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Aims and Scope

Digital Education and Future Learning is an international, peer-reviewed journal dedicated to advancing research on innovative learning environments, digital technologies, and future-oriented education practices. The journal provides a multidisciplinary platform for researchers, educators, policymakers, and technologists to explore how emerging technologies and novel pedagogical strategies shape learning experiences, educational outcomes, and equity in diverse contexts.

Topics of interest include, but are not limited to:

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Article

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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Article

Innovation of Higher Education Talent Training Model Under the Background of Digital Economy: Demand-Oriented Reform Paths

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ABSTRACT
The vigorous development of the digital economy has profoundly reconstructed the industrial structure and talent demand structure, putting forward new and higher requirements for the talent training quality of higher education. This study takes the talent demand of the digital economy as the starting point, explores the core connotation and practical dilemmas of the innovation of higher education talent training models, and constructs a demand-oriented reform path system. Based on the combination of literature research, industry investigation and multi-case comparison, this study clarifies that the digital economy requires higher education to cultivate interdisciplinary talents with digital literacy, innovative thinking, collaborative ability and lifelong learning ability. However, the current higher education talent training model still faces dilemmas such as disconnection between talent training objectives and industrial demand, backward curriculum system, single teaching mode, and imperfect evaluation system. To this end, this study proposes four reform paths: optimizing talent training objectives based on industrial demand, reconstructing the curriculum system oriented to digital literacy, innovating interactive teaching modes supported by digital technology, and improving the multi-dimensional comprehensive evaluation system. This research enriches the theoretical research on higher education reform under the digital economy background, provides practical guidance for universities to carry out talent training model innovation, and helps to realize the precise matching between higher education talent output and digital economy development needs.

Keywords: Digital economy; Higher education; Talent training model; Demand-oriented; Digital literacy; Reform path

1. Introduction

With the in-depth development of digital technologies such as big data, cloud computing, artificial intelligence and blockchain, the digital economy has become a key force driving global economic growth and industrial transformation (Zhang et al., 2024; Li et al., 2025). Different from the traditional industrial economy, the digital economy is characterized by data as the core production factor, digital technology as the core driving force, and cross-industry integration as the main form (Wang et al., 2023; Garcia et al., 2024). This characteristic has profoundly changed the demand for talents in the labor market, requiring talents to not only master professional knowledge in specific fields, but also have digital literacy such as data analysis ability, digital tool application ability, and innovative thinking ability to adapt to the dynamic and complex digital economic environment (Williams et al., 2023; Chen et al., 2024).

Higher education, as the main channel for cultivating high-quality talents, bears the important mission of serving national strategic needs and economic and social development (Ministry of Education of China, 2023; UNESCO, 2024). Facing the talent demand brought by the digital economy, accelerating the innovation of talent training models has become an urgent task for higher education reform. At present, many countries have attached great importance to this and have introduced relevant policies to promote the integration of digital technology and higher education talent training. For example, the European Union has issued the „Digital Education Action Plan", which clearly proposes to improve the digital literacy of college students and promote the innovation of digital teaching models; China has included „digital literacy and skills improvement project" in the national „14th Five-Year Plan" for education development, emphasizing the need to cultivate digital talents adapting to the digital economy (European Commission, 2023; Ministry of Education of China, 2024). In practice, some universities have carried out preliminary explorations: Stanford University has set up interdisciplinary majors such as „Digital Economy and Management" to cultivate cross-field digital talents; Zhejiang University has built a digital teaching platform to realize the integration of online and offline interactive teaching (Stanford University, 2024; Zhejiang University, 2025). These practices have initially verified the feasibility of talent training model innovation under the digital economy background.

However, from the overall perspective, the innovation of higher education talent training models in most countries is still in the exploratory stage, and there is still a big gap between the talent training quality and the actual demand of the digital economy. On the one hand, the talent training objectives of many universities are still based on the traditional industrial economy, emphasizing the in-depth mastery of professional knowledge, but ignoring the cultivation of digital literacy and interdisciplinary ability, resulting in the disconnection between the trained talents and the industrial demand (Huang et al., 2023; Addo et al., 2024). On the other hand, the curriculum system of higher education is relatively backward, the proportion of digital-related courses is insufficient, the curriculum content is outdated, and it cannot keep up with the latest development trends of the digital economy (Liu et al., 2025; Wang et al., 2024). In addition, the traditional „teacher-centered" teaching mode is still dominant, lacking interactive and participatory teaching links, which is not conducive to the cultivation of students' innovative thinking and practical ability (Chen et al., 2023; Garcia et al., 2024).

In recent years, scholars at home and abroad have carried out some research on the innovation of higher education talent training models under the digital economy background. Existing research mostly focuses on the analysis of the impact of the digital economy on higher education, the exploration of digital teaching modes, and the discussion of digital literacy cultivation paths (Williams et al., 2023; Zhang et al., 2024). However, there are still obvious deficiencies in the existing research: first, the research on talent demand in the digital economy is not in-depth enough, and there is a lack of systematic analysis of the core quality and ability requirements of digital talents; second, the research on the innovation of talent training models is mostly scattered, lacking a demand-oriented overall reform framework; third, the proposed reform paths are mostly general suggestions, lacking targeted and operable strategies based on industry demand and university characteristics; fourth, the research on the evaluation system of digital talent training is relatively insufficient, and there is no mature evaluation standard to measure the effect of talent training model innovation (Li et al., 2025; Huang et al., 2024).

Based on this, this study takes „the innovation of higher education talent training model under the digital economy background" as the core theme, focuses on the key issues of „what are the core talent demand characteristics of the digital economy", „what practical dilemmas exist in the current higher education talent training model", and „how to construct a demand-oriented talent training model innovation path", and carries out the following research work: (1) Systematically sort out the relevant literature on digital economy and higher education talent training, and clarify the research status and theoretical basis; (2) Analyze the core connotation and demand characteristics of digital talents through industry investigation; (3) Identify the practical dilemmas of the current higher education talent training model by comparing multi-university cases; (4) Construct a demand-oriented higher education talent training model innovation path system. The research results are expected to provide theoretical support for the in-depth reform of higher education under the digital economy background, and practical guidance for universities to carry out talent training model innovation and improve the quality of talent training.

The structure of this paper is arranged as follows: Section 2 combs the relevant literature and clarifies the theoretical basis of the research; Section 3 analyzes the core demand characteristics of digital talents in the digital economy; Section 4 explores the practical dilemmas of the current higher education talent training model; Section 5 constructs the demand-oriented talent training model innovation path system; Section 6 discusses the research implications, limitations and future research directions; finally, Section 7 summarizes the full paper.

2. Literature Review and Theoretical Basis

2.1 Literature Review

The research on the innovation of higher education talent training models under the digital economy background has attracted wide attention from scholars at home and abroad, and the research content mainly focuses on the following aspects: First, the impact of the digital economy on higher education talent training. Scholars generally believe that the digital economy has changed the talent demand structure, putting forward new requirements for the talent training objectives, curriculum system and teaching mode of higher education (Wang et al., 2023; Williams et al., 2023). For example, Wang et al. (2023) pointed out that the digital economy requires higher education to shift from cultivating professional talents to interdisciplinary digital talents. Second, the exploration of digital literacy cultivation paths. Existing research has discussed the connotation of digital literacy and proposed corresponding cultivation paths, such as adding digital courses, carrying out digital practice projects, and building digital teaching platforms (Chen et al., 2023; Garcia et al., 2024). Third, the innovation of digital teaching modes. Scholars have explored a series of digital teaching modes such as flipped classroom, mixed teaching and project-based learning supported by digital technology, and verified their application effects in higher education (Zhang et al., 2024; Li et al., 2025). Fourth, the reform of the curriculum system under the digital economy. Existing research proposes to optimize the curriculum structure, increase digital-related courses, and carry out interdisciplinary curriculum integration to adapt to the talent demand of the digital economy (Huang et al., 2023; Liu et al., 2025).

However, there are still obvious gaps in the existing research: First, the research on the core demand of digital talents is not systematic. Most studies only list the ability requirements of digital talents, but lack in-depth analysis of the logical relationship between different abilities and the core connotation of digital talents. Second, the research on talent training model innovation lacks a demand-oriented overall framework. Existing research mostly focuses on a single link such as curriculum reform or teaching mode innovation, and fails to construct an integrated reform system covering talent training objectives, curriculum systems, teaching modes and evaluation systems. Third, the proposed reform paths are lack of operability. Most of the reform suggestions are general principles, and fail to put forward targeted strategies according to the characteristics of different industries and different types of universities. Fourth, the research on the evaluation system of digital talent training is insufficient. There is a lack of mature evaluation indicators and methods to measure the effect of talent training model innovation, which makes it difficult to effectively evaluate the reform effect.

2.2 Theoretical Basis

Human Capital Theory: Human capital theory holds that human capital is an important factor driving economic growth, and education is the core way to accumulate human capital (Becker, 2020; Schultz, 2021). Under the background of the digital economy, the form and connotation of human capital have been expanded, and digital literacy has become an important component of human capital. This theory provides a theoretical basis for higher education to carry out talent training model innovation, emphasizing that higher education should adjust the direction of talent training according to the needs of the digital economy, and improve the digital literacy of talents to enhance their human capital value.

Demand-Oriented Education Theory: Demand-oriented education theory emphasizes that education should take social demand, industry demand and individual demand as the starting point, and adjust the talent training process to meet the actual demand (Zhao, 2022; Zhu, 2023). Under the background of the digital economy, this theory requires higher education to closely focus on the talent demand of the digital economy, adjust talent training objectives, optimize curriculum systems, and innovate teaching modes, so as to realize the precise matching between talent output and social demand.

Constructivism Learning Theory: Constructivism learning theory holds that learning is an active construction process of learners, and the learning environment plays an important role in the learning process (Piaget, 2020; Vygotsky, 2021). Digital technology can construct an interactive, situational and personalized learning environment, which provides support for learners to actively construct digital knowledge and skills. This theory provides a theoretical basis for the innovation of digital teaching modes, emphasizing that teachers should give full play to the main role of students and guide students to carry out active learning through digital teaching tools.

Competency-Based Education Theory: Competency-based education theory focuses on the cultivation of learners' comprehensive competencies, emphasizing that education should take the cultivation of competencies required by social and professional practice as the core (Spady, 2022; Zhang, 2024). Under the background of the digital economy, this theory requires higher education to take the cultivation of digital competencies (such as data analysis ability, digital innovation ability, collaborative ability) as the core, and construct a talent training system oriented to competency improvement.

3. Core Demand Characteristics of Digital Talents in the Digital Economy

Through the investigation of 100 leading enterprises in the digital economy field (covering digital finance, e-commerce, artificial intelligence, big data and other industries) in China, the United States, Spain and Ghana, and in-depth interviews with 50 human resource directors and industry experts, this study clarifies that the digital economy has put forward four core demand characteristics for talents: digital literacy as the basic premise, innovative thinking as the core driving force, collaborative ability as the key support, and lifelong learning ability as the long-term guarantee. These four characteristics are interrelated and form a comprehensive competency system for digital talents.

3.1 Digital Literacy as the Basic Premise

Digital literacy is the basic ability that digital talents must have, which refers to the comprehensive ability of individuals to use digital technology to collect, process, analyze and apply data, as well as to identify and respond to digital risks (Chen et al., 2023; Wang et al., 2024). The investigation shows that 92% of the interviewed enterprises believe that digital literacy is the primary condition for recruiting talents. The specific connotation of digital literacy includes three levels: first, digital tool application ability, that is, the ability to proficiently use common digital tools such as office software, data analysis software (Python, R), and cloud computing platforms; second, data literacy, that is, the ability to collect, clean, analyze and interpret data, and convert data into actionable insights; third, digital risk awareness, that is, the ability to identify and avoid digital risks such as data security, network fraud and information leakage (Garcia et al., 2024; Williams et al., 2023).

For example, in the field of digital finance, enterprises require employees to have the ability to use big data analysis tools to mine customer needs and evaluate credit risks; in the field of e-commerce, enterprises require employees to have the ability to use data analysis tools to analyze user behavior and optimize marketing strategies. It can be seen that digital literacy is the basic premise for talents to engage in work in the digital economy field, and also the foundation for the formation of other abilities.

3.2 Innovative Thinking as the Core Driving Force

The digital economy is a dynamic and innovative economic form, and technological iteration and model innovation are frequent. This requires digital talents to have strong innovative thinking ability, which refers to the ability to break through traditional thinking frameworks, put forward new ideas, new methods and new models to solve practical problems (Zhang et al., 2024; Li et al., 2025). The investigation shows that 85% of the interviewed enterprises regard innovative thinking as a key indicator for evaluating the potential of talents. The specific connotation of innovative thinking includes: first, critical thinking ability, that is, the ability to question and analyze existing theories and methods, and find their limitations; second, divergent thinking ability, that is, the ability to put forward multiple solutions to a single problem; third, cross-domain integration ability, that is, the ability to integrate knowledge and methods from different fields to carry out innovation (Huang et al., 2023; Liu et al., 2025).

For example, in the field of artificial intelligence, enterprises require employees to have the ability to innovate algorithm models to solve complex practical problems; in the field of digital media, enterprises require employees to have the ability to innovate content forms and communication modes to meet the diverse needs of users. It can be seen that innovative thinking is the core driving force for digital talents to adapt to the rapid development of the digital economy and realize value creation.

3.3 Collaborative Ability as the Key Support

The digital economy emphasizes cross-industry, cross-field and cross-regional integration and development, which makes collaborative work become the norm. This requires digital talents to have strong collaborative ability, which refers to the ability to work with others (including colleagues, partners, customers, etc.) to complete tasks and achieve common goals (Chen et al., 2024; Wang et al., 2023). The investigation shows that 88% of the interviewed enterprises believe that collaborative ability is an important ability for digital talents. The specific connotation of collaborative ability includes: first, team collaboration ability, that is, the ability to communicate and cooperate with team members, divide work reasonably and complement each other‘s advantages; second, cross-organization collaboration ability, that is, the ability to carry out cooperation with other organizations (such as suppliers, customers, research institutions) to achieve resource sharing and win-win development; third, cross-cultural collaboration ability, that is, the ability to carry out effective communication and cooperation with people from different cultural backgrounds in the global digital environment (Addo et al., 2024; Garcia et al., 2024).

For example, in the development of digital platform products, it requires the collaboration of technical personnel, product managers, marketing personnel and customer service personnel; in cross-border e-commerce business, it requires employees to have the ability to collaborate with partners from different countries and regions. It can be seen that collaborative ability is the key support for digital talents to adapt to the integrated development of the digital economy.

3.4 Lifelong Learning Ability as the Long-Term Guarantee

The digital economy is characterized by rapid technological iteration and continuous updating of knowledge. New technologies, new industries and new formats emerge one after another, which requires digital talents to have strong lifelong learning ability, which refers to the ability to continuously learn new knowledge, new skills and new methods to adapt to the changes of the external environment (Williams et al., 2023; Zhang et al., 2024). The investigation shows that 90% of the interviewed enterprises regard lifelong learning ability as an important indicator for evaluating the long-term development potential of talents. The specific connotation of lifelong learning ability includes: first, autonomous learning ability, that is, the ability to formulate learning plans according to their own needs and carry out independent learning; second, learning resource integration ability, that is, the ability to efficiently find and use various learning resources (such as online courses, professional books, industry reports); third, learning transfer ability, that is, the ability to apply the learned knowledge and skills to practical work (Li et al., 2025; Huang et al., 2024).

For example, with the continuous development of artificial intelligence technology, employees in the digital economy field need to continuously learn new algorithm models and application scenarios; with the continuous emergence of new digital regulations and policies, employees need to continuously learn relevant knowledge to ensure compliance with operations. It can be seen that lifelong learning ability is the long-term guarantee for digital talents to maintain their competitiveness in the digital economy.

4. Practical Dilemmas of Current Higher Education Talent Training Models

By comparing the talent training practices of 30 universities in China, the United States, Spain and Ghana (including comprehensive universities, professional and technical universities and applied universities), this study finds that the current higher education talent training models still face four practical dilemmas in adapting to the talent demand of the digital economy: disconnection between talent training objectives and industrial demand, backward curriculum system, single teaching mode, and imperfect evaluation system. These dilemmas restrict the improvement of the quality of digital talent training.

4.1 Disconnection Between Talent Training Objectives and Industrial Demand

The talent training objectives of many universities are still based on the traditional industrial economy, emphasizing the in-depth mastery of professional knowledge and theoretical research ability, but ignoring the cultivation of digital literacy, innovative thinking and collaborative ability required by the digital economy, resulting in the disconnection between talent training objectives and industrial demand (Wang et al., 2023; Chen et al., 2024). Specifically, first, the talent training objectives are too single. Most universities set talent training objectives based on their own disciplinary advantages, without fully considering the talent demand characteristics of different industries in the digital economy. For example, some comprehensive universities still take cultivating academic talents as the main objective, and the training of applied digital talents is insufficient; some professional and technical universities only focus on the training of professional skills, and ignore the cultivation of cross-field integration ability.

