C., Sadler, B. M., Chao, W.-L., & Su, Y. (2023). LLM-planner: Few-shot grounded planning for embodied agents with large language models. *arXiv Preprint*, arXiv:2212.04088.
- Sonlu, S., Bendiksen, B., Durupinar, F., & Güdükbay, U. (2024). The effects of embodiment and personality expression on learning in LLM-based educational agents. *arXiv Preprint*, arXiv:2407.10993.
- Sreenivas, S. T., Muralidharan, S., Joshi, R., Chochowski, M., Mahabaleshwar, A. S., Shen, G., Zeng, J., Chen, Z., Suhara, Y., Diao, S., & et al. (2024). LLM pruning and distillation in practice: The minitron approach. *arXiv Preprint*, arXiv:2408.11796.
- Sung, G., Guillain, L., & Schneider, B. (2025). Using AI to care: Lessons learned from leveraging generative AI for personalized affective-motivational feedback. *International Journal of Artificial Intelligence in Education*. (in press).
- Swan, M., Kido, T., Roland, E., & dos Santos, R. P. D. (2025). Math agents: Computational infrastructure, mathematical embedding, and genomics. *arXiv Preprint*, arXiv:2307.02502.
- Wang, X., Zhong, Y., Huang, C., & Huang, X. (2024). ChatPRCS: A personalized support system for english reading comprehension based on ChatGPT. *IEEE Transactions on Learning Technologies*, 99, 1–16.
- Xu, B., Huang, Z., Liu, J., Shen, S., Liu, Q., Chen, E., Wu, J., & Wang, S. (2023a). Learning behavior-oriented knowledge tracing. In: *Proceedings of the 29th ACM SIGKDD Conference*

- on Knowledge Discovery and Data Mining*. New York: Association for Computing Machinery, 2789–2800.
- Xu, Y., Xiao, M., Wu, J., Tan, H., & Gao, G. (2023b). A personalized privacy preserving mechanism for crowdsourced federated learning. *IEEE Transactions on Mobile Computing*, 23(2), 1568–1585.
- Yang, J. (2024). Deep integration of generative AI with higher education: Scenarios, risks and recommendations, *China Higher Education*, 5, 52–56. (in Chinese).
- Yildiz Durak, H. (2023). Conversational agent-based guidance: Examining the effect of chatbot usage frequency and satisfaction on visual design self-efficacy, engagement, satisfaction, and learner autonomy. *Education and Information Technologies*, 28(1), 471–488.
- Yu, J., Zhang, Z., Zhang-li, D., Tu, S., Hao, Z., Li, R. M., Li, H., Wang, Y., Li, H., Gong, L., & et al. (2024). From MOOC to MAIC: Reshaping online teaching and learning through LLM-driven agents. *arXiv Preprint*, arXiv:2409.03512.
- Zhang, J., Bao, K., Wang, W., Zhang, Y., Shi, W., Xu, W., Feng, F., & Chua, T. S. (2024a). Prospect personalized recommendation on large language model-based agent platform. *arXiv Preprint*, arXiv:2402.18240.
- Zhang, Y., Kong, F., Wang, P., Sun, S., Wang, L., Feng, S., Wang, D., Zhang, Y., & Song, K. (2024b). STICKERCONV: Generating multimodal empathetic responses from scratch. *arXiv Preprint*, arXiv:2402.01679.