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Generative AI Learning: A New Learning Paradigm Following Distance Learning and Mobile Learning

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ABSTRACT

With the development of information technology, learning methods have continuously evolved from distance learning to mobile learning. Distance learning breaks through the limitations of time and space, enabling educational resources to be disseminated across geographical regions; mobile learning further utilizes smart terminals to achieve a learning experience anytime, anywhere. However, the rapid development of generative artificial intelligence in recent years is driving the learning paradigm into a new stage. Based on summarizing the development characteristics of distance learning and mobile learning, this paper systematically proposes the concept of ”Generative AI Learning (GAL)” for the first time and constructs its theoretical framework and core mechanism. This paradigm emphasizes a closed-loop learning process of ”content generation—interactive construction—personalized adaptation—dynamic feedback,” transforming learners from ”content recipients” to ”knowledge co-creators.” This paper further analyzes the application models and potential challenges of GAL in education, providing theoretical reference for the future development of intelligent education.

General Terms

Generative AI Learning, Learning Paradigm

Keywords

Generative AI Learning; Learning Paradigm; Distance Learning; Mobile Learning; Human-AI Co-creation

1. INTRODUCTION

The development of educational technology has always revolved around the core issue of ”how to achieve learning more efficiently” [1], and has shown obvious paradigm evolution characteristics at different technological stages. Starting with distance education in the 20th century, the education system gradually broke through the time and space limitations of traditional classrooms, enabling learners to establish connections with remote teachers and teaching resources through communication technology, thus opening up a cross-regional and cross-institutional educational dissemination model [2]. The core value of this stage lies in the expansion of ”educational accessibility”, that is, enabling more learners to receive systematic education in non-on-site environments [3].

After entering the 21st century, with the popularization of mobile Internet and smart terminals, learning methods have undergone further structural changes, and mobile learning has gradually become a new mainstream form [4]. The development of smartphones, tablet devices, and wireless network infrastructure has shifted learning activities from fixed places to daily life scenarios, and learning behavior has begun to show fragmented, instantaneous, and contextualized characteristics. Learners can acquire knowledge and train skills during commutes, rest, or any free time [5]. The key breakthrough of this stage lies in the ”anytime accessibility” of learning, but its essence still relies on pre-designed digital content resources. However, both distance learning and mobile learning still have some structural limitations in existing learning models, which are becoming increasingly apparent in the context of increasingly personalized and complex educational needs. First, the learning content is still centered on ”pre-designed textbooks,” and the content production process relies heavily on the advance design of experts or educational institutions, lacking dynamic generation capabilities and making it difficult to adjust in real time according to the learner’s status. Second, the learning path is usually linear or semi-structured. Although the system can provide a certain degree of recommendation, it still relies on a static course structure and lacks true adaptive evolution capabilities. Finally, the learning feedback mechanism is still biased towards one-way output, such as test scoring or delayed feedback, which cannot achieve real-time error correction and deep interaction in the learning process, thus limiting the possibility of learning efficiency and cognitive deepening [6]. In recent years, the rapid development of generative artificial intelligence [7], especially the maturity of large language models and multimodal generative models, has provided new technical paths for addressing the above problems [8]. Unlike traditional information retrieval or recommendation systems, generative AI can not only organize and present existing knowledge, but also dynamically generate new explanations, examples, questions, and learning tasks based on context, thereby fundamentally changing the way knowledge is supplied [9]. At the same time, generative AI can simulate the role of a teacher through dialogue mechanisms, achieving continuous interactive teaching, and adjusting the complexity and expression of content in real time based on learner feedback, making the learning process closer to a state of ”real-time construction” [10]. Furthermore, this technology can support the dynamic construction of learning paths, making learning no longer a process of executing a preset path, but an adaptive process of continuous generation and reconstruction [11].

Based on the above development trends, it can be considered that educational technology is entering a new stage, its core feature no longer being "acquiring knowledge" or "accessing knowledge," but rather "generating and co-creating knowledge." In this context, it is necessary to propose a new learning paradigm to systematically describe the structural impact of generative artificial intelligence on the learning process. Therefore, this paper proposes the concept of "Generative AI Learning (GAL)" and attempts to theoretically construct it as a new generation learning paradigm following distance learning and mobile learning.