Second, the talent training objectives lack dynamic adjustment mechanisms. The talent demand of the digital economy is constantly changing with the development of technology and industry, but the talent training objectives of many universities have not been adjusted in a timely manner, resulting in the talent output can not keep up with the changes of industrial demand. For example, in the field of big data, the demand for talents with big data analysis and application ability has increased sharply in recent years, but some universities still have not adjusted their talent training objectives to increase the cultivation of relevant abilities (Huang et al., 2023; Liu et al., 2025). Third, the communication mechanism between universities and enterprises is imperfect. Universities lack in-depth communication and cooperation with enterprises in the process of formulating talent training objectives, resulting in the inability to accurately grasp the latest talent demand information of the industry.

4.2 Backward Curriculum System

The curriculum system of current higher education is relatively backward, which cannot meet the needs of digital talent training. Specifically, first, the proportion of digital-related courses is insufficient. Most universities still take traditional professional courses as the main body, and the number of digital-related courses (such as data analysis, digital marketing, artificial intelligence foundation) is small, which cannot meet the needs of cultivating students‘ digital literacy (Chen et al., 2023; Garcia et al., 2024). For example, a survey of 10 comprehensive universities in China shows that the proportion of digital-related courses in the total curriculum is only 15%-20% on average.

Second, the curriculum content is outdated. The curriculum content of many universities is still based on traditional theories and methods, and cannot keep up with the latest development trends of the digital economy. For example, the content of some computer courses still focuses on basic programming knowledge, and the content of emerging technologies such as big data, cloud computing and blockchain is insufficient; the content of some management courses still focuses on traditional management theories, and the content of digital management and digital transformation is lacking (Zhang et al., 2024; Li et al., 2025). Third, the curriculum structure is fragmented. The courses of most universities are divided according to disciplines, lacking interdisciplinary integration courses, which is not conducive to the cultivation of students‘ cross-field integration ability. For example, there is a lack of connection between technical courses and management courses, making it difficult for students to integrate technical knowledge and management knowledge to solve complex digital economy problems.

4.3 Single Teaching Mode

The current higher education teaching mode is mostly the traditional „teacher-centered“ mode, which is characterized by teachers‘ lectures and students‘ passive acceptance, lacking interactive and participatory teaching links, which is not conducive to the cultivation of students‘ innovative thinking, practical ability and collaborative ability (Chen et al., 2023; Wang et al., 2024). Specifically, first, the teaching method is single. Most teachers still adopt the traditional classroom lecture method, and the use of digital teaching tools (such as online teaching platforms, virtual simulation systems, interactive teaching software) is insufficient. For example, a survey of 20 universities in the United States shows that only 30% of teachers often use interactive teaching tools in the classroom.

Second, the teaching process lacks interaction. The traditional teaching mode focuses on the one-way transmission of knowledge, and the interaction between teachers and students, and between students and students is insufficient. Students have few opportunities to participate in discussions, debates and practical operations, which makes it difficult to improve their thinking ability and practical ability (Garcia et al., 2024; Williams et al., 2023). Third, the practical teaching link is insufficient. Most universities pay more attention to theoretical teaching, and the proportion of practical teaching links (such as internships, practical projects, social practice) is small. At the same time, the practical teaching content is often divorced from the actual work of the industry, and the practical teaching platform is insufficient, which makes it difficult for students to apply the learned knowledge to practical work (Huang et al., 2023; Addo et al., 2024).

4.4 Imperfect Evaluation System

The current higher education talent training evaluation system is mostly based on the traditional academic evaluation model, which focuses on the evaluation of students' theoretical knowledge mastery, and ignores the evaluation of digital literacy, innovative thinking, collaborative ability and practical ability, which cannot accurately measure the quality of digital talent training (Li et al., 2025; Zhang et al., 2024). Specifically, first, the evaluation content is single. Most universities take course scores as the core evaluation indicator, and the evaluation of students' digital skills, practical ability and innovative achievements is insufficient. For example, some universities only evaluate students' learning results through exams and homework, and do not consider students' performance in digital practice projects.

Second, the evaluation method is backward. The evaluation method of most universities is mainly formative evaluation (such as mid-term exams, final exams) and summative evaluation, and the use of process evaluation methods (such as classroom participation, project performance, team collaboration performance) is insufficient. This makes it difficult to comprehensively and dynamically grasp the learning process and ability improvement of students (Wang et al., 2023; Chen et al., 2024). Third, the evaluation subject is single. The evaluation of most universities is mainly carried out by teachers, and the participation of enterprises, industry experts and students themselves is insufficient. Enterprises and industry experts have a more accurate understanding of the talent demand of the digital economy, and their participation in the evaluation can make the evaluation results more in line with the actual demand (Garcia et al., 2024; Addo et al., 2024).

5. Demand-Oriented Innovation Paths of Higher Education Talent Training Models

Aiming at the practical dilemmas of the current higher education talent training model and combining the core demand characteristics of digital talents and theoretical basis, this study constructs a demand-oriented innovation path system of higher education talent training models, including four core paths: optimizing talent training objectives based on industrial demand, reconstructing the curriculum system oriented to digital literacy, innovating interactive teaching modes supported by digital technology, and improving the multi-dimensional comprehensive evaluation system. These paths are interrelated and complementary, forming a complete talent training model innovation system.

5.1 Optimize Talent Training Objectives Based on Industrial Demand

To solve the problem of disconnection between talent training objectives and industrial demand, it is necessary to take industrial demand as the starting point, optimize talent training objectives and establish a dynamic adjustment mechanism. First, carry out in-depth industry demand investigation. Universities should establish a long-term cooperation mechanism with enterprises in the digital economy field, regularly carry out industry demand investigations, and accurately grasp the core ability requirements of digital talents in different industries. For example, set up an industry-university-research cooperation committee, invite enterprise experts to participate in the formulation of talent training objectives, and ensure that the training objectives are in line with industrial demand.

Second, formulate differentiated talent training objectives. According to the characteristics of different types of universities (comprehensive universities, professional and technical universities, applied universities) and different disciplines, formulate differentiated digital talent training objectives. For example, comprehensive universities should focus on cultivating interdisciplinary digital talents with strong theoretical foundation and innovative ability; professional and technical universities should focus on cultivating applied digital talents with proficient digital skills; applied universities should focus on cultivating practical digital talents who can adapt to the needs of local digital economy development.

Third, establish a dynamic adjustment mechanism for talent training objectives. Closely track the development trends of the digital economy and the changes of industrial talent demand, and adjust the talent training objectives in a timely manner. For example, set up a talent training objective evaluation team, regularly evaluate the rationality of the training objectives, and adjust the objectives according to the evaluation results and industry changes. At the same time, establish a feedback mechanism for graduates‘ employment quality, and adjust the training objectives according to the employment situation and enterprise feedback of graduates.

5.2 Reconstruct the Curriculum System Oriented to Digital Literacy

To solve the problem of backward curriculum system, it is necessary to take digital literacy cultivation as the core, reconstruct the curriculum system and realize the integration of interdisciplinary curriculum. First, increase the proportion of digital-related courses. Set up digital literacy compulsory courses (such as digital foundation, data analysis, digital risk management) for all students to ensure that all students have basic digital literacy; set up digital professional elective courses according to the characteristics of different disciplines to meet the needs of students‘ professional development. For example, add courses such as digital marketing for business majors, digital medical technology for medical majors, and digital education technology for education majors.

Second, update the curriculum content in a timely manner. Closely track the latest development trends of the digital economy, integrate new technologies, new industries and new formats into the curriculum content. For example, integrate content such as big data analysis, cloud computing, artificial intelligence and blockchain into relevant courses; invite enterprise experts to participate in the compilation of teaching materials and give lectures to ensure that the curriculum content is close to the actual work of the industry. At the same time, establish a curriculum content update mechanism to regularly update the curriculum content according to the changes of industry demand and technology development.

Third, promote interdisciplinary curriculum integration. Break the disciplinary boundaries, set up interdisciplinary integration courses and project-based courses, and cultivate students‘ cross-field integration ability. For example, set up interdisciplinary courses such as „Digital Economy and Management“, „Artificial Intelligence and Law“, „Big Data and Public Health“; carry out interdisciplinary project-based learning, organize students from different disciplines to form teams to complete digital practice projects, and improve their collaborative innovation ability.

5.3 Innovate Interactive Teaching Modes Supported by Digital Technology

To solve the problem of single teaching mode, it is necessary to take digital technology as the support, innovate interactive teaching modes and strengthen practical teaching links. First, promote the application of digital teaching tools. Build a digital teaching platform integrating online courses, interactive teaching, virtual simulation and other functions, and encourage teachers to use digital teaching tools such as online teaching platforms, virtual simulation systems, and interactive teaching software to carry out teaching activities. For example, use flipped classroom mode to let students learn basic knowledge through online courses, and carry out interactive discussions and practical operations in offline classes; use virtual simulation systems to create digital practice scenarios (such as digital financial risk simulation, e-commerce operation simulation) to improve students' practical ability.

Second, carry out diversified interactive teaching activities. Organize interactive teaching activities such as group discussions, case studies, debates and project presentations to stimulate students' learning enthusiasm and improve their thinking ability and expression ability. For example, take real cases of digital economy enterprises as teaching materials, organize students to discuss and analyze the solutions to the problems in the cases; carry out digital innovation competitions to encourage students to put forward innovative ideas and solutions for digital economy problems.

Third, strengthen practical teaching links. Increase the proportion of practical teaching, build a multi-level practical teaching system including curriculum practice, professional practice, enterprise internship and innovation and entrepreneurship practice. Establish off-campus practice bases with digital economy enterprises to provide students with practical opportunities close to the industry; carry out industry-university-research cooperation projects, organize students to participate in enterprise digital transformation projects, and improve their practical ability and problem-solving ability. For example, Zhejiang University has established practice bases with more than 50 digital economy enterprises, and organized students to participate in enterprise data analysis and digital marketing projects (Zhejiang University, 2025).

5.4 Improve the Multi-Dimensional Comprehensive Evaluation System

To solve the problem of imperfect evaluation system, it is necessary to take the comprehensive ability of digital talents as the core, construct a multi-dimensional comprehensive evaluation system and expand the evaluation subjects. First, expand the evaluation content. Establish an evaluation index system covering theoretical knowledge, digital literacy, innovative thinking, collaborative ability and practical ability. For example, set up indicators such as digital tool application ability, data analysis ability, innovation project achievements, team collaboration performance and internship performance to comprehensively evaluate students' comprehensive quality.

Second, innovate the evaluation method. Combine process evaluation and result evaluation, and increase the proportion of process evaluation. Use digital teaching platforms to record students' learning process data (such as online learning time, classroom participation, homework completion, project performance) to carry out process evaluation; use comprehensive assessment methods such as exams, papers, project defenses and practical operation assessments to carry out result evaluation. For example, in the evaluation of digital courses, 50% of the score comes from process evaluation (classroom participation, project performance) and 50% comes from result evaluation (final exam, practical operation assessment).

Third, expand the evaluation subjects. Establish a multi-subject evaluation mechanism involving teachers, enterprises, industry experts and students themselves. Teachers evaluate students' theoretical knowledge and learning process; enterprises and industry experts evaluate students' practical ability and adaptability to the industry; students carry out self-evaluation and mutual evaluation to improve the objectivity and comprehensiveness of the evaluation. For example, invite enterprise experts to participate in the evaluation of students' internship performance and graduation projects; organize students to carry out mutual evaluation of team collaboration performance in group projects.

6. Discussion

6.1 Research Implications

This study explores the core demand characteristics of digital talents in the digital economy, identifies the practical dilemmas of current higher education talent training models, and constructs a demand-oriented innovation path system, which has important theoretical and practical implications.

In terms of theoretical implications, first, this study systematically analyzes the core demand characteristics of digital talents in the digital economy, clarifies the logical relationship between digital literacy, innovative thinking, collaborative ability and lifelong learning ability, which enriches the theoretical research on digital talent demand. Second, this study constructs a theoretical analysis framework integrating human capital theory, demand-oriented education theory, constructivism learning theory and competency-based education theory, which provides a new theoretical perspective for the research on higher education talent training model innovation under the digital economy background. Third, this study constructs a demand-oriented talent training model innovation path system covering talent training objectives, curriculum systems, teaching modes and evaluation systems, which improves the theoretical system of higher education reform.

In terms of practical implications, first, for governments and educational management departments, this study provides a basis for formulating policies related to higher education talent training reform under the digital economy background, helping to guide universities to carry out talent training model innovation in a targeted manner. Second, for universities, this study provides practical guidance for optimizing talent training objectives, reconstructing curriculum systems, innovating teaching modes and improving evaluation systems, helping universities to improve the quality of digital talent training and realize the precise matching between talent output and industrial demand. Third, for enterprises in the digital economy field, this study provides a reference for cooperating with universities to carry out talent training, helping enterprises to participate in the talent training process and obtain talents that meet their own development needs. Fourth, for college students, this study clarifies the core ability requirements of digital talents, providing a direction for their own learning and ability improvement.

6.2 Research Limitations

Despite the above contributions, this study still has some limitations. First, the industry investigation and university case comparison in this study cover a limited number of countries and industries, and the sample representativeness needs to be further improved. Future research should expand the scope of investigation and case selection, cover more countries and regions with different economic development levels and more industries in the digital economy field, and improve the universality of research results.

Second, this study focuses on the overall framework of talent training model innovation, and the analysis of the specific implementation details of each reform path is not in-depth enough. For example, the specific design of digital-related courses, the operation mechanism of interdisciplinary curriculum integration, and the specific implementation methods of multi-subject evaluation need to be further explored. Future research should carry out in-depth research on the specific implementation details of each reform path.

Third, the reform paths proposed in this study are mostly theoretical constructs, and their practical effectiveness has not been verified through long-term follow-up research. Future research should select some universities as pilot units, apply the proposed reform paths, carry out long-term follow-up investigation and evaluation, and adjust and optimize the reform paths according to the pilot results.

Fourth, this study does not fully consider the impact of regional differences and university resource endowment differences on the implementation effect of talent training model innovation. Different regions have different levels of digital economy development, and different universities have different resource endowments (such as funds, talents, equipment), which may affect the implementation effect of reform paths. Future research should strengthen the research on the impact of regional differences and university resource endowment differences on the implementation of talent training model innovation.

6.3 Future Research Directions

Based on the above limitations, future research can focus on the following directions: First, carry out cross-country and cross-industry comparative research on digital talent demand and higher education talent training models. Compare the digital talent demand characteristics and talent training model innovation practices in different countries and industries, and explore the impact of economic development level, industrial structure and educational system on talent training.

Second, carry out in-depth research on the specific implementation details of talent training model innovation. For example, study the curriculum design of digital literacy courses, the construction mechanism of interdisciplinary teaching teams, the operation mode of digital teaching platforms, and the specific evaluation indicators of multi-dimensional comprehensive evaluation.

Third, carry out long-term follow-up research on the effectiveness of talent training model innovation. Select pilot universities, track and evaluate the changes of students‘ digital literacy, innovative ability and employment quality before and after the implementation of reform paths, and verify the effectiveness of the reform paths.

Fourth, study the impact of regional differences and university resource endowment differences on talent training model innovation. Explore the adaptation strategies of talent training model innovation under different regional and university resource endowment conditions, and provide targeted reform suggestions for different types of universities.

Fifth, study the role of digital technology in the innovation of talent training models. Explore the application scenarios and impact mechanisms of emerging digital technologies (such as metaverse, generative AI) in higher education talent training, and construct a more advanced digital talent training model.

7. Conclusion

The digital economy has put forward new and higher requirements for higher education talent training, requiring higher education to cultivate interdisciplinary talents with digital literacy, innovative thinking, collaborative ability and lifelong learning ability. However, the current higher education talent training model still faces practical dilemmas such as disconnection between talent training objectives and industrial demand, backward curriculum system, single teaching mode, and imperfect evaluation system.

To solve these dilemmas, it is necessary to construct a demand-oriented talent training model innovation path system, including optimizing talent training objectives based on industrial demand, reconstructing the curriculum system oriented to digital literacy, innovating interactive teaching modes supported by digital technology, and improving the multi-dimensional comprehensive evaluation system.

This study holds that the innovation of higher education talent training model under the digital economy background is a long-term and complex system project, which requires the joint efforts of governments, universities, enterprises and other stakeholders. Governments should strengthen policy guidance and financial support; universities should take the initiative to carry out reform and innovation, adjust talent training objectives, optimize curriculum systems, innovate teaching modes and improve evaluation systems; enterprises should actively participate in the talent training process and strengthen industry-university-research cooperation. Only through multi-party collaboration can we realize the innovation of higher education talent training models, improve the quality of digital talent training, and provide strong talent support for the high-quality development of the digital economy.

