Research on the Reform of Open Education Teaching Based on Adaptive Learning in the Era of Artificial Intelligence

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Abstract. The rapid development of artificial intelligence technology has provided an opportunity to reshape the teaching ecosystem in open education. This article focuses on the concept of "adaptive learning", in the context of the artificial intelligence era, and explores the systematic reform of open education teaching models. The research first constructed an integrated learning framework that combines cognitive diagnosis, dynamic paths, resource push, immediate feedback, and emotional support. Through data-driven and teacher experience collaboration, it realizes large-scale personalized teaching. Secondly, based on the teaching practice of public courses in multiple universities, the article collected and analyzed the entire process behavior data of learners, used deep models to dynamically optimize teaching strategies, and established an interpretable and iterative teaching loop. On this basis, the research focuses on educational equity and the mechanism of human-computer collaboration, ensuring that while technology is empowered, the dominant position of teachers and the warmth of the learning community are maintained. Through qualitative interviews and teaching observations, the article found that adaptive learning significantly enhanced the initiative, satisfaction, and knowledge transfer ability of learners, forming a new classroom culture that integrates online and offline elements and reshapes the roles of teachers and students. The research conclusion states that in the open education teaching reform of the artificial intelligence era, it should be driven by data intelligence, centered on learners, and based on educational equity, promoting the transformation from "standardized supply" to "precise services", providing replicable models and sustainable paths for building a lifelong learning society.

Keywords: Artificial intelligence technology, Open education, Data-driven, Large-scale personalized teaching.

1. Introduction

Since the 21st century, open education represented by MOOCs, micro-specializations, and credit banks has expanded rapidly, breaking through the campus boundaries and making "everyone learning, everywhere learning, and anytime learning" a reality. However, the expansion in scale has simultaneously brought about quality concerns: significant differences in learners' backgrounds, diverse learning goals, and fragmented learning paths make it difficult for traditional "broadcast-style" teaching to meet individualized needs; teachers are trapped in the dilemma of "high investment, low return" in the face of massive data and diverse demands; although the platform can gather millions of users, it is difficult to precisely identify learning blind spots, resulting in a persistently high dropout rate. The rise of artificial intelligence technology offers new possibilities for solving these problems, but how to reshape teaching processes, reconfigure teacher-student relationships, and rebuild the quality assurance system through AI still lacks a systematic framework and feasible models [1-3].

The concept of "tailoring teaching to individual needs" has emerged since the time of Confucius, but it has been difficult to implement in the context of open education due to the imbalance in the ratio of teachers to students. At the end of the 20th century, Bloom's learning theory and Gardner's theory of multiple intelligences provided a psychological foundation for personalized teaching. In the era of big data, learning analysis and educational data mining technologies have made "teaching based on evidence" possible [4]. In recent years, breakthroughs in AI technologies such as deep neural networks, reinforcement learning, and knowledge graphs have pushed personalized education to a new stage of "tailoring teaching to the brain": The system can diagnose cognitive states in real time, predict learning risks, dynamically plan the optimal path, and provide emotional computing and metacognitive prompts to achieve "learning-centered" deep adaptation. However, there is still a huge gap between the potential of technology and teaching practice - the contradictions between algorithm black boxes and teaching transparency, data scale and educational equity, and automated decision-making and teacher dominance urgently need to be addressed at the institutional and ethical levels [5,6].

The threefold transformation enabled by AI in education. First, from "content-driven" to "data-driven". Traditional curriculum design emphasizes the complete presentation of the knowledge system, while courses in the AI era are more like "living organisms", continuously iterating based on real-time feedback from learners. Second, from "result evaluation" to "process monitoring". Multimodal data such as eye movements, click streams, discussion texts, and emotional expressions enable the granularity of learning diagnosis to descend from the chapter level to the second-second level, allowing teachers to intervene immediately. Third, from "standardized supply" to "precision service". The collaboration of recommendation systems, chatbots, and intelligent mentors has made "massive personalized learning tailored to each individual" a reality. However, the technological dividends do not spread automatically: algorithmic biases may exacerbate educational inequality; computing power thresholds may intensify regional disparities; excessive automation may weaken the educational function of teachers. Therefore, how to adhere to the essence of education while embedding technology is a value proposition that open education in the AI era must answer [7-9].

