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Article

The impact of AI enablement on students' personalized learning and countermeasures—A dialectical approach to thinking

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Abstract: This study aims to use dialectical thinking to explore the impacts and responses of Artificial Intelligence (AI) empowerment on students' personalized learning. The effect of AI empowerment on student personalization is dissected through a literature review and empirical cases. The study finds that AI plays a significant role in promoting personalized learning by enhancing students' learning effectiveness through intelligent recommendation, automated feedback, improving students' independent learning ability, and optimizing learning paths, however, the wide application of AI also brings problems such as technological dependence, cheating in exams, weakening of critical thinking ability, educational fairness, and data privacy protection to students. The study proposes recommendations to strengthen technology regulation, enhance the synergy between teachers and AI, and optimize the personalized learning model. AI-enabled personalized learning is expected to play a greater role in improving learning efficiency and educational fairness.

Keywords: AI enablement; personalized learning; educational equity; dialectical thinking; data privacy

1. Introduction

Artificial Intelligence (hereinafter: AI), as a revolutionary technology, is gradually integrating into the field of education, especially playing an increasingly important role in personalized learning (Chen et al., 2020). AI provides students with personalized learning paths and feedback to enhance learning efficiency and effectiveness through technical means such as big data analytics, machine learning, natural language processing, etc. (Maghsudi et al., 2021). However, with the wide application of AI in education, its technical and ethical issues have triggered extensive academic discussions (Zawacki-Richter et al., 2019; Zhong et al., 2023).

The process of AI-enabled personalized learning faces multiple challenges in technology, ethics, and education policy. The issues of data privacy and security are particularly critical, especially in the field of children and youth education, and protecting the security of user information needs to be emphasized along with technical implementation; the fairness and transparency of AI algorithms remain a hot topic of research, and the bias of algorithms may exacerbate the imbalance in the distribution of educational resources, which in turn affects the learning opportunities of different groups of students; in the process of implementing AI educational technology, how to guarantee its fairness in different regions and groups has become an urgent issue; the ethical challenges of AI, especially how to balance the relationship between the freedom of personalized learning and educational fairness, is also an important topic in current research. The purpose of this paper is to explore the impacts, challenges, and response strategies of AI-enabled personalized learning from a discursive perspective, and to provide theoretical references for educators, policy makers, and technology developers.1 Definition of relevant concepts

1.1. Artificial intelligence enabled learning

Artificial Intelligence Enabled Learning, also known as Artificial Intelligence in Education (AIEd) refers to including learning experience and learning process through AIED (Zhang and Dong, 2022). It refers to the framework for building personalized learning systems, including technologies such as social networking sites and chatbots, educational expert systems, intelligent tutors and agents, machine learning, personalized education systems and virtual educational environments (Tapalova and Zhiyenbayeva, 2022). These technologies include intelligent tutoring systems, automated assessment tools and personalized recommendation systems that enable automated learning management and personalized teaching.

1.2. Personalized learning

Personalized learning refers to the customization of learning content and pathways to provide a differentiated educational experience based on students' individual needs, interests and learning styles (Chang and Ouyang, 2022; Pataranutaporn et al., 2021; Zhou, 2020). Through personalized learning, students can take ownership of their learning progress, enhance their learning autonomy, and receive more targeted support and feedback during the learning process. In this ecosystem, all parties can collaborate to promote the development of personalized learning (Ouyang et al., 2022).

2. Impact of AI empowerment on personalized learning

Chen et al. (2020), and Zhang et al. (2023) pointed out that AI technology has significant positive effects in supporting personalized learning, such as the application of intelligent analytics and personalized recommendation technology, which can effectively meet the personalized needs of learners. However, Shen and Wang (2019), Zhao and Liu (2024) also pointed out that this technology faces challenges such as the reinforcement of educational standardization, conflicts in human-computer collaboration, and learning technology and ethical issues, while AI-enabled education faces dilemmas such as the unknown mechanism and law of technological generalization and the dilemma of human-computer fusion and mutual trust (Liu et al., 2021).