2. RELATED WORK

2.1 Distance Learning

Distance learning is based on communication technology, enabling the separation of teachers and learners in space, thereby breaking the dependence of traditional classrooms on geographical location [12]. In this model, teaching activities are usually organized using tools such as video conferencing systems, online course platforms, and email, and its core structure still maintains the "teacher-centered" characteristics of traditional education [13]. The learning content is usually uniformly designed and standardized by educational institutions, and learners learn according to the established course schedule, thereby ensuring the systematicness and manageability of teaching [14]. In terms of advantages, distance learning significantly improves the coverage of educational resources, making cross-regional and even cross-national education possible, but its limitations are also quite obvious, especially in terms of the depth of learning interaction and personalized support, and learners are often in a relatively passive state of acceptance [15].

2.2 Mobile Learning

Mobile learning is based on the widespread popularity of mobile Internet and smart terminals, enabling learning activities to further break away from the limitations of fixed places and enter more flexible and life-oriented usage scenarios [16]. In this model, learners can access learning resources anytime via mobile devices, making learning behavior highly flexible and context-embedded [17]. Mobile learning emphasizes "learning anytime" and "learning anywhere," and achieves instant access to and management of knowledge through applications, online platforms, and cloud services [18]. However, the core of this model still relies on pre-built content resource libraries. The learning system is mainly responsible for content distribution and recommendation, rather than content generation. Therefore, its adaptability is still limited when facing complex learning needs, especially in scenarios that require higher-order cognitive support and personalized knowledge construction [19].

2.3 Artificial Intelligence and Education

In recent years, artificial intelligence technology has gradually penetrated into the field of education and has had an impact on multiple levels, including intelligent recommendation systems, adaptive learning platforms, and automatic scoring and feedback systems [20]. These systems are usually based on data analysis and pattern recognition technology, and optimize learning paths by predicting learner behavior or matching learning resources, thereby improving learning efficiency [21]. However, such methods are essentially still "optimization systems based on existing data," and their core capabilities lie in prediction and matching, rather than creating new learning content or generating new knowledge structures. Therefore, existing AI education systems still have significant limitations in terms of learning content generation capabilities and the depth of interactive teaching, and have not yet truly changed the generation mechanism of the learning process.

3. THE CONCEPT OF GENERATIVE AI LEARNING (GAL)

3.1 Definition

Generative AI Learning (GAL) refers to a new learning model driven by generative artificial intelligence. It involves dynamically generating learning content, constructing an interactive knowledge building process, and providing continuous personalized feedback mechanisms, enabling learners and AI systems to jointly participate in knowledge production and cognitive construction. In this model, the learning process is no longer limited to acquiring and understanding existing knowledge, but extends to a continuously generating, adjusting, and optimizing dynamic system. Learning content, learning paths, and learning objectives can all evolve in real time according to the learner's state, thus forming a highly adaptive learning ecosystem.

3.2 Core Characteristics

GAL has four interrelated and mutually reinforcing core characteristics, which together constitute its theoretical foundation. The first is generativity, meaning that learning content no longer relies on fixed textbooks or pre-set courses, but is generated in real time by generative AI based on learning needs, context, and learning objectives. This includes explanatory content, examples, practice tasks, and extended knowledge, thus transforming the knowledge supply method from "static provision" to "dynamic generation." Secondly, there is interactivity. The learning process is achieved through a continuous dialogue mechanism, where learners can continuously ask questions, correct their understanding, and guide the AI to adjust its output, making learning a multi-round feedback-driven cognitive interaction process. Thirdly, there is personalization. The system can dynamically adjust the content difficulty, expression, and learning path based on learning behavior data, error patterns, and learning progress, thereby achieving truly individualized learning. Finally, there is co-creation. In this model, learners are no longer merely recipients of knowledge, but participate in the construction of knowledge structures with the AI, including concept generation, problem design, and knowledge reorganization, essentially transforming the learning process into a human-machine collaborative knowledge production activity.

