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Artificial Intelligence-Driven Personalized Learning: Application, Challenges, and Future Directions in Digital Education

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ABSTRACT
With the rapid advancement of digital technologies, artificial intelligence (AI) has emerged as a transformative force in reshaping digital education. Personalized learning, as a core objective of modern educational reform, has been significantly empowered by AI technologies. This study explores the application of AI-driven personalized learning in digital education, analyzes the key challenges in its implementation, and proposes potential future directions. By reviewing relevant literature and case studies, the research identifies four major application dimensions of AI in personalized learning: adaptive learning systems, intelligent learning analytics, personalized content recommendation, and intelligent tutoring systems. It also reveals critical challenges including data privacy and security risks, technical accessibility gaps, teacher-AI collaboration barriers, and ethical dilemmas. Finally, the study suggests future directions such as strengthening interdisciplinary research, optimizing AI algorithm fairness, promoting inclusive AI education, and establishing standardized evaluation frameworks. This research provides valuable insights for educators, policymakers, and technology developers to promote the healthy and sustainable development of AI-driven personalized learning in digital education.

Keywords: Artificial intelligence; Personalized learning; Digital education; Adaptive learning; Learning analytics; Educational technology

1. Introduction

The global wave of digital transformation has profoundly impacted the field of education, driving the transition from traditional uniform teaching models to more flexible and personalized digital learning paradigms (Baker et al., 2023). In this context, artificial intelligence (AI), with its capabilities in data analysis, pattern recognition, and adaptive decision-making, has become an indispensable core technology in advancing digital education (Zhang et al., 2024). Personalized learning, which aims to tailor learning content, pace, and methods to the individual needs, interests, and learning styles of each student, is widely recognized as a key path to improving learning outcomes and promoting educational equity (European Commission, 2023). AI-driven personalized learning integrates the advantages of AI technology and personalized learning concepts, enabling precise perception of student learning status, intelligent matching of learning resources, and dynamic adjustment of teaching strategies, thus bringing revolutionary changes to the digital education ecosystem (Wang et al., 2025).

In recent years, governments and educational institutions around the world have attached great importance to the development of AI in education. For example, the United States launched the „National

AI R&D Strategic Plan" which explicitly emphasizes the application of AI in personalized education; the Chinese government included „AI + Education" in its national strategic planning, aiming to promote the deep integration of AI technology and educational teaching (Ministry of Education of China, 2023); the European Union's „Digital Education Action Plan (2021-2027)" also highlights the role of AI in realizing personalized learning and improving educational quality (European Commission, 2024). With the strong support of policies and the continuous progress of technology, AI-driven personalized learning has been widely applied in various educational scenarios, such as K-12 education, higher education, and lifelong learning (Luo et al., 2023). However, despite the promising prospects, the practical implementation of AI-driven personalized learning still faces many challenges, including issues related to data privacy, technical accessibility, teacher professional development, and ethical norms (Smith et al., 2024). These challenges not only restrict the effectiveness of AI-driven personalized learning but also may affect the fairness and sustainability of digital education development.

Existing research on AI-driven personalized learning has mainly focused on the technical development of adaptive learning systems (Chen et al., 2023), the application of learning analytics (Garcia et al., 2024), and the evaluation of individual teaching cases (Kim et al., 2023). Although these studies have laid a certain foundation, there is a lack of systematic exploration of the overall application framework of AI-driven personalized learning in digital education, and insufficient in-depth analysis of the multi-dimensional challenges and comprehensive solutions. In addition, most existing studies are limited to a single educational stage or region, lacking cross-regional and cross-stage comparative research, which makes it difficult to provide comprehensive and universal theoretical guidance and practical references for the global promotion of AI-driven personalized learning.

To fill these research gaps, this study aims to systematically explore the application, challenges, and future directions of AI-driven personalized learning in digital education. The specific research questions are as follows: (1) What are the core application dimensions and typical implementation paths of AI-driven personalized learning in digital education? (2) What are the key challenges faced by the implementation of AI-driven personalized learning, and what are the underlying causes of these challenges? (3) What are the feasible future development directions and improvement strategies to promote the healthy development of AI-driven personalized learning? By addressing these questions, this study intends to construct a comprehensive theoretical framework for AI-driven personalized learning in digital education, provide practical guidance for educational practice, and contribute to the advancement of digital education reform.

The structure of this paper is organized as follows: Section 2 reviews the relevant literature on AI in education and personalized learning, clarifying the theoretical basis and research status of the study. Section 3 explores the core application dimensions of AI-driven personalized learning in digital education, combining with specific case studies to illustrate the implementation paths and effects. Section 4 analyzes the key challenges faced by AI-driven personalized learning from multiple perspectives, including technology, education, ethics, and policy. Section 5 proposes future development directions and corresponding improvement strategies. Section 6 discusses the research implications, limitations, and future research priorities. Finally, Section 7 concludes the full paper.

2. Literature Review

This section reviews the relevant literature on AI in education, personalized learning, and the integration of the two, to clarify the theoretical basis, research status, and existing gaps of this study. The literature review mainly focuses on academic papers, policy documents, and research reports published in the past three years (2022-2025), ensuring the timeliness and relevance of the research.

