

Research on the Evaluation Mechanism of Artificial Intelligence-Enabled Education and Teaching Innovation in Colleges and Universities

Kebiao Yuan*, Shengyi Li

School of Economics and Management, Ningbo University of Technology, Ningbo, 315211, China

*Corresponding author: Kebiao Yuan, ykbjob@163.com

Copyright: 2025 Author(s). This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY-NC 4.0), permitting distribution and reproduction in any medium, provided the original author and source are credited, and explicitly prohibiting its use for commercial purposes.

Abstract: The report of the 20th National Congress of the Communist Party of China first positioned ‘educational digitization’ as the core path to building a learning-oriented nation. The ‘China Education Modernization 2035’ plan further clarified that artificial intelligence is the key to achieving the organic integration of large-scale education and personalized cultivation. However, the traditional educational evaluation system suffers from static lag and insufficient adaptability, urgently requiring the reconstruction of evaluation mechanisms through artificial intelligence technology. Therefore, analyzing the role of artificial intelligence in empowering innovative evaluation mechanisms for higher education teaching and learning is of great significance. This article takes university students, teachers, and university administrators as the survey subjects and uses structural equation modeling to explore the innovative evaluation mechanisms of university education and teaching empowered by artificial intelligence. The research findings indicate that AI drives innovation in higher education evaluation mechanisms across six dimensions: learning outcomes, teaching processes, feedback on results, data privacy and security, acceptance, and social empowerment. Therefore, this paper suggests that the application of AI in higher education evaluation can be promoted by accelerating the construction of a national intelligent education evaluation standards system and advancing institutional evaluation innovation mechanisms, and provides relevant recommendations.

Keywords: Artificial Intelligence; Teaching and Learning in Higher Education; Innovation Evaluation; Structural Equation Modeling

Published: Aug 26, 2025

DOI: <https://doi.org/10.62177/amit.v1i4.549>

1.Introduction

The report of the 20th National Congress of the Communist Party of China emphasized the need to accelerate the digital transformation of education, build a modern education system for lifelong learning for all, and promote the development of a learning society and a learning nation. For education, artificial intelligence is not just a strategic issue, but a strategic and comprehensive issue that affects and even determines the high-quality development of education^[1]. The document ‘China’s Education Modernization 2035’ highlights the advantages of new technologies such as artificial intelligence in transforming the role of teachers, explaining that artificial intelligence is key to achieving a combination of large-scale education and personalized training^[2]. Artificial intelligence technology is reshaping the spatial boundaries and teaching activity processes

of education, opening up new horizons for innovative development in the education ecosystem. Empowering higher education evaluation with artificial intelligence is a key component of the important task of deepening the implementation of artificial intelligence empowerment initiatives, and it is also an urgent issue facing the deepening reform of higher education evaluation. How to use artificial intelligence to empower innovative evaluation standards for higher education teaching and learning, construct a scientific, efficient, and intelligent higher education evaluation system, and improve the quality and efficiency of higher education is of paramount importance^[3].

In March 2024, the Ministry of Education launched an initiative to empower education with artificial intelligence, aiming to use artificial intelligence to promote the integration of teaching and learning, improve the digital literacy and skills of the entire population, and regulate the scientific ethics of artificial intelligence use^[4]. Deepening education evaluation reform is a key task and an important component of comprehensive education reform. It holds significant strategic importance for accelerating the modernization of education, building an education powerhouse, and providing education that satisfies the people. Therefore, based on existing research, this paper constructs an innovative evaluation system for artificial intelligence-enabled higher education teaching and attempts to analyze the mechanisms of artificial intelligence-enabled higher education teaching.

2. Literature Review

2.1 The Value of Artificial Intelligence in Empowering Higher Education Teaching

Some scholars believe that the integrated application of artificial intelligence in classroom teaching is the key to driving the evolution of education^[4]. The application of artificial intelligence in university teaching can provide students with a highly personalized learning experience through precise personalized learning support, thereby promoting comprehensive improvement in students' knowledge acquisition, skill development, and cognitive abilities. Personalized learning can enhance classroom engagement and stimulate learning interest, thereby significantly improving students' learning interest and initiative, and effectively optimizing learning outcomes while promoting students' comprehensive development^[7]. In terms of teaching effectiveness, artificial intelligence can help teachers identify student needs more accurately and improve the management and implementation of classroom teaching through the optimization of the teaching process.