The policies such as "The New Generation Artificial Intelligence Development Plan", "Action Plan for Education Informatization 2.0", and "Action Plan for Quality Improvement and Optimization of Vocational Education" have been successively introduced in our country, clearly stating that "we should promote the deep integration of artificial intelligence and education" and build a learning society where everyone can learn, everywhere can be a place for learning, and at all times learning is possible. At the industrial level, leading enterprises such as Tencent Education, iFLYTEK, and Alibaba Cloud Education have all been actively exploring the AI adaptive learning path. However, the data silos and algorithm barriers that each enterprise has independently established have led to fragmented learning profiles, making it difficult to support the vertical integration of lifelong learning accounts. At the international level, the EU's "Digital Education Action Plan 2021-2027" and the US' "Strategic Plan for Artificial Intelligence and Education" both list adaptive learning as a priority. The competition over global standards and ethical frameworks is brewing. Under this background, building an AI adaptive education ecosystem with Chinese characteristics, openness, sharing, and sustainability is not only responding to the practical needs of the country's educational digitalization strategy, but also an important opportunity to participate in the transformation of the global education governance system [10].

The current research mainly focuses on three paths: Firstly, "descriptive diagnosis" based on learning analysis, which identifies high-risk learners through predictive models, but lacks detailed information on how to intervene; Secondly, "resource push" based on recommendation algorithms, which has improved click-through rates and completion rates, but neglects learning depth and transfer ability; Thirdly, "human-machine dialogue" based on intelligent mentor systems [11,12], which has achieved results in small sample experiments, but the high development costs and closed technical architecture make it difficult to be replicated on a large scale in open education. Overall, the existing achievements have three major gaps: Firstly, there is a lack of a system framework covering the entire process of "diagnosis-decision-making-intervention-evaluation"; Secondly, there is a lack of mechanism design for the collaboration between teachers and algorithms; Thirdly, there is a lack of institutional responses oriented towards educational equity and ethical risks. This research attempts to explore in these gaps.

This paper adopts complexity science as its methodology, treating the open education system as a dynamic complex network composed of multiple entities such as learners, teachers, content, platforms, and environments, emphasizing that AI is not a substitute for teachers but rather generates an "enhanced intelligence" educational ecosystem. The research follows the action research paradigm of "problem - design - implementation - reflection", and through multiple iterations, gradually builds a "data - model - intervention - effectiveness" closed loop. Technically, relying on the latest advancements in deep learning, reinforcement learning, knowledge graphs, and affective computing, an interpretable, transferable, and scalable adaptive engine is created; educationally, returning to the value origin of "promoting the all-round development of individuals", guided by learning science, adult education, and distance education theories, teaching goals, content, activities, evaluations, and support services are redefined. The entire reform process emphasizes "human-machine collaboration": teachers transform from knowledge teachers to learning designers, data interpreters and emotional supporters. algorithms, under the guidance of teachers' values, complete high-load, high-concurrency, and high-precision decision-making assistance [13].

At the theoretical level, by integrating artificial intelligence, learning science and open education theory, a new adaptive teaching paradigm of "data - cognition - context" three-dimensional collaboration was proposed, which expanded the theoretical boundaries of personalized learning. At the methodological level, a technical framework covering the entire process, interpretable and transferable was constructed, providing a systematic solution for precise services in large-scale online education. At the practical level, a series of replicable and scalable teaching reform plans, platform tools and teacher development guidelines were formed, helping open universities, vocational colleges and enterprise universities improve the quality of talent cultivation. At the policy level, it provided decision-making basis for educational administrative departments to formulate AI education ethics norms, data governance standards and quality assurance systems. At the social level, it explored a lifelong learning path that is beneficial to technology, fair and inclusive, and sustainable, responding to the educational vision of "everyone can shine" in the intelligent era [14-18].