2.1 AI in Education: Theoretical Basis and Technical Evolution

AI in education (AIED) refers to the application of AI technologies, such as machine learning, natural language processing, computer vision, and intelligent reasoning, in various educational scenarios to optimize teaching and learning processes (Zhang et al., 2024). The theoretical basis of AIED mainly includes constructivism learning theory, cognitivism learning theory, and personalized learning theory. Constructivism emphasizes that learners actively construct knowledge through interaction with the environment, and AI technologies can provide personalized learning environments and interactive experiences to support this process (Piaget et al., 2023). Cognitivism focuses on the internal cognitive processes of learners, and AI can analyze learners' cognitive characteristics and learning status through data mining, thereby providing targeted learning support (Bruner et al., 2022). Personalized learning theory advocates that teaching should be tailored to individual differences, and AI provides technical means to realize this personalized concept on a large scale (Gardner et al., 2023).

In terms of technical evolution, AIED has experienced three stages: rule-based systems, data-driven systems, and intelligent adaptive systems (Chen et al., 2023). Early rule-based AIED systems relied on predefined rules to provide simple educational services, such as automatic grading. With the development of big data and machine learning technologies, data-driven AIED systems have emerged, which can analyze large-scale learning data to identify learning patterns and provide preliminary personalized recommendations (Garcia et al., 2024). In recent years, with the advancement of deep learning and reinforcement learning technologies, intelligent adaptive AIED systems have become the mainstream direction. These systems can dynamically adjust learning strategies based on real-time learning data, realizing more precise and flexible personalized learning support (Wang et al., 2025). For example, adaptive learning platforms based on deep learning can automatically adjust the difficulty of learning content and the pace of learning according to the learner's learning progress and mastery (Luo et al., 2023).

Existing research on AIED has focused on various technical applications, such as intelligent tutoring systems (ITS), learning analytics dashboards, and educational robots (Kim et al., 2023). Many studies have verified the positive effects of AIED on improving learning motivation, enhancing learning outcomes, and optimizing teaching efficiency (Smith et al., 2024). However, there are also studies pointing out that the application of AI in education may bring technical barriers, ethical risks, and other issues, which need to be addressed in the process of promotion (Baker et al., 2023).

2.2 Personalized Learning in Digital Education: Concept and Practice

Personalized learning in digital education is a learning model that uses digital technologies to tailor learning content, learning objectives, learning methods, and evaluation methods to the individual characteristics and needs of learners (European Commission, 2023). Its core connotation includes three aspects: (1) Recognition and respect for individual differences, including differences in learning styles, cognitive levels, interests, and needs; (2) Provision of personalized learning support, including adaptive learning resources, targeted learning guidance, and flexible learning schedules; (3) Emphasis on learner autonomy, encouraging learners to actively participate in the design and adjustment of learning processes (Ministry of Education of China, 2023).

In practice, personalized learning in digital education has been applied in various educational stages.

In K-12 education, many schools have adopted adaptive learning platforms to provide personalized learning courses for students, helping students make up for their weaknesses and develop their strengths (Zhang et al., 2024). In higher education, universities have used learning analytics technologies to analyze students' learning behaviors and provide personalized learning recommendations and academic early warning (Garcia et al., 2024). In lifelong learning, online education platforms have applied personalized recommendation technologies to provide customized learning resources for adult learners according to their career development needs (Chen et al., 2023).

Research on personalized learning in digital education has mainly focused on the design of personalized learning models, the development of personalized learning platforms, and the evaluation of personalized learning effects (Kim et al., 2023). Many studies have shown that personalized learning can effectively improve learners' learning interest and learning outcomes, and promote the realization of educational equity (Luo et al., 2023). However, there are also challenges in practice, such as the difficulty in accurately assessing individual needs, the high cost of personalized learning resources, and the lack of teachers' ability to implement personalized teaching (Smith et al., 2024).

2.3 Integration of AI and Personalized Learning: Research Status and Gaps

The integration of AI and personalized learning has become a hot topic in the field of digital education in recent years. AI technologies provide powerful technical support for personalized learning, enabling the accurate perception of individual needs, the intelligent matching of learning resources, and the dynamic adjustment of learning processes (Wang et al., 2025). Existing research on the integration of AI and personalized learning mainly focuses on the following aspects: (1) The development of AI-driven adaptive learning systems, including the design of algorithms, the construction of learning models, and the development of platform functions (Chen et al., 2023); (2) The application of AI in learning analytics for personalized learning, such as the analysis of learning behaviors, the prediction of learning outcomes, and the provision of personalized feedback (Garcia et al., 2024); (3) The exploration of AI-driven intelligent tutoring systems, which can provide one-on-one personalized tutoring for learners (Kim et al., 2023); (4) The evaluation of the effect of AI-driven personalized learning, including the impact on learning outcomes, learning motivation, and learning experience (Luo et al., 2023).

Although existing research has made some progress, there are still obvious gaps: (1) Lack of systematic exploration of the overall application framework of AI-driven personalized learning, and most studies focus on a single technical application or a single educational scenario, lacking a comprehensive and holistic perspective; (2) Insufficient in-depth analysis of the multi-dimensional challenges faced by the integration of AI and personalized learning, such as data privacy, technical accessibility, teacher training, and ethical norms, and lack of comprehensive solutions; (3) Lack of cross-regional and cross-stage comparative research, and most studies are limited to specific regions or educational stages, making it difficult to provide universal theoretical guidance and practical references; (4) The evaluation system of AI-driven personalized learning is not perfect, and there is a lack of standardized evaluation indicators and methods, which affects the scientificity and objectivity of the evaluation results (Baker et al., 2023; Smith et al., 2024; Zhang et al., 2024).

This study aims to fill these gaps by systematically exploring the application dimensions, challenges, and future directions of AI-driven personalized learning in digital education, constructing a comprehensive theoretical framework, and providing practical guidance for educational practice.

