

Generative AI Driving the Paradigm Shift in Smart Education: Technology Layering, Application Scenarios, and Collaborative Governance

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Abstract

The explosive development of generative artificial intelligence is profoundly reshaping the technological pathways and application forms of smart education. Employing a narrative review methodology, this paper systematically examines the technological evolution and application trajectory of AI-empowered smart education. The study finds that the layering of technological capabilities determines the depth boundaries of application scenarios—from traditional Intelligent tutoring systems to large language models, each technological leap corresponds to a paradigm shift in educational applications, progressing from “automation” towards “generation” and “personalization.” Based on this framework, the paper identifies five core application directions: personalized learning, intelligent assessment, teacher empowerment, content generation, and educational equity. Furthermore, it recognizes three key challenges: technological adaptability, human-AI collaboration models, and ethical governance. Finally, a collaborative evolutionary research framework encompassing “Technology—Pedagogy—Governance” is proposed to provide a reference for the practical implementation of AI in education.

Keywords

artificial intelligence, smart education, large language models (LLMs), personalized learning, human-AI collaboration

1. Introduction

The digital economy and the digital transformation of education have become core driving forces reshaping the global educational landscape. The China Education Modernization 2035 plan explicitly proposes to “accelerate the reform of talent cultivation models using modern technology and achieve the organic integration of large-scale education and personalized cultivation” [1]. In recent years, the strategic deployment of education digitization, shifting from “3C” to “3I,” has further emphasized the empowering role of artificial intelligence in education. The outbreak of Generative AI, represented by Large Language Models (LLMs), is triggering a paradigm-level impact, transitioning from technological “empowerment” to intelligent “collaboration” [2]. Unlike incremental optimizations in traditional AI education, Generative AI, with its capabilities in natural language understanding, content generation, and logical reasoning, is profoundly altering

knowledge production methods, teacher-student interaction patterns, and evaluation mechanisms within the educational ecosystem [3].

Against this backdrop, a core research question demands attention: How does the current AI technology stack support different applications in smart education at various levels? What are the core opportunities and bottlenecks in the era of Generative AI?

The evolution of AI education research can be delineated into three distinct stages. The first stage, the era of traditional Intelligent Tutoring Systems (ITS), represented by Bayesian Knowledge Tracing (BKT) and ITS, focused on guiding and recommending structured knowledge paths [4]. The second stage, the era of deep learning, marked by Deep Knowledge Tracing (DKT) and NLP semantic understanding, achieved perception, classification, and prediction of the learning process but remained limited in generative and creative capabilities [5-6]. The third stage, the era of Generative AI, with the Transformer architecture, LLMs, and multimodal large models as its technological foundation, realizes a leap from “judgment” to “generation” and from “passive” to “interactive” capabilities [7].

Existing review studies tend to enumerate application scenarios, yet few conduct in-depth analysis of the matching relationship between technological capabilities and application scenarios. Furthermore, systematic reviews of the new Generative AI stage remain insufficient. This paper adopts a narrative review approach, centered on the theme of “technology layering driving application deepening,” focusing on the new progress in the Generative AI era, with the aim of providing a clear panoramic view of AI-empowered smart education.

2. The Technological Layering Foundation of AI-Empowered Smart Education

2.1 Layer 1: Rule- and Knowledge-Driven Traditional AI Educational Technology

The first layer is centered on domain knowledge models and learner models, forming the early foundation of smart education. Typical representatives include Intelligent Tutoring Systems (ITS) and knowledge tracing models. Bayesian Knowledge Tracing (BKT) models students' knowledge states as binary variables using Hidden Markov Models, predicting subsequent correct responses by estimating guess and slip probabilities [4]. Building upon this, researchers have extended BKT models by introducing personalized parameters, knowledge correlations, and continuous representations of node states to enhance precision and interpretability [4]. Logistic models (such as LFA and PFA) and factor analysis models estimate student abilities and item parameters from historical data through regression methods [5]. This layer of technology excels in automating structured and deterministic teaching processes but is limited in handling complex learning situations and high-dimensional features.