2.1. Improvement of students' learning efficiency and improving student learning efficiency and potential risks

Tsinghua University has carried out a project on "100 billion parameter multimodal large model GLM", by letting the AI large model learn a large number of contents of the same subject, such as the same famous textbook, catechism courseware, the latest Chinese and English papers, and individual report cases, and also inputs the knowledge map constructed in the virtual teaching and research room, so that the AI model has the latest, broadest, and deepest knowledge in the field. The latest, broadest, and deepest theoretical expertise in the field, the study showed that with the AI-assisted tutoring system, the correctness of students' answers increased from 80% to 95%, and the students who received it believed that the AI system provided inspiration and ideas for research, and facilitated positive feedback on personalized learning; Xu et al. (2023) conducted an AI-assisted empirical study with 200 secondary school students, and the study showed that students who used the AI tutoring system improved students' performance in mathematics learning by more than 20%, and the AI system enabled students to master more knowledge in a short period through automated feedback and optimization of personalized learning paths; Li (2024), by constructing an AI-based learning model, showed that the students' learning efficiency increased by 20% on average, and the students' satisfaction increased by 30%.

However, Yang and Wang (2023) showed that this technology also faces challenges such as the reinforcement of educational standardization and conflicts in human-computer collaboration, and Youmei et al. (2023) found that over-reliance on AI can lead to cheating on exams or homework assignments, that AI can help to generate answers, and that students lose the ability to think on their own and their sense of creativity, and that AI-generated answers are not completed correctly and can play a bad role such as misleading to students.

2.2. Real-time feedback and learning behavior prediction

Wang (2024) pointed out through a study of ten domestic and international cases of the intelligentsia that AI technology can help students adjust their learning strategies promptly by monitoring and analyzing their learning behavior in real-time and providing instant feedback. Zeng et al. (2020) argued that traditional teaching methods usually difficult to quickly assess each student's learning, while AI can provide instant feedback and make dynamic adjustments based on students' real-time performance. Tiwari (2023) showed through an empirical study that students using AI tutoring systems received 2.5 times more feedback than in traditional classrooms, which allowed students in the learning process to quickly correct errors and improve learning strategies. Research studies by Song et al. (2022) and Zhang et al. (2020) also demonstrated that AI-enabled learning mechanisms are independent of time and environment and that they can learn and receive feedback as long as the network allows. Wang (2024) stated that AI-enabled learning can provide students with 24/7 round-the-clock services, respond to students' needs in real-time, shorten the waiting time, and deal with learning problems efficiently, and this kind of learning path optimization helps students to focus on the content they need, which saves time and improves the learning efficiency (Wu and Zhao, 2014).

However, achieving effective information feedback and learning prediction requires a large amount of pre-language and knowledge input and theoretical model training for the AI model. Gai and Huang (2022) argued that this mechanical learning model produces outputs of standardized format content and fails to provide students with vivid presentations and dialectical thinking aids, and Song and Zhang (2023) showed that generative AI, while empowering large-scale personalized learning, also carries the risks of quantifying stress, ignoring socialization, and blocking critical thinking skills and other risks. In addition, Liu et al. (2022) in Multimodal Learning Analytics (MMLA) pointed out that current research mostly focuses on the prediction of learning behavioral performance, while neglecting the process explanation and decision support of mental development.

2.3. Personalized push of learning resources

AI technology can intelligently push suitable learning resources according to student's learning needs and preferences (Li et al., 2023). This includes not only traditional learning materials such as text and video but also new learning tools such as virtual agents and intelligent adjustment, thus realizing the transformation from 'one person with one face' to 'thousands of people with thousands of faces' (Bai et al., 2024). Jiang et al. (2015) found that a personalized adaptive online learning analytics model based on big data can provide students with personalized adaptive learning based on their needs and abilities. In addition, Qian (2017) showed that the push of personalized learning resources can also provide richer and more diverse learning resources to meet students' personalized learning needs.

However, a study by Seo et al. (2021) found that student's motivation to actively access other learning materials decreased significantly after long-term use of an AI-personalized push system. Murtaza et al. (2022) pointed out that AI-pushed resources are often based on algorithmic recommendations, and students may not have access to content beyond their interests, thus exacerbating the 'information cocoon effect', which restricts students' broad exposure to different domains and their ability to think interdisciplinarity, leading to a narrowing of their learning horizons (Jin et al., 2011). This effect limits students' broad exposure to different fields and their ability to think across disciplines, leading to a narrow horizon of learning (Jin and Li, 2023). Grace et al. (2023) found that although AI technology can rapidly analyze and push a large number of learning materials, the quality of the content it pushes is variable and may contain inaccurate information, which can affect students' learning experience and cognitive development.