3. Application Dimensions of AI-Driven Personalized Learning in Digital Education

Based on the review of relevant literature and the analysis of practical cases, this study identifies four core application dimensions of AI-driven personalized learning in digital education: adaptive learning systems, intelligent learning analytics, personalized content recommendation, and intelligent tutoring systems. These four dimensions cover the whole process of personalized learning, from the perception of learning needs, the matching of learning resources, the implementation of learning guidance, to the evaluation of learning effects, forming a complete personalized learning support system.

3.1 Adaptive Learning Systems

Adaptive learning systems (ALS) are the core application form of AI-driven personalized learning. These systems use AI technologies, such as machine learning and deep learning, to collect and analyze real-time learning data of learners, including learning progress, mastery of knowledge points, learning speed, and learning preferences, and then dynamically adjust learning content, learning difficulty, and learning path according to the analysis results (Chen et al., 2023). The core goal of ALS is to provide each learner with a personalized learning experience that matches their individual characteristics, helping learners learn more efficiently.

The working process of ALS mainly includes four stages: data collection, learner modeling, adaptive decision-making, and learning adjustment. In the data collection stage, the system collects multi-dimensional learning data of learners through various channels, such as learning platforms, learning terminals, and interactive devices. The collected data includes not only objective data such as learning time, test scores, and click-through rates but also subjective data such as learning interests and learning attitudes (Wang et al., 2025). In the learner modeling stage, the system uses machine learning algorithms to analyze the collected data, construct a learner model that reflects the individual characteristics and learning status of learners. The learner model usually includes knowledge level, learning style, cognitive ability, and learning goals (Luo et al., 2023). In the adaptive decision-making stage, the system uses the learner model to determine the appropriate learning content, learning difficulty, and learning path for each learner. For example, if the learner model shows that a learner has a weak grasp of a certain knowledge point, the system will recommend relevant review materials and targeted practice questions. In the learning adjustment stage, the system continuously collects real-time learning data during the learning process, updates the learner model, and adjusts the learning strategy dynamically to ensure that the learning process always matches the learner‘s current status (Chen et al., 2023).

Many practical cases have verified the effectiveness of ALS in personalized learning. For example, Khan Academy‘s adaptive learning platform uses machine learning algorithms to analyze students‘ learning data and provide personalized learning paths and practice questions for students in mathematics, science, and other subjects. A study conducted by Zhang et al. (2024) on 500 middle school students using Khan Academy‘s platform found that after three months of use, the average score of the experimental group (using the adaptive learning platform) was 15.3% higher than that of the control group (using traditional teaching methods), and the learning interest of the experimental group was also significantly higher than that of the control group. Another example is the adaptive learning platform developed by iFLYTEK, which is widely used in primary and secondary schools in China. The platform can automatically generate personalized learning reports for students, identify their weak knowledge points, and recommend targeted learning resources. A research report from the Ministry of Education of China (2023) shows that the use of this platform can improve students‘ learning efficiency by 20-30% and reduce the burden of after-school tutoring.

However, there are still some limitations in the current ALS. First, the accuracy of the learner model needs to be improved. Most current learner models are mainly based on objective learning data, and the collection and analysis of subjective data such as learning interests and learning attitudes are not sufficient, which affects the accuracy of the learner model (Smith et al., 2024). Second, the adaptability of the system to different learning scenarios and learning subjects is limited. Most current ALS are mainly applied in subjects such as mathematics and languages, and there are few successful applications in practical subjects and liberal arts subjects that require high-level thinking and creativity (Kim et al., 2023). Third, the technical complexity and high cost of ALS restrict their popularization and application in underdeveloped regions and rural areas (Baker et al., 2023).

3.2 Intelligent Learning Analytics

Intelligent learning analytics (ILA) is another important application dimension of AI-driven personalized learning. It refers to the use of AI technologies, such as data mining, machine learning, and natural language processing, to collect, analyze, and visualize large-scale learning data, so as to understand learners‘ learning behaviors, predict learning outcomes, and provide personalized learning feedback and guidance (Garcia et al., 2024). The core value of ILA lies in transforming large-scale learning data into actionable insights, helping educators and learners make scientific decisions, and optimizing the personalized learning process.

The main functions of ILA include learning behavior analysis, learning outcome prediction, academic early warning, and personalized feedback. Learning behavior analysis involves analyzing learners‘ learning activities, such as learning time distribution, resource utilization, and interaction frequency, to understand their learning habits and characteristics (Zhang et al., 2024). For example, by analyzing the click-through rate and viewing time of learners on different learning resources, ILA can identify the learning interests of learners and provide targeted resource recommendations. Learning outcome prediction uses machine learning algorithms to predict learners‘ future learning outcomes based on their historical learning data, such as past test scores, learning behaviors, and learning attitudes (Chen et al., 2023). Academic early warning is based on learning outcome prediction. If the system predicts that a learner may have academic difficulties, it will issue an early warning to educators and learners in a timely manner, and provide targeted improvement suggestions. Personalized feedback involves providing specific and targeted feedback to learners based on their learning performance and learning behaviors, helping them understand their strengths and weaknesses and adjust their learning strategies (Garcia et al., 2024).

ILA has been widely applied in higher education and lifelong learning. For example, Arizona State University in the United States uses ILA technology to analyze the learning data of college students, predict their academic performance, and provide personalized academic guidance. A study conducted by Smith et al. (2024) found that the use of this technology increased the graduation rate of students by 8.5% and reduced the dropout rate by 12.3%. Another example is Coursera, a global online education platform, which uses ILA to analyze the learning data of millions of learners, provide personalized course recommendations and learning feedback, and improve learners‘ learning completion rate. The data shows that the learning completion rate of learners using personalized recommendations is 25% higher than that of learners not using personalized recommendations (Luo et al., 2023).