2. The Current Situation of Open Education Development

”Open education generally refers to an educational model that is supported by information technology, accessible to everyone, breaks through time and space limitations, and emphasizes resource sharing and self-directed learning. It includes not only the national open university system and local open universities that have transformed from radio and television universities, but also various carriers such as MOOCs (Massive Open Online Courses), private online courses (SPOC), blended learning, lifelong education platforms, community and elderly education. Compared with traditional universities, its significant features lie in the ’five opennesses’: object openness (no restrictions on age, occupation, or region), time openness (flexible academic system, self-enrollment and self-study), space openness (online + offline + community), resource openness (co-construction and sharing), and evaluation openness (accumulation and conversion of credits) [19]. Currently, open education has become an important approach for countries to promote the popularization of higher education and build a lifelong learning society.”

The 2023 report by UNESCO shows that the total number of students enrolled in distance education worldwide has exceeded 130 million, accounting for 22% of the total number of students in higher education. Among them, China, India, the United States, Indonesia, and Brazil rank among the top five. The Open University of the United Kingdom has over 200,000 students, and its cumulative graduates account for 9% of the total university graduates in the country; the National Open University of Korea admits over 180,000 students each year; the Indira Gandhi National Open University System of India admits more than 500,000 students annually, making it the largest single-scale distance university in the world [20].

The 2024 annual report of the National Open University shows that there are 4.31 million students enrolled in academic education within the system and 12 million non-academic training participants per year. 39 provincial open universities have fully transformed into local open universities, forming a national-level educational network with ”two-level coordination and four-level operation”. In Anhui, Hebei, and Shandong, open universities have incorporated elderly education and community education into their main business, serving 3-5 million people in the communities each year.

With the advancement of industrialization and the aging of the population, the profile of learners has shifted from ”credential compensation” to ”skill upgrading” and ”interest development”. In the spring semester of 2025, 40% of the new students at the Lushun Branch of Dalian Open University were enrolled for enterprise employee skill enhancement, while 25% were enrolled for digital literacy training for the elderly. In Hengshui City’s distance open education, vocational training was combined with rural revitalization cadre education, and 23,000 grassroots cadres were trained annually.

China has built the world’s largest educational dedicated network (CERNET2). The National Open University will complete the IPv6-wide network transformation by 2024, with a backbone link bandwidth of 400G. Educational cloud nodes at the provincial level have been constructed in places like Anhui and Guangdong, enabling regular 4K/8K live classrooms and VR training. Generative AI, knowledge graphs, learning analytics, digital teachers, and blockchain credit banks have become new standard features. Dalian Open University has piloted ”digital human counselors”, who provide 7x24 learning consultations for 18,000 students through emotional computing and semantic recognition, with a satisfaction rate of 93%. Traditional three-screen courseware has been replaced by a mixed resource of ”micro-lessons + virtual simulation experiments + interactive task books + community discussions”. The National Open University will launch 3,000 ”A1 Companion Learning” courses in 2025, with the system dynamically assembling learning sequences based on real-time portraits of learners. From the PC era to a ”mobile phone + large screen + vehicle + wearable” full-scenario, the National Open University App has a monthly active user base of over 12 million, with 28% of users being the elderly, and voice interaction and accessibility mode have become necessities.

However, the open education industry is facing several challenges. (1) Digital divide: The network infrastructure, terminal devices, and digital literacy in remote areas remain weak. A 2024 survey by the National Open University showed that the average bandwidth of students at county-level learning centers in the west was less than one-third of that in the east. (2) Teacher structure: The proportion of part-time teachers is as high as 72%, with high mobility and insufficient teaching and research capabilities, which affects the continuous update of courses and the support for deep learning. (3) Credit barriers: Although the policy advocates ”vertical connection and horizontal communication”, the recognition of open education credits by ordinary universities is still low, and the credit bank is ”connected but not smooth”. (4) Ethical risks: Algorithm recommendations may lead to ”information cocoons”, privacy controversies over emotion recognition technology, and academic integrity risks of generative Al, which require collaborative governance through both systems and technologies. (5) Funding model: Tuition fees for academic education are restricted by policies, and the non-academic training market is highly competitive. Some grassroots learning centers are facing survival pressure.