Through intelligent tools and data analysis powered by artificial intelligence, teachers can monitor classroom learning dynamics in real time, accurately identify students' knowledge gaps, and implement dynamic adjustments to teaching content and methods based on data feedback, thereby optimizing teaching design to achieve precise and efficient teaching goals^[8]. Scholar Zhang Yu believes that artificial intelligence technology reconstructs classroom teaching paradigms through data-driven mechanisms. On the one hand, it achieves the precise allocation of educational resources, and on the other hand, it promotes the intelligent upgrading and refined management of teaching management processes^[4]. Through the smart education platform, school administrators can dynamically monitor classroom teaching plans in terms of progress, student engagement, teaching quality, and other aspects^[9].

At the societal level, the application of artificial intelligence in higher education not only meets society's demand for high-quality, innovative talent but also enhances societal competitiveness and sustainable development. Scholar Wu Zhongyuan conducted an in-depth analysis of the innovative evaluation concepts, subject diversification, technological innovation integration, and technological boundaries enabled by artificial intelligence. He found that the foundation of artificial intelligence-enabled higher education evaluation reform lies in enhancing the scientific rigor, fairness, personalization, and efficiency of educational evaluation, thereby driving the high-quality, inclusive development of higher education^[10].

2.2 The Need for Artificial Intelligence to Empower Innovative Evaluation of Higher Education Teaching and Learning

In the new era, the new development pattern requires high-level talent support. As an important platform for cultivating high-quality talent, the reform of the evaluation system in higher education is particularly important^[10]. The traditional education evaluation system suffers from issues such as a single standard framework and static indicator design, making it difficult to adapt to the new requirements of the intelligent era for students' core competencies, such as information literacy, innovative

thinking, and critical thinking. This can lead to lagging evaluation mechanisms. A paradigm dominated by quantification lacks qualitative analysis dimensions, weakening the applicability and flexibility of evaluation and failing to meet the needs of personalized development and educational diversity for high-level talent^[11].

In the context of globalization, reforming higher education evaluation is one of the key means of enhancing a country's educational competitiveness. The application of artificial intelligence to higher education evaluation reform has also become a new focal point of technological competition among countries^[11]. To ensure that students remain competitive in the age of artificial intelligence, American universities are adopting intelligent question banks and assessment systems to assist in teaching and introducing intelligent tutoring systems to improve learning outcomes and independent learning abilities^[12]. Japanese universities focus on using AI to empower higher education by applying personalized learning evaluation systems that provide personalized learning recommendations and feedback based on students' learning data and behavioral characteristics^[13]. The Singaporean government is rethinking the development model of AI-enabled higher education from the ground up and providing strong support for AI technology research and application through the establishment of innovation centers and scientific research platforms^[14]. The experience of using artificial intelligence technology in higher education evaluation abroad provides reference and inspiration for China's higher education evaluation reform and the construction of a higher education evaluation system with Chinese characteristics and international standards.

