Research on the Dual-Pathway Impact of Artificial Intelligence Technology on Teachers' Human-Machine Collaboration

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Abstract: Based on the Job Demands-Resources (JD-R) theory and the Unified Theory of Acceptance and Use of Technology (UTAUT) model, the study proposed and tested the dual-pathway impact of artificial intelligence (AI) technology on teachers' human-machine collaboration. The results indicated that AI had both negative and positive effects on teachers' human-machine collaboration. Specifically, perceived risk, through the partial mediating effect of AI anxiety, negatively influenced the collaboration between teachers and AI. Conversely, technology acceptance had a positive influence on teachers' human-machine collaboration through the partial mediation of human-machine compatibility.

Keywords: teachers' human-machine collaboration, JD-R theory, UTAUT model, dualpathway impact

1. Introduction

With the deep integration of artificial intelligence and education, the extent to which teachers apply intelligent technologies is crucial for the breadth and depth of their collaborative efforts with AI in teaching. On the one hand, intelligent technology plays an important role in assisting teachers in designing curriculums, innovating pedagogical strategies and conducting teaching evaluations (Kim et al., 2022; Rudolph et al., 2023; Moore et al., 2022). These advantages have stimulated teachers' enthusiasm for using technology for teaching and have promoted knowledge creation through human-machine collaboration (Shang et al., 2022). On the other hand, the high complexity brought by AI technology, along with potential issues such as data leakage and algorithmic discrimination, hinder collaboration between teachers and technology, leading to an imbalance in the relationship between AI and education (Gillani et al., 2023). From the perspective of the current state of educational development, the impact of intelligent technology on teachers' human-machine collaboration is not one-sided but may exhibit the "double-edged sword" effect where both positive and negative impacts coexist.

Previous studies have analyzed the potential single-sided impacts of intelligent technology application from various perspectives, but have not yet delved into the "doubleedged sword" effect of intelligent technology application on teacher-human machine collaboration from an integrated perspective. To reveal the dual-pathway impact of the synergy between teachers and intelligent technology, this paper selects the Job Demands-Resources (JD-R) model, a mature theoretical framework, as support to explore both positive and negative impacts mechanisms of intelligent technology on teachers' human-machine collaboration.

2. Theoretical Framework

In the fields of psychology and management, the JD-R model provides a comprehensive theoretical framework to explore the bidirectional impact of work on workers. This model

suggests that all job characteristics can be categorized into two types: job demands and job resources (Demerouti et al., 2001). This model is applicable to various occupational environments.

In the domain of human-machine collaborative teaching, the work content involved when teachers utilize intelligent technology for instructional support can also be divided into two categories: resources and demands. Among these, the perceived risk that teachers encounter during the application of intelligent technology can be seen as a job demand. When teachers are concerned about technological risks such as information leakage and operational errors, it becomes difficult for them to establish information sharing and trust with artificial intelligence (Pillai & Sivathanu, 2020). Emotionally, this can lead to anxiety or fear towards the technology, which significantly reduces their willingness to engage with it (Kaplan & Haenlein, 2019).

The job resources of teachers using intelligent technology to assist teaching refer to resources that aid in achieving instructional goals, reducing job demands and promoting personal development. Teachers' acceptance of artificial intelligence technology, which encompasses the process of adaptation, acceptance, and internalization of intelligent technology by teachers, can be regarded as a key foundational resource for collaborative teaching (Zhang et al., 2023). Furthermore, the proponents of human-machine compatibility, Coll and Coll (1989), suggested that if intelligent agents can interact with target users according to human thinking patterns and gain users' trust, the user's willingness to use them will significantly increase and greatly affect the performance of human-machine collaboration. When teachers have a higher degree of acceptance and reliance on artificial intelligence, they are able to generate more collective knowledge and achieve higher educational benefits (Choi et al., 2023).

This study further combined the UTAUT model proposed by Venkatesh et al. (2003) to predict the factors that affect teachers' technology acceptance and use behavior. This model has been widely applied in the field of artificial intelligence technology (Venkatesh, 2022). Starting from factors such as perceived risk, technology acceptance, AI anxiety, and human-machine compatibility, this study explored how AI technology impacts human-machine collaboration among primary and secondary school teachers. On one hand, it examined the loss path stemming from perceived risk and the mediating role of AI anxiety therein. On the other hand, it investigated the gain path initiated by technology acceptance and the mediating role of human-machine compatibility. As shown in Figure 1, this study investigated the mechanisms by which intelligent technology brings about both negative and positive impacts on the human-machine collaboration among teachers.