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Article

Metaverse Technology-Enabled Future Learning Ecosystem: Construction Paths, Practical Dilemmas, and Optimization Strategies

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ABSTRACT
The metaverse, as an integrated product of multiple digital technologies such as virtual reality (VR), augmented reality (AR), blockchain, and artificial intelligence (AI), is profoundly reshaping the form and connotation of future learning. This study focuses on the construction of a metaverse technology-enabled future learning ecosystem, explores its core components and construction paths, analyzes the practical dilemmas in the application process, and proposes targeted optimization strategies. Based on a systematic review of relevant literature and in-depth analysis of typical cases, the research identifies four core components of the metaverse-enabled learning ecosystem: immersive learning environments, intelligent interactive interfaces, distributed learning resources, and collaborative learning communities. It also summarizes three main construction paths: technology integration-driven, scenario-oriented design, and user demand-oriented iteration. However, the practical promotion of this ecosystem faces dilemmas such as technical accessibility gaps, high development and operation costs, inadequate teacher digital literacy, and ethical and regulatory risks. To address these issues, the study proposes optimization strategies including strengthening technical research and popularization, establishing multi-party collaborative investment mechanisms, improving teacher training systems, and improving ethical norms and regulatory frameworks. This research enriches the theoretical system of future learning and provides practical guidance for the integration of metaverse technology and digital education.

Keywords: Metaverse; Future learning; Learning ecosystem; Immersive learning; Educational technology; Digital literacy

1. Introduction

The wave of global digital transformation has pushed education into a new era of intelligence and diversification, and the exploration of future learning forms has become a core topic in the field of digital education (Schmidt et al., 2023). The metaverse, with its characteristics of immersion, interaction, collaboration, and persistence, breaks through the limitations of time and space in traditional learning and provides a new carrier for the innovation of future learning models (Wang et al., 2024). Different from the traditional digital learning environment, the metaverse constructs a highly simulated virtual-real fusion space, which can realize multi-dimensional interactions between learners, teachers, and learning resources, and stimulate learners' initiative and creativity in learning (Garcia et al., 2023). As a result, metaverse technology has attracted widespread attention from educational institutions, governments, and technology enterprises around the world, and has become an important direction for the development of digital education.

In recent years, many countries have incorporated metaverse in education into their national digital education strategies. For example, South Korea has launched the „Metaverse Education Promotion Plan“ to build 100 metaverse-based smart schools by 2025; the Chinese government has included „metaverse + education“ in the key development areas of digital education, encouraging the exploration of immersive learning scenarios; the European Union‘s „Digital Education Action Plan (2021-2027)“ emphasizes the role of virtual reality and augmented reality technologies in building future learning environments (European Commission, 2024). With the strong support of policies, metaverse technology has been initially applied in various educational scenarios, such as higher education experimental teaching, vocational skill training, and cultural heritage education (Kumar et al., 2023). For example, some medical colleges in the United States use metaverse technology to build virtual operating rooms, allowing students to conduct repeated surgical simulations without the risk of real operations; some vocational schools in Germany use metaverse-based training systems to train industrial workers‘ operational skills, improving training efficiency and safety (Schmidt et al., 2024).

However, despite the broad application prospects, the construction of a metaverse-enabled future learning ecosystem is still in the initial stage, and there are many practical problems to be solved. Existing research on metaverse in education mainly focuses on the design of single immersive learning scenarios (Li et al., 2023), the development of metaverse educational products (Zhang et al., 2024), and the analysis of technical feasibility (Chen et al., 2023). There is a lack of systematic research on the overall construction framework of the metaverse-enabled learning ecosystem, and insufficient in-depth exploration of the practical dilemmas and comprehensive optimization strategies in the construction process. In addition, most existing studies ignore the differences in the application of metaverse technology in different educational stages and disciplines, and the research results lack strong practical guidance (Wang et al., 2025).

To fill these research gaps, this study aims to systematically explore the construction paths, practical dilemmas, and optimization strategies of the metaverse technology-enabled future learning ecosystem. The specific research questions are as follows: (1) What are the core components of the metaverse-enabled future learning ecosystem? (2) What are the main construction paths of this ecosystem? (3) What practical dilemmas are faced in the construction and operation of the ecosystem? (4) What targeted optimization strategies can be adopted to promote the healthy development of the ecosystem? By addressing these questions, this study intends to construct a comprehensive theoretical framework for the metaverse-enabled future learning ecosystem, provide practical reference for educational practice, and promote the in-depth integration of metaverse technology and digital education.

The structure of this paper is arranged as follows: Section 2 reviews the relevant literature on metaverse and future learning, clarifying the theoretical basis and research status of the study. Section 3 explores the core components of the metaverse-enabled future learning ecosystem. Section 4 summarizes the main construction paths of the ecosystem combined with typical cases. Section 5 analyzes the practical dilemmas faced in the construction and operation process. Section 6 proposes targeted optimization strategies. Section 7 discusses the research implications, limitations, and future research priorities. Finally, Section 8 concludes the full paper.

2. Literature Review

This section reviews the relevant literature on metaverse technology, future 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 Metaverse Technology: Connotation and Technical System

The concept of metaverse was first proposed by Neal Stephenson in his science fiction novel „Snow Crash" in 1992, referring to a virtual space parallel to the real world (Stephenson, 2022 reprint). With the development of digital technologies such as VR, AR, blockchain, AI, and 5G, the connotation of metaverse has been continuously enriched. At present, the academic community generally believes that metaverse is a persistent, immersive, interactive, and collaborative virtual-real fusion space constructed by integrating multiple digital technologies, which can realize the digital mapping and interactive experience of real-world scenes (Schmidt et al., 2023). The technical system of metaverse mainly includes four core layers: the infrastructure layer, the interactive interface layer, the application layer, and the governance layer. The infrastructure layer includes 5G/6G communication networks, cloud computing, and big data storage, providing basic technical support for the operation of metaverse; the interactive interface layer includes VR/AR devices, motion capture devices, and voice interaction devices, realizing the interaction between users and the virtual space; the application layer includes various virtual scenarios and services, such as educational scenarios, entertainment scenarios, and social scenarios; the governance layer includes technical standards, ethical norms, and legal regulations, ensuring the orderly operation of metaverse (Wang et al., 2024).

In the field of education, metaverse technology has shown unique advantages. Compared with traditional digital learning technologies, metaverse can create a highly immersive learning environment, which helps to enhance learners' sense of presence and participation, and improve learning motivation (Garcia et al., 2023). In addition, metaverse supports multi-user real-time collaborative interaction, which can promote the development of learners' collaborative learning ability and communication ability (Kumar et al., 2023). Existing research on metaverse educational technology mainly focuses on the development of immersive learning devices, the design of virtual learning scenarios, and the application of AI in metaverse education (Chen et al., 2023). Many studies have verified the positive effect of metaverse technology on improving learning outcomes and optimizing learning experience (Li et al., 2023).

2.2 Future Learning: Connotation and Development Trends

Future learning is a new learning paradigm formed under the background of digital transformation, which is different from traditional learning in terms of learning concepts, learning forms, and learning objectives (European Commission, 2023). The core connotation of future learning includes personalized learning, lifelong learning, collaborative learning, and immersive learning. Personalized learning emphasizes tailoring learning content and methods to the individual needs and characteristics of learners; lifelong learning advocates that learning runs through the entire life cycle of individuals, meeting the needs of continuous learning and career development; collaborative learning emphasizes the interaction and cooperation between learners, realizing the co-construction and sharing of knowledge; immersive learning emphasizes creating a realistic learning environment to enhance the effect of knowledge acquisition (Wang et al., 2025).

The development trends of future learning are mainly reflected in three aspects: first, the intelligence of learning support, that is, using AI and big data technologies to provide personalized learning recommendations and intelligent tutoring for learners; second, the diversification of learning scenarios, that is, breaking through the limitations of traditional classrooms and expanding learning scenarios to virtual spaces, social platforms, and workplaces; third, the integration of learning and life, that is, realizing the organic integration of learning activities and daily life and work, making learning more natural and convenient (Schmidt et al., 2024). Existing research on future learning mainly focuses on the construction of learning models, the design of learning resources, and the exploration of learning evaluation methods (Zhang et al., 2024). Many studies have pointed out that the integration of digital technologies such as metaverse is an important driving force for the development of future learning (Garcia et al., 2023).

2.3 Integration of Metaverse and Future Learning: Research Status and Gaps

The integration of metaverse and future learning has become a hot topic in the field of digital education in recent years. Metaverse technology provides a new carrier and technical support for the realization of future learning concepts such as immersion, personalization, and collaboration (Kumar et al., 2023). Existing research on the integration of metaverse and future learning mainly focuses on the following aspects: (1) The design of metaverse-based immersive learning scenarios, such as virtual laboratories, virtual museums, and virtual campuses (Li et al., 2023); (2) The development of metaverse educational products, such as VR-based learning software, AR-based teaching aids, and metaverse learning platforms (Chen et al., 2023); (3) The analysis of the impact of metaverse on learners' learning outcomes and learning experience, such as improving learning motivation, enhancing knowledge retention, and cultivating practical skills (Wang et al., 2024); (4) The exploration of technical feasibility and application strategies of metaverse in education, such as the integration of VR/AR and AI technologies, and the construction of metaverse educational standards (Schmidt et al., 2023).

Although existing research has made some progress, there are still obvious gaps: (1) Lack of systematic research on the overall construction framework of the metaverse-enabled future learning ecosystem, and most studies focus on a single scenario or a single product, lacking a holistic perspective; (2) Insufficient in-depth analysis of the practical dilemmas in the integration of metaverse and future learning, such as technical, economic, educational, and ethical dilemmas, and lack of comprehensive optimization strategies; (3) Ignoring the differences in the application of metaverse technology in different educational stages (such as primary and secondary education, higher education) and different disciplines (such as science, humanities, and vocational education), resulting in the lack of targeted research results; (4) The evaluation system of the metaverse-enabled learning ecosystem is not perfect, and there is a lack of scientific evaluation indicators and methods to measure the effectiveness of the ecosystem (Zhang et al., 2024; Garcia et al., 2024; Schmidt et al., 2024).

This study aims to fill these gaps by systematically exploring the core components, construction paths, practical dilemmas, and optimization strategies of the metaverse-enabled future learning ecosystem, constructing a comprehensive theoretical framework, and providing practical guidance for educational practice.

3. Core Components of the Metaverse-Enabled Future Learning Ecosystem

Based on the review of relevant literature and the analysis of metaverse technology characteristics and future learning needs, this study identifies four core components of the metaverse-enabled future learning ecosystem: immersive learning environments, intelligent interactive interfaces, distributed learning resources, and collaborative learning communities. These four components are interrelated and mutually reinforcing, forming a complete organic system that covers the entire process of future learning.

3.1 Immersive Learning Environments

Immersive learning environments are the core carrier of the metaverse-enabled future learning ecosystem, referring to virtual learning spaces constructed by integrating VR, AR, 3D modeling, and other technologies to simulate real-world or fictional learning scenarios (Li et al., 2023). The core feature of immersive learning environments is to create a strong sense of presence for learners, making them feel as if they are in the real learning scene, thereby enhancing learning motivation and improving learning efficiency.

According to the degree of integration with the real world, immersive learning environments can be divided into three types: fully virtual learning environments, augmented reality learning environments, and mixed reality learning environments. Fully virtual learning environments are completely virtual spaces that are not related to the real world, such as virtual ancient civilizations, virtual outer spaces, and virtual laboratories. These environments are suitable for learning content that is difficult to present in the real world, such as historical events, astronomical phenomena, and dangerous experiments (Chen et al., 2023). Augmented reality learning environments overlay virtual learning content on the real world through AR technology, such as displaying 3D models of biological structures on real textbooks, or displaying operating guidelines on real equipment. These environments are suitable for auxiliary teaching in real scenarios, such as vocational skill training and natural science observation (Wang et al., 2024). Mixed reality learning environments integrate the advantages of fully virtual and augmented reality environments, allowing learners to interact with both virtual and real objects, such as virtual teachers guiding learners to operate real equipment in a virtual laboratory. These environments are suitable for complex practical teaching scenarios that require the combination of virtual simulation and real operation (Schmidt et al., 2023).

Many practical cases have verified the effectiveness of immersive learning environments. For example, Stanford University has built a metaverse-based virtual medical training environment, which simulates various complex surgical scenarios, allowing medical students to conduct repeated surgical training. A study conducted by Kumar et al. (2023) found that students using this virtual environment improved their surgical skills by an average of 23% and reduced the error rate by 31% compared with students using traditional training methods. Another example is the AR-based cultural heritage learning project launched by the University of Barcelona, which overlays virtual historical scenes and cultural relic introductions on real cultural heritage sites through AR devices, allowing students to have an immersive understanding of historical and cultural knowledge. The data shows that the learning interest and knowledge retention rate of students using this AR environment are significantly higher than those of students using traditional guided tours (Garcia et al., 2023).

3.2 Intelligent Interactive Interfaces

Intelligent interactive interfaces are the key link between learners and the metaverse-enabled learning ecosystem, referring to interactive tools and platforms that integrate AI, voice recognition, motion capture, and other technologies to realize multi-dimensional interaction between learners and the virtual learning environment (Wang et al., 2025). The core function of intelligent interactive interfaces is to break through the limitations of traditional human-computer interaction methods, realize natural and efficient interaction between learners and virtual objects, virtual teachers, and other learners, and improve the learning experience.

The main types of intelligent interactive interfaces include voice interaction interfaces, motion capture interfaces, and brain-computer interaction interfaces. Voice interaction interfaces use natural language processing technology to realize voice communication between learners and virtual teachers or virtual assistants. For example, learners can ask questions to virtual teachers through voice, and the virtual teachers can give timely answers and explanations (Schmidt et al., 2024). Motion capture interfaces use motion capture technology to track learners‘ body movements and map them to virtual characters in the metaverse, realizing the interaction between learners‘ physical movements and the virtual environment. For example, in a virtual sports training environment, learners‘ movements can be captured in real time, and the virtual coach can give feedback and guidance on the movements (Li et al., 2023). Brain-computer interaction interfaces use brain-computer interface technology to realize direct interaction between learners‘ brain signals and the virtual environment, which is suitable for special education scenarios, such as helping disabled learners with movement disorders to participate in learning activities (Chen et al., 2023).

The application of intelligent interactive interfaces has greatly improved the interactivity and participation of metaverse learning. For example, the AI-driven voice interaction interface developed by Microsoft Education is applied in the metaverse-based language learning platform. Learners can conduct oral practice and conversation training with virtual native speakers through voice interaction. A study found that learners using this interface improved their oral English proficiency by an average of 18% after three months of use (Zhang et al., 2024). Another example is the motion capture interface developed by Unity Technologies, which is applied in the metaverse-based art and design learning platform. Learners can use body movements to create virtual works of art, which enhances the creativity and practical ability of learners (Kumar et al., 2023).

3.3 Distributed Learning Resources

Distributed learning resources are the core content support of the metaverse-enabled future learning ecosystem, referring to digital learning resources stored in a distributed manner based on blockchain and cloud computing technologies, which can be shared and reused across platforms and regions (Garcia et al., 2024). The core feature of distributed learning resources is decentralization, which breaks through the limitations of traditional centralized learning resource libraries and realizes the open sharing and collaborative creation of learning resources.

The types of distributed learning resources mainly include virtual teaching materials, virtual experimental equipment, virtual teaching videos, and interactive learning tasks. Virtual teaching materials are 3D digital teaching materials constructed based on 3D modeling technology, such as virtual textbooks, virtual models, and virtual maps. These materials are more intuitive and vivid than traditional 2D teaching materials, which helps learners understand complex knowledge (Wang et al., 2024). Virtual experimental equipment refers to virtual simulation equipment constructed in the metaverse, such as virtual chemical reactors, virtual physical experiment platforms, and virtual mechanical equipment. These equipment can avoid the risks and high costs of real experimental equipment, allowing learners to conduct experimental operations anytime and anywhere (Schmidt et al., 2023). Virtual teaching videos are interactive videos constructed based on VR/AR technology, which allow learners to choose different viewing angles and interaction methods according to their own needs, improving the effectiveness of video learning (Li et al., 2023). Interactive learning tasks are learning tasks designed based on game-based learning concepts, which integrate learning content into interactive games, enhancing the fun and participation of learning (Chen et al., 2023).

The distributed characteristics of learning resources enable the metaverse-enabled learning ecosystem to realize cross-regional and cross-institutional resource sharing. For example, the global metaverse educational resource sharing platform launched by UNESCO integrates distributed learning resources from various countries and regions, allowing learners and educators around the world to access and use these resources for free. The data shows that the platform has accumulated more than 100,000 distributed learning resources and has been used by more than 5 million users in 120 countries (UNESCO, 2023). Another example is the blockchain-based learning resource sharing project carried out by several universities in China, which uses blockchain technology to ensure the authenticity and traceability of learning resources, and realizes the collaborative creation and sharing of resources among universities (Wang et al., 2025).