2.3 The Content of Artificial Intelligence-Empowered Evaluation of Higher Education Teaching and Learning

Artificial Intelligence Empowering Higher Education Evaluation Reform Based on the development needs of higher education in the new era, the application of artificial intelligence technology in higher education evaluation must establish a learner-centered approach, shift from knowledge transfer to ability cultivation, focus on the comprehensive development of students, integrate intelligent technology into educational objectives, cultivate AI literacy and digital citizenship literacy, develop AI application abilities, and enhance complex problem-solving abilities^[10]. During the evaluation process, teachers transition from traditional evaluators to interpreters of evaluation results and providers of feedback. Artificial intelligence-enabled classroom teaching greatly enhances teachers' teaching effectiveness, helping them to more accurately identify students' needs, optimize teaching design, and improve the management and implementation quality of classroom teaching. Teachers can dynamically obtain classroom interaction data, identify students' weaknesses in certain knowledge points, and then flexibly adjust teaching content and strategies to achieve a more precise classroom teaching design^[4]. Artificial intelligence technology can help build feedback systems and continuous improvement mechanisms. Based on assessment results and user feedback, educational evaluation programs can be regularly assessed and adjusted, evaluation indicator systems and methods can be optimized, intelligent evaluation tools and AI evaluation systems can be continuously optimized, evaluation models and algorithms can be adjusted, and the accuracy and reliability of evaluation systems can be improved^[10]. In the process of higher education evaluation, the legitimate rights and interests of all evaluation entities should be respected and protected. An ethical review mechanism should be established to clarify the procedures and standards for ethical review. Privacy protection is an important aspect of AI-enabled evaluation. A sound data management system and privacy protection policy should be established to ensure data security and privacy. When collecting and using individual information, not only should their right to informed consent be fully respected, but the transparency of the evaluation process and results should also be maintained to enhance the credibility and satisfaction of the evaluation results^[15].

Artificial intelligence technology can autonomously establish course learning outcomes, describe evaluation weights, map learning outcomes to each evaluation method, and formulate learning activity plans and course schedules to achieve coordination between expected learning outcomes, teaching strategies, learning activities, and evaluation methods, thereby ensuring that students participate in meaningful learning experiences^[16]. The ultimate goal of empowering higher education evaluation with artificial intelligence is to serve society. It is an inevitable trend in the modernization and high-quality development of education, which needs to meet society's demand for high-quality, innovative talent, and also provide support for society's sustainable development and competitiveness^[4].

3. Research Design

3.1 Questionnaire Design

3.1.1 Basic Information

This study aims to analyze the innovative evaluation of AI-enabled higher education teaching and learning from the perspectives of students, teachers, and school administrators. Therefore, based on the above analysis, this paper constructs evaluation indicators from six dimensions: learning outcomes, teaching process, feedback on results, data privacy and security, acceptance, and social empowerment. An evaluation innovation survey questionnaire is designed to understand the innovative evaluation mechanism of AI-enabled higher education teaching and learning. The questionnaire employs a five-point Likert scale for measurement and utilizes an integer allocation algorithm to ensure that the number of respondents for each option strictly aligns with the theoretical probability distribution.

3.1.2 Evaluation Questions

The questionnaire items for evaluating innovation are designed as shown in Table 1. In terms of learning outcomes, there are three items: whether AI can identify learning difficulties, whether it can generate personalized evaluation reports, and whether it can integrate multidimensional data. In terms of the teaching process, there are three items: whether AI technology can objectively record teachers' teaching performance, whether it can generate real-time teaching feedback, and whether AI-assisted teaching evaluation reduces subjective bias, making the results more fair. In terms of feedback on results, the questionnaire is divided into three items: whether AI-generated evaluation reports are instructive, whether they effectively promote professional development, and whether they enhance overall educational quality; In terms of data privacy and security, there are three sub-items: whether AI systems can be trusted to collect personal data, whether there are clear regulatory mechanisms in place, and whether users can understand the purpose of personal data collection. In terms of acceptance, there are three sub-items: whether AI platforms are compatible with existing teaching platforms, whether users are willing to actively use AI evaluation functions, and whether related training can help users become proficient in using the evaluation system. In terms of social empowerment, it is also divided into three sub-questions: whether AI evaluation can help individuals understand the alignment between their own capabilities and societal needs, whether it can enhance the ability to address real-world societal issues, and whether it can promote educational equity.