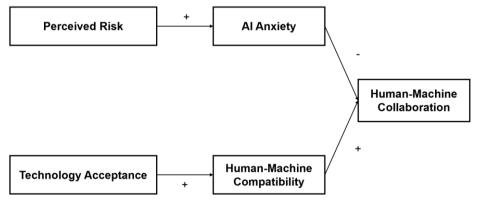


Figure 1. The Dual-pathway of AI Technology Affecting Teachers' Human-Machine Collaboration.

3. Method

3.1 Participants

Participants were 254 Chinese primary and secondary school teachers who have used intelligent technology to assist in teaching activities. Among them, there were 56 male teachers, accounting for 22.05%, and 198 female teachers, accounting for 77.95%. 68 teachers with 16 years or less of teaching experience, making up 26.77%, and 186 teachers with more than 16 years of teaching experience, constituting 73.23%.

3.2 Measures

Perceived risk. Perceived risk was measured by adapting 4 items from Chatterjee et al. (2020). This dimension measured the extent to which teachers perceive potential risks such as distracting student attention and reducing teaching efficiency when using intelligent technology during teaching. The Cronbach's Alpha was 0.884.

Technology acceptance. Technology acceptance is influenced by two main factors: perceived usefulness and perceived ease of use (Davis, 1989). To measure the technology acceptance, 3 items adapted by Venkatesh et al. (2003) were used. The Cronbach's Alpha was 0.887.

Al anxiety. Al anxiety is caused by the panic and tension of humans towards the unclear direction of artificial intelligence development (Johnson & Verdicchio, 2017), which was measured using 4 items adapted by Venkatesh et al. (2003). The Cronbach's Alpha was 0.892.

Human-machine compatibility. By adapting 3 items from Wang et al. (2020) to measure human-machine compatibility, evaluated the degree to which teachers perceive the alignment of AI technology with their values, experiences, and needs. The Cronbach's Alpha was 0.929.

Human-machine collaboration. Human-machine collaboration was measured with 4 items, adapting from Timothy et al. (2010), Li et al. (2023) and Zhu et al. (2021). The Cronbach's Alpha was 0.966.

All items were measured through a 5-point Likert scale ordered from 1(Totally disagree) to 5 (Totally agree).

4. Results

4.1 Descriptive analysis

Table 1 Shows the means, standard deviation and correlations of the study variables.

	Μ	SD	(1)	(2)	(3)	(4)	(5)
(1) Perceived risk	2.73	0.85	1				
(2) Technology acceptance	3.96	0.78	08	1			
(3) AI anxiety	2.66	0.82	.24**	35**	1		
(4) Human-machine compatibility	3.96	0.74	23**	.75**	37**	1	
(5) Human-machine collaboration	4.02	0.75	22**	.76**	37**	.91**	1

 Table 1. Descriptive Statistics and Correlation Coefficients of Variables

Notes: * p < 0.05; ** p < 0.01; M = mean; SD = standard deviation

Perceived risk showed a positive correlation with AI anxiety (r = 0.24, p < 0.01), while it was negatively correlated with human-machine collaboration (r=-0.22, p<0.01). Additionally, AI anxiety exhibited a negative relation with human-machine collaboration (r=-0.37, p<0.01). Technology acceptance was positively correlated with Human-machine compatibility (r=0.75, p<0.01) and human-machine collaboration (r=0.76, p<0.01). Furthermore, human-machine compatibility showed a strong positive relation with human-machine collaboration (r=0.91, p<0.01). Collectively, these correlations aligned with the anticipated relationships between the variables.

4.2 Mediation effect analysis

We used the PROCESS plugin of SPSS for mediating effect analysis. Table 2 and Table 3 show the test results of the mediating effect of AI anxiety between perceived risk and human-machine collaboration.

Table 2. Regression Analysis Results of the Relationship between Perceived Risk, AI Anxiety and Human-Machine Collaboration in the Chain Mediation Model

Dependent Variable	Independent Variable	R	R ²	F	β	t
Human-Machine Collaboration	Perceived Risk	.29	.09	4.62***	20	-3.76***
AI Anxiety	Perceived Risk	.31	.10	5.45***	.25	4.25***
Human-Machine Collaboration	Perceived Risk Al Anxiety	.43	.19	9.39***	13 31	-2.39* -5.52***

Notes: * p < 0.05; ** p < 0.01; *** p < 0.001

Table 3. The Direct and Mediating Effects between Perceived Risk and Human-Machine Collaboration