2.2 Layer 2: Deep Learning and NLP-Driven Perceptual Understanding Technology

The second layer utilizes deep neural networks and Natural Language Processing (NLP) as its core, achieving perception, classification, and prediction of the learning process. Deep Knowledge Tracing (DKT) first introduced Recurrent Neural Networks (RNNs) into knowledge tracing, enabling the capture of deeper student knowledge states without explicit knowledge annotation [6]. Subsequent research evolved into various knowledge tracing models based on memory networks (e.g., DKVMN), self-attention mechanisms (e.g., SAKT, AKT), and Graph Neural Networks (e.g., GKT, GIKT), enhancing the portrayal of student cognitive states from multiple dimensions [5-6]. Additionally, pre-trained language models (such as BERT) were early adopters for semantic understanding, automated grading, and intelligent Q&A, while learning analytics utilized behavioral sequence modeling to predict learning performance. The boundary of this layer lies in its effective processing and prediction of structured information, yet it remains insufficient in creative content generation and deep logical reasoning.

2.3 Layer 3: Generative AI and LLM-Driven Content Generation and Interaction Technology

The third layer, grounded in the Transformer architecture and Large Language Models (LLMs), realizes a significant leap in educational technology capabilities. LLMs like ChatGPT and DeepSeek possess robust contextual understanding, natural language generation, and Chain-of-Thought (CoT) reasoning abilities [7-8]. By decomposing complex tasks into simpler steps, CoT technology enables LLMs to exhibit human-like reasoning in logical inference [8]. Concurrently, the development of multimodal LLMs facilitates the unified

representation of text, images, audio, and video, significantly expanding the boundaries of educational content generation [9]. At the vertical application level, Educational Large Models (EduLLMs) enhance accuracy and safety in educational scenarios through domain knowledge injection, Retrieval-Augmented Generation (RAG), and instruction fine-tuning [2]. The essential leap of this layer is the upgrade of AI from “understanding and judgment” to “generation, dialogue, and reasoning,” opening up new possibilities for genuinely personalized interaction [7]. Beyond these core technologies, affective computing, multimodal perception, VR/AR, and immersive learning technologies are deeply integrated with AI, providing environmental awareness and spatial support for smart education, collectively constituting a technological ecosystem for smart education [2].

3. Core Application Scenarios of AI + Smart Education

3.1 Personalized Learning and Adaptive Learning

Technological foundation: Layer 1 (BKT and recommendation systems) and Layer 2 (DKT) evolve toward Layer 3 LLM-powered personalized content generation. Personalized learning is the core pursuit of AI-empowered education. Traditional knowledge-tracing methods can already automatically assess students' mastery of knowledge points and recommend adaptive learning paths accordingly [5]. With Generative AI support, the granularity of personalization is further refined to real-time “one-to-one” content generation [7]. LLMs can generate personalized explanations, examples, and interpretations on demand, based on students' current knowledge states and learning styles, thereby realizing true individualized instruction. Lin et al. pointed out that large AI models can assist students' autonomous learning in pre-class, in-class, and post-class phases, providing personalized resources and suggestions based on learning situations [1]. Zhong et al. further proposed constructing a data-driven personalized learning logic from three dimensions: “context perception—subject understanding—intelligent intervention,” achieving efficient and personalized learning interventions through precise perception of teaching and learning behavioral data, accurate assessment of knowledge states, and intelligent planning of learning paths [11].

3.2 Intelligent Assessment and Instant Feedback

Technological foundation: Layer 2 NLP-based text classification and sequence labeling evolve toward Layer 3 LLM-enabled generative feedback. From automated grading of objective questions using traditional NLP to semantic-level scoring of subjective questions and instant feedback supported by Generative AI, evaluation methods are undergoing profound changes. LLMs can not only assign scores but also generate targeted improvement suggestions, shifting evaluation from “result diagnosis” to “process feedback” [9]. Liu et al. noted that Generative AI demonstrates significant advantages in test generation, intelligent grading, speaking proficiency assessment, and student core competency evaluation [2]. Meanwhile, students can engage in multi-turn interactions with intelligent learning assistants, continuously exploring and deepening their understanding of knowledge through ongoing dialogue [2].