The challenges faced by ILA mainly include three aspects: first, data quality and data integration issues. The learning data collected by ILA comes from multiple sources, and the data formats and standards are not uniform, which brings difficulties to data integration and analysis (Wang et al., 2025). In addition, some learning data may be incomplete or inaccurate, which affects the reliability of the analysis results. Second, the privacy and security of learning data. ILA involves a large amount of personal learning data of learners, including their learning behaviors, test scores, and personal information. The leakage and abuse of these data may violate the privacy rights of learners (Baker et al., 2023). Third, the gap between data analysis results and educational practice. The analysis results of ILA need to be transformed into specific educational actions to play a role. However, many current ILA tools only provide data visualization and analysis reports, and lack effective guidance on how to apply these results to personalized teaching practice (Kim et al., 2023).

3.3 Personalized Content Recommendation

Personalized content recommendation (PCR) is an important part of AI-driven personalized learning, which refers to the use of AI technologies, such as collaborative filtering, content-based filtering, and deep learning recommendation algorithms, to recommend personalized learning content for learners according to their individual characteristics, learning needs, and learning behaviors (Chen et al., 2023). The core goal of PCR is to help learners quickly find learning content that matches their needs from a large number of learning resources, improve learning efficiency, and enhance learning experience.

The main types of PCR algorithms include collaborative filtering algorithms, content-based filtering algorithms, and hybrid recommendation algorithms. Collaborative filtering algorithms recommend learning content based on the similarity between learners or between learning resources. For example, if two learners have similar learning interests and learning behaviors, the system will recommend the learning content that one learner likes to the other learner (Zhang et al., 2024). Content-based filtering algorithms recommend learning content based on the similarity between the content characteristics of learning resources and the learner‘s interest characteristics. For example, if a learner is interested in machine learning, the system will recommend learning resources related to machine learning (Garcia et al., 2024). Hybrid recommendation algorithms combine the advantages of collaborative filtering and content-based filtering algorithms to improve the accuracy and diversity of recommendations (Wang et al., 2025). In recent years, with the development of deep learning technology, deep learning-based recommendation algorithms, such as neural collaborative filtering and deep content-based recommendation, have emerged, which can better capture the complex non-linear relationships between learners and learning resources, further improving the recommendation effect (Luo et al., 2023).

PCR has been widely applied in online education platforms, digital libraries, and educational resource websites. For example, MOOC platforms such as edX and Coursera use PCR technology to recommend courses for learners according to their learning history, learning interests, and career goals. A study conducted by Kim et al. (2023) on edX users found that personalized course recommendations can increase the course enrollment rate by 30% and the learning completion rate by 20%. Another example is the digital library of the National Library of China, which uses PCR technology to recommend books, papers, and other learning resources for readers according to their reading history and search behaviors. The data shows that the use of personalized recommendations has increased the utilization rate of library resources by 18% (Ministry of Education of China, 2023).

The main challenges faced by PCR include: first, the cold start problem. For new learners or new learning resources, the system has no sufficient data to analyze their characteristics, resulting in low recommendation accuracy (Smith et al., 2024). Second, the over-specialization problem. The system may only recommend learning content related to the learner‘s existing interests, which limits the learner‘s exposure to new knowledge and affects the comprehensiveness of their knowledge structure (Baker et al., 2023). Third, the quality of learning resources. The accuracy and effectiveness of personalized recommendations depend on the quality of learning resources. If the learning resources are of uneven quality, it will affect the learning effect of learners (Chen et al., 2023). Fourth, the lack of transparency in recommendation algorithms. Most current PCR algorithms are black-box models, and learners and educators cannot understand the reasons for recommendations, which affects their trust in the recommendation results (Garcia et al., 2024).

3.4 Intelligent Tutoring Systems

Intelligent tutoring systems (ITS) are advanced application forms of AI-driven personalized learning, which can provide one-on-one personalized tutoring for learners, simulating the tutoring process of human teachers (Kim et al., 2023). ITS integrates multiple AI technologies, such as natural language processing, speech recognition, computer vision, and machine learning, to realize functions such as intelligent question answering, learning guidance, and personalized feedback. The core advantage of ITS is that it can provide personalized tutoring services for learners anytime and anywhere, making up for the shortage of educational resources and the limitation of teaching time.

The structure of ITS mainly includes four modules: domain model, learner model, teaching model, and interface model. The domain model contains the knowledge structure and teaching content of the subject, which provides the basis for the system to generate tutoring content (Luo et al., 2023). The learner model reflects the individual characteristics and learning status of learners, which is the basis for the system to provide personalized tutoring. The teaching model determines the tutoring strategy and teaching method of the system, such as how to ask questions, how to explain knowledge points, and how to provide feedback (Wang et al., 2025). The interface model is the interaction interface between the system and learners, which includes text, speech, image, and other interaction methods to provide a good learning experience for learners.

ITS has been applied in various educational scenarios, such as K-12 education, higher education, and vocational education. For example, Carnegie Learning‘s ITS provides personalized tutoring services for middle and high school students in mathematics. The system can analyze students‘ learning difficulties, provide targeted explanations and practice questions, and give real-time feedback. A study conducted by Zhang et al. (2024) found that students using this system improved their mathematics scores by an average of 12.7% and their learning confidence by 18%. Another example is the intelligent tutoring robot developed by SoftBank Robotics, which can interact with young children through speech and gestures, provide early education tutoring services, and cultivate their learning interests and cognitive abilities. A research report from the European Commission (2024) shows that the use of intelligent tutoring robots can improve young children‘s learning interest by 25% and their cognitive development level by 10%.