2.4. Improving students' independent learning ability

Experiments have shown that AI-enabled technology models can provide objective, accurate and timely scoring and feedback on students' answers and essays, helping students to recognize their strengths and weaknesses to adjust their learning strategies, this kind of intelligent feedback system greatly enhances students' learning autonomy and self-improvement. Maghsudi et al. (2021) did a study on the AI system to help high school students customize their study plans according to their personal interests and learning progress, and the results showed that students with low self-directed learning ability increased their self-directed learning time by 40% with the support of AI tutoring system and significantly improved their academic performance. AI-enabled personalized learning promotes the self-directed learning ability of students and can customize study plans and resources according to students' learning habits and preferences, which in turn enhance students' motivation and engagement in learning (Hasibuan and Azizah, 2023).

However, Seo et al. (2021) showed that students exhibited feelings of anxiety and powerlessness when faced with learning tasks or exams that were not supported by AI, and some students reported decreased motivation to learn and lower self-confidence in the absence of AI support. Tiwari's (2023) study noted that the immediate feedback and automated instruction provided by AI systems reduced students' autonomous opportunities for exploration and reflection, thus weakening their ability to identify problems and think independently. A study by Hasibuan and Azizah (2023) found that in a group of students who used an AI system for a long period, the students' behavior of searching for learning materials on their own declined by about 35%. Students tend to lack the ability to think multidimensionally and show strong dependence when facing complex problems, leading to the inhibition of their critical thinking skills (Lin and Zhu, 2020) as well as not actively exploring diverse solutions, resulting in them showing weaker thinking skills when dealing with complex or uncertain problems (Murtaza et al., 2022).

3. Challenges and limitations of AI-enabled personalized learning

3.1. Data privacy and security issues

It has been argued that AI can provide personalized learning paths and recommended resources for each student by collecting students' learning behaviors, grades and interest preferences. Li and Li (2023) study that these data analyses help teachers and students better understand learning needs and customize teaching content, thus improving learning outcomes. For example, Xu et al. (2021) showed that learning programmers created by AI systems using student data can help students master course priorities faster and improve grades and learning satisfaction. Meanwhile, Chen et al. (2023) found that AI systems can automatically detect unauthorized access attempts through behavioral analysis, reducing the risk of system hacking.

It has also been argued that AI-personalized learning systems rely on a large amount of student data, such as personal information, learning behaviors, interest preferences and performance records, and the centralized storage and processing of this data increases the risk of data leakage (Prinsloo et al., 2022). Seo et al. (2021) showed that 35% of students and parents lacked a clear understanding of how the AI system handled their data and believed that the privacy policy was complex and opaque. Cukurova et al. (2020) Multimodal learning analytics involves the collection and processing of a large amount of personal data, which raises privacy protection and ethical issues, and how to reasonably use this data for learning analytics without violating personal privacy is an important challenge that is currently being faced. A study by the China Institute of Information and Communication Research (CIICR) points out that the development and application of generative AI technology raises issues such as prejudice discrimination, privacy invasion, uncertainty of responsibility, and dissemination of false content, as well as impacting ethical risks such as education and employment.

3.2. Equity and inclusiveness of technology

Some empirical data prove that AI-enabled personalized learning shows significant potential to enhance equity and inclusiveness in education. For example, in a study of 300 students with learning disabilities, Xu et al. (2021) found that an AI-enabled personalized learning system significantly improved the academic performance of these students by more than 25% in one semester through voice-assisted, text-to-speech, etc. Hasibuan and Azizah (2023) in an empirical study on global online education, the application of AI-enabled personalized learning systems in developing countries significantly increased education access. The study showed that about 75% of students in remote areas had access to the same quality of educational resources as students in urban areas through AI online learning platforms. Tiwari (2023), in a study of 500 schools, AI-powered personalized learning systems reduced the cost of learning by 30% and increased learning efficiency by 20%. This has enabled more students to enjoy high-quality personalized education regardless of financial constraints. Maghsudi et al. (2021) in a study of 1000 international students, 85% reported that AI technology helped them to master the course content faster and learn 15% more efficiently. Hu (2024) through a study based on 31 published 36 experimental and quasi-experimental studies from published articles, a meta-analysis of empirical studies revealed that AI-assisted personalized learning had a moderately positive impact on student learning outcomes, including knowledge, competence and affective development.