Table 1: Questionnaire Design and Items

Variable	Number	Question
Learning outcomes	C1	Capturing learning difficulties
	C2	Personalized evaluation report
	C3	Integrate multidimensional data
Teaching process	C4	Teacher performance
	C5	Real-time teaching feedback
	C6	Fair evaluation results
Feedback on results	C7	The evaluation report is instructive.
	C8	Effectively promote professional development
	C9	Improving overall educational quality
Data privacy and security	C10	The trust evaluation system collects personal data
	C11	Clarify regulatory mechanisms
	C12	Knowing how your data is used
Acceptance	C13	Compatible with existing teaching platforms
	C14	willing to use proactively
	C15	Related technical training

Variable	Number	Question
Social empowerment	C16	Individual abilities and social needs
	C17	Technology + Social Problem Solving
	C18	Promoting educational equity

3.2 Research Methods

To explore the evaluation mechanism for innovation in higher education enabled by artificial intelligence, this study conducted a survey using a questionnaire. The questionnaire included six dimensions: learning outcomes, teaching process, feedback on results, data privacy and security, acceptance, and social empowerment. Each dimension had three items, totaling 18 items. To enhance the accuracy and authenticity of this survey, the respondents were current students, faculty members, and administrative staff at higher education institutions. The survey was distributed in June 2025, with a total of 1,321 questionnaires distributed and 1,218 formally returned. After internal logical checks, 94 questionnaires were excluded, leaving 1,124 valid questionnaires, with a validity rate of 92.28%. SPSS software was used for reliability and validity analysis of the questionnaires, and AMOS software was used to construct the relevant structural equation model.

4. Research Findings

4.1 Validity and Reliability Analysis

Reliability and validity analysis were conducted using SPSS 27.0, and Cronbach's Alpha was used to assess the internal consistency of the survey questionnaire's research variables, as shown in Table 2. The Cronbach's Alpha coefficient for the survey questionnaire was 0.713, which is greater than 0.7, indicating that the data reliability is suitable for further analysis. Validity analysis reflects whether the scale effectively measures the intended content^[17]. As shown in Table 3, the KMO value of the survey questionnaire was 0.853, and the Bartlett's sphericity test value was 0.000, which was statistically significant at the 0.05 level. This indicates that the questionnaire data is highly suitable for information extraction and can be used for further research analysis.

Table 2: Cronbach's Reliability Analysis

Cronbach's Alpha	number of items
0.713	18

Table 3: KMO and Bartlett's Test

Indicator	Indicator Value
KMO sampling adequacy measure	0.853
Approximate Chi-square	1480.616
Degree of Freedom	153
Significance	0.000

4.2 Structural Equation Model

4.2.1 Initial Model

The initial structural equation model was constructed using AMOS software, as shown in Figure 1. In Figure 1, the ellipses represent latent variables, the rectangles represent observed variables, and the circles represent the residuals of each variable. The coefficients in the model were estimated using the maximum likelihood estimation algorithm^[16].

Before conducting path analysis, it is necessary to test the model for goodness of fit. This paper selects the chi-square degree of freedom ratio, root mean square error of approximation (RMSEA), goodness of fit index (GFI), incremental fit index (IFI), Tucker-Lewis index (TLI), and comparative fit index (CFI) as goodness of fit indicators, as shown in Table 4.