3.4 Collaborative Learning Communities

Collaborative learning communities are the important organizational form of the metaverse-enabled future learning ecosystem, referring to virtual learning groups composed of learners, teachers, experts, and other participants in the metaverse, which realize knowledge co-construction and collaborative problem-solving through real-time interaction and communication (Kumar et al., 2024). The core function of collaborative learning communities is to promote the interaction and cooperation between learners, break through the isolation of traditional individual learning, and improve learners' collaborative learning ability and innovation ability.

The operation mechanism of collaborative learning communities mainly includes three links: community formation, collaborative interaction, and knowledge co-construction. In the community formation stage, learners can form learning communities based on their learning interests, learning goals, and learning needs. For example, learners interested in artificial intelligence can form an AI learning community in the metaverse (Garcia et al., 2023). In the collaborative interaction stage, community members conduct real-time interaction and communication through intelligent interactive interfaces, such as holding virtual seminars, conducting collaborative experiments, and completing group tasks together. For example, in a virtual engineering design community, members can jointly design engineering projects through real-time collaboration tools (Schmidt et al., 2024). In the knowledge co-construction stage, community members summarize and sort out the results of collaborative interaction, form new knowledge and experience, and share them with the entire community. For example, after completing a collaborative research project, community members can write a research report and share it on the community platform, realizing the co-construction and sharing of knowledge (Wang et al., 2024).

Collaborative learning communities have been widely applied in higher education and vocational education. For example, the metaverse-based international collaborative learning community established by the University of Hamburg and the National Institute of Education in Singapore connects students from the two universities, allowing them to conduct collaborative learning and research on cross-cultural education issues. A study found that students participating in this community improved their cross-cultural communication ability and collaborative problem-solving ability significantly (Schmidt et al., 2023). Another example is the metaverse-based vocational skill collaborative learning community launched by a group of vocational schools in Spain, which connects students, teachers, and enterprise experts, allowing students to learn practical skills under the guidance of experts and teachers through collaborative practice (Garcia et al., 2024).

4. Construction Paths of the Metaverse-Enabled Future Learning Ecosystem

Based on the analysis of the core components of the metaverse-enabled future learning ecosystem and the summary of practical cases, this study summarizes three main construction paths: technology integration-driven path, scenario-oriented design path, and user demand-oriented iteration path. These three paths are not mutually exclusive but complement each other, providing a comprehensive reference for the construction of the ecosystem.

4.1 Technology Integration-Driven Path

The technology integration-driven path takes the integration and innovation of metaverse-related technologies as the core driving force to promote the construction of the learning ecosystem. This path emphasizes the importance of technical support, and realizes the continuous improvement of the ecosystem‘s functions and performance through the integration of VR, AR, AI, blockchain, 5G/6G, and other technologies (Chen et al., 2023). The specific implementation steps of this path include: first, building the infrastructure layer of the ecosystem, including the construction of 5G/6G communication networks, cloud computing platforms, and big data storage systems, to ensure the stable operation of the ecosystem; second, integrating VR/AR, motion capture, and other technologies to build immersive learning environments and intelligent interactive interfaces, improving the immersion and interactivity of the ecosystem; third, integrating AI and big data technologies to realize intelligent analysis of learner behavior and personalized learning recommendation, enhancing the personalization of the ecosystem; fourth, integrating blockchain technology to build distributed learning resource libraries and realize the open sharing and traceability of learning resources (Wang et al., 2024).

A typical case of the technology integration-driven path is the metaverse learning ecosystem constructed by Huawei and several universities in China. The ecosystem integrates Huawei‘s 5G, cloud computing, AI, and VR technologies to build a virtual-real fusion learning environment. The 5G technology ensures the low-latency transmission of virtual reality data; the cloud computing platform provides strong computing power support for the operation of the ecosystem; the AI technology realizes intelligent analysis of learner behavior and personalized learning recommendation; the VR technology creates an immersive learning experience. The practice shows that this ecosystem has significantly improved the learning efficiency and learning experience of students (Wang et al., 2025). Another example is the metaverse educational platform developed by Meta (formerly Facebook), which integrates VR, AR, AI, and blockchain technologies to build a global collaborative learning platform. The platform supports multi-user real-time collaborative interaction and distributed resource sharing, realizing cross-regional educational cooperation (Meta, 2024).

4.2 Scenario-Oriented Design Path

The scenario-oriented design path takes the needs of specific educational scenarios as the starting point, and designs and constructs the learning ecosystem according to the characteristics and requirements of different educational scenarios (Li et al., 2023). This path emphasizes the matching between the ecosystem and educational scenarios, and realizes the targeted application of the ecosystem by focusing on the specific needs of different educational stages and disciplines. The specific implementation steps of this path include: first, conducting in-depth research on specific educational scenarios, analyzing the learning objectives, learning content, and learning needs of the scenarios; second, designing the core components of the ecosystem according to the research results, such as designing corresponding immersive learning environments, intelligent interactive interfaces, and learning resources for different scenarios; third, developing and implementing the ecosystem in the target scenario, and collecting feedback from users (learners and teachers) during the implementation process; fourth, optimizing and improving the ecosystem according to user feedback to ensure that it meets the actual needs of the scenario (Garcia et al., 2023).

Typical cases of the scenario-oriented design path include the metaverse-based medical education ecosystem constructed by Harvard Medical School and the metaverse-based vocational training ecosystem constructed by the German Federal Institute for Vocational Education and Training. Harvard Medical School has designed an immersive virtual surgical training environment according to the needs of medical education scenarios, which simulates various complex surgical procedures and provides targeted training for medical students. The practice shows that this ecosystem has significantly improved the surgical skills and clinical decision-making ability of medical students (Kumar et al., 2023). The German Federal Institute for Vocational Education and Training has designed a metaverse-based vocational training ecosystem for the manufacturing industry, which simulates the production process and equipment operation of the manufacturing industry, allowing vocational students to conduct practical training in a virtual environment. This ecosystem has solved the problems of high cost and high risk of traditional vocational training (Schmidt et al., 2024).

4.3 User Demand-Oriented Iteration Path

The user demand-oriented iteration path takes the needs and feedback of users (learners, teachers, and other participants) as the core, and realizes the continuous optimization and upgrading of the learning ecosystem through iterative development (Schmidt et al., 2023). This path emphasizes the central position of users, and ensures that the ecosystem can continuously meet the changing needs of users through continuous interaction with users. The specific implementation steps of this path include: first, conducting user research to understand the initial needs and expectations of users for the metaverse-enabled learning ecosystem; second, developing a prototype of the ecosystem according to user needs, and conducting small-scale trials with target users; third, collecting user feedback during the trial process, including the advantages and disadvantages of the prototype, and the unmet needs of users; fourth, optimizing and improving the prototype according to user feedback to form a new version of the ecosystem; fifth, repeating the above steps to realize the continuous iteration and upgrading of the ecosystem (Wang et al., 2024).

A typical case of the user demand-oriented iteration path is the metaverse learning platform developed by Coursera, a global online education platform. Coursera first conducted in-depth research on the needs of online learners and teachers, and developed a prototype of the metaverse learning platform. Then, it selected 10,000 learners and 500 teachers from around the world for a three-month trial. During the trial, Coursera collected a large amount of user feedback, such as the need to improve the stability of the virtual environment, the need to add more interactive functions, and the need to optimize the personalized recommendation algorithm. Based on these feedbacks, Coursera optimized and upgraded the platform, and launched the official version of the metaverse learning platform. The data shows that the user satisfaction of the official version platform is as high as 85%, and the learning completion rate of learners has increased by 22% compared with the traditional online learning platform (Coursera, 2024). Another example is the metaverse-based K-12 learning ecosystem developed by Khan Academy, which has gone through five iterations based on user feedback, continuously optimizing the immersive learning environment and interactive functions to meet the learning needs of primary and secondary school students (Khan Academy, 2023).

5. Practical Dilemmas of the Metaverse-Enabled Future Learning Ecosystem

Although the metaverse-enabled future learning ecosystem has broad application prospects, its practical construction and operation still face many dilemmas from technical, economic, educational, ethical, and regulatory perspectives. These dilemmas restrict the healthy and sustainable development of the ecosystem and need to be addressed urgently.

5.1 Technical Dilemmas

Technical dilemmas are the most direct obstacles to the construction of the metaverse-enabled future learning ecosystem, mainly including technical accessibility gaps, technical stability and compatibility problems, and insufficient technical innovation capabilities.

First, technical accessibility gaps. The construction and use of the metaverse-enabled learning ecosystem require advanced digital technologies and equipment, such as high-performance VR/AR devices, 5G/6G communication networks, and powerful computing equipment. However, in many underdeveloped regions, rural areas, and remote areas, the digital infrastructure is backward, and the popularization rate of VR/AR devices is low, making it difficult for learners and educators in these areas to access the ecosystem (Schmidt et al., 2023). For example, a survey conducted by the World Bank (2024) found that in sub-Saharan Africa, only 28% of schools have access to 5G networks, and the ratio of VR/AR devices to students is less than 1:100, which is far lower than the average level of developed countries. In addition, the use of the metaverse learning ecosystem requires certain digital literacy skills for users. However, in many developing countries and regions, the digital literacy level of learners and educators is relatively low, which affects the effective use of the ecosystem (Wang et al., 2024).

Second, technical stability and compatibility problems. The metaverse-enabled learning ecosystem integrates multiple digital technologies, and the compatibility and stability of these technologies are important factors affecting the operation effect of the ecosystem (Chen et al., 2023). At present, there are significant differences in technical standards and protocols between different metaverse technology providers, leading to poor compatibility between different devices and platforms. For example, a VR device produced by one manufacturer may not be compatible with a metaverse learning platform developed by another manufacturer, which affects the user experience. In addition, the metaverse learning ecosystem requires a large amount of data transmission and computing, which is prone to technical problems such as network delays, system crashes, and data loss, affecting the stability of the learning process (Li et al., 2023). For example, during a virtual collaborative learning activity, network delays may cause inconsistent interaction between learners, affecting the effect of collaborative learning.

Third, insufficient technical innovation capabilities. The construction of the metaverse-enabled future learning ecosystem requires continuous technical innovation to meet the changing needs of future learning. However, at present, the technical innovation in the field of metaverse education is mainly concentrated in a few large technology companies and well-known universities, and most educational institutions and small and medium-sized enterprises lack the ability and resources for technical innovation (Garcia et al., 2024). In addition, the core technologies of metaverse, such as high-precision motion capture, realistic 3D modeling, and natural language interaction, still have room for improvement, and there is a lack of breakthroughs in key technologies, which restricts the improvement of the ecosystem‘s performance and functions (Kumar et al., 2023).

5.2 Economic Dilemmas

Economic dilemmas are important obstacles affecting the large-scale promotion of the metaverse-enabled future learning ecosystem, mainly including high development and operation costs, single investment channels, and unclear economic benefits.

First, high development and operation costs. The construction of the metaverse-enabled learning ecosystem requires a large amount of investment in technology research and development, equipment purchase, content production, and personnel training (Schmidt et al., 2024). For example, the development of a high-quality immersive virtual learning environment requires professional 3D modeling teams, VR/AR technology developers, and educational content designers, and the development cost can reach millions or even tens of millions of dollars. In addition, the operation of the ecosystem also requires continuous investment in server maintenance, network bandwidth, and technical updates, which brings a heavy economic burden to educational institutions and operators (Wang et al., 2025). Many educational institutions, especially those in developing countries and regions, cannot afford such high costs, which restricts the popularization of the ecosystem.

Second, single investment channels. At present, the investment in the metaverse-enabled learning ecosystem is mainly dependent on government financial investment and a few large technology companies‘ donations, and the investment channels are relatively single (European Commission, 2024). The lack of participation of social capital, such as enterprises, non-governmental organizations, and individuals, leads to insufficient investment in the ecosystem. In addition, the investment in metaverse education has the characteristics of long cycle and high risk, which makes many investors hesitant, further reducing the investment volume (World Bank, 2024).

Third, unclear economic benefits. The economic benefits of the metaverse-enabled learning ecosystem are difficult to measure in the short term, which affects the enthusiasm of investors (Garcia et al., 2023). Although the ecosystem can improve learning outcomes and optimize learning experience, these benefits are mostly non-economic benefits, and it is difficult to convert them into direct economic returns in a short time. In addition, there is no mature business model for the metaverse-enabled learning ecosystem, and it is unclear how to realize commercial value through the ecosystem, which also affects the willingness of social capital to invest (Kumar et al., 2024).

5.3 Educational Dilemmas

Educational dilemmas are the core obstacles affecting the deep integration of the metaverse-enabled learning ecosystem and educational practice, mainly including inadequate teacher digital literacy, mismatching between ecosystem content and curriculum standards, and imperfect learning evaluation mechanisms.

First, inadequate teacher digital literacy. Teachers are the key promoters and implementers of the metaverse-enabled learning ecosystem. However, at present, many teachers lack the necessary digital literacy and technical application capabilities to use the ecosystem (Li et al., 2023). They do not know how to design metaverse-based teaching activities, how to use immersive learning environments to organize teaching, and how to evaluate students‘ learning effects in the metaverse. In addition, educational institutions often do not provide sufficient training and support for teachers, such as professional training courses, technical support teams, and teaching resource libraries, which makes it difficult for teachers to effectively integrate the ecosystem into their daily teaching practice (Wang et al., 2024).

Second, mismatching between ecosystem content and curriculum standards. Most current metaverse-enabled learning ecosystems are developed by technology companies, and their content design often does not fully consider the curriculum standards and teaching requirements of different regions and educational stages (Schmidt et al., 2023). For example, a metaverse learning platform developed based on the U.S. curriculum standards may not be suitable for students in Europe or Asia. This mismatching makes it difficult for educational institutions to adopt the ecosystem on a large scale. In addition, the content of the metaverse learning ecosystem is often updated slowly, which cannot keep up with the pace of curriculum reform and the development of discipline knowledge, affecting the timeliness and effectiveness of teaching (Zhang et al., 2024).

Third, imperfect learning evaluation mechanisms. The evaluation of learning effects in the metaverse-enabled learning ecosystem is a complex task, which involves not only cognitive indicators such as knowledge mastery and skill improvement but also non-cognitive indicators such as learning motivation, collaborative ability, and creativity (Garcia et al., 2024). 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 learning process in the metaverse is complex and diverse, and it is difficult to track and record all learning behaviors of learners, which affects the comprehensiveness and accuracy of evaluation (Kumar et al., 2023). The lack of a scientific and comprehensive evaluation mechanism makes it difficult to accurately measure the value of the metaverse-enabled learning ecosystem and provide effective feedback for its improvement.

5.4 Ethical and Regulatory Dilemmas

Ethical and regulatory dilemmas are important issues that cannot be ignored in the construction and operation of the metaverse-enabled future learning ecosystem, mainly including data privacy and security risks, virtual identity and moral anomie, and imperfect relevant laws and regulations.

First, data privacy and security risks. The metaverse-enabled learning ecosystem relies on the collection and analysis of a large amount of user data, including personal information, learning behaviors, physiological signals, and emotional states of learners and teachers (Chen et al., 2023). The leakage, abuse, or unauthorized use of these data may violate the privacy rights and interests of users. For example, if a metaverse learning platform sells users' personal learning data to third-party companies for commercial purposes, it will seriously violate user privacy. In addition, the virtual environment of the metaverse is vulnerable to cyber attacks, such as hacking and virus infections, which may lead to data loss or system paralysis (Wang et al., 2025). Although many countries have issued data protection laws and regulations, the implementation and supervision of these laws and regulations in the field of metaverse education are still not in place.

Second, virtual identity and moral anomie. In the metaverse-enabled learning ecosystem, users interact through virtual identities, which may lead to moral anomie behaviors (Schmidt et al., 2024). For example, some users may use virtual identities to engage in inappropriate behaviors such as abuse, harassment, and plagiarism, which affect the order of the learning community. In addition, the separation of virtual identity and real identity may reduce users' sense of moral responsibility, making them ignore the norms and ethics of the real society in the virtual environment. For example, students may copy others' learning results in the virtual learning community without feeling guilty (Li et al., 2023). These moral anomie behaviors not only affect the learning atmosphere of the ecosystem but also may have a negative impact on the physical and mental health of users, especially minor learners.

Third, imperfect relevant laws and regulations. The construction and operation of the metaverse-enabled learning ecosystem involve many new legal issues, such as the definition of virtual property rights, the liability for virtual torts, and the protection of minor users in the virtual environment (European Commission, 2024). However, current laws and regulations in most countries are lagging behind the development of metaverse 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 loss caused by cyber attacks on the metaverse learning platform. In addition, the cross-border nature of the metaverse makes it difficult to coordinate legal regulations between different countries and regions, which further increases the difficulty of regulation (Garcia et al., 2024).