3.3 Teacher Teaching Assistance and Efficiency Enhancement

Technological foundation: Layer 2 NLP-powered question-and-answer systems evolve toward Layer 3 LLM-based content generation and instructional design. AI is becoming a powerful assistant for teachers. In instructional design, Generative AI can provide tailored teaching plans based on requirements; in instructional resource creation, it assists teachers in generating rich and diverse content [2]. Zhang et al. proposed the concept of a “New Educational Entity,” where “human teachers” and “machine mentors” jointly constitute the teaching subject. Adhering to the “principle of maximum and minimum workload,” programmable tasks are delegated to the machine mentor, allowing teachers to focus more on unprogrammable educational work [10]. In human-AI collaborative teaching practice, Yuan et al. designed a five-stage teaching process including scenario guidance, knowledge understanding, hands-on practice, thought mirroring, and transfer innovation. Utilizing the DeepSeek dual-model architecture (V3 and R1), they achieved instant knowledge support and explicit cognitive presentation, effectively supporting teachers' instructional design and classroom guidance [13].

3.4 Intelligent Generation of Educational Content

Technological Support: Layer 3 Generative AI (LLM + Multimodal Large Models).

The content generation capabilities of Generative AI are reshaping the supply model of educational resources. Based on LLMs, the automatic generation of test banks and test papers, as well as multimodal generation of instructional materials including text, images, and explanatory video scripts, has become feasible [2]. For students at different levels, the system can automatically adjust the difficulty and phrasing of content to generate differentiated learning resources. Xiao et al. pointed out that the generative capability of educational LLMs makes them a powerful source of learning resources, capable of automatically generating test questions, exercise analyses, and course content [7].

3.5 Educational Equity and Special Education

Technological foundation: Layer 2 speech and NLP technologies evolve toward Layer 3 LLM-supported personalized interaction. AI technology provides new breakthroughs for educational equity. Intelligent learning companions and virtual teachers can alleviate the shortage of high-quality teachers in remote areas, providing personalized intervention plans for children with special needs. With the intervention of AI agents, remote education has seen significant improvements in interactivity and personalized support [2].

4. Emerging Research Frontiers: Paradigm Evolution Enabled by Generative AI

4.1 Vertical Educational Large Models

The applicability of general-purpose LLMs in educational scenarios still faces challenges. Domain fine-tuning, RAG, and instruction fine-tuning have become key technological pathways for building specialized educational large models. Li et al. proposed the teaching thinking chain theory, which transforms implicit teaching experience into a computable structural model, driving educational large models to evolve from “black boxes” to “gray boxes,” effectively addressing issues such as opaque reasoning and generation hallucinations [8]. Currently, domestic and international educational vertical large models such as EduChat, Zhihai-Sanle, and Xinghuo Yuban have emerged, covering diverse scenarios like heuristic teaching, AI teaching assistants, and language learning [7].

4.2 AI Agents in Education

The development of educational agents is transitioning from knowledge-support types to thought-guiding and transfer-expanding types [13]. Leveraging “Chain of Thought” (CoT) and “Chain of Action” (CoA) technologies, agents can not only perform logical reasoning but also complete complex tasks by invoking external tools [7]. Based on the Coze platform, Yuan et al. developed four types of functional educational agents: knowledge support, knowledge diagnosis, thought guidance, and knowledge transfer, providing new ideas for constructing intelligent learning companions, role-playing teaching agents, and multi-agent collaborative teaching environments [13].

4.3 Human-AI Collaborative Teaching Models

The arrival of generative AI is driving human-AI collaboration from “tool empowerment” to “intelligent synergy” [2]. In education, this paradigm manifests as a new “Teacher-Machine-Student” triadic interactive teaching model [13]. Zhang et al.'s “Human-AI Collaborative Deep Teaching” model scientifically divides teaching tasks into programmable, non-programmable, and partially programmable categories, constructing a new teaching ecosystem where “human teachers” and “machine mentors” collaborate in division of labor, dedicated to promoting students' knowledge acquisition, ability depth, subject depth, and life depth in an all-round manner [10].

5. Core Challenges and Debates

5.1 Technological Challenges

The large-scale application of educational LLMs faces multiple technical bottlenecks. Firstly, the hallucination problem of LLMs is particularly fatal in educational scenarios. Li et al. pointed out that current technologies lack fact-checking mechanisms and may produce erroneous content based on probabilistic associations [8]. Secondly, general-purpose LLMs find it difficult to meet the high demands of educational

scenarios for professionalism, safety, and adaptability. Finally, computational costs and the economic viability of large-scale deployment remain significant barriers to widespread adoption [7].