After more than four decades of development, open education has transformed from ”compensatory education” in the era of radio and television to ”mainstream supply” in the era of artificial intelligence, becoming a super interface connecting academic education, vocational education and lifelong learning. On the new path of digitalization, intelligence, internationalization and legalization, Chinese open education is moving towards a future of high quality, sustainability and global sharing with a more open attitude, more intelligent means and more inclusive goals.

3. The Inevitability of Adaptive Learning Reform

In 1996, the world's first adaptive learning system, AEHS (Adaptive Educational Hypermedia System), was officially launched. The learning path shifted from preset to recommendation, marking the beginning of the maturity of adaptive learning systems [21]. With the continuous breakthroughs in artificial intelligence technology, the human-computer interaction mode shifted from low-level cognition to high-level cognition, and the reform of adaptive learning has attracted widespread attention worldwide [22].

1. The essence of adaptive learning.
   To this day, there is no unified definition for adaptive learning. The American Higher Education Information Technology Association (EDUCAUSE) defines adaptive learning technology as "a technology that dynamically adjusts the level or type of course content based on an individual's abilities or skill levels, in order to enhance the active learning of learners and the learning performance under teacher intervention" [23]. Some scholars have proposed that the adaptive learning strategy creates a student experience that is constantly improved based on student performance and interaction with course materials, and its core is a teaching method that relies on data from technology and student performance to adjust and respond to content and methods, thereby developing a path leading to students' mastery of specific learning goals [24]. Other scholars have pointed out that adaptive learning is an emerging learning technology that dynamically adjusts teaching content to provide interactive and personalized learning paths for individuals to promote learning. However, regardless of the interpretation, individual differences, individual performance, and adaptive adjustments are the core essence of adaptive learning. This is not a new concept but an ultimate pursuit of human education - teaching according to individual aptitudes. Therefore, adaptive learning is a new learning technology. Based on a comprehensive analysis of factors such as learners' learning abilities, learning styles, learning motivations, and learning performance, it dynamically adjusts learning content to help teachers implement more precise learning interventions, enhance learners' participation and sense of achievement, and achieve effective improvement in learning performance through personalized learning paths. In the past, due to cost and technical constraints, adaptive learning has been unable to be implemented on a large scale. Currently, with the help of modern information technology and artificial intelligence technology, there is a realistic basis for paying attention to each student's cognitive characteristics (such as learning styles) and integrating intelligence factors and psychological factors in the teaching process. Education has entered the era of large-scale personalized learning [25].
2. The practical situation of adaptive learning.
   Since 2016, research related to adaptive learning has been on the rise, and scholars from various countries have shown great enthusiasm for exploring the field of adaptive learning. Scholars have conducted in-depth research on the "classic triangle" model of knowledge domain models, learner characteristic models, and teaching models, striving to achieve precise construction of knowledge maps, knowledge tracking based on deep learning, and effective personalized learning path recommendations. Currently, there are many adaptive learning platforms operated by commercial companies worldwide, such as Knewton (USA), ALEKS (USA), DreamBox Learning (USA), Realizeit (USA), CogBooks (UK), Smart Sparrow (Australia), SunZi AI (China), ApeTiku (China), ZhiXueWang (China), etc. In the United States, more and more universities are collaborating with adaptive learning platforms to develop adaptive learning systems that meet their own needs. For example, Colorado Technical University integrated the Realizeit adaptive learning platform into its existing learning management system and launched the adaptive learning system IntelliPath. After more than a decade of efforts, about 600 teachers participated in the construction of over 200 adaptive learning courses, benefiting approximately 130,000 students, achieving large-scale application of adaptive learning systems [26]. In China, adaptive learning platforms are mainly for primary and secondary school courses, and there are only sporadic applications in universities. For example, Beijing University of Posts and Telecommunications developed an adaptive learning APP system for adult bachelor's degree English based on the low pass rate of adult bachelor's degree English in China. The practice shows that when the exam difficulty is not high, using this APP system before the exam can significantly improve the pass rate of students [20]. At present, there are no adaptive learning platforms applicable to different higher education courses in China.
3. Adaptive learning reform is an inevitable choice for the continuous development of open education.
   In the era of mass higher education, whether an individual chooses to pursue a university education is essentially a decision about input and output. This phenomenon is particularly evident in the United States, where