4. GAL THEORETICAL FRAMEWORK

This paper proposes a "four-layer structural model" to systematically explain the operating mechanism and structural composition of generative AI learning (GAL). This model views the learning process as a dynamic system composed of data input, content generation, interactive construction, and feedback optimization. Each layer not only has an independent function but also interacts with the AI through continuous cycles, forming a holistic adaptive learning ecosystem. The core idea of this framework is to transform the traditional linear learning process into a multi-layered, collaboratively driven generative system, making learning no longer a one-way transmission but a continuously evolving, structured process.

4.1 Learner Input Layer

The input layer is the foundation of the entire GAL system. Its role is to structurally model the learner's multi-dimensional state, providing a basis for subsequent generation and interaction. This layer mainly includes three core types of information: the learner's knowledge level, learning objectives, and behavioral data. Knowledge level characterizes the learner's current cognitive foundation and ability boundaries; learning objectives define the directionality and expected results of the learning task; and behavioral data records click behavior, question content, error patterns, and learning path selection during the learning process, forming a dynamically updated learner profile. In more complex application scenarios, this input layer can be extended to implicit variables such as emotional state, learning motivation, and cognitive load, further enhancing the system's understanding of the learner's state. Through this multi-dimensional input information, the system can construct a continuously updated representation of the learning state, providing precise conditional constraints for the generation layer.

4.2 Generation Layer

The generation layer is the core computational and content production module in the GAL framework. Its main function is to dynamically generate learning content through generative artificial intelligence based on the learner's state information provided by the input layer. In this layer, the AI not only performs traditional knowledge retrieval or recommendation tasks, but also actively generates various types of learning resources, including knowledge explanations, example analyses, and knowledge extensions. It can also generate complex learning scenarios, such as case simulations, problem scenario reconstructions, and interdisciplinary application scenarios. Furthermore, this layer can automatically generate practice tasks and test questions based on learning objectives, thus achieving a fundamental shift from "content supply" to "content creation." More importantly, the generation layer is not a static execution module, but continuously adjusts its generation strategy based on changes in the input layer and feedback from the interaction layer, ensuring that the output content always maintains a high degree of matching with the learner's current state.

4.3 Interaction Layer

The interaction layer constitutes the core interface for human-machine collaborative learning in the GAL system. Its role is to achieve continuous two-way interaction between the learner and the generative AI. In this layer, the learning process primarily unfolds through a conversational question-and-answer mechanism. Learners can continuously ask questions, clarify concepts, and guide the AI to adjust its explanations, thereby achieving highly flexible cognitive alignment. Simultaneously, this layer supports reflective learning, where learners re-evaluate their understanding after receiving AI-generated content and further optimize their learning path through feedback. Furthermore, a multi-round reasoning learning mechanism allows complex problems to be gradually decomposed and deepened through continuous interaction, thereby enhancing the development of higher-order cognitive abilities. The essence of the interaction layer lies in transforming the traditional static learning process into a dynamic cognitive construction process driven by continuous dialogue, making learning a cyclical system that continuously generates meaning and corrects understanding.

4.4 Feedback Optimization Layer

The feedback optimization layer is a key mechanism for the adaptive evolution of the GAL system. Its main task is to dynamically adjust the entire system based on multi-source feedback information during the learning process. This layer comprehensively analyzes learners' learning performance, error patterns, and learning speed to determine the learning progress status and cognitive biases, and feeds this information back to the input and generation layers to optimize subsequent content generation and learning path design. In higher-order implementations, this layer can also incorporate a predictive mechanism to analyze trends in learners' future performance, thereby enabling early intervention and personalized adjustments. Through this closed-loop feedback mechanism, the GAL system can continuously improve learning outcomes, causing the entire learning process to gradually converge to the optimal cognitive path.