5.2 Pedagogical Challenges

Students' excessive reliance on AI may lead to the dulling of thinking abilities and a decline in creativity [12]. Pei noted that over-reliance on intelligent learning tools could cause “digital dementia,” where learners become mere “transmitters” of knowledge [12]. Simultaneously, academic integrity and the governance of AI-assisted cheating have become increasingly prominent issues. Furthermore, the generally inadequate AI literacy of teachers hinders the deep advancement of human-AI collaborative teaching. Zhang et al.'s research indicates that current empirical studies on Generative AI in higher education are relatively scarce, highlighting the urgent need to improve research quality and teachers' digital literacy [11].

5.3 Ethical and Governance Challenges

Wu et al. point out that the ethical principles of AI in education currently suffer from issues of overly broad elements and unclear boundaries, urgently requiring improvements in “relevance” and “implementability” [3]. Wang et al. constructed an ethical risk assessment index system covering four primary indicators—educational technology ontology risk, educational data risk, machine algorithm risk, and educational application risk—along with 31 tertiary indicators, providing a quantitative basis for AI governance in education [14]. Huang et al. further summarized the root causes of risk into three levels: untrustworthiness of technology tools, anomie in educational practice, and insufficient literacy of teachers and students, proposing regulatory recommendations from perspectives such as technology upgrading, risk management, and accountability supervision [15].

5.4 Essential Debates

The positioning of Generative AI in education remains a subject of debate: does AI replace or empower teachers? The academic consensus is gradually moving towards “human-AI collaboration,” emphasizing a return to the essence of education [10]. Pei argues that while actively embracing technological opportunities, it is necessary to carefully scrutinize its risks and hidden dangers, exploring practical paths in a dialectical manner that combines innovation with principled adherence [12]. Wu et al. also emphasize that the development-oriented principle requires that the design and application of AI in education must transcend the role of an auxiliary tool and evolve into an “empowerer” that stimulates learners' intrinsic motivation, cultivates core competencies, and shapes sound character [3]. Crucially, these essential debates are not merely philosophical; they pose direct challenges to policy-making and governance design. The tension between “AI replacement” and “AI empowerment” fundamentally influences how we define the boundaries of machine autonomy, allocate responsibilities for algorithmic decisions, and establish ethical standards for pedagogical interactions. For instance, if the risk of AI replacing human roles is taken seriously, strict accountability mechanisms and human oversight must be legally mandated. Conversely, if the emphasis is on empowerment, governance frameworks must prioritize capacity building, teacher training, and adaptability. These nuanced and sometimes conflicting demands require governance frameworks to be flexible, responsive, and context-aware, rather than adopting a one-size-fits-all rigid regulatory approach. Consequently, the governance policies discussed in Section 6.3 must explicitly address these fundamental debates, constructing a pluralistic and adaptive regulatory ecosystem that balances innovation with essential risk containment.

6. Future Research Directions

6.1 Technological Research Directions

Future efforts should focus on developing safer, more interpretable educational specialized LLMs, exploring lightweight and low-cost deployment solutions, and deepening research on multimodal learning analytics [9]. Among these, the explicit representation of teaching thinking chains, the construction of dynamic knowledge graphs, and the optimization of RAG technologies will be key breakthroughs for enhancing the knowledge accuracy of educational LLMs [8].

6.2 Pedagogical Research Directions

The optimal models for human-AI collaborative teaching, new laws of learning sciences in AI environments, and the systematic cultivation of teachers' AI literacy will become important directions for pedagogical research [10-11]. Future classrooms will exhibit a new form of “human-AI co-teaching and co-education,” urgently necessitating the establishment of standards and evaluation systems for human-AI collaborative teaching throughout the entire teaching process [13].

6.3 Governance and Policy Directions

The sustainable development of AI in education cannot be achieved without the coordinated support of policy and governance. It is imperative to accelerate the establishment of ethical norms and industry standards for AI in education, strengthen data protection legislation, and improve the access evaluation mechanisms for educational AI products [3]. The ethical risk assessment index system proposed by Wang et al. has already provided a quantifiable operational tool for AI governance in education [14].