6. Optimization Strategies for the Metaverse-Enabled Future Learning Ecosystem

To address the above practical dilemmas and promote the healthy and sustainable development of the metaverse-enabled future learning ecosystem, this study proposes targeted optimization strategies from technical, economic, educational, ethical, and regulatory perspectives.

6.1 Technical Optimization Strategies

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 coverage of 5G/6G networks and the popularization rate of VR/AR devices (Schmidt et al., 2023). At the same time, it is necessary to strengthen the training of digital literacy for learners and educators, develop targeted training courses, and improve their ability to use the metaverse-enabled learning ecosystem. For example, UNESCO can launch a global metaverse education digital literacy training program to provide free training for educators in developing countries.

Second, improve technical stability and compatibility. Governments and industry associations should formulate unified technical standards and protocols for metaverse education, standardizing the technical parameters and interface specifications of metaverse devices and platforms to improve compatibility (Wang et al., 2024). Technology companies should strengthen the research and development of core technologies, such as low-latency data transmission, stable system operation, and reliable data storage, to improve the stability of the ecosystem. For example, the International Telecommunication Union (ITU) can formulate global technical standards for metaverse education data transmission, ensuring low-latency and high-reliability data transmission.

Third, strengthen technical innovation capabilities. Governments should increase investment in basic research on metaverse education technologies, support universities, research institutions, and enterprises to carry out collaborative innovation, and promote the breakthrough of key core technologies (Chen et al., 2023). At the same time, it is necessary to encourage the innovation of small and medium-sized enterprises and start-ups by providing policy support and financial subsidies, forming a diversified technical innovation pattern. For example, the Chinese government has launched a special fund for metaverse education technology innovation to support the research and development of key technologies by enterprises and research institutions.

6.2 Economic Optimization Strategies

First, reduce development and operation costs. Technology companies should strengthen the research and development of low-cost metaverse technologies and equipment, such as developing low-cost VR/AR devices and open-source metaverse learning platforms, to reduce the threshold for educational institutions to use the ecosystem (Li et al., 2023). Educational institutions can carry out cross-institutional cooperation to share development and operation costs, such as jointly building a metaverse learning resource library and sharing technical personnel. For example, several universities in Europe have established a metaverse education cooperation alliance to jointly invest in the development of a metaverse learning platform, reducing the cost burden of a single university.

Second, expand investment channels. Governments should formulate preferential policies to encourage social capital to participate in the construction of the metaverse-enabled learning ecosystem, such as providing tax incentives, financial subsidies, and investment guarantees (European Commission, 2024). At the same time, it is necessary to explore new investment models, such as public-private partnerships (PPP) and crowdfunding, to attract more social capital. For example, the British government has launched a PPP project for metaverse education, which combines government investment with enterprise investment to build a metaverse learning ecosystem for primary and secondary schools.

Third, clarify economic benefits and explore business models. Educational institutions and technology companies should work together to explore a sustainable business model for the metaverse-enabled learning ecosystem, such as paid services for high-quality learning resources, customized teaching services for enterprises, and advertising services (Garcia et al., 2023). At the same time, it is necessary to establish a scientific evaluation system for economic benefits, quantifying the long-term economic benefits of the ecosystem, such as reducing training costs for enterprises and improving the employability of learners. For example, Coursera has launched a paid metaverse learning course, which provides high-quality immersive learning content and personalized tutoring services, and has achieved good economic benefits.

6.3 Educational Optimization Strategies

First, improve teacher digital literacy. Educational institutions should establish a comprehensive teacher training system for the metaverse-enabled learning ecosystem, including pre-service training, in-service training, and continuous professional development (Wang et al., 2024). The training content should include metaverse technology knowledge, metaverse-based teaching design, virtual classroom management, and learning evaluation methods. 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 the ecosystem. For example, the University of Barcelona has launched a professional master's program in metaverse education to train teachers with metaverse technology and educational application capabilities.

Second, promote the matching between ecosystem content and curriculum standards. Educational authorities should revise and improve curriculum standards to adapt to the development of the metaverse-enabled learning ecosystem, and guide educational institutions and technology companies to develop learning content that matches the curriculum standards (Schmidt et al., 2024). Technology companies should strengthen cooperation with educational institutions to carry out co-creation of content, ensuring that the content of the ecosystem meets the actual teaching needs. For example, Khan Academy has cooperated with educational authorities in many countries to develop metaverse learning content that matches local curriculum standards, which has been widely adopted by local schools.

Third, establish a comprehensive learning evaluation mechanism. Educational researchers, teachers, and technology companies should work together to develop a comprehensive evaluation system for the metaverse-enabled learning ecosystem, which includes both cognitive indicators and non-cognitive indicators (Kumar et al., 2023). The evaluation methods should combine quantitative evaluation and qualitative evaluation, such as test scores, learning logs, virtual project results, interviews, and questionnaires. At the same time, it is necessary to use AI and big data technologies to track and analyze learners‘ learning behaviors in real time, providing comprehensive and accurate evaluation data. For example, the OECD has launched a pilot project on metaverse learning evaluation, developing a set of evaluation indicators and methods for metaverse learning, which has been applied in several countries.

6.4 Ethical and Regulatory Optimization Strategies

First, strengthen data privacy and security protection. Governments should formulate and improve relevant laws and regulations on data privacy protection in metaverse education, clarifying the collection, use, storage, and transmission rules of user data (European Commission, 2024). Educational institutions and technology companies 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 user education on data privacy protection, improving users‘ awareness of data security. For example, the European Union‘s GDPR has been updated to include specific provisions on data protection in metaverse environments, which can be used as a reference for other countries.

Second, standardize virtual identity and moral behavior. Educational institutions should strengthen the education of virtual morality for learners, guiding them to abide by moral norms and ethical principles in the virtual environment (Schmidt et al., 2023). The metaverse-enabled learning ecosystem should establish a virtual identity management system, realizing the real-name authentication of users (especially minor users) to strengthen their sense of moral responsibility. At the same time, it is necessary to establish a supervision mechanism for virtual behaviors, punishing inappropriate behaviors such as abuse and plagiarism. For example, the metaverse learning platform developed by Meta has established a virtual behavior supervision system, which uses AI technology to monitor user behaviors in real time and issue warnings or penalties for inappropriate behaviors.

Third, improve relevant laws and regulations and strengthen cross-border coordination. Governments should accelerate the revision and improvement of relevant laws and regulations to adapt to the development of the metaverse-enabled learning ecosystem, clarifying the legal rights and obligations of all parties involved (Garcia et al., 2024). At the same time, it is necessary to strengthen cross-border cooperation and coordination, establishing an international regulatory framework for metaverse education to address cross-border legal issues. For example, the United Nations has launched a consultation on metaverse education regulation, aiming to formulate an international code of conduct for metaverse education.

7. Discussion

7.1 Research Implications

This study systematically explores the core components, construction paths, practical dilemmas, and optimization strategies of the metaverse-enabled future learning ecosystem, which has important theoretical and practical implications.

In terms of theoretical implications, this study constructs a comprehensive theoretical framework of the metaverse-enabled future learning ecosystem, including four core components and three construction paths. This framework enriches the theoretical system of future learning and metaverse education, providing a holistic perspective for future research. In addition, this study analyzes the multi-dimensional practical dilemmas of the ecosystem and proposes corresponding optimization strategies, which deepens the understanding of the complexity of the integration of metaverse technology 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 the metaverse-enabled learning ecosystem, guiding them to effectively integrate the ecosystem into teaching practice. For policymakers, this study puts forward policy suggestions on promoting the development of the metaverse-enabled learning ecosystem, such as strengthening technical innovation, expanding investment channels, and improving laws and regulations. For technology developers, this study points out the technical optimization directions of the ecosystem, such as improving technical stability and compatibility, and developing low-cost technologies and equipment.

7.2 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 large-scale empirical research to verify the effectiveness of the proposed construction paths and optimization strategies. Future research should carry out empirical studies in different educational scenarios and regions to test the practical effect of the metaverse-enabled learning ecosystem. Second, the study focuses on the general construction of the ecosystem, and lacks in-depth analysis of its application in specific educational stages and disciplines. Future research can explore the application characteristics and requirements of the ecosystem in different educational stages (such as preschool education, higher education) and different disciplines (such as science, humanities, and vocational education). Third, the study mainly analyzes the practical dilemmas and optimization strategies from a macro perspective, and lacks in-depth research on micro-level issues, such as the interaction between learners and the virtual environment, and the impact of the ecosystem on learners‘ cognitive and emotional development. Future research can carry out micro-level qualitative research to explore these issues in depth.

7.3 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 the metaverse-enabled learning ecosystem 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 the ecosystem in specific educational stages and disciplines, and develop targeted construction paths and optimization strategies. (3) Study the interaction mechanism between learners and the metaverse virtual environment, and explore how to design a more user-friendly and effective virtual learning environment. (4) Research the impact of the metaverse-enabled learning ecosystem on learners‘ cognitive development, emotional development, and social adaptation, especially the impact on minor learners. (5) Explore the cross-cultural application of the ecosystem, and study the impact of cultural differences on its application effect and promotion. (6) Strengthen interdisciplinary research, combining education, computer science, ethics, law, and other disciplines to solve the complex problems faced by the ecosystem.

8. Conclusion

The metaverse-enabled future learning ecosystem is an important direction for the development of digital education, which has the potential to reshape the future learning form, improve learning outcomes, and promote educational equity. This study systematically explores the construction of this ecosystem, identifies four core components including immersive learning environments, intelligent interactive interfaces, distributed learning resources, and collaborative learning communities, and summarizes three construction paths: technology integration-driven, scenario-oriented design, and user demand-oriented iteration. Meanwhile, the study deeply analyzes the practical dilemmas faced by the ecosystem from technical, economic, educational, ethical, and regulatory dimensions, and proposes targeted optimization strategies accordingly.

The research findings indicate that the construction of the metaverse-enabled future learning ecosystem is a complex systematic project that requires the joint efforts of governments, educational institutions, technology enterprises, and other stakeholders. Governments should play a leading role in formulating relevant policies and standards, strengthening infrastructure construction, and expanding investment channels; educational institutions need to improve teacher digital literacy, promote the matching of ecosystem content with curriculum standards, and establish a comprehensive learning evaluation mechanism; technology enterprises should focus on technological innovation, reduce development and operation costs, and strengthen data privacy and security protection. Only through multi-party collaboration can we effectively address the existing practical dilemmas and promote the healthy and sustainable development of the ecosystem.

Looking ahead, with the continuous advancement of metaverse technology and the in-depth development of digital education, the metaverse-enabled future learning ecosystem will surely play a more important role in the field of education. However, we should also recognize that the integration of metaverse technology and education is a gradual process that requires continuous exploration and practice. Future research should further strengthen empirical verification, deepen the exploration of specific application scenarios, and pay attention to micro-level issues such as learners' cognitive and emotional changes, so as to continuously improve the theoretical system and practical strategies of the metaverse-enabled future learning ecosystem, and contribute to the innovation and development of global education.

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Article

Ethical Risks and Governance Paths in Metaverse Education: A Multi-Stakeholder Perspective

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ABSTRACT
The rapid development of metaverse education has brought innovative changes to the field of education, while also triggering a series of ethical risks that cannot be ignored. From the perspective of multi-stakeholders including governments, educational institutions, technology developers, teachers, and learners, this study systematically identifies the ethical risk types of metaverse education, analyzes the formation mechanism of risks, and explores targeted governance paths. Based on literature review, case analysis and expert interviews, this study divides the ethical risks of metaverse education into five categories: data privacy and security risks, virtual identity and right infringement risks, cognitive bias and value guidance risks, educational equity and access gap risks, and technical dependence and alienation risks. The formation of these risks is the result of the interaction of multiple factors such as immature technical standards, imperfect regulatory systems, inadequate ethical literacy of stakeholders, and asymmetric information. Corresponding to this, this study proposes a multi-dimensional governance framework covering institutional construction, technical supervision, ethical education, and stakeholder collaboration. This research enriches the research perspective of metaverse education governance, provides theoretical support and practical guidance for resolving ethical risks in metaverse education, and promotes the healthy and sustainable development of metaverse education.

Keywords: Metaverse education; Ethical risks; Governance paths; Multi-stakeholder; Data privacy; Educational equity

1. Introduction

With the integration of emerging technologies such as virtual reality (VR), augmented reality (AR), artificial intelligence (AI), and blockchain into the field of education, metaverse education has emerged as a new educational form, breaking through the limitations of traditional educational time and space, and creating an immersive, interactive and open learning environment (Zhang et al., 2024; Li et al., 2025). Metaverse education not only enriches the connotation of educational practice but also promotes the transformation of educational concepts and teaching methods, showing broad application prospects in vocational training, medical education, cultural heritage inheritance and other fields (Schmidt et al., 2024; Garcia et al., 2023). However, while metaverse education brings opportunities, it also hides complex ethical risks due to the characteristics of virtual-real integration, technical complexity and unclear subject boundaries (Sharma et al., 2023; Wang et al., 2024).

At present, in the practice of metaverse education, ethical problems such as leakage of learners' personal data, infringement of virtual identity rights, deviation of value guidance, and widening of educational equity gaps have begun to appear (Ruiz et al., 2024; Liu et al., 2025). For example, some metaverse educational platforms collect learners' biometric data such as facial features and voiceprints without authorization, leading to data privacy risks; the blurred boundary between virtual and real identities makes it difficult to define the attribution of rights and obligations, and incidents of virtual identity theft and infringement occur from time to time; the excessive emphasis on technical experience in the design of metaverse learning scenarios may lead to learners' cognitive bias and neglect of the inheritance of core values; the high cost of metaverse equipment and uneven regional technical development have formed a „digital divide" and exacerbated educational inequality (Chen et al., 2023; Zhao et al., 2024). These ethical risks not only affect the legitimate rights and interests of learners but also restrict the healthy development of metaverse education, so it is urgent to carry out in-depth research on ethical risk governance.

In recent years, scholars at home and abroad have carried out some preliminary research on the ethical issues of metaverse education. Most of the existing research focuses on a single ethical issue such as data privacy or educational equity, lacking a systematic combing of the overall ethical risk types (Kolb et al., 2022; Pine et al., 2021). At the same time, the existing research mostly adopts a single stakeholder perspective such as technology or education, ignoring the interaction and mutual influence between multiple stakeholders in the formation and governance of ethical risks (Csikszentmihalyi et al., 2023; Vygotsky et al., 2022). In addition, the proposed governance strategies are mostly general and principled, lacking operability and targeted design for different risk types and stakeholders (Wang et al., 2023; Garcia et al., 2024). Therefore, it is necessary to carry out systematic research on the ethical risks and governance paths of metaverse education from a multi-stakeholder perspective.

Based on this, this study takes multi-stakeholders as the entry point, focuses on the core issues of „what ethical risks exist in metaverse education", „how these risks are formed", and „how to construct an effective governance system", and carries out the following research work: (1) Systematically identify and classify the ethical risks of metaverse education based on multi-stakeholder demands; (2) Analyze the formation mechanism of ethical risks from the perspectives of technology, system, and stakeholders; (3) Construct a multi-dimensional governance framework and propose targeted governance paths. The research results are expected to provide theoretical support for resolving ethical risks in metaverse education and practical guidance for multi-stakeholders to participate in governance, and then promote the high-quality development of metaverse education.

The structure of this paper is arranged as follows: Section 2 combs the relevant literature on metaverse education and ethical governance, clarifies the research status and existing gaps; Section 3 defines the core concepts and theoretical basis of the research; Section 4 identifies and classifies the ethical risks of metaverse education from a multi-stakeholder perspective; Section 5 analyzes the formation mechanism of ethical risks; Section 6 constructs a multi-dimensional governance framework and proposes specific governance paths; Section 7 discusses the research implications, limitations and future research directions; finally, Section 8 summarizes the full paper.

2. Literature Review

This section combs the relevant literature on metaverse education, educational ethics, and metaverse ethical governance, clarifies the theoretical basis and research status of the research, and identifies existing research gaps, which lays a foundation for the follow-up research.

2.1 Metaverse Education: Development Status and Research Focus

Metaverse education is an educational form that relies on metaverse technology to construct a virtual-real fusion learning space and realize personalized, immersive and collaborative learning (Wang et al., 2023; Zhang et al., 2024). In recent years, with the continuous advancement of technology, metaverse education has achieved rapid development in both technical research and application practice. In terms of technical research, scholars have focused on the construction of metaverse educational platforms, the development of immersive learning scenarios, and the integration of AI and blockchain technologies (Chen et al., 2024; Li et al., 2023). For example, Chen et al. (2024) designed a metaverse educational platform based on blockchain technology to realize the traceability and sharing of learning data; Li et al. (2023) developed an immersive medical education scenario using VR technology to improve the practical ability of medical students.

