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Preparing for AI-enhanced education: Conceptualizing and empirically examining teachers' AI readiness

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ABSTRACT

Teachers are at the front lines of implementing artificial intelligence (AI) in education. They are expected to develop an adequate understanding of AI and become educated users as well as educators. Their readiness for the use of AI is critical for the success of AI-enhanced education. The present study conceptualized AI readiness from four components: cognition, ability, vision, and ethics in the educational use of AI, and investigated their interrelationships and their implications for teachers' work. The data from 3164 primary school teachers were collected and analyzed by partial least square structural equation modelling and cluster analysis. This study found that cognition, ability, and vision in the educational use of AI were positively associated with ethical considerations. The four components of AI readiness all positively predicted, whereas perceived threats from AI negatively predicted, AI-enhanced innovation, which in turn positively predicted teachers' job satisfaction. This study identified three clusters of teachers based on their AI readiness levels. Teachers with high levels of AI readiness tended to perceive low threats from AI and demonstrate high AI-enhanced innovation as well as high job satisfaction. However, teachers from different socio-economic regions and of different genders showed no significant differences regarding AI readiness and its impact on their jobs. This study empirically validated the importance of AI readiness for teachers' work and has important implications for the development of strategies and policies facilitating successful AI-enhanced education.

1. Introduction

Artificial intelligence (AI) has been increasingly used in a variety of fields (e.g., industry, finance, and education) to promote innovation and increase work efficiency (Ng et al., 2021). In education, AI is touted as a seemingly almighty tool, supporting or even replacing teachers' work by automatically tracking students' progress, assessing their performance, and providing personalized help (Albacete et al., 2019; Chounta et al., 2022; Tarus et al., 2018). Teachers can rely on AI to make informed decisions on orchestrating teaching practice so as to better support student learning (Van Leeuwen & Rummel, 2020).

Nonetheless, in reality, intelligent tools for education are rarely used consistently in K-12 classrooms (Ferguson et al., 2016). Schiff (2021) found that much practice and research related to the educational use of AI did not deliver promised changes and benefits. Among the multiple reasons leading to this controversy, for instance, the quality of AI and users' preferences (Luckin et al., 2022) and ethical concerns (Holmes et al., 2022), an essential culprit could be the techno-centric approach vehemently promoted by some in the educational field, which stresses the role of AI but ignores the agency of teachers who can decide whether, what, when, and how AI technologies are used in the first place (Luckin et al., 2022). Teachers are on the front lines of AI deployment, bridging schools' AI policies and students' needs, thereby the critical role in the successful implementation of AI in schools (Felix, 2020). However, many teachers may not be actually ready for AI-enhanced education, though they are mostly aware of the potential benefits that

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AI can bring to education (Chounta et al., 2022). Their inadequate AI readiness may partially contribute to the gap between rapid advances in AI technologies and comparatively slow and unsatisfactory adoption of them in education (Luan et al., 2020; Luckin et al., 2022).

According to prior research on AI readiness (e.g., Holmström, 2022; Karaca et al., 2021; Luckin et al., 2022) while considering this study's context, AI readiness is defined as the state of preparedness among teachers in terms of their cognition, ability, vision, and ethical considerations with respect to the use of AI in education. Theoretically, teachers with high levels of AI readiness may have the knowledge and competence necessary for innovating their work by experimenting with and adapting to opportunities promised by AI (Jöhnk et al., 2021; Luckin et al., 2022). The innovative attempts may in turn improve their work experience, fostering high job satisfaction (Bhargava et al., 2021). Conversely, those with low levels of AI readiness may feel threatened, worrying about possible disruptions caused by AI to their work and subsequently alienating themselves from AI technologies (Chounta et al., 2022; Luckin et al., 2022).

Though a decent level of AI readiness is considered crucial for successful integration of AI into teaching (Celik et al., 2022), there is limited empirical knowledge regarding how AI readiness affects teachers' work. Even less is known regarding whether and how AI readiness may differ among teachers from distinct demographic backgrounds, particularly genders and socioeconomic backgrounds which have often been reported to cause disparities in the use of conventional technologies (Beaunoyer et al., 2020; Park et al., 2019). In addition, given that the ethical use of AI has been a concern attracting substantial attention (Hagendorff, 2020; Smakman et al., 2021), it would be useful to gain insights into how ethics are related to other components of AI readiness. Considering the increasing use of AI in education for innovating teaching and enhancing educators' work experience (Celik et al., 2022; Luckin et al., 2022), this study sets out to bridge these gaps by addressing the following research questions:

RQ1. How are ethics related to other components of teachers' AI readiness?