Effect Relationship	Effect	LLCI	ULCI	Effect Proportion
Total Effect	20	31	10	
Direct Effect	13	23	02	62.5%
Indirect Effect	08	14	02	37.5%

When Bootstrap=5000, the analysis results showed that perceived risk significantly impacted on human-machine collaboration (β =-0.20, p<0.001), confirming the overall effect's validity. Additionally, perceived risk had a significant impact on AI anxiety (β =0.25, p<0.001). Upon entering both perceived risk and AI anxiety into the regression equation, perceived risk continued to show a significant effect on human-machine collaboration (β =-0.13, p<0.05), while AI anxiety also significantly affected teachers' human-machine collaboration (β =-0.31, p<0.001). This suggests that AI anxiety played a valid mediating role, partially mediating the relationship between perceived risk and human-machine collaboration. The mediating effect of AI anxiety was substantial, accounting for 37.5% of the total effect.

Table 4 and Table 5 show the test results of the mediating effect of human-machine compatibility between technology acceptance and human-machine collaboration.

Table 4. Regression Analysis Results of the Relationship between Technology Acceptance, Human-Machine Compatibility and Human-Machine Collaboration in the Chain Mediation Model

Dependent Variable	Independent Variable	R	R ²	F	β	t
Human-Machine Collaboration	Technology Acceptance	.76	.58	68.41***	.73	17.96***
Human-Machine Compatibility	Technology Acceptance	.75	.57	64.51***	.71	17.53***
Human-Machine	Technology Acceptance	.92	.84	220.82***	.17	4.46***
Collaboration	Human-Machine Compatibility	.92	.04	220.02	.79	20.34***

Notes: * p < 0.05; ** p < 0.01; *** p < 0.001

Table 5. The Direct and Mediating Effects between Technology Acceptance and Human-Machine Collaboration

Effect Relationship	Effect	LLCI	ULCI	Effect Proportion
Total Effect	.73	.65	.81	
Direct Effect	.17	.09	.24	22.8%
Indirect Effect	.57	.45	.67	77.2%

Similarly, the results showed a significant impact of technology acceptance on humanmachine collaboration (β =0.73, p<0.001), confirming the validity of the overall effect. There was a significant impact of technology acceptance on human-machine compatibility (β =0.71, p<0.001). When both technology acceptance and human-machine compatibility entered the regression equation, technology acceptance maintained a significant effect on humanmachine collaboration (β =0.17, p<0.001), human-machine compatibility also had a significant impact on human-machine collaboration (β =0.79, p<0.001), indicating that the mediating role of human-machine compatibility was valid and partially mediated. The mediating effect of human-machine compatibility accounted for 77.2% of the total effect.

5. Discussion

Overall, the results confirmed that artificial intelligent technology, as a double-edged sword, had a dual impact on teachers' human-machine collaboration.

On one hand, Perceived risk, through the partial mediating role of AI anxiety, diminished the level of teachers' human-machine collaboration. As an emerging technology, the application of AI in teaching activities also comes with certain risks, such as the infringement of learners' personal privacy, surveillance, and manipulative behaviors (Li & Huang, 2020). Teachers, facing new demands of AI in education, are prone to anxiety, which is generally attributed to the intervention of AI has brought the teaching process into a "black box" that cannot be recognized by humans. To avoid the risks associated with AI, some teachers may choose to reduce the application of intelligent technology in their teaching, directly lowering their performance in human-machine collaboration. Concurrently, these risk issues can lead to a sense of distrust and fear towards the educational value of AI among teachers, intensifying AI anxiety and thereby weakening their willingness to use intelligent technology for teaching assistance, which reduces the depth of collaboration between teachers and intelligent technology (Kummer et al., 2017).

On the other hand, the partial mediating effect of technology acceptance through human-machine compatibility had a positive impact on teachers' human-machine collaboration. The analysis reveals that the more teachers perceive the effectiveness of Al technology in enhancing teaching performance and its ease of use, the more likely they are to incorporate intelligent technology into the design of teaching content and activity processes. During this process, teachers recognize the potential of intelligent technology to align with the needs of educational and teaching development, which contributes to improving their humanmachine compatibility and subsequently encourages them to engage in human-machine collaborative teaching (Nazaretsky et al., 2022).

Based on a dual-pathway analysis of the impact of intelligent technology on teachers' human-machine collaboration, this study proposes that technology acceptance, as the "benefit edge," and perceived risk, as the "harm edge," jointly influence the degree of teachers' human-machine collaboration. The rapid development of intelligent technology inevitably brings risks and issues, which puts higher demands on teachers. Teachers need to establish a scientific perspective on technology, correctly recognize that technology is a "double-edged sword", and use intelligent technology reasonably in teaching practice to optimize the teaching process.