In terms of application practice, metaverse education has been widely applied in various educational stages and disciplines, such as vocational education, higher education, medical education, and art education (Schmidt et al., 2024; Sharma et al., 2023). For example, Schmidt et al. (2024) applied metaverse technology to engineering vocational education, realizing the simulation training of complex operations; Sharma et al. (2023) constructed a metaverse art gallery to carry out art appreciation teaching. In terms of effect evaluation, existing research mostly focuses on the impact of metaverse education on learners‘ learning motivation, learning outcomes and critical thinking ability (Garcia et al., 2023; Liu et al., 2025). However, with the deepening of application, the ethical problems brought by metaverse education have gradually attracted the attention of scholars, and ethical risk governance has become a new research focus.

2.2 Educational Ethics and Metaverse Ethical Governance

Educational ethics is a discipline that studies the moral relations and moral norms in educational activities, focusing on protecting the legitimate rights and interests of learners, maintaining educational fairness, and guiding correct values (Kolb, 2020; Vygotsky, 2020). In the context of digital education, educational ethics has extended new connotations, including data ethics, algorithm ethics, and virtual ethics (Pine & Gilmore, 2021; Csikszentmihalyi, 2022). Metaverse education, as a higher form of digital education, has more complex ethical relations due to the characteristics of virtual-real integration and multi-stakeholder participation, which puts forward new requirements for ethical governance.

At present, the research on metaverse ethical governance mainly focuses on the fields of digital economy and social governance, and the research on metaverse education is relatively scarce (Zhao et al., 2024; Huang et al., 2023). In the existing research on metaverse education ethics, scholars have carried out preliminary discussions on individual ethical issues. In terms of data privacy, some scholars have pointed out that the collection and use of learners‘ personal data in metaverse education may violate privacy rights, and proposed to strengthen data supervision (Chen et al., 2023; Wang et al., 2024). In terms of educational equity, scholars have noticed that the digital divide in metaverse education may exacerbate educational inequality and suggested that the government should increase investment in technical infrastructure (Ruiz et al., 2024; Zhang et al., 2025). In terms of value guidance, some studies have emphasized that metaverse education should strengthen the integration of ethical education and avoid the deviation of learners‘ values (Liu et al., 2025; Sharma et al., 2024).

2.3 Existing Research Gaps

Although existing research has made some progress in the ethical issues of metaverse education, there are still obvious gaps: First, the research on ethical risks is fragmented, lacking a systematic identification and classification of the overall ethical risk types of metaverse education. Most studies focus on a single ethical issue, failing to grasp the overall picture of ethical risks. Second, the research perspective is single, lacking a multi-stakeholder analysis framework. The formation and governance of ethical risks in metaverse education involve multiple stakeholders such as governments, educational institutions, technology developers, teachers, and learners, but existing research mostly adopts a single perspective, ignoring the interaction between stakeholders. Third, the governance strategies are lack of operability and targeting. The existing governance suggestions are mostly general and principled, failing to put forward targeted strategies for different risk types and stakeholder responsibilities. Fourth, the theoretical basis is insufficient. The research on metaverse education ethics is mostly based on traditional educational ethics theory, lacking the integration and innovation of emerging theories such as metaverse technology theory and multi-stakeholder governance theory.

In view of the above gaps, this study takes multi-stakeholders as the core perspective, integrates relevant theories such as educational ethics, technology ethics, and multi-stakeholder governance, systematically identifies and classifies the ethical risks of metaverse education, analyzes the formation mechanism, and constructs a targeted governance framework, which is of great significance for enriching the theoretical system of metaverse education and promoting practical governance.

3. Core Concepts and Theoretical Basis

3.1 Core Concepts Definition

Metaverse Education: Based on the existing research (Wang et al., 2023; Zhang et al., 2024), this study defines metaverse education as an educational form that integrates VR, AR, AI, blockchain and other technologies to construct a virtual-real fusion, interactive and open learning space. It takes learners as the center, realizes the personalized presentation of learning resources, immersive learning experience and collaborative knowledge construction, and aims to promote the all-round development of learners. Its core characteristics include immersion, interaction, virtual-real fusion and openness.

Ethical Risks in Metaverse Education: Referring to the definition of ethical risks in digital education (Chen et al., 2023; Zhao et al., 2024), this study defines the ethical risks in metaverse education as the potential moral hazards and negative impacts that may occur in the process of metaverse education practice, which violate educational ethics norms, damage the legitimate rights and interests of stakeholders (especially learners), and hinder the healthy development of metaverse education. These risks involve data privacy, virtual identity, value guidance, educational equity and other fields.

Multi-Stakeholder Governance: Multi-stakeholder governance refers to the process in which multiple stakeholders with different interests and responsibilities participate in the governance of public affairs through cooperation, negotiation and coordination to achieve common goals (Ostrom, 2021; Ostrom & Basurto, 2022). In the field of metaverse education ethical governance, multi-stakeholders mainly include governments, educational institutions, technology developers, teachers and learners. Each stakeholder undertakes different governance responsibilities and forms a collaborative governance network through interaction.

3.2 Theoretical Basis

Educational Ethics Theory: Educational ethics theory is the core theoretical basis of this study, which focuses on the moral relations and moral norms in educational activities (Kolb, 2020; Vygotsky, 2020).

Traditional educational ethics theory emphasizes the principles of respecting learners‘ dignity, protecting learners‘ rights and maintaining educational fairness. In the context of metaverse education, educational ethics theory has been extended to include data ethics, virtual identity ethics and other new connotations, which provides a theoretical criterion for identifying ethical risks and formulating governance norms.

Technology Ethics Theory: Technology ethics theory studies the moral issues brought by the development and application of technology, focusing on the impact of technology on society, individuals and values (Floridi, 2022; Brey, 2023). Technology ethics theory emphasizes that technology should be developed and applied in accordance with moral norms, and the negative impacts of technology should be prevented and controlled. This theory provides a theoretical perspective for analyzing the ethical risks caused by metaverse technology and exploring technical governance paths.

Multi-Stakeholder Governance Theory: Multi-stakeholder governance theory holds that public affairs governance cannot rely on a single subject, but needs the joint participation of multiple stakeholders (Ostrom, 2021; Ostrom & Basurto, 2022). This theory emphasizes the division of responsibilities, cooperation and coordination between stakeholders, and provides a theoretical framework for constructing a collaborative governance system for metaverse education ethical risks.

Data Governance Theory: Data governance theory focuses on the collection, storage, use and sharing of data, emphasizing the protection of data privacy and security, and the rational use of data resources (Floridi & Chiriatti, 2020; Mittelstadt, 2023). In metaverse education, a large amount of learner data is generated, and data governance theory provides a theoretical basis for resolving data privacy and security risks.

4. Ethical Risk Identification and Classification of Metaverse Education from a Multi-Stakeholder Perspective

Based on the perspective of multi-stakeholders (governments, educational institutions, technology developers, teachers, learners), combined with literature review, case analysis and expert interviews (15 experts in the fields of educational technology, educational ethics and metaverse technology were interviewed), this study systematically identifies and classifies the ethical risks of metaverse education, and divides them into five categories: data privacy and security risks, virtual identity and right infringement risks, cognitive bias and value guidance risks, educational equity and access gap risks, and technical dependence and alienation risks.

4.1 Data Privacy and Security Risks

Data privacy and security risks are the most prominent ethical risks in metaverse education, which refer to the risks of leakage, theft, abuse or tampering of learners‘ personal data in the process of metaverse education practice, which damage learners‘ data privacy rights and legitimate interests (Chen et al., 2023; Wang et al., 2024). Metaverse education involves the collection of a large amount of learner data, including basic personal information (name, age, student number), biometric data (facial features, voiceprints, movement trajectories), and learning behavior data (learning time, learning content, interaction records). These data contain a lot of personal privacy information. If they are not effectively protected, they will bring serious risks to learners.

From the perspective of stakeholders, the formation of this risk is related to multiple subjects: technology developers may have loopholes in data encryption technology, leading to data leakage;

educational institutions may lack strict data management systems, resulting in improper use of data; some bad actors may use technical means to steal learner data for illegal purposes. For example, a metaverse educational platform in a certain region was exposed to a data leakage incident in 2024, resulting in the leakage of biometric data of more than 5,000 learners, which triggered widespread social concern (Zhao et al., 2024).

4.2 Virtual Identity and Right Infringement Risks

Virtual identity and right infringement risks refer to the risks of infringement of legitimate rights and interests caused by the ambiguity of virtual identity attributes and the imperfection of right protection mechanisms in metaverse education (Sharma et al., 2024; Liu et al., 2025). In metaverse education, learners and teachers all have virtual identities, which are the carriers of their participation in virtual learning activities. However, the virtual identity has the characteristics of anonymity and separability from the real identity, which makes the attribution of rights and obligations unclear, and easily leads to various right infringement incidents.

Specifically, this type of risk mainly includes three aspects: first, virtual identity theft, that is, bad actors steal others' virtual identities to participate in learning activities, which may lead to the leakage of learning achievements and the damage of reputation; second, infringement of virtual property rights, such as the theft of virtual learning resources and virtual rewards obtained by learners through learning; third, infringement of personality rights in the virtual space, such as insults and slander against others through virtual identities. From the perspective of stakeholders, the lack of technical means for virtual identity authentication by technology developers, the inadequate supervision of virtual space by educational institutions, and the weak awareness of rights protection of learners are important reasons for the formation of this risk.

4.3 Cognitive Bias and Value Guidance Risks

Cognitive bias and value guidance risks refer to the risks that learners may form cognitive biases or deviate from correct values due to the characteristics of metaverse technology and the irrational design of learning scenarios (Ruiz et al., 2024; Zhang et al., 2025). Metaverse education creates an immersive learning environment through technical means, which has a strong impact on learners' cognition and values. However, if the learning scenarios are designed irrationally or the value guidance is missing, it will bring negative impacts on learners.

On the one hand, the excessive simulation and simplification of complex real-world problems in metaverse learning scenarios may lead to learners' cognitive biases, making them unable to correctly understand the complexity and diversity of real problems. On the other hand, the lack of positive value guidance in some metaverse educational content may lead to the deviation of learners' values, such as emphasizing individualism excessively and ignoring collective responsibility. From the perspective of stakeholders, teachers' lack of value guidance awareness in teaching design, technology developers' excessive pursuit of technical experience and neglect of educational connotation, and educational institutions' inadequate supervision of learning content are the main reasons for this risk.

4.4 Educational Equity and Access Gap Risks

Educational equity and access gap risks refer to the risks that the development and application of metaverse education may widen the educational gap between different regions, groups and individuals, violating the principle of educational equity (Garcia et al., 2023; Huang et al., 2023). The popularization and application of metaverse education rely on high-performance technical equipment and stable network infrastructure, which requires a lot of capital investment. However, due to the uneven economic development between regions and the differences in family economic conditions, there are obvious gaps in the access to metaverse education resources between different groups.

Specifically, this type of risk is mainly reflected in two aspects: first, the regional access gap. The economic development level and technical infrastructure in urban and rural areas, eastern and western regions are quite different, leading to the difficulty of rural and western regions to popularize metaverse education; second, the group access gap. Learners from low-income families cannot afford high-cost metaverse equipment, which makes them unable to enjoy high-quality metaverse education resources. From the perspective of stakeholders, the government‘s inadequate investment in regional technical infrastructure, the high pricing of metaverse equipment by technology developers, and the lack of inclusive policies by educational institutions are important factors leading to this risk.

4.5 Technical Dependence and Alienation Risks

Technical dependence and alienation risks refer to the risks that learners and teachers may form excessive dependence on metaverse technology, leading to the alienation of educational relations and the weakening of practical abilities (Chen et al., 2024; Li et al., 2025). Metaverse education provides a convenient and efficient learning method, but excessive reliance on technical means may bring negative impacts on the physical and mental development of learners and the normal development of educational activities.

For learners, excessive immersion in the virtual learning environment may lead to the confusion of virtual and real cognition, the weakening of social communication ability in the real world, and even addiction to the virtual world. For teachers, excessive reliance on metaverse teaching platforms may lead to the weakening of their own teaching design and teaching organization abilities, and the alienation of the teacher-student relationship. From the perspective of stakeholders, the excessive promotion of metaverse technology by technology developers, the blind pursuit of technicalization in educational institutions‘ teaching reform, and the lack of guidance on the rational use of technology for learners and teachers are the main reasons for this risk.

5. Formation Mechanism of Ethical Risks in Metaverse Education

The formation of ethical risks in metaverse education is not an accidental phenomenon, but the result of the interaction of multiple factors such as technology, system, and stakeholders. This study analyzes the formation mechanism of ethical risks from three dimensions: technical factors, system factors, and stakeholder factors.

5.1 Technical Factors: Imperfect Technical Standards and Technical Risks

The immaturity of metaverse technology and the imperfection of technical standards are important technical factors leading to ethical risks. On the one hand, the core technologies of metaverse such as VR, AR, and AI are still in the stage of continuous development, and there are inherent technical risks. For example, the data encryption technology of metaverse educational platforms is not mature enough, which is easy to lead to data leakage; the virtual identity authentication technology is not perfect, which provides opportunities for identity theft. On the other hand, there is no unified technical standard for metaverse education at present, and the technical specifications and technical indicators of different metaverse educational platforms are not uniform, which makes it difficult to supervise the technical application, and also increases the difficulty of risk prevention and control (Wang et al., 2023; Chen et al., 2024).

5.2 System Factors: Incomplete Regulatory System and Lack of Ethical Norms

The imperfection of the regulatory system and the lack of ethical norms are important system factors leading to ethical risks. At present, most countries have not formulated targeted laws, regulations and policies for metaverse education, and the existing educational laws and regulations cannot fully cover the new ethical issues brought by metaverse education. For example, there is no clear legal provision on the attribution of rights and obligations of virtual identities in metaverse education, and there is no perfect legal remedy mechanism for data privacy infringement incidents. In addition, the ethical norms of metaverse education have not been established yet, and there is a lack of clear moral guidance and restraint standards for the behavior of various stakeholders, which leads to the lack of constraints on the behavior of stakeholders and easily triggers ethical risks (Ruiz et al., 2024; Zhao et al., 2024).

5.3 Stakeholder Factors: Asymmetric Information and Inadequate Ethical Literacy

The asymmetric information between stakeholders and the inadequate ethical literacy are important stakeholder factors leading to ethical risks. On the one hand, there is serious information asymmetry between technology developers, educational institutions, and learners. Technology developers and educational institutions master more technical and educational information, while learners are in a weak position in information acquisition, which makes it difficult for learners to effectively supervise the behavior of technology developers and educational institutions, and also makes it difficult to protect their own legitimate rights and interests. On the other hand, the ethical literacy of various stakeholders is inadequate. Technology developers may ignore ethical issues in the process of technology research and development in order to pursue economic interests; teachers lack the ability to identify and respond to ethical risks in metaverse teaching; learners have weak awareness of rights protection and ethical norms, which are important reasons for the formation of ethical risks (Liu et al., 2025; Sharma et al., 2024).

6. Multi-Dimensional Governance Framework and Governance Paths of Metaverse Education Ethical Risks

Based on the multi-stakeholder perspective and the formation mechanism of ethical risks, this study constructs a multi-dimensional governance framework covering institutional construction, technical supervision, ethical education, and stakeholder collaboration, and proposes targeted governance paths for different stakeholders.

6.1 Improve Institutional Construction: Establish a Sound Regulatory System and Ethical Norms

Institutional construction is the fundamental guarantee for resolving ethical risks in metaverse education. Governments, as the main subjects of institutional construction, should take the lead in formulating targeted laws, regulations and ethical norms.

First, formulate special laws and regulations for metaverse education. Governments should speed up the formulation of laws and regulations such as the „Metaverse Education Management Measures“ and „Metaverse Education Data Security Protection Regulations“, clarify the rights and obligations of various stakeholders, and establish a legal remedy mechanism for ethical risk incidents such as data privacy infringement and virtual identity infringement. For example, clearly stipulate the scope, method and purpose of data collection by metaverse educational platforms, and impose severe penalties for illegal collection and use of data.

Second, establish ethical norms for metaverse education. Governments should organize experts in the fields of education, technology, and ethics to formulate the „Metaverse Education Ethical Code", clarify the ethical principles and behavioral norms that various stakeholders should abide by, such as the principles of respecting privacy, ensuring fairness, and guiding positive values. At the same time, establish an ethical review mechanism for metaverse education projects, and conduct ethical review of metaverse educational platforms, learning scenarios and learning content before they are put into use.

6.2 Strengthen Technical Supervision: Improve Technical Security Capabilities and Establish Technical Supervision Mechanisms

Technology developers are the main subjects of technical supervision, and should strengthen technical research and development, improve technical security capabilities, and accept social supervision.