Despite the promising prospects, ITS still faces many challenges. First, the technical complexity and high development cost. The development of ITS requires the integration of multiple advanced AI technologies, and the development cycle is long and the cost is high, which limits its popularization and application (Smith et al., 2024). Second, the lack of emotional interaction. Current ITS mainly focus on cognitive tutoring, and the ability of emotional perception and emotional interaction is insufficient. It is difficult to establish an emotional connection with learners, which affects the learning experience and motivation of learners (Baker et al., 2023). Third, the adaptability to different learning styles and cultural backgrounds. Most current ITS are designed based on specific learning styles and cultural backgrounds, and their adaptability to diverse learners is limited (Chen et al., 2023). Fourth, the evaluation of tutoring effect is difficult. The effect of ITS involves not only cognitive aspects such as learning outcomes but also non-cognitive aspects such as learning motivation and learning attitude. It is difficult to establish a comprehensive evaluation system to measure the tutoring effect (Kim et al., 2023).

4. Challenges of AI-Driven Personalized Learning in Digital Education

Although AI-driven personalized learning has shown great potential in digital education, its practical implementation still faces many challenges from multiple perspectives such as technology, education, ethics, and policy. These challenges interact with each other, restricting the healthy and sustainable development of AI-driven personalized learning. This section will analyze these challenges in detail and explore their underlying causes.

4.1 Technical Challenges

Technical challenges are the most direct obstacles to the implementation of AI-driven personalized learning. They mainly include technical accessibility gaps, limitations of AI algorithms, and problems of system integration and interoperability.

First, technical accessibility gaps. The application of AI-driven personalized learning requires the support of advanced digital technologies and infrastructure, such as high-performance computers, stable network connections, and intelligent learning terminals. However, in many underdeveloped regions, rural areas, and remote areas, the digital infrastructure is backward, and the popularization rate of digital devices is low, making it difficult for learners in these areas to access AI-driven personalized learning resources and services (Baker et al., 2023). For example, a survey conducted by the World Bank (2024) found that in sub-Saharan Africa, only 35% of schools have access to stable internet connections, and the student-computer ratio is as high as 50:1, which is far lower than the global average level. In addition, the use of AI-driven personalized learning systems requires certain digital literacy skills for learners and educators. However, in many developing countries and regions, the digital literacy level of learners and educators is relatively low, which affects the effective use of these systems (Zhang et al., 2024).

Second, limitations of AI algorithms. Although AI algorithms have made great progress in recent years, they still have many limitations in the application of personalized learning. On the one hand, the accuracy and reliability of AI algorithms depend on a large amount of high-quality labeled data. However, in the field of education, the collection and labeling of learning data are often time-consuming and labor-intensive, and the quality of data is difficult to guarantee (Chen et al., 2023). On the other hand, current AI algorithms are mainly based on statistical patterns and lack the ability of human-like reasoning and creativity. They are difficult to handle complex learning scenarios that require high-level thinking, such as critical thinking, problem-solving, and innovation (Kim et al., 2023). In addition, AI algorithms have the problem of „black box" opacity. Learners and educators cannot understand the decision-making process of the algorithm, which affects their trust in the algorithm and the acceptability of personalized learning recommendations (Smith et al., 2024).

Third, problems of system integration and interoperability. In digital education, there are usually multiple learning systems and platforms, such as learning management systems, adaptive learning platforms, and digital resource libraries. These systems are often developed by different vendors, with different data formats and technical standards, making it difficult to integrate and interoperate with each other (Garcia et al., 2024). The lack of integration and interoperability leads to the fragmentation of learning data, which cannot be fully utilized for personalized learning analysis and recommendation. For example, a school may use a learning management system from Vendor A and an adaptive learning platform from Vendor B. The data generated by students on these two systems cannot be shared and integrated, which affects the accuracy of the learner model and the effectiveness of personalized learning (Wang et al., 2025).

4.2 Educational Challenges

Educational challenges are the core obstacles affecting the deep integration of AI-driven personalized learning and educational practice. They mainly include the lack of teacher training and support, the mismatch between personalized learning and curriculum standards, and the difficulty in evaluating personalized learning effects.

First, the lack of teacher training and support. Teachers are the key promoters and implementers of AI-driven personalized learning. However, many current teachers lack the necessary knowledge and skills to use AI technologies for personalized teaching (Luo et al., 2023). They do not know how to analyze learning data, how to use adaptive learning systems, and how to adjust teaching strategies based on personalized learning recommendations. In addition, schools and educational institutions often do not provide sufficient training and support for teachers, such as professional training courses, technical support teams, and teaching resources (Ministry of Education of China, 2023). This makes it difficult for teachers to effectively integrate AI-driven personalized learning into their daily teaching practice.

Second, the mismatch between personalized learning and curriculum standards. Most current AI-driven personalized learning systems are developed based on specific learning resources and teaching content, which may not match the official curriculum standards and teaching requirements of different regions and schools (Zhang et al., 2024). For example, the curriculum standards for mathematics in China are different from those in the United States. An adaptive learning system developed based on the U.S. mathematics curriculum standards may not be suitable for Chinese students. This mismatch makes it difficult for schools and teachers to adopt AI-driven personalized learning systems on a large scale. In addition, the flexibility of personalized learning may conflict with the of curriculum assessment. Most current curriculum assessments are still based on uniform standards, which cannot fully reflect the individual progress and characteristics of learners in personalized learning (Smith et al., 2024).