7. Conclusion

The three-layer capability evolution of AI technology drives smart education from automation towards generation and personalization. Generative AI represents the core variable at the current stage, yet its widespread implementation must rely on the synergistic advancement of technology, pedagogy, and governance. Looking ahead, it is essential to consistently adhere to a human-centered stance, clearly recognizing that AI is an empowering tool, while human development remains the ultimate goal. Only by achieving the dialectical unity of technological rationality and educational value rationality can smart education be genuinely propelled towards a high-quality and sustainable future. It is important to acknowledge the limitations inherent in this narrative review. First, while the literature search was conducted across multiple authoritative databases, the selection was limited to publications primarily in English and Chinese, potentially introducing language bias. Second, as a narrative review, the categorization of technological layers and application scenarios relies on the authors' interpretative framework. As noted by Wang et al. [14] in their construction of ethical risk indicators, and Li et al. [7] in their proposal of the teaching thinking chain, conceptual frameworks in AI education often require extensive practical validation. Therefore, the proposed “Technology—Pedagogy—Governance” framework remains theoretical; its adaptability across diverse educational contexts (K-12, vocational, or specific disciplines) and the practicality of its operational strategies require further empirical testing and localized case studies. These limitations highlight the need for more granular, data-driven, and localized studies in the future.

References

- [1] Lin H S, Liu S F, Zhao L. Research on Human-AI Collaborative Teaching Strategies of “AI Large Model + Teacher”[J]. China Educational Technology & Equipment, 2026(3): 16-19.
- [2] Liu B Q, Nie X L, Wang Y F, et al. Generative AI Empowering Education: Technical Framework, Application Field and Value—2024 Intelligent Education Development Research Report[J]. China Educational Technology, 2025(3): 61-70.
- [3] [3] Wu D, Gui X J, Bai J Y, et al. Ethical Framework for Artificial Intelligence in Education: Evolutionary Trajectory and Construction Principles[J]. E-education Research, 2026 (forthcoming).
- [4] Zeng F Z, Xu L Q, Zhou Y, et al. Review of Knowledge Tracing Model for Intelligent Education[J]. Computer Science, 2022, 16(8).
- [5] Cui S G, Xu S, Wang M Y, et al. Research Progress on Deep Learning Knowledge Tracing for Intelligent Education[J]. Computer Engineering, 2026, 52(4).
- [6] Xiao J L, Huang X Y, Jiang F. A Survey of Large Language Models in Smart Education[J]. CAAI Transactions on Intelligent Systems, 2025, 20(5): 1054-1070.
- [7] Li Y Z, Cao P J, Wu H Z, et al. Research on Explicit Reasoning in Educational Large Language Models Based on Teaching Thinking Chain[J]. Open Education Research, 2025, 31(4): 4-11.

- [8] Yuan L, Xu J Y, Liu W Q. Human-Machine Collaborative Teaching Paradigm Transformation in Digital-Intelligent Education Ecosystem[J]. Open Education Research, 2025, 31(2): 108-117.
- [9] Zhang H R, Wei L, Li S Z. Human-AI Collaborative Deep Teaching: Connotations, Characteristics and Practice Logic[J]. Modern Educational Technology, 2025.
- [10] Zhong S C, Yang L, Fan J R. Data-driven Personalized Learning: Real Problems, Ought-to-be Logic and Implementation Paths[J]. Modern Educational Technology, 2025(1).
- [11] Zhang Q, Chen Y J. Current Status of Application and Development Roadmap of Generative Artificial Intelligence in Domestic Higher Education—Visualization and Analysis Based on Literature Data[J]. Journal of North University of China (Social Science Edition), 2025, 41(5): 56-66.
- [12] Pei R. Generative Artificial Intelligence Empowering Education and Teaching: Transformational Impact, Risk Challenges, and Practical Paths[J]. Contemporary Education Forum, 2025(2).
- [13] Huang R H, Zhang G L, Liu M Y. The Technology Ethical Orientation and Risk Governance for Smart Education[J]. Modern Educational Technology, 2024, 34(2): 13-22.
- [14] Wang Y M, Huang F Q, Liu C C. Research on the Construction and Application of Ethical Risk Assessment Indicators for Artificial Intelligence in Education[J]. Journal of East China Normal University (Educational Sciences), 2026, 44(6): 92-102.
- [15] Su S Y. Research Landscape of Gen AI Applications in Education in China—Investigation Based on 532 Core Literatures from CNKI[J]. Modern Information Technology, 2025, 9(15): 53-56.

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Conflicts of Interest

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