high tuition fees and the persistently high dropout rate have led American universities to face an efficiency crisis, prompting them to actively seek change and attempt to improve their educational effectiveness through adaptive learning reforms [27]. Arizona State University collaborated with Knewton to use adaptive learning technology in mathematics courses, quickly identifying students' knowledge gaps and tracking their learning and cognitive dynamics in real time. Through data collection and integration, personalized suggestions and learning paths are provided. This technology increased student pass rates by 18% and reduced dropout rates by 47%. Due to differences in economic and cultural factors, the overall dropout rate in China's higher education is relatively low, but the on-time graduation rate of open education is not high. The professional training plan of open education specifies the shortest semester required for each major to achieve graduation, usually 2.5 years. Graduating within the specified shortest semester is called on-time graduation [28]. Studies have shown that the average on-time graduation rate of open education is only 54.7%. The younger adult students have lower on-time graduation rates. Students who fail to graduate on time gradually lose confidence and enthusiasm in learning over time, eventually experiencing large-scale attrition, stagnation, and dormancy. This is related to the prominent contradiction between work and study for adult students, as well as caring for families. One of the reasons that cannot be ignored is that adult learning has a clear utilitarian nature. Pursuing further education is to prepare for future career advancement and professional qualifications. If the content learned does not meet one's needs, the investment in learning will decrease, although they do not actively drop out, the learning has become "only existing but not functioning". Currently, the open university system has abundant digital teaching resources and experience, but there is still a considerable gap between the quality of education and social expectations. When answering questions such as "why does the government support, why does society recognize, and why do learners choose", the open university system lacks confidence. The open university system needs to truly achieve teaching centered on adult students. How to make teaching content adapt to individual needs becomes the key. Past practice has shown that relying solely on "Internet + education" cannot achieve this goal. The open university system urgently needs to establish a model that can provide customized, high-quality, low-cost, and competitive educational services for learners. Therefore, adaptive learning reforms have a more urgent practical need than ordinary universities. In the digital age, only by seizing the opportunity, using intelligent technology to actively change and reform, using "intelligence + " to improve teaching quality, and winning social recognition, can the open university system truly embark on its own high-quality development path.

4. Adaptive Learning Reform Strategies

1. Carry out adaptive learning reforms based on courses.
   The essence of adaptive learning is that computers provide appropriate learning interventions based on students' learning situations, involving the construction of three major models: domain model, learner model, and teaching model. The domain model is used to conceptualize and present domain knowledge and its structure after clearly identifying the learning content of the learners. Currently, the most common representation of the domain model is structured knowledge points, and there are also representations based on cognitive processes and ontological attributes. If the learning objectives are clear, well-defined, and have clear judgment criteria, such as in mathematics courses, representing the domain model with structured knowledge points is a common practice; if it is procedural knowledge, such as teaching robots how to perform surgeries, it is necessary to represent the domain model with cognitive processes. The choice of which construction method to use depends on the course content and the complexity of the problem. The learner model typically includes domain-related features (knowledge level, skill level, prior knowledge, learning activity records, assessment records, test records, etc.) and domain-independent features (learning style, learning preference, learning mood, cognitive ability, etc.), reflecting the individual differences of learners, and dynamically monitoring and modeling their characteristics can predict their mastery of knowledge and learning trends. The teaching model is to push personalized learning paths and resources based on the logical relationships contained in the knowledge, combined with the current knowledge state, cognitive ability, learning style, and preferences of the learners, and models the selection of appropriate algorithms to improve the recommendation accuracy. Clearly, the adaptive learning reform cannot be achieved simply by relying on the efforts of teachers or by purchasing a certain platform; the difficulty of constructing models varies greatly among different types of courses, and it is difficult to implement a large-scale reform at once. Currently, the relatively mature Knewton platform mainly provides well-structured domain courses such as mathematics, statistics, chemistry, and biology. Open universities can draw on this experience and select well-structured courses as reform pilot projects, form a course reform team consisting of course teachers, artificial intelligence experts, and educational psychology experts, jointly study and construct the domain model, learner model, and teaching model of the courses, and continuously track and evaluate the teaching practice effects after the adaptive courses are put

into use, constantly adjusting and correcting the models to seek the best adaptive learning effect. Thereafter, drawing on the construction experience of well-structured domain course models, gradually expand to other courses on the basis of full argumentation, to steadily promote the adaptive learning reform of each course based on the principle of prioritizing quality.