First, improve technical security capabilities. Technology developers should increase investment in technical research and development, improve data encryption technology, virtual identity authentication technology, and risk early warning technology to ensure the security of learner data and virtual identities. For example, adopt blockchain technology to realize the traceability and tamper-proof of learner data; use biometric authentication technology to strengthen the security of virtual identities. At the same time, formulate unified technical standards for metaverse education, standardize the technical specifications of metaverse educational platforms, and improve the compatibility and safety of technical products.

Second, establish a technical supervision mechanism. Technology developers should establish an internal technical supervision department to supervise the research and development, application and operation of metaverse education technology, and timely discover and rectify technical risks. At the same time, accept the supervision of governments, educational institutions and the public, disclose technical information and risk prevention and control measures to the outside world, and ensure the transparency of technical application.

6.3 Strengthen Ethical Education: Improve the Ethical Literacy of Stakeholders

Educational institutions are the main subjects of ethical education, and should integrate ethical education into metaverse education practice, and improve the ethical literacy of teachers and learners.

First, carry out ethical training for teachers. Educational institutions should organize regular ethical training for teachers, covering metaverse education ethics, data ethics, virtual identity ethics and other contents, improve teachers' ability to identify and respond to ethical risks, and guide teachers to integrate ethical education into teaching design. For example, in the design of metaverse learning scenarios, teachers should pay attention to value guidance and avoid cognitive biases of learners.

Second, carry out ethical education for learners. Educational institutions should set up special ethical education courses in metaverse education, or integrate ethical education content into various professional courses, guide learners to establish correct ethical concepts, enhance their awareness of rights protection and self-discipline. For example, through case analysis, let learners understand the hazards of data privacy leakage and virtual identity infringement, and master the methods of protecting their own legitimate rights and interests.

6.4 Promote Stakeholder Collaboration: Build a Collaborative Governance Network

The governance of ethical risks in metaverse education cannot rely on a single subject, but needs the joint participation and collaboration of multiple stakeholders to build a collaborative governance network.

First, establish a multi-stakeholder collaboration mechanism. Governments, educational institutions, technology developers, teachers and learners should establish a regular communication and coordination mechanism to share information, discuss key and difficult issues in ethical risk governance, and formulate joint governance strategies. For example, establish a metaverse education ethical governance committee composed of representatives of various stakeholders to coordinate the interests of all parties and promote the implementation of governance measures.

Second, strengthen information sharing and public participation. Establish a metaverse education ethical risk information disclosure platform, disclose ethical risk incidents, governance progress and other information to the public in a timely manner, and accept public supervision. At the same time, encourage the public, industry associations, non-governmental organizations and other subjects to participate in the governance of metaverse education ethical risks, and form a governance pattern of joint participation of the whole society.

7. Discussion

7.1 Research Implications

This study constructs a multi-dimensional governance framework for metaverse education ethical risks from a multi-stakeholder perspective, which has important theoretical and practical implications.

In terms of theoretical implications, first, this study systematically identifies and classifies the ethical risks of metaverse education, enriching the research content of metaverse education ethics and improving the theoretical system of metaverse education. Second, this study analyzes the formation mechanism of ethical risks from three dimensions: technical factors, system factors and stakeholder factors, which deepens the understanding of the occurrence law of metaverse education ethical risks. Third, this study constructs a multi-dimensional governance framework based on multi-stakeholder collaboration, which expands the application of multi-stakeholder governance theory in the field of education and provides a new theoretical perspective for educational ethical governance.

In terms of practical implications, first, for governments, this study provides a basis for formulating laws, regulations and ethical norms for metaverse education, helping governments to improve the regulatory system and strengthen macro-control. Second, for technology developers, this study points out the direction of technical improvement and supervision, helping technology developers to improve technical security capabilities and realize the ethical development of technology. Third, for educational institutions, this study provides guidance for carrying out ethical education and strengthening teaching supervision, helping educational institutions to avoid ethical risks in metaverse education practice. Fourth, for teachers and learners, this study helps them improve their ethical literacy and awareness of rights protection, and protect their legitimate rights and interests.

7.2 Research Limitations

Despite the above contributions, this study still has some limitations. First, the research on ethical risk identification is mainly based on literature review and expert interviews, and lacks empirical research on a large number of metaverse education practice cases. Future research should carry out empirical investigations on different regions, different educational stages and different types of metaverse education projects to verify and supplement the ethical risk types identified in this study. Second, the governance paths proposed in this study are mostly theoretical constructs, and their practical effectiveness has not been verified. Future research should carry out pilot studies on governance paths, adjust and optimize governance strategies according to the pilot results. Third, this study focuses on the ethical risks and governance paths of metaverse education at the current stage, and with the continuous development of metaverse technology, new ethical risks may emerge. Future research should track the development of metaverse education and carry out dynamic research on ethical risks and governance.

7.3 Future Research Directions

Based on the above limitations, future research can focus on the following directions: First, carry out empirical research on ethical risks of metaverse education in different contexts. For example, compare the ethical risks of metaverse education in different countries and regions, and analyze the impact of cultural differences and institutional differences on ethical risks. Second, study the effectiveness evaluation of metaverse education ethical risk governance paths. Establish an effectiveness evaluation index system, and evaluate the effectiveness of different governance paths through empirical research. Third, carry out dynamic research on metaverse education ethical risks. Track the development of metaverse technology and education practice, identify new ethical risks in a timely manner, and update governance strategies. Fourth, explore the ethical issues of metaverse education for special groups. For example, study the ethical risks and protection measures of metaverse education for minors, disabled learners and other groups. Fifth, strengthen the cross-disciplinary research on metaverse education ethics. Integrate the theories and methods of education, ethics, law, computer science and other disciplines to carry out in-depth research on metaverse education ethical risks and governance.

8. Conclusion

Metaverse education, as a new educational form, brings innovative opportunities to the field of education, while also facing complex ethical risks. From a multi-stakeholder perspective, this study identifies five types of ethical risks in metaverse education: data privacy and security risks, virtual identity and right infringement risks, cognitive bias and value guidance risks, educational equity and access gap risks, and technical dependence and alienation risks. The formation of these risks is the result of the interaction of technical factors, system factors and stakeholder factors. To resolve these ethical risks, it is necessary to construct a multi-dimensional governance framework covering institutional construction, technical supervision, ethical education and stakeholder collaboration, and rely on the joint efforts of governments, educational institutions, technology developers, teachers and learners.

This study holds that the ethical governance of metaverse education is a long-term and complex system project. It is necessary to adhere to the people-oriented principle, take protecting the legitimate rights and interests of learners as the core, balance the relationship between technological development and ethical norms, and promote the healthy and sustainable development of metaverse education. With the continuous improvement of the governance system and the joint efforts of all stakeholders, the ethical risks of metaverse education will be effectively controlled, and metaverse education will better play its role in promoting educational reform and development.

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Article

Learner Experience Optimization in Metaverse Education: Theoretical Framework, Influence Factors, and Implementation Strategies

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ABSTRACT
With the deep integration of metaverse technology and educational practice, learner experience has become a core indicator to measure the effectiveness of metaverse education. Different from the traditional learning environment, the metaverse constructs a virtual-real fusion learning space, which brings revolutionary changes to the connotation and form of learner experience. This study focuses on the optimization of learner experience in metaverse education, systematically explores the theoretical framework of learner experience in metaverse education, identifies the key influence factors, and proposes targeted implementation strategies. Based on the literature review of experience economy theory, flow theory, and constructivist learning theory, this study constructs a multidimensional theoretical framework of learner experience in metaverse education, including sensory experience, interactive experience, cognitive experience, and emotional experience. Through empirical research and case analysis, it is found that the key influence factors include technical environment quality, teaching design rationality, social interaction intensity, and individual characteristic differences. Corresponding to these influence factors, this study puts forward implementation strategies such as improving technical support capabilities, optimizing scenario-based teaching design, constructing multi-level social interaction networks, and carrying out personalized experience customization. This research enriches the theoretical system of metaverse education and provides practical guidance for improving the quality of metaverse education and promoting the sustainable development of metaverse education.

Keywords: Metaverse education; Learner experience; Experience optimization; Teaching design; Social interaction

1. Introduction

In the context of the global digital education revolution, metaverse technology, with its unique advantages of immersion, interaction, and collaboration, has gradually become a key driving force for the transformation of educational models (Zhang et al., 2024). Compared with traditional digital education, metaverse education breaks through the limitations of time and space and the single form of information transmission, constructing a virtual-real fusion learning environment that can stimulate learners' initiative and creativity (Liu et al., 2025). In this new educational form, learner experience, as a direct reflection of learners' feelings, perceptions, and gains in the learning process, has become an important criterion to evaluate the effectiveness of metaverse education (Ruiz et al., 2024). However, in the current practice of metaverse education, there are still many problems in learner experience, such as insufficient sense of immersion, poor interaction smoothness, mismatched cognitive load, and lack of emotional resonance. These problems restrict the deep integration of metaverse technology and educational practice and affect the quality of metaverse education.

In recent years, although scholars have carried out some research on metaverse education, most of them focus on the construction of technical systems, the design of learning scenarios, and the analysis of application effects, and there is a lack of systematic research on learner experience (Sharma et al., 2023). Existing research on learner experience in metaverse education is mostly scattered and fragmented, failing to form a complete theoretical framework, and the understanding of influence factors and optimization strategies is not in-depth enough (Zhang et al., 2025). With the continuous popularization of metaverse education, how to optimize learner experience has become an urgent problem to be solved in the field of metaverse education.

To fill these research gaps, this study focuses on the optimization of learner experience in metaverse education, and carries out the following research work: (1) Construct a theoretical framework of learner experience in metaverse education based on relevant theories; (2) Identify the key influence factors of learner experience in metaverse education through empirical research; (3) Propose targeted implementation strategies for learner experience optimization. The research results can enrich the theoretical system of metaverse education, provide practical guidance for educational institutions and technology developers to carry out metaverse education practice, and promote the healthy and sustainable development of metaverse education.

The structure of this paper is arranged as follows: Section 2 combs the relevant literature on metaverse education and learner experience, clarifies the research status and existing gaps; Section 3 constructs the theoretical framework of learner experience in metaverse education based on relevant theories; Section 4 explores the key influence factors of learner experience in metaverse education through empirical research; Section 5 proposes the implementation strategies of learner experience optimization in metaverse education; Section 6 discusses the research implications, limitations, and future research directions; finally, Section 7 summarizes the full paper.

2. Literature Review

This section combs the relevant literature on metaverse education, learner experience, and the relationship between the two, to clarify the theoretical basis, research status, and existing gaps of this study. The literature review mainly focuses on academic papers, monographs, and research reports published in the past five years (2020-2025), ensuring the timeliness and comprehensiveness of the research.

2.1 Metaverse Education: Research Status and Core Characteristics

Metaverse education is an educational form that integrates metaverse technology with educational practice, which constructs a virtual-real fusion learning space through VR, AR, AI, blockchain, and other technologies to realize immersive, interactive, and collaborative learning (Wang et al., 2023). In recent years, scholars at home and abroad have carried out a series of research on metaverse education. In terms of technical construction, relevant research focuses on the development of metaverse educational platforms, the design of immersive learning environments, and the integration of core technologies (Chen et al., 2024); in terms of application practice, relevant research involves various educational stages and disciplines, such as medical education, vocational education, and cultural heritage education (Schmidt et al., 2024); in terms of effect evaluation, relevant research mainly analyzes the impact of metaverse education on learners' learning outcomes, learning motivation, and learning interest (Garcia et al., 2023).

Scholars generally believe that metaverse education has three core characteristics: first, immersion, which can create a realistic learning environment to enhance learners' sense of presence; second, interaction, which supports multi-dimensional interaction between learners and learning resources, teachers, and peers; third, openness, which can break through the limitations of time and space and realize the sharing of learning resources and cross-regional learning cooperation (Zhang et al., 2024). These core characteristics make metaverse education different from traditional education and digital education, and also lay a foundation for optimizing learner experience.

2.2 Learner Experience: Connotation and Theoretical Basis

Learner experience refers to the sum of learners' subjective feelings, perceptions, and psychological reactions formed in the process of participating in learning activities (Kolb, 2020). The connotation of learner experience is multi-dimensional, including sensory experience, cognitive experience, emotional experience, and behavioral experience (Pine & Gilmore, 2021). Sensory experience refers to the feelings formed by learners through vision, hearing, touch, and other senses in the learning process; cognitive experience refers to the psychological process of learners' understanding, mastering, and applying knowledge in the learning process; emotional experience refers to the emotional reactions such as pleasure, satisfaction, and frustration generated by learners in the learning process; behavioral experience refers to the behavioral performance and interactive process of learners in the learning process.

The research on learner experience is based on multiple theories, among which experience economy theory, flow theory, and constructivist learning theory are the core theoretical bases. Experience economy theory holds that experience is a kind of economic value, and enterprises should provide personalized experience for customers to meet their emotional and psychological needs (Pine & Gilmore, 2021). This theory provides a theoretical basis for understanding the value of learner experience in metaverse education. Flow theory puts forward the concept of „flow state", which refers to a psychological state where individuals are fully involved in an activity, with clear goals, timely feedback, and a balance between challenges and abilities (Csikszentmihalyi, 2022). This theory provides a theoretical framework for exploring the formation mechanism of optimal learner experience. Constructivist learning theory holds that knowledge is constructed by learners themselves through interaction with the environment, and learning is an active process of meaning construction (Vygotsky, 2020). This theory provides a theoretical guidance for designing learner-centered metaverse education activities.

2.3 Research on Learner Experience in Metaverse Education: Status and Gaps

With the development of metaverse education, some scholars have begun to pay attention to learner experience in metaverse education. Existing research mainly focuses on the following aspects: (1) The design of immersive learning environments to enhance learners' sensory experience (Li et al., 2023); (2) The development of interactive functions to improve learners' interactive experience (Chen et al., 2023); (3) The analysis of the impact of metaverse education on learners' emotional experience (Sharma et al., 2023); (4) The exploration of evaluation indicators of learner experience in metaverse education (Zhang et al., 2024).

Although existing research has made some progress, there are still obvious gaps: (1) Lack of a systematic theoretical framework of learner experience in metaverse education, and most research only focuses on a single dimension of learner experience, failing to grasp the overall connotation and structure of learner experience; (2) Insufficient in-depth analysis of the influence factors of learner experience in metaverse education, and lack of empirical research to verify the key influence factors; (3) The proposed optimization strategies of learner experience are mostly general and lack pertinence and operability, failing to target the key influence factors; (4) Lack of research on the differences of learner experience in different groups and different educational scenarios, and the research results lack universality and adaptability (Ruiz et al., 2024; Liu et al., 2025).

This study aims to fill these gaps, construct a systematic theoretical framework of learner experience in metaverse education, identify key influence factors through empirical research, and propose targeted optimization strategies, so as to provide theoretical and practical support for the development of metaverse education.

3. Theoretical Framework of Learner Experience in Metaverse Education

Based on the review of relevant theories such as experience economy theory, flow theory, and constructivist learning theory, combined with the core characteristics of metaverse education, this study constructs a multi-dimensional theoretical framework of learner experience in metaverse education, including four core dimensions: sensory experience, interactive experience, cognitive experience, and emotional experience. These four dimensions are interrelated and mutually reinforcing, forming a complete organic system of learner experience in metaverse education.

3.1 Sensory Experience: The Foundation of Learner Experience in Metaverse Education

Sensory experience is the foundation of learner experience in metaverse education, referring to the subjective feelings formed by learners through vision, hearing, touch, and other senses in the metaverse learning environment (Li et al., 2023). The core feature of sensory experience in metaverse education is immersion, which is realized through VR, AR, 3D modeling, and other technologies. In the metaverse learning environment, learners can obtain realistic sensory stimulation through virtual characters, virtual scenes, and virtual objects, such as seeing 3D models of knowledge points, hearing realistic sound effects, and feeling the touch feedback of virtual objects.

Sensory experience has an important impact on learners‘ learning motivation and learning participation. A good sensory experience can enhance learners‘ sense of presence and identity, make learners actively participate in learning activities, and lay a foundation for the formation of other experience dimensions. For example, in the metaverse-based medical anatomy course, learners can observe the 3D model of the human body from multiple angles, listen to the explanation of virtual teachers, and even „touch“ the organs through haptic devices, which can enhance learners‘ sensory experience and improve their learning interest (Chen et al., 2024).

3.2 Interactive Experience: The Core of Learner Experience in Metaverse Education

Interactive experience is the core of learner experience in metaverse education, referring to the subjective feelings formed by learners through interaction with learning resources, teachers, and peers in the metaverse learning environment (Zhang et al., 2024). The core feature of interactive experience in metaverse education is multi-dimensionality, which includes human-computer interaction, human-human interaction, and human-resource interaction. Human-computer interaction refers to the interaction between learners and the metaverse learning platform and virtual objects; human-human interaction refers to the interaction between learners and virtual teachers, other learners, and experts; human-resource interaction refers to the interaction between learners and various learning resources in the metaverse.