Figure 1: Initial Structural Equation Model

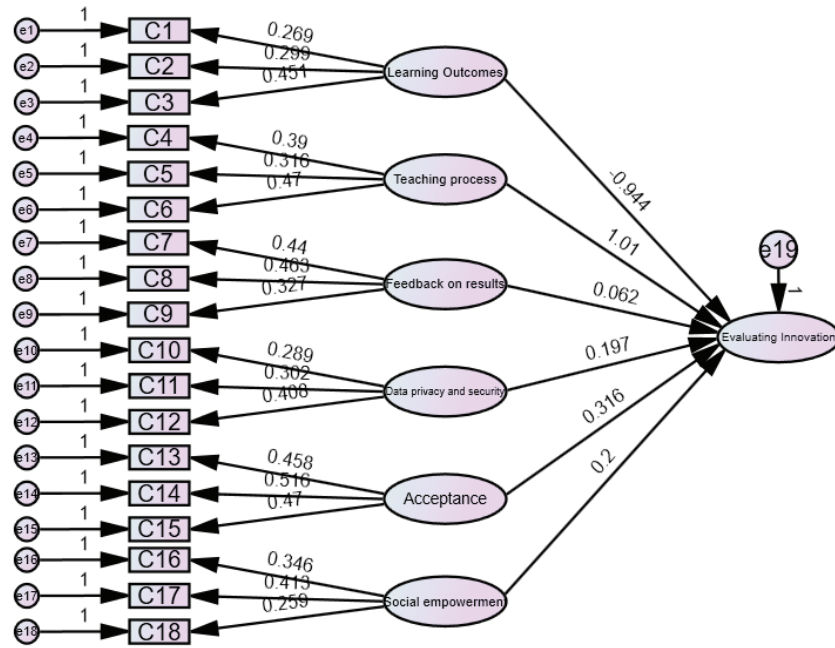


Table 4: Initial Model Goodness-of-Fit Test

Indicator	χ^2/d_f	GFI	IFI	TLI	CFI	RMSEA
Requirements	<3	>0.9	>0.9	>0.9	>0.9	<0.05
Indicator Value	1.208	0.986	0.981	0.976	0.981	0.004~0.021

According to Table 4, the chi-square degree of freedom ratio of the initial model is 1.208, which is less than 3. The goodness-of-fit index is 0.986, meeting the research standard of being greater than 0.9. The incremental goodness-of-fit index is 0.981. The Tucker-Lewis index is 0.976, and the comparative fit index is 0.981, both of which are greater than 0.9. The approximate root mean square error ranges from 0.004 to 0.021, which is less than 0.05, indicating that the initial model meets the goodness-of-fit requirements.

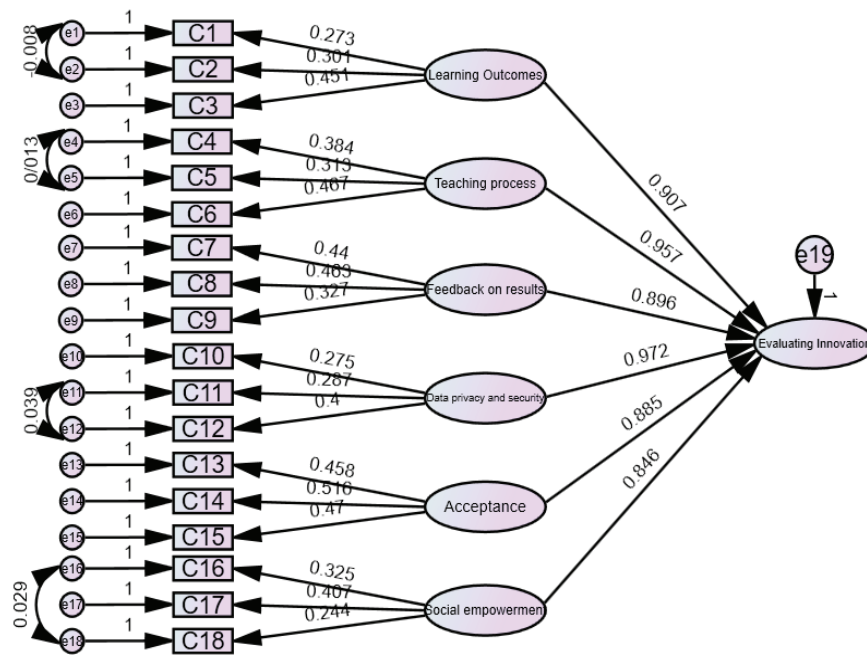
4.2.2 Model correction

Based on practical experience, the accuracy of AI diagnostic results is a prerequisite for generating personalized reports, so items C1 and C2 are related; AI data collection is the basis for generating feedback reports. If AI records are considered to be biased, the validity of the feedback results will be questioned, so items C4 and C5 are related. Users' trust in AI's collection of personal information is a prerequisite for algorithm transparency. If users are concerned about data breaches, it may undermine the effectiveness of regulatory mechanisms. Therefore, items C10 and C11 are interrelated. Item C16 represents the conversion of individual capabilities, while item C18 represents system fairness. These belong to different levels of social empowerment but share the common goal of promoting social fairness, thereby influencing each other. Therefore, the error terms of the above related items were set as related relationships, and the model was revised accordingly. The revised model is shown in Figure 2. IFI, TLI, and CFI meet the requirements, and all fitting indicators meet the standards, as shown in Table 5.