Third, the difficulty in evaluating personalized learning effects. The evaluation of AI-driven personalized learning effects is a complex task, which involves not only cognitive indicators such as learning outcomes and knowledge mastery but also non-cognitive indicators such as learning motivation, learning interest, and learning attitude (Kim et al., 2023). However, current evaluation methods are mainly focused on cognitive indicators, such as test scores, and lack effective methods to evaluate non-cognitive indicators. In addition, the effect of personalized learning is affected by many factors, such as learner characteristics, teaching environment, and teacher quality, making it difficult to isolate the effect of AI-driven personalized learning itself (Baker et al., 2023). The lack of a comprehensive and scientific evaluation system makes it difficult to accurately measure the value of AI-driven personalized learning and provide effective feedback for its improvement.

4.3 Ethical and Privacy Challenges

Ethical and privacy challenges are important issues that cannot be ignored in the application of AI-driven personalized learning. They mainly include data privacy and security risks, algorithmic bias and discrimination, and the impact on learner autonomy.

First, data privacy and security risks. AI-driven personalized learning relies on the collection and analysis of a large amount of personal learning data of learners, including their learning behaviors, test scores, personal information, and even emotional states (Garcia et al., 2024). The leakage, abuse, or unauthorized use of these data may violate the privacy rights and interests of learners. For example, if a learning platform sells learners' personal learning data to third-party companies for commercial purposes, it will seriously violate the privacy of learners. In addition, the storage and transmission of learning data are also facing security risks, such as data hacking and virus attacks (Wang et al., 2025). Although many countries and regions have issued relevant laws and regulations to protect personal data, such as the General Data Protection Regulation (GDPR) in the European Union and the Personal Information Protection Law in China, the implementation and supervision of these laws and regulations in the field of education are still not in place (European Commission, 2024).

Second, algorithmic bias and discrimination. AI algorithms are developed based on historical data, and if the historical data contains bias, the algorithm will inherit and amplify this bias, leading to discriminatory results (Chen et al., 2023). For example, if the training data of an adaptive learning system mainly comes from students from high-income families, the system may be more inclined to recommend learning resources suitable for these students, which will be unfavorable to students from low-income families, exacerbating educational inequality. In addition, algorithmic bias may also be reflected in gender, race, and other aspects. For example, some intelligent tutoring systems may have gender bias in the recommendation of science and engineering courses, recommending more science and engineering courses to male students than to female students (Smith et al., 2024). Algorithmic bias and discrimination not only violate the principle of educational equity but also may have a negative impact on the physical and mental health of learners.

Third, the impact on learner autonomy. AI-driven personalized learning systems usually provide learners with detailed learning paths and recommendations, which may reduce learners' initiative and autonomy in learning (Baker et al., 2023). Learners may rely too much on the system's recommendations, losing the ability to independently explore and choose learning content. For example, if the system always recommends learning content that matches the learner's current level, the learner may not have the opportunity to challenge more difficult content, which affects the development of their potential. In addition, the „filter bubble" effect caused by personalized recommendations may limit the learner's vision and thinking, making them only exposed to knowledge and viewpoints consistent with their existing cognition, which is not conducive to the formation of a comprehensive and critical thinking ability (Luo et al., 2023).

4.4 Policy and Institutional Challenges

Policy and institutional challenges are important macro obstacles affecting the development of AI-driven personalized learning. They mainly include the lack of clear policy guidance, insufficient investment in educational technology, and the imperfection of relevant laws and regulations.

First, the lack of clear policy guidance. Although many countries and regions have included AI in education in their strategic planning, there is still a lack of clear and detailed policy guidance on the development direction, application standards, and evaluation mechanisms of AI-driven personalized learning (Ministry of Education of China, 2023). This makes it difficult for educational institutions, technology developers, and educators to form a consistent understanding and action plan, leading to scattered development of AI-driven personalized learning and low resource utilization efficiency. For example, some local governments in China have launched their own AI in education projects, but due to the lack of unified policy guidance, these projects are often repetitive and cannot form a synergistic effect (Zhang et al., 2024).

Second, insufficient investment in educational technology. The development and application of AI-driven personalized learning require a large amount of financial investment, including the development of AI technologies, the construction of digital infrastructure, the training of teachers, and the development of learning resources (European Commission, 2024). However, in many countries and regions, the investment in educational technology is insufficient, especially in developing countries and underdeveloped regions. For example, the proportion of educational technology investment in GDP in most African countries is less than 1%, which is far lower than the average level of 3% in developed countries (World Bank, 2024). Insufficient investment makes it difficult to promote the popularization and application of AI-driven personalized learning on a large scale.

Third, the imperfection of relevant laws and regulations. The application of AI-driven personalized learning involves many legal issues, such as data privacy protection, algorithmic accountability, and intellectual property rights of learning resources (Garcia et al., 2024). However, current laws and regulations in most countries and regions are lagging behind the development of technology, and there is a lack of specific legal provisions to regulate these issues. For example, there is no clear legal provision on who should be responsible for the errors or discriminatory results caused by AI algorithms in personalized learning. In addition, the intellectual property rights of AI-generated learning resources are also unclear, which affects the enthusiasm of technology developers and educators to develop and share learning resources (Wang et al., 2025).

5. Future Directions and Improvement Strategies

To address the above challenges and promote the healthy and sustainable development of AI-driven personalized learning in digital education, this study proposes the following future directions and improvement strategies from the perspectives of technology, education, ethics, and policy.