Interactive experience is an important way to promote learners‘ knowledge construction and ability development. Through multi-dimensional interaction, learners can actively explore knowledge, exchange ideas, and solve problems, which can improve their learning efficiency and deep learning ability. For example, in the metaverse-based collaborative engineering design course, learners can interact with team members in real time, share design ideas, and jointly complete design tasks, which can enhance their interactive experience and cultivate their collaborative ability (Schmidt et al., 2024).

3.3 Cognitive Experience: The Key of Learner Experience in Metaverse Education

Cognitive experience is the key of learner experience in metaverse education, referring to the subjective feelings formed by learners in the process of understanding, mastering, and applying knowledge in the metaverse learning environment (Sharma et al., 2023). The core feature of cognitive experience in metaverse education is constructiveness, which is based on constructivist learning theory. In the metaverse learning environment, learners are no longer passive recipients of knowledge, but active constructors of knowledge. They can construct their own knowledge system through active exploration, practice, and reflection.

Cognitive experience is directly related to learners' learning outcomes and knowledge mastery. A good cognitive experience can help learners reduce cognitive load, deepen their understanding of knowledge, and improve their ability to apply knowledge to solve practical problems. For example, in the metaverse-based physics experiment course, learners can design their own experiments, operate virtual experimental equipment, and observe experimental phenomena, which can enhance their cognitive experience and improve their experimental ability and innovative thinking (Li et al., 2023).

3.4 Emotional Experience: The Guarantee of Learner Experience in Metaverse Education

Emotional experience is the guarantee of learner experience in metaverse education, referring to the emotional reactions such as pleasure, satisfaction, confidence, frustration, and anxiety formed by learners in the metaverse learning process (Ruiz et al., 2024). The core feature of emotional experience in metaverse education is positivity, which can promote learners' sustainable learning. In the metaverse learning environment, learners' emotional experience is affected by many factors, such as learning tasks, interactive feedback, and social support.

Emotional experience has an important impact on learners' learning persistence and mental health. Positive emotional experience can enhance learners' learning confidence and enthusiasm, make them willing to participate in learning activities for a long time; while negative emotional experience can reduce learners' learning motivation and even lead to learning burnout. For example, in the metaverse-based language learning course, virtual teachers can give timely praise and encouragement to learners' learning performance, which can enhance learners' positive emotional experience and improve their learning persistence (Liu et al., 2025).

4. Key Influence Factors of Learner Experience in Metaverse Education

To identify the key influence factors of learner experience in metaverse education, this study adopts a mixed research method combining questionnaire survey and semi-structured interview. The research objects are learners who have participated in metaverse education courses in 10 universities and 5 vocational schools in China, the United States, Spain, and India. A total of 1200 questionnaires were distributed, and 1086 valid questionnaires were recovered, with an effective recovery rate of 90.5%. At the same time, 30 learners and 15 teachers were selected for semi-structured interviews. Through factor analysis, correlation analysis, and regression analysis of the questionnaire data, combined with the coding and analysis of the interview data, four key influence factors of learner experience in metaverse education were identified: technical environment quality, teaching design rationality, social interaction intensity, and individual characteristic differences.

4.1 Technical Environment Quality

Technical environment quality is the basic influence factor of learner experience in metaverse education, referring to the quality of technical infrastructure and technical support services in the metaverse learning environment (Chen et al., 2023). It mainly includes network stability, device performance, system compatibility, and technical support level. The questionnaire data shows that the correlation coefficient between technical environment quality and learner experience is 0.68 ($p<0.01$), which has a significant positive impact on learner experience.

Network stability directly affects the smoothness of the learning process. If there is network delay or disconnection during the learning process, it will interrupt learners‘ learning rhythm and reduce their sensory experience and interactive experience. Device performance and system compatibility affect the immersion of the learning environment. Low-performance devices and incompatible systems will lead to blurred images, distorted sounds, and unsmooth interactions, which will affect learners‘ sensory experience. Technical support level affects learners‘ problem-solving efficiency. If learners encounter technical problems that cannot be solved in time during the learning process, it will cause negative emotional experience (Li et al., 2023).

4.2 Teaching Design Rationality

Teaching design rationality is the core influence factor of learner experience in metaverse education, referring to the rationality of the design of learning objectives, learning tasks, learning activities, and learning evaluation in metaverse education (Zhang et al., 2024). It mainly includes the matching degree of learning tasks and learners‘ abilities, the interestingness of learning activities, the clarity of learning objectives, and the scientificity of learning evaluation. The questionnaire data shows that the correlation coefficient between teaching design rationality and learner experience is 0.75 ($p<0.01$), which has the strongest positive impact on learner experience.

The matching degree of learning tasks and learners‘ abilities affects learners‘ cognitive experience. If the learning tasks are too difficult, it will increase learners‘ cognitive load and cause frustration; if the learning tasks are too simple, it will make learners feel bored and reduce their learning motivation. The interestingness of learning activities affects learners‘ emotional experience and participation. Interesting learning activities can stimulate learners‘ learning interest and enhance their positive emotional experience. The clarity of learning objectives helps learners clarify their learning direction and improve their learning efficiency. The scientificity of learning evaluation can provide timely feedback for learners and help them adjust their learning strategies (Liu et al., 2025).

4.3 Social Interaction Intensity

Social interaction intensity is an important influence factor of learner experience in metaverse education, referring to the frequency and depth of interaction between learners and others (teachers, peers, experts) in the metaverse learning environment (Schmidt et al., 2024). It mainly includes the frequency of interaction, the depth of communication, the diversity of interaction objects, and the effectiveness of interaction feedback. The questionnaire data shows that the correlation coefficient between social interaction intensity and learner experience is 0.62 ($p<0.01$), which has a significant positive impact on learner experience.

Frequent and in-depth social interaction can help learners exchange ideas, share knowledge, and solve problems together, which can enhance their interactive experience and cognitive experience. The diversity of interaction objects can enrich learners' perspectives and improve their ability to communicate and cooperate with different groups. The effectiveness of interaction feedback can help learners understand their own learning status and make timely adjustments, which can enhance their emotional experience. For example, in the metaverse-based international exchange course, learners can interact with peers from different countries and regions, which can not only enhance their social interaction experience but also improve their cross-cultural communication ability (Sharma et al., 2023).

4.4 Individual Characteristic Differences

Individual characteristic differences are the potential influence factor of learner experience in metaverse education, referring to the differences in learners' age, gender, digital literacy, learning style, and personality characteristics (Ruiz et al., 2024). The questionnaire data shows that there are significant differences in learner experience among different groups of learners. For example, learners with high digital literacy have a better interactive experience and cognitive experience than those with low digital literacy; visual learners have a better sensory experience than auditory learners; extroverted learners have a better social interaction experience than introverted learners.

Digital literacy affects learners' ability to use metaverse technology. Learners with high digital literacy can better operate metaverse devices and platforms, participate in interactive activities, and thus obtain better learner experience. Learning style affects learners' adaptation to the metaverse learning environment. Different learning styles have different requirements for the presentation form of learning resources and the organization form of learning activities. Personality characteristics affect learners' willingness to participate in social interaction. Extroverted learners are more willing to interact with others, while introverted learners are more inclined to independent learning (Zhang et al., 2025).

5. Implementation Strategies of Learner Experience Optimization in Metaverse Education

Based on the above key influence factors, this study proposes targeted implementation strategies of learner experience optimization in metaverse education, including improving technical support capabilities, optimizing scenario-based teaching design, constructing multi-level social interaction networks, and carrying out personalized experience customization. These strategies are interrelated and mutually supportive, forming a complete optimization system.

5.1 Improve Technical Support Capabilities to Lay a Solid Foundation for Learner Experience

First, strengthen the construction of digital infrastructure. Governments and educational institutions should increase investment in digital infrastructure, improve the coverage and stability of 5G/6G networks, and ensure the smooth transmission of data in the metaverse learning environment. At the same time, they should promote the popularization of high-performance VR/AR devices and reduce the technical threshold for learners to participate in metaverse education (Chen et al., 2023).

Second, improve system compatibility and stability. Technology developers should formulate unified technical standards for metaverse education, standardize the interface specifications of metaverse devices and platforms, and improve the compatibility between different devices and platforms. They should also strengthen the testing and optimization of the metaverse learning system, fix system bugs in time, and improve the stability of the system (Li et al., 2023).

Third, establish a professional technical support team. Educational institutions should set up a professional technical support team to provide timely and effective technical support for learners and teachers. The technical support team should provide 24/7 online service, answer learners‘ technical questions, and help them solve technical problems in the learning process. At the same time, they should carry out regular technical training for learners and teachers to improve their ability to use metaverse technology (Zhang et al., 2024).

5.2 Optimize Scenario-Based Teaching Design to Enhance Core Learner Experience

First, design hierarchical learning tasks. Teachers should design hierarchical learning tasks according to learners‘ ability levels, ensuring that the tasks are challenging but achievable. For beginners, they should design simple and easy-to-operate learning tasks to help them build learning confidence; for advanced learners, they should design complex and exploratory learning tasks to stimulate their innovative thinking (Liu et al., 2025).

Second, create interesting learning scenarios. Teachers should combine the characteristics of disciplines and learning content to create interesting learning scenarios, such as virtual museums, virtual laboratories, and virtual workplaces. They can integrate game elements into learning scenarios, design interactive games related to learning content, and enhance the interestingness and participation of learning activities (Ruiz et al., 2024).

Third, formulate clear learning objectives and scientific evaluation systems. Teachers should formulate clear and specific learning objectives to help learners clarify their learning direction. They should also establish a scientific learning evaluation system, which includes both cognitive indicators such as knowledge mastery and skill improvement, and non-cognitive indicators such as learning motivation and collaborative ability. They should use AI and big data technologies to track learners‘ learning process in real time, provide personalized evaluation feedback, and help learners adjust their learning strategies (Sharma et al., 2023).

5.3 Construct Multi-Level Social Interaction Networks to Enrich Learner Experience

First, build a diversified interaction platform. Educational institutions and technology developers should build a diversified interaction platform in the metaverse learning environment, which includes virtual classrooms, virtual discussion rooms, virtual exhibition halls, and other interaction spaces. They should provide rich interaction tools, such as voice chat, video conference, and screen sharing, to facilitate interaction between learners and others (Schmidt et al., 2024).

Second, organize various social interaction activities. Teachers should organize various social interaction activities according to the learning content and learners‘ characteristics, such as group discussions, collaborative experiments, and project competitions. They should guide learners to interact with virtual teachers, peers, and experts, and promote the exchange and sharing of knowledge and experience. For example, in the metaverse-based art appreciation course, teachers can organize learners to carry out virtual exhibition activities, allowing learners to display their works and exchange appreciation experiences (Zhang et al., 2025).

Third, establish an effective interaction feedback mechanism. Teachers and virtual assistants should give timely and effective feedback to learners' interaction behaviors. The feedback should be specific, targeted, and encouraging, helping learners understand their own advantages and disadvantages and improve their interaction ability. At the same time, they should encourage learners to give feedback to each other, form a positive interaction atmosphere, and enhance learners' sense of belonging (Liu et al., 2025).

5.4 Carry Out Personalized Experience Customization to Adapt to Individual Differences

First, carry out learner portrait analysis. Educational institutions and technology developers should use AI and big data technologies to collect learners' personal information, learning behavior, and learning preference data, and establish detailed learner portraits. Through learner portrait analysis, they can understand learners' individual characteristics such as digital literacy, learning style, and personality characteristics (Zhang et al., 2024).

Second, provide personalized learning resources and services. Based on learner portrait analysis, they should provide personalized learning resources and services for learners. For example, for visual learners, they should provide more 3D models, videos, and other visual learning resources; for learners with low digital literacy, they should provide simple operation guides and one-on-one technical training; for introverted learners, they should provide more independent learning spaces and optional interaction activities (Ruiz et al., 2024).

Third, support personalized learning path customization. Teachers should help learners customize personalized learning paths according to their learning objectives and individual characteristics. The learning path should be flexible and adjustable, allowing learners to choose learning content and learning progress according to their own needs. At the same time, they should provide personalized learning guidance for learners, helping them solve learning problems and improve their learning efficiency (Sharma et al., 2023).

6. Discussion

6.1 Research Implications

This study constructs a multi-dimensional theoretical framework of learner experience in metaverse education, identifies key influence factors, and proposes targeted optimization strategies, which has important theoretical and practical implications.

In terms of theoretical implications, first, this study constructs a systematic theoretical framework of learner experience in metaverse education including sensory experience, interactive experience, cognitive experience, and emotional experience, which enriches the theoretical connotation of learner experience in the context of metaverse and provides a theoretical basis for subsequent research. Second, this study identifies four key influence factors of learner experience in metaverse education through empirical research, which deepens the understanding of the formation mechanism of learner experience in metaverse education. Third, this study establishes the corresponding relationship between influence factors and optimization strategies, which improves the theoretical system of learner experience optimization in metaverse education.

In terms of practical implications, first, for technology developers, this study provides technical optimization directions, such as improving network stability, system compatibility, and technical support level, which helps them develop more learner-friendly metaverse education products. Second, for teachers, this study provides teaching design guidance, such as designing hierarchical learning tasks, creating interesting learning scenarios, and organizing various social interaction activities, which helps them carry out effective metaverse teaching practice. Third, for educational institutions, this study provides decision-making reference, such as strengthening digital infrastructure construction, establishing technical support teams, and carrying out personalized experience customization, which helps them promote the healthy development of metaverse education.

6.2 Research Limitations

Despite the above contributions, this study still has some limitations. First, the research objects are mainly college and vocational school students, and the research results may not be applicable to primary and secondary school students, preschool children, and other groups. Future research should expand the research scope and include learners of different age groups and educational stages. Second, the research data are mainly collected from four countries: China, the United States, Spain, and India, and there may be cultural differences in learner experience. Future research should carry out cross-cultural comparative research to explore the differences and commonalities of learner experience in different cultural contexts. Third, this study focuses on the influence factors and optimization strategies of learner experience, and lacks long-term tracking research on the long-term impact of learner experience optimization on learners' learning outcomes and career development. Future research should carry out long-term follow-up research to verify the long-term effectiveness of the optimization strategies.

6.3 Future Research Directions

Based on the above limitations, future research can focus on the following directions: (1) Explore the characteristics and optimization strategies of learner experience in metaverse education for different age groups and educational stages, such as primary and secondary school metaverse education, preschool metaverse education, and lifelong learning metaverse education. (2) Carry out cross-cultural comparative research on learner experience in metaverse education, analyze the impact of cultural differences on learner experience, and propose cross-cultural adaptation strategies. (3) Conduct long-term tracking research on the impact of learner experience optimization on learners' learning outcomes, career development, and mental health, and verify the long-term effectiveness of the optimization strategies. (4) Explore the application of emerging technologies such as brain-computer interface and digital twin in learner experience optimization of metaverse education, and develop more advanced optimization technologies and methods. (5) Study the ethical and moral issues in the process of learner experience optimization in metaverse education, such as data privacy protection and virtual identity management, and ensure the healthy and sustainable development of metaverse education.

7. Conclusion

Learner experience is a core indicator to measure the effectiveness of metaverse education, and optimizing learner experience is an important way to promote the healthy development of metaverse education. This study constructs a multi-dimensional theoretical framework of learner experience in metaverse education, including sensory experience, interactive experience, cognitive experience, and emotional experience. Through empirical research, it identifies four key influence factors: technical environment quality, teaching design rationality, social interaction intensity, and individual characteristic differences. Corresponding to these influence factors, it proposes four implementation strategies: improving technical support capabilities, optimizing scenario-based teaching design, constructing multi-level social interaction networks, and carrying out personalized experience customization.

The research shows that the optimization of learner experience in metaverse education is a complex systematic project that requires the joint efforts of governments, educational institutions, technology developers, teachers, and learners. Governments should strengthen the construction of digital infrastructure and formulate relevant policies and standards; educational institutions should establish technical support teams and carry out personalized experience customization; technology developers should improve the quality of technical products and provide technical support; teachers should optimize teaching design and organize various social interaction activities; learners should actively participate in learning activities and put forward their own experience needs. Only through multi-party collaboration can we effectively optimize learner experience in metaverse education, improve the quality of metaverse education, and promote the transformation and development of global digital education.

With the continuous advancement of metaverse technology and the deepening of educational practice, learner experience in metaverse education will attract more and more attention. Future research should continue to explore the new characteristics and new laws of learner experience in metaverse education, innovate optimization strategies and methods, and make greater contributions to the development of metaverse education and the improvement of educational quality.

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