Table 5: Fitting Test of the Corrected Model

Indicator	χ^2/d_f	GFI	IFI	TLI	CFI	RMSEA
Requirements	<3	>0.9	>0.9	>0.9	>0.9	<0.05
Indicator Value	1.173	0.984	0.984	0.980	0.984	0.003~0.020

Figure 2: Revised Structural Equation Model



4.2.3 Model Results Analysis

The evaluation of AI-empowered innovation in higher education teaching is influenced by many factors. This paper constructs evaluation indicators based on relevant literature and uses a structural equation model to reflect the evaluation mechanism of AI-empowered innovation in higher education teaching. The results are shown in Table 6. The path relationships between learning outcomes, teaching process, feedback on results, data privacy and security, acceptance, and social empowerment are all significant, and all hypotheses are valid.

Table 6: Factor Loadings of the Revised Structural Equation Model

			Estimate	S.E.	C.R.	P
C1	<—	Learning Outcomes	1.000	-	-	-
C2	<—	Learning Outcomes	1.098	0.201	0.000	***
C3	<—	Learning Outcomes	1.623	0.258	0.000	***
C4	<—	Teaching process	1.000	-	-	-
C5	<—	Teaching process	0.859	0.123	0.000	***
C6	<—	Teaching process	1.245	0.145	0.000	***
C7	<—	Feedback on results	1.000	-	-	-
C8	<—	Feedback on results	1.057	0.118	0.000	***
C9	<—	Feedback on results	0.633	0.087	0.000	***
C10	<—	Data privacy	1.000	-	-	-
C11	<—	Data privacy	1.023	0.177	0.000	***
C12	<—	Data privacy	1.449	0.225	0.000	***
C13	<—	Acceptance	1.000	-	-	-
C14	<—	Acceptance	1.186	0.120	0.000	***
C15	<—	Acceptance	1.110	0.117	0.000	***
C16	<—	Social empowerment	1.000	-	-	-

			Estimate	S.E.	C.R.	P
C17	<—	Social empowerment	1.247	0.189	0.000	***
C18	<—	Social empowerment	0.662	0.129	0.000	***
Evaluating	<—	Learning Outcomes	1.000	-	-	-
Evaluating	<—	Teaching process	1.456	0.245	0.000	***
Evaluating	<—	Feedback on results	1.510	0.247	0.000	***
Evaluating	<—	Data privacy	1.091	0.208	0.000	***
Evaluating	<—	Acceptance	1.463	0.237	0.000	***
Evaluating	<—	Social empowerment	1.076	0.199	0.000	***

Note: *** indicates $P < 0.001$.

As shown in the figure above and the revised structural equation model, the standardized path coefficients for learning outcomes, teaching process, feedback on results, data privacy and security, acceptance, and social empowerment are 0.907, 0.957, 0.896, 0.972, 0.885, and 0.846, respectively. This indicates that these six indicators drive innovation in the evaluation of higher education teaching and learning enabled by artificial intelligence.

Among the observed variables of learning outcomes, the factor loading coefficient of artificial intelligence in integrating multidimensional data is 0.451, which is higher than the other two items, indicating that it has a significant impact on the evaluation of learning outcomes. Promoting the use of artificial intelligence to integrate multidimensional data can provide an analytical basis for identifying learning difficulties and generating personalized reports, thereby achieving the goals outlined in the ‘Overall Plan for Deepening the Reform of Education Evaluation in the New Era’ to improve outcome evaluation, strengthen process evaluation, explore value-added evaluation, and improve comprehensive evaluation.

Among the observed variables in the teaching process, the factor loading coefficient for whether artificial intelligence can ensure fairness in evaluation results is 0.467, which is higher than the other two factors, indicating that it has a significant impact on the evaluation of the teaching process. Teaching performance and real-time feedback can be optimized through algorithms, but issues with the fairness of evaluation results can lead to systemic trust crises. The ‘Overall Plan for Deepening the Reform of Educational Evaluation in the New Era’ explicitly requires that we ‘adhere to scientific effectiveness, improve result-based evaluation, strengthen process-based evaluation, and establish a comprehensive evaluation system.’ Fairness is the bottom-line standard for ‘scientific and effective’ evaluation.