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References

- Kim, J., Lee, H., & Cho, Y. H. (2022). Learning design to support student-AI collaboration: Perspectives of leading teachers for AI in education. *Education and Information Technologies*, 27(5), 6069-6104.
- Rudolph, J., Tan, S., & Tan, S. (2023). ChatGPT: Bullshit spewer or the end of traditional assessments in higher education?. *Journal of applied learning and teaching*, 6(1), 342-363.
- Chatterjee, S., & Bhattacharjee, K. K. (2020). Adoption of artificial intelligence in higher education: A quantitative analysis using structural equation modelling. *Education and Information Technologies*, 25, 3443-3463.
- Choi, S., Jang, Y., & Kim, H. (2023). Influence of pedagogical beliefs and perceived trust on teachers' acceptance of educational artificial intelligence tools. *International Journal of Human–Computer Interaction*, 39(4), 910-922.
- Coll, R., & Coll, J. H. (1989). Cognitive match interface design, a base concept for guiding the development of user friendly computer application packages. *Journal of Medical Systems*, 13, 227-235.
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 319-340.
- Demerouti, E., Bakker, A. B., Nachreiner, F., & Schaufeli, W. B. (2001). The job demands-resources model of burnout. *Journal of Applied psychology*, 86(3), 499.
- Gillani, N., Eynon, R., Chiabaut, C., & Finkel, K. (2023). Unpacking the "Black Box" of AI in education. Educational Technology & Society, 26(1), 99-111.
- Johnson, D. G., & Verdicchio, M. (2017). Reframing AI discourse. Minds and Machines, 27, 575-590.
- Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business horizons*, 62(1), 15-25.
- Kummer, T. F., Recker, J., & Bick, M. (2017). Technology-induced anxiety: manifestations, cultural influences, and its effect on the adoption of sensor-based technology in German and Australian hospitals. *Information & Management*, 54(1), 73-89.
- Li, J., & Huang, J. S. (2020). Dimensions of artificial intelligence anxiety based on the integrated fear acquisition theory. *Technology in Society*, 63, 101410.
- Li, Z., Zhu, X., & Guo, J. (2023). Influence of Man-Machine Cooperation Degree on Employees' Job Crafting in Al Application Scenarios: The Mediating Role of Psychological Empowerment. *Chinese Personnel Science*, (09), 35-45.
- Moore, S., Nguyen, H. A., Bier, N., Domadia, T., & Stamper, J. (2022). Assessing the quality of studentgenerated short answer questions using GPT-3. *European conference on technology enhanced learning (pp. 243-257)*. Cham: Springer International Publishing.
- Nazaretsky, T., Ariely, M., Cukurova, M., & Alexandron, G. (2022). Teachers' trust in AI-powered educational technology and a professional development program to improve it. *British journal of educational technology*, 53(4), 914-931.
- Pillai, R., & Sivathanu, B. (2020). An empirical study on the online learning experience of MOOCs: Indian students' perspective. *International Journal of Educational Management*, 34(3), 586-609.
- Shang, H., & Sivaparthipan, C. B. (2022). Interactive teaching using human-machine interaction for higher education systems. *Computers and Electrical Engineering*, 100, 107811.
- Timothy, T., Chee, T. S., Beng, L. C., Sing, C. C., Ling, K. J. H., Li, C. W., & Mun, C. H. (2010). The self-directed learning with technology scale (SDLTS) for young students: An initial development and validation. *Computers & Education*, 55(4), 1764-1771.
- Venkatesh, V. (2022). Adoption and use of AI tools: a research agenda grounded in UTAUT. *Annals of Operations Research*, 308(1), 641-652.
- Wang, S., Yu, H., Hu, X., & Li, J. (2020). Participant or spectator? Comprehending the willingness of faculty to use intelligent tutoring systems in the artificial intelligence era. *British Journal of Educational Technology*, 51(5), 1657-1673.
- Zhang, C., Schießl, J., Plößl, L., Hofmann, F., & Gläser-Zikuda, M. (2023). Acceptance of artificial intelligence among pre-service teachers: a multigroup analysis. *International Journal of Educational Technology in Higher Education*, 20(1), 49.
- Zhu, X., Wang, S., & He, Q. (2021). Impact of Skill Requirements on Employees" Thriving at Work: From the Perspective of Artificial Intelligence Embedding. *Foreign Economics & Management*, 43(11), 15-25.