Another empirical study went but exposed issues such as inequality of technological resources and system design bias. For example, a global study by Hashim et al. (2022) found that about 40% of rural students are unable to participate in AI-personalized learning due to a lack of internet access and hardware devices exacerbating educational inequalities between developed and poor areas. Millions more students globally are unable to access the service due to the digital network divide, and pre-existing severe social and educational inequalities (Bulathwela et al., 2024).

3.3. Repositioning of the teacher’s role

Cope et al. (2021) found that the teacher’s role in the classroom may be weakened as AI gradually assumes the functions of feedback and assessment in the teaching task. Meanwhile, teachers may gradually lose certain teaching duties, which may affect their professional status and teaching effectiveness. Shao et al. (2018) conducted a survey on rural primary school teachers in the ethnic areas of Qian dong nan, Guizhou Province, which showed that more than 20% of primary school teachers showed burnout due to heavy workload and work pressure. Choi et al. (2021) conducted a study on the human factors of accepting education with artificial intelligence tools (EAIT) on 215 teachers in South Korea, and it was found that the prevalence of AI technology reduces their decision-making power in teaching and affects the emotional interaction between teachers and students.

While Zhang et al. (2020) found that the application of AI technology can help students to personalize their load reduction according to their learning input and subjective coursework load, and through scientific classification and personalized load reduction programmers, AI can enhance the quality of students' learning, which reduces the psychological burden of students as well as the burden of teachers. Hasan et al. (2024) stated that AI technology can automatically assess students' assignments and exams and provide detailed feedback, thus reducing teachers' workload and improving the efficiency and accuracy of assessment, while virtual assistants and chatbots can increase classroom interaction and make the learning process more lively and interesting. The role of teachers in future education needs to be redefined, and the synergy between teachers and AI systems will become an important part of the future education model.

3.4. Ethical issues in the use of AI

Through research, it has been found that AI personalized learning systems rely on large amounts of data to train models, which may contain historically unfair or discriminatory information. Shen and Wang (2021) found that if there is bias in the training data concerning gender, race, or other social attributes, then the model may exhibit similar bias when processing these attributes (Shen and Wang, 2021). There also exists a bias introduced by the design team's mindset and decision-making process during the development process. If the design team has preconceived notions about certain groups of students, this may affect the design and optimization of the algorithm, which may lead to underestimation or overestimation of certain groups of students, resulting in some groups of students receiving more learning resources and support due to the algorithm's bias, while other groups of students may be neglected or marginalized (Ni et al., 2022). In addition, the "black box" effect of algorithms makes it difficult to detect and correct these biases (Feng and Zhao, 2022).AI personalized learning systems usually need to interact with users to understand their learning needs and preferences and recommend content that is consistent with their prior knowledge rather than content that challenges their existing knowledge (Ni et al., 2022). not content that challenges their existing knowledge (Chinta et al., 2024).

4. Countermeasures to promote AI-enabled personalized learning

4.1. Establishing a robust data privacy protection mechanism

To ensure the sustainable application of AI technologies in education the design of personalized learning tools should take into account user privacy and ethical issues. For example, providing transparency and controllability to enable students to choose the amount of data they are willing to share for a personalized learning experience is a design principle that helps to balance the need for privacy and personalized learning (Halkiopoulos and Gkintoni, 2024; Toth, 2024). Governments and educational institutions should develop strict privacy protection policies to ensure the secure and transparent use of student data (Chen and Hao, 2020). In addition, developers should adopt data encryption and anonymization techniques to reduce the risk of data leakage (Lie et al., 2022). A specialized ethical review committee should be set up to conduct ethical assessments of the development and application of AI systems to ensure that the application of technology does not infringe on students' privacy and other fundamental rights (Zhao et al., 2022).

4.2. Promoting fairness in technology

In personalized learning systems, algorithms usually rely on large amounts of student behavioral data to generate learning paths and recommended content (Wu et al., 2024). However, these data are often biased; for example, data from certain groups may be underestimated or ignored, resulting in algorithms failing to accurately capture the learning needs and characteristics of these groups (Zong et al., 2023). Students from minority or economically disadvantaged groups may not be able to access learning resources and pathways that are appropriate for them due to insufficient data or algorithmic bias, which can affect their learning outcomes and educational equity (Hu and Rangwala, 2020). To address the issue of technology fairness, education policies should promote the popularization of AI technologies in different regions (Yu and Zhang, 2023), and ensure that economically underdeveloped regions can also enjoy AI-enabled education technologies through policy support (Cui and Feng, 2020). At the same time, unified technical standards should be developed to ensure the interoperability of AI technologies across different educational platforms (Jiang et al., 2023).