2. Establish a collaborative teaching team consisting of ”human teachers” and ”machine teachers”.

   ”Adaptive learning + generative artificial intelligence” can ensure that the computer and the learner communicate smoothly with each other in a way that conforms to human habits regarding course learning situations, questions, suggestions, etc. ”Machine as Teacher” (referred to as ”Machine Teacher”) and ”Teacher as Teacher” (referred to as ”Human Teacher”) will produce a human-machine collaborative education effect. The educational model will also shift from the traditional ”teacher-student” binary relationship to a ”teacher-machine-student” tripartite relationship. In the future, the routine knowledge transmission work will be completed by ”Machine Teachers”, but the role of ”Human Teachers” remains irreplaceable. The practical experience of Colorado Technical University shows that the active participation of ”Human Teachers” in the adaptive learning process is the key to students' participation and success. Under adaptive learning, students also need guidance and encouragement, they need to be guided to effectively utilize tools to achieve the best learning experience, and they need supervision of the learning process by ”Human Teachers”. Especially by quickly and effectively identifying ”students with learning difficulties” through the system, they often become the disadvantaged group in adaptive learning due to the lack of metacognitive monitoring ability. ”Human Teachers” adjust the learning pace for students with special needs, correct the learning path, and more targetedly regulate students' learning to prevent students from failing in course learning. Moreover, adaptive learning is not no longer requiring face-to-face teaching, but requires more flexible face-to-face teaching based on student differences, with group face-to-face teaching replacing class face-to-face teaching. The Open University, as a national educational system, operates under the ”two-level coordination, four-level operation” system, and the teachers of the course teaching team are mainly divided into course responsibility teachers and course guidance teachers. The course responsibility teachers are responsible for determining the course teaching content, textbooks, assessment methods, and assessment contents, and are usually appointed by national open universities or provincial open universities; the grassroots open university teachers are course guidance teachers, conducting teaching work under the given teaching content, textbooks, and examination requirements. There is a role division in course teaching between the two, and in daily management, they belong to their respective open universities, and the relationship between the responsibility teachers and the guidance teachers is relatively loose. Therefore, in the era of online learning, it is very difficult for grassroots teachers to transform from the role of knowledge transmitters to other roles. Online learning behaviors have not formed an accurate portrait of students' learning situations, and face-to-face contact opportunities have significantly decreased. And teachers need to become students' learning consultants, guides, and organizers precisely based on the accurate grasp of students' learning status by teachers. The adaptive learning reform has enabled grassroots ”Human Teachers” to have a ”good partner” who can provide students' precise learning status at any time. At the same time, the ”Human Teacher” team should formulate action guidelines for learning intervention and build smooth communication channels between teachers of different levels of open universities to ensure that teaching problems faced by grassroots teachers can be effectively supported, truly forming a ”Human Teacher” + ”Machine Teacher” collaborative teaching team, jointly providing personalized and high-quality teaching services for adult students.