Among the observed variables in the feedback results, the factor loadings for whether the evaluation report is instructive and whether it can effectively promote professional development are 0.44 and 0.463, respectively, indicating that they have a high impact on the feedback results. Together, they constitute the substantive vehicle for educational evaluation to empower teaching reform: an instructive evaluation report can ensure the conversion efficiency of evaluation results, while promoting professional development can achieve improvements in educational quality.

Among the observed variables related to data privacy and security, the factor loading coefficient for awareness of data usage is 0.4, which is higher than the other two items, indicating that it has a significant impact on the evaluation of data privacy and security. Educational data contains highly sensitive information, and awareness of the purpose of such data is fundamental to data privacy and security. Without transparency regarding the purpose of data usage, users’ trust may turn into passive compliance.

Among the observed variables of acceptance, the factor loadings of the three items were 0.458, 0.516, and 0.47, respectively. The factor loading of willingness to actively use was relatively high, indicating that it had a greater impact on acceptance. Willingness to actively use is a direct reflection of users’ ultimate behavioral intention to adopt the technology, while compatibility and related training are only external moderating variables. Promoting active willingness can achieve the sustainability of educational innovation behavior.

Among the observed variables of social empowerment, the factor loading coefficient of ‘technology + social problem solving’ is 0.407, indicating that it has a high impact on social empowerment. ‘technology + social problem solving’ requires the collaborative participation of the government, enterprises, communities, and individuals to ensure that resources are accurately matched to social needs, build public trust, and stimulate social participation.

5. Conclusions and Recommendations

5.1 Conclusions

This paper aims to explore the innovative evaluation mechanisms for higher education teaching and learning enabled by artificial intelligence. Through a literature review, the paper analyzes the innovative evaluation mechanisms for higher education teaching and learning enabled by AI, identifies relevant evaluation indicators, and designs an AI-enabled higher education teaching and learning evaluation innovation survey questionnaire. Using data from current students, faculty members, and administrative staff at relevant universities as the sample, the paper analyzes the innovative evaluation mechanisms for higher education teaching and learning enabled by AI. Through structural equation modeling, it was confirmed that six dimensions—learning outcomes, teaching processes, feedback on results, data privacy and security, acceptance, and social empowerment—significantly drive the innovation of the evaluation system. Among these, the integration of multi-dimensional data is the core foundation for optimizing learning diagnostics, while the fairness of evaluation results and the transparency of data usage are the foundation of trust in teaching reforms and the key to privacy protection. After refining the model, the error correlations between learning diagnosis and personalized reports, data collection and feedback generation, and privacy trust and regulatory mechanisms validated the dynamic interconnectivity of the innovative evaluation mechanism. Among these, in terms of social empowerment, the ability to combine ‘technology with social problem-solving’ is the key link between individual development and societal needs. It is hoped that the findings of this study can provide insights for the innovative evaluation mechanism of AI-empowered higher education teaching and learning.

5.2 Policy Recommendations

First, accelerate the construction of a national intelligent education evaluation standard system. Based on the characteristics of artificial intelligence, establish a basic framework for evaluating educational artificial intelligence, with a focus on multi-dimensional data integration mechanisms to ensure the comprehensiveness of the model. In terms of model algorithms, establish relevant systems for algorithm transparency, publicly disclose the parameter logic of evaluation models to increase user trust, and have third-party institutions regularly test the fairness of the model. Central government special funds can be used to deploy lightweight evaluation systems in resource-poor areas, thereby addressing resource barriers that affect educational equity.

Second, promote innovation in university evaluation mechanisms. Based on feedback data on educational quality, optimize existing university evaluation models to build dynamic and accurate evaluation models; establish a verification mechanism for models, allowing universities to combine student peer evaluation data with AI analysis results to adjust the evaluation system, thereby preventing excessive quantification of the evaluation system; Universities can actively encourage teachers to participate in training and practical operations of artificial intelligence evaluation tools, cultivating their ability to interpret artificial intelligence reports. This can be transformed into teaching improvement strategies. In terms of data security, university teachers should take the lead in maintaining data security to enhance students’ and parents’ trust in the system. Universities can also convert students’ ability evaluation results into relevant credits and link them with industry certification systems to increase social benefits.