5. GAL OPERATION MECHANISM MODEL

The operation mechanism of GAL can be abstracted as a continuously iterative learning closed-loop system. Its core logic can be represented as follows: the learner's state S passes through the AI generation function G(S) and enters the interaction process I. Subsequently, the learning result is adjusted through the feedback mechanism F, and finally the learner's state S' is updated, thus entering the next cycle. In this process, learning is no longer a single linear process, but a continuously optimizing dynamic system.
Formally represented as follows:

$$S_{t+1} = f(S_t, G(S_t), I_t, F_t)$$

Where S_t represents the learner's cognitive state at time t, $G(S_t)$ represents the learning content generated based on the current state, I_t represents the interaction behavior between the learner and the AI, and F_t represents the system's feedback adjustment mechanism for the learning result. The function f represents the state update rule of the entire system, which is essentially a nonlinear mapping process integrating generation, interaction, and feedback. Through this mechanism, GAL achieves continuous evolution from an initial state to an optimized state, giving the learning process significant adaptive and convergent characteristics.

6. THE EVOLUTIONARY LOGIC FROM MOBILE LEARNING TO GAL

From the overall path of educational technology development, learning paradigms have evolved from distance learning to mobile learning, and then to generative AI learning. Each stage corresponds to a structural upgrade in technological capabilities and learning methods. In the distance learning stage, its core relies on network communication technology to achieve teacher-led cross-space teaching. Its learning content mainly comes from static textbook systems, emphasizing the expansion of accessibility to educational resources. In the mobile learning stage, with the popularization of smart terminals, learning behavior further enters a contextualized environment anytime, anywhere. Learners can access digital resources through mobile devices, achieving more flexible knowledge acquisition, but the essence of the content is still the dynamic retrieval of pre-set resources. In the generative AI learning stage, generative artificial intelligence becomes the core driving force. The learning system no longer relies solely on existing resources but can generate learning content in real time based on the learner's state, transforming learning from "acquiring information" to "generating knowledge," and upgrading from "accessing resources" to "knowledge co-creation."

7. APPLICATION SCENARIOS

At the application level, GAL demonstrates broad applicability and expansion potential. In personalized learning assistant scenarios, the system can automatically generate customized course content based on learners' ability levels and learning history, making the learning path highly personalized and dynamically adjustable. In virtual tutor systems, generative AI can simulate the role of expert teachers, providing explanations, guidance, and feedback through continuous dialogue, achieving an interactive experience close to one-on-one teaching. In adaptive examination systems, the system can dynamically generate test questions of varying difficulty based on learners' real-time performance, thereby achieving more accurate ability assessment. In project-based learning support scenarios, GAL systems not only provide knowledge support but can also participate in research design, writing guidance, and problem decomposition processes, making learning activities closer to real research and practice environments.

8. CHALLENGES AND PROBLEMS

Although GAL shows great potential at both the theoretical and application levels, its development still faces a series of key challenges. First, there is the issue of knowledge accuracy. Due to the inherent uncertainty of generative AI, its output may contain errors or inconsistencies, affecting learning quality. Second, there is the issue of learning dependency. Learners may become overly reliant on AI assistance during long-term use, thereby weakening their independent thinking and self-learning abilities. Thirdly, there is the challenge of assessment. Traditional educational evaluation systems struggle to effectively measure the quality of knowledge construction during generative learning, making the evaluation of learning outcomes more complex. Finally, there is the issue of educational equity. Due to the uneven distribution of generative AI technology resources, new gaps in access to learning resources may arise between different regions and groups, exacerbating educational inequality.

9. CONCLUSION

This paper proposes "Generative AI Learning (GAL)" as a new educational paradigm following distance learning and mobile learning, attempting to systematically explain the structural impact of generative artificial intelligence on the learning process from a theoretical perspective. This paper is the first to systematically propose and construct the overall theoretical framework of Generative AI Learning (GAL). GAL, by constructing a dynamic learning mechanism driven by generative artificial intelligence, achieves real-time generation of learning content and personalized optimization of learning paths, thereby transforming the learning process from a traditional "resource acquisition model" to a "human-machine co-creation model." This transformation not only changes the way learning content is supplied but also reshapes the interaction structure and feedback mechanism in the learning process. With the continuous development of large model technology and the expansion of educational application scenarios, GAL is expected to become one of the core theoretical frameworks in the future intelligent education system, and further promote the evolution of the education paradigm towards a higher degree of adaptability and generativeness.

10. REFERENCES

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