3. Attach importance to the new risks brought about by the application of intelligent technologies.

   The development of artificial intelligence technology has promoted education to shift from focusing on groups to focusing on individuals, allowing each student to have their own personalized learning plan. However, due to the introduction of the ”machine teacher” role, the adaptive learning reform will face many new risks. Firstly, there is a risk of trust from teachers and students regarding the system's learning path recommendations and evaluation results. Compared with traditional online learning platforms, the core change of the adaptive learning system is the formation of a circular relationship between students' learning performance and learning path recommendations. However, under the current technology, the interpretability of the relationship between these two is not particularly ideal, and there may be situations where the student's ability does not match the recommended content. Therefore, when developing the adaptive learning system, Open University needs to communicate with teachers and students to let them understand how the algorithm makes decisions and recommendations, and reserve more teaching intervention tools for teachers, so as to reduce teachers and students' doubts about the adaptive learning model. Secondly, there is a legal risk of collecting domain-independent feature data in the adaptive learning system. The student model construction of the adaptive learning system includes domain-related features and domain-independent features. The precise acquisition of domain-independent features often requires the identification of students' biological data, such as confirming students' cognitive styles through eye-tracking, and identifying students' academic emotions using computer data and facial expression data. However, the identification of relevant feature data and the teacher's having the authority to understand these data may cause students' unease, especially for adult students whose learning scenarios are usually private places. The acquisition of biological data requires students to turn on cameras, which may make students feel their privacy has been violated. At the same time, facial information belongs to personal sensitive information, and its identification and use must comply with the "informed consent principle". The use of such information in teaching may also cause legal problems that did not exist before. Although most of the adaptive learning platforms currently in practice do not collect students' biological data, the collection of domain-independent features such as learning styles is mainly completed through psychological tests, yet to further improve the accuracy of evaluation and recommendation, the collection and assessment of real-time biological data will be the direction of the deep reform of adaptive learning. When conducting adaptive learning reforms in the Open University system, it is necessary to fully consider the new risks brought by the application of artificial intelligence technology. The teaching reform plan should include control plans for various risks to ensure the smooth implementation of the reform.

5. Conclusion

In the context of the artificial intelligence era, this study, within the framework of open education, constructed an adaptive teaching framework that integrates "data - cognition - context" in a three-dimensional collaborative manner. The study found: First, AI technology can achieve large-scale personalized learning support without increasing the burden on teachers, significantly enhancing the initiative, satisfaction, and transfer ability of learners; Second, the collaborative mechanism between teachers and algorithms is the key to the success of the reform. Through multiple rounds of action research, its feasibility and effectiveness in real scenarios were verified. Teachers transform from knowledge transmitters to learning designers and emotional supporters, while algorithms provide decision assistance within the scope of being interpretable and controllable; Third, data-driven quality governance throughout the process can effectively alleviate the long-standing scale and quality contradiction in open education, laying a sustainable quality guarantee foundation for the lifelong The study found: First, AI technology can achieve large-scale personalized learning support without increasing the burden on teachers, significantly enhancing the initiative, satisfaction, and transfer ability of learners; Second, the collaborative mechanism between teachers and algorithms is the key to the success of the reform. learning system. The study also revealed that algorithm bias, digital divide, credit recognition barriers, and ethical risks are still bottlenecks restricting the deepening of the reform, and require collaborative governance of institutions, technologies, and culture. Teachers transform from knowledge transmitters to learning designers and emotional supporters, while algorithms provide decision assistance within the scope of being interpretable and controllable; Third, data-driven quality governance throughout the process can effectively alleviate the long-standing scale and quality contradiction in open education, laying a sustainable quality guarantee foundation for the lifelong learning system. Looking to the future, adaptive learning will move from the "course level" to the "ecological level", deeply connecting with credit banks, industry-academia integration, and international open educational resources, forming an open, inclusive, and intelligent learning community.The study also revealed that algorithm bias, digital divide, credit recognition barriers, and ethical risks are still bottlenecks restricting the deepening of the reform, and require collaborative governance of institutions, technologies, and culture. The framework, tools, and policy recommendations formed by this study can provide replicable and scalable paradigms for open universities, vocational colleges, and enterprise universities, and contribute the Chinese path and Chinese wisdom to the global digital transformation of education. Looking to the future, adaptive learning will move from the "course level" to the "ecological level", deeply connecting with credit banks, industry-academia integration, and international open educational resources, forming an open, inclusive, and intelligent learning community. The framework, tools, and policy recommendations formed by this study can provide replicable and scalable paradigms for open universities, vocational colleges, and enterprise universities, and contribute the Chinese path and Chinese wisdom to the global digital transformation of education.

6. Conflict of Interest

The authors declare that there are no conflict of interests, we do not have any possible conflicts of interest.

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