Funding

This research was supported by Zhejiang Province Education Science Planning Project (grant no. 2025SCG104) and Higher Education Research Project from Ningbo University of Technology (grant no. 2025NGGJA01).

Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

Reference

- [1] Wu, Y. (2024, July 4). Specialized educational large models will first be launched in 10 disciplines with vertical applications. [EB/OL].
- [2] Zheng, Y., Wang, Y., Wu, G., et al. (2023). The realistic prospects and development direction of educational information science and technology research: An analysis and prospect of F0701 funding in 2018–2022. *Modern Distance Education Research*, 35(1), 10–19.
- [3] Zhao, T., & Li, G. (2023). From connotation to high-quality: The evolution and transformation of the development policies of China's higher education. *Journal of Higher Education*, (5), 8–18.
- [4] Li, Y. (2025). International reference from artificial intelligence-enabled evaluation reform in higher education. *e-Education Research*, 46(02), 32–40. <https://doi.org/10.13811/j.cnki.eer.2025.02.005>
- [5] Xin, T. (2023). The four key links in deepening the reform of educational evaluation. *Journal of China Examinations*, (10), 1–8.
- [6] Zhang, Y. (2025). AI empowering classroom teaching: Value implications, realistic challenges, and practical paths. *Theory and Practice of Education*, 45(18), 51–55.
- [7] Cui, J., & Ma, Y. (2023). The research progress and future prospect of artificial intelligence education in China. *Journal of Higher Education Management*, 17(6), 31–39.
- [8] Li, Q., Gao, H., & Li, S. (2020). Focus on crossover technology in education and social development: Introduction to *Innovating Pedagogy 2020*. *Journal of Distance Education*, 38(2), 17–26.
- [9] Zhang, D., & Nie, Z. (2023). Digital transformation of school education: Driving factors and promotion path. *Contemporary Education Sciences*, (4), 54–62.
- [10] Wu, Z. (2025). Motivation, connotation and path for artificial intelligence to empower higher education evaluation reform. *Heilongjiang Higher Education Research*, 43(02), 133–139. <https://doi.org/10.19903/j.cnki.cn23-1074/g.2025.02.010>
- [11] Xie, S. (2024). The basic direction, key issues, and critical pathways for deepening comprehensive reform in higher education in the new era. *China Higher Education*, (11), 22–26.
- [12] Du, J. (2025). Research on the artificial intelligence literacy education services in American university libraries and its implications. *Library and Information Service*, 69(14), 135–148. <https://doi.org/10.13266/j.issn.0252-3116.2025.14.012>
- [13] Niu, K., & Gu, Y. (2025). Research on the strategy and layered system design of artificial intelligence talent cultivation in Japanese universities. *Studies in Foreign Education*, 52(06), 60–75. <https://doi.org/10.20250/j.sfe.2025.06.008>
- [14] Lin, J., & Liu, Y. (2024). Achieving interdisciplinarity via de-departmentalization: Organizational innovation in Singapore University of Technology and Design. *Modern University Education*, (4), 38–48 + 112.
- [15] Bao, X. (2021). Risks and countermeasures to data sharing: Taking online lending platforms for example. *Journal of Shanghai University of Political Science and Law (The Rule of Law Forum)*, (5), 122–136.
- [16] Pereira, E., Nsair, S., Pereira, L. R., et al. (2024). Constructive alignment in a graduate-level project management course: An innovative framework using large language models. *International Journal of Educational Technology in Higher Education*, (21), 1–21.
- [17] Li, C., & Xin, L. (2008). Research on methods for evaluating the reliability and validity of survey questionnaires. *Chinese Journal of Health Statistics*, (05), 541–544.
- [18] Fan, Z., & Wang, N. (2021). On the unsafe or reckless behaviors of the seafarer based on the structural equation model (SEM). *Journal of Safety and Environment*, 21(2), 682–687. <https://doi.org/10.13637/j.issn.1009-6094.2019.1387>