4.3. Enhance the integration of teachers and AI technology

Through the 'teaching and learning terminal' to obtain diversified 'resource' services and multi-state 'platform' services, to enhance teachers' rational cognition of technology, master the intelligent teaching environment, innovative teaching, Adaptation of human-computer collaborative teaching, and enhancement of data literacy (He and Guo, 2021). Kim et al. (2022) advocate that teachers should keep up with the times and that teachers and students will collaborate with AI through three phases: 1) Understanding AI;2) Learning from AI; and 3) Co-learning with a systematic AIED policy, a flexible school system, collaborative learning culture, and a safe environment are all important. Teachers need to not only learn new technologies and methods to cope with the speed of AIisation but also increase their pedagogically constructed thinking skills. Tapalova and Zhiyenbayeva (2022) study explored a framework for AIED to build a personalized learning system, including social networking sites and chatbots, educational expert systems, intelligent tutors and agents, machine learning, personalized education systems and virtual educational environments, which help educators to develop and introduce personalized approaches to acquire new knowledge and develop professional competencies.

4.4. Establishing a federated learning algorithm system and code of ethics

It has been shown by several empirical case studies that the risk of privacy violation can be reduced by Federated Learning (FL), which is a distributed machine learning framework that allows multiple clients to co-train global models without sharing raw data, thus effectively protecting data privacy.

Yin and Qu (2022) study proposed a Personalized Differential Privacy Federated Learning Algorithm (PDP-FL), which enhances privacy protection through a two-phase approach: in the first phase, user privacy is graded according to the user's privacy preferences and noise is added to satisfy the user's privacy preferences to achieve personalized privacy protection, and in the second phase, a simultaneous local and central protection strategy and add noise that meets the global differential privacy (DP) threshold according to the user's uploaded privacy level to quantify the global privacy protection level. This approach not only improves the classification accuracy of the model but also meets the needs of personalized privacy protection. Wu et al. (2024) study proposed an attack-resistant federated learning privacy protection algorithm: the algorithm combines the malicious client detection mechanism and the local differential privacy technique, determines and identifies potentially malicious clients through the gradient similarity, and based on the sensitivity of different queries and the individual privacy needs of users to design a local differential privacy algorithm based on dynamic privacy budget. This method performs well in improving the security and model performance of federated learning, especially the experimental results on MNIST, CIFAR-10 and MR datasets show that the algorithm has a significant improvement in accuracy. Zhang et al. (2024) study proposes an adaptive differential privacy-based and Client Selection Optimization with the Federated Learning Method (CS&AGC DPFL): This method performs adaptive gradient trimming for different clients in different rounds by considering the heterogeneity of the gradient, which makes the noise size adaptively adjusted. At the same time, it combines the client sampling methods of roulette and elite retention to further improve the model performance. Experimental results show that this approach can make the final model classification accuracy increase under the same level of privacy constraints, and there is a significant improvement in convergence speed.

It is also necessary to establish effective ethical norms and regulatory mechanisms, and when formulating ethical norms, refer to international successful cases and standards, the EU's Ethical Guidelines for Trustworthy Artificial Intelligence, and adjust and optimize them in the light of local realities, which will help to ensure that the norms are universally applicable and adaptable (Shen and Wang, 2019).

5. Conclusion

In summary, the application of AI technology in personalized learning demonstrates great potential; it improves student learning through data-driven learning path customization, instant feedback and personalized recommendations. The AI model forms an AI-supported adaptive learning path construction through deep learning with core functional modules such as a model library, a learning process database, and an adaptive learning path construction engine. The model is capable of generating concise and accurate adaptive learning paths from complex learning resources and activities, effectively improving learners' learning efficiency, learning performance and learning satisfaction (Kong et al., 2020). The popularization of distance education can effectively improve learning efficiency and educational equity aspects while increasing the degree of personalized education for students. In future development of educational policies, technology developers and teachers should strengthen collaboration to ensure the widespread and effective application of AI technology in personalized learning through the establishment of robust data protection mechanisms and ethical guidelines, the promotion of technological fairness, and the enhancement of the integration of teachers and AI.

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