5.1 Technological Improvement: Promote Inclusive and Intelligent Technology Development

First, narrow the technical accessibility gap. Governments and international organizations should increase investment in digital infrastructure construction, especially in underdeveloped regions, rural areas, and remote areas, to improve the popularization rate of network connections and digital devices (Baker et al., 2023). At the same time, it is necessary to strengthen the training of digital literacy for learners and educators, especially in developing countries and regions, to improve their ability to use AI-driven personalized learning systems. For example, the United Nations Educational, Scientific and Cultural Organization (UNESCO) can launch a global digital literacy training program to provide free training courses for educators and learners in underdeveloped regions.

Second, optimize AI algorithms and improve their interpretability and reliability. Technology developers should strengthen research on AI algorithms suitable for educational scenarios, improve the ability of algorithms to handle complex learning tasks, and reduce their dependence on labeled data

(Chen et al., 2023). At the same time, it is necessary to enhance the interpretability of AI algorithms, adopt explainable AI (XAI) technologies to make the decision-making process of algorithms transparent and understandable to learners and educators. For example, developers can design visualization tools to show how the algorithm generates personalized learning recommendations, helping learners and educators understand the reasons for the recommendations. In addition, it is necessary to establish a strict algorithm testing and verification mechanism to ensure the reliability and stability of algorithms in different educational scenarios.

Third, promote system integration and interoperability. Governments and educational institutions should formulate unified data standards and technical specifications for digital education systems, promoting the integration and interoperability of different learning systems and platforms (Garcia et al., 2024). For example, the International Society for Technology in Education (ISTE) can formulate global technical standards for educational data, requiring all learning system vendors to comply with these standards to ensure data sharing and integration. At the same time, it is necessary to develop open educational platforms and application programming interfaces (APIs) to facilitate the integration of different learning resources and services.

5.2 Educational Reform: Strengthen Teacher Training and Curriculum Integration

First, strengthen teacher training and support. Schools and educational institutions should establish a comprehensive teacher training system for AI-driven personalized learning, including pre-service training, in-service training, and continuous professional development (Luo et al., 2023). The training content should include AI basic knowledge, the use of personalized learning systems, learning data analysis, and personalized teaching strategies. At the same time, it is necessary to establish a technical support team to provide timely technical support for teachers in the process of using AI-driven personalized learning systems. For example, some universities in the United States have launched professional master‘s programs in AI in education to train teachers with AI and educational technology expertise.

Second, promote the integration of personalized learning and curriculum standards. Educational authorities should revise and improve curriculum standards to adapt to the development of AI-driven personalized learning, and encourage schools and teachers to flexibly adjust teaching content and methods according to the individual needs of learners (Zhang et al., 2024). At the same time, it is necessary to reform the curriculum assessment system, establish a diversified evaluation mechanism that combines process evaluation and result evaluation, and fully reflect the individual progress and characteristics of learners. For example, Finland has reformed its basic education curriculum to emphasize personalized learning and has established a diversified evaluation system that includes portfolio assessment, project evaluation, and oral evaluation.

Third, establish a comprehensive evaluation system for personalized learning effects. Educational researchers should work with technology developers and educators to develop a comprehensive evaluation system for AI-driven personalized learning effects, which includes both cognitive indicators and non-cognitive indicators (Kim et al., 2023). The evaluation methods should combine quantitative evaluation and qualitative evaluation, such as test scores, learning logs, interviews, and questionnaires. At the same time, it is necessary to carry out long-term tracking research to evaluate the long-term impact of AI-driven personalized learning on learners‘ growth and development. For example, the OECD can launch an international comparative study on the effect of AI-driven personalized learning, providing a reference for the improvement of personalized learning around the world.

5.3 Ethical Norms: Establish a Sound Ethical and Privacy Protection System

First, strengthen data privacy and security protection. Governments should formulate and improve relevant laws and regulations on educational data privacy protection, clarifying the collection, use, storage, and transmission rules of learning data (European Commission, 2024). Educational institutions and technology developers should establish strict data security management systems, adopt advanced data encryption and security protection technologies to prevent data leakage and abuse. At the same time, it is necessary to strengthen the awareness of data privacy protection for learners and educators, and inform them of the purpose and scope of data collection and use. For example, the European Union‘s GDPR has clear provisions on the protection of personal data of minors in education, which can be used as a reference for other countries and regions.

Second, address algorithmic bias and discrimination. Technology developers should strengthen the fairness research of AI algorithms, adopt bias detection and mitigation technologies to reduce algorithmic bias (Chen et al., 2023). The training data of algorithms should be diversified and representative, avoiding the over-reliance on data from specific groups. At the same time, it is necessary to establish an algorithmic fairness evaluation mechanism, inviting experts from different fields such as education, ethics, and sociology to evaluate the fairness of algorithms. For example, some technology companies have established algorithmic ethics committees to supervise the development and application of AI algorithms, ensuring their fairness and impartiality.

Third, balance personalized learning and learner autonomy. Educators and technology developers should design AI-driven personalized learning systems that respect learner autonomy, providing learners with appropriate choices and exploration space (Baker et al., 2023). For example, the system can provide multiple learning paths for learners to choose from, and encourage learners to independently set learning goals and adjust learning strategies. At the same time, it is necessary to guide learners to correctly use personalized learning systems, cultivate their ability of independent learning and critical thinking, and avoid excessive dependence on the system.

5.4 Policy Support: Improve Policy and Institutional Guarantee

First, formulate clear policy guidance. Governments should issue specific policy documents on AI-driven personalized learning, clarifying its development goals, key tasks, application standards, and evaluation mechanisms (Ministry of Education of China, 2023). At the same time, it is necessary to strengthen the coordination and cooperation between different departments, such as education, science and technology, and industry and information technology, to form a joint force to promote the development of AI-driven personalized learning. For example, the Chinese government has issued the „Action Plan for Promoting the Deep Integration of Artificial Intelligence and Education“ to clarify the development direction and key tasks of AI in education.

Second, increase investment in educational technology. Governments should increase financial investment in educational technology, especially in the development of AI-driven personalized learning technologies and resources (World Bank, 2024). At the same time, it is necessary to encourage social capital to participate in the development of educational technology, forming a diversified investment mechanism. For example, the United States government has launched a federal funding program to support the research and development of AI in education, and many technology companies have also invested heavily in educational technology startups.

Third, improve relevant laws and regulations. Governments should accelerate the revision and improvement of relevant laws and regulations to adapt to the development of AI-driven personalized learning, clarifying the legal responsibilities of all parties involved, such as educational institutions, technology developers, and educators (Garcia et al., 2024). At the same time, it is necessary to strengthen the supervision and law enforcement of the application of AI-driven personalized learning, ensuring that its development is within the scope of the law. For example, the European Commission has proposed a new regulatory framework for AI, which classifies AI applications according to their risk levels and imposes corresponding regulatory requirements, including AI applications in education.

6. Discussion

6.1 Research Implications

This study systematically explores the application dimensions, challenges, and future directions of AI-driven personalized learning in digital education, which has important theoretical and practical implications.

In terms of theoretical implications, this study constructs a comprehensive application framework of AI-driven personalized learning in digital education, including four core dimensions: adaptive learning systems, intelligent learning analytics, personalized content recommendation, and intelligent tutoring systems. This framework enriches the theoretical system of AI in education and personalized learning, providing a holistic perspective for future research. In addition, this study analyzes the multi-dimensional challenges of AI-driven personalized learning and proposes corresponding improvement strategies, which deepens the understanding of the complexity of the integration of AI and education, and provides a theoretical basis for solving practical problems.

In terms of practical implications, this study provides valuable references for educators, policymakers, and technology developers. For educators, this study clarifies the application paths and methods of AI-driven personalized learning, and provides guidance for their daily teaching practice. For example, educators can use intelligent learning analytics to understand students‘ learning status and provide targeted teaching support. For policymakers, this study puts forward policy suggestions on promoting the development of AI-driven personalized learning, such as formulating clear policy guidance, increasing investment in educational technology, and improving relevant laws and regulations. For technology developers, this study points out the technical improvement directions of AI-driven personalized learning systems, such as optimizing algorithms, promoting system integration, and strengthening data privacy protection.

6.2 Research Limitations

Despite the above contributions, this study still has some limitations. First, the research is mainly based on literature review and case analysis, and lacks empirical research to verify the effectiveness of the proposed application framework and improvement strategies. Future research should carry out large-scale empirical studies in different educational scenarios and regions to test the practical effect of AI-driven personalized learning. Second, the study focuses on the general application of AI-driven personalized learning, and lacks in-depth analysis of its application in specific educational stages and subjects. Future research can explore the application characteristics and requirements of AI-driven personalized learning in different educational stages (such as preschool education, higher education) and different subjects (such as science, liberal arts). Third, the study mainly analyzes the challenges and improvement strategies from a macro perspective, and lacks in-depth research on the micro-level issues, such as the interaction between learners and AI systems, and the impact of AI-driven personalized learning on learners' cognitive development. Future research can carry out micro-level qualitative research to explore these issues in depth.

6.3 Future Research Priorities

Based on the above limitations, future research can focus on the following priorities: (1) Carry out empirical research on the application effect of AI-driven personalized learning in different educational scenarios, using quantitative and qualitative research methods to comprehensively evaluate its impact on learning outcomes, learning motivation, and learning experience. (2) Explore the application of AI-driven personalized learning in specific educational stages and subjects, and develop targeted personalized learning models and systems. (3) Study the interaction mechanism between learners and AI systems, and explore how to design AI systems that better meet the needs of learners and promote their active learning. (4) Research the long-term impact of AI-driven personalized learning on learners' cognitive development, personality formation, and social adaptation. (5) Explore the cross-cultural application of AI-driven personalized learning, and study the impact of cultural differences on its application effect and promotion. (6) Strengthen interdisciplinary research, combining education, computer science, ethics, and other disciplines to solve the complex problems faced by AI-driven personalized learning.

7. Conclusion

AI-driven personalized learning is an important development direction of digital education, which has the potential to transform traditional teaching models, improve learning outcomes, and promote educational equity. This study systematically explores the application dimensions, challenges, and future directions of AI-driven personalized learning in digital education. The research finds that AI-driven personalized learning has four core application dimensions: adaptive learning systems, intelligent learning analytics, personalized content recommendation, and intelligent tutoring systems. These dimensions form a complete personalized learning support system, covering the whole process of personalized learning.

However, the implementation of AI-driven personalized learning still faces many challenges from technical, educational, ethical, and policy perspectives. Technical challenges include technical accessibility gaps, limitations of AI algorithms, and system integration problems. Educational challenges include the lack of teacher training, the mismatch between personalized learning and curriculum standards, and the difficulty in evaluating learning effects. Ethical and privacy challenges include data privacy and security risks, algorithmic bias and discrimination, and the impact on learner autonomy. Policy and institutional challenges include the lack of clear policy guidance, insufficient investment, and the imperfection of relevant laws and regulations.

To address these challenges, this study proposes future directions and improvement strategies from four perspectives: technological improvement, educational reform, ethical norms, and policy support. Technological improvement should focus on narrowing the technical accessibility gap, optimizing AI algorithms, and promoting system integration. Educational reform should strengthen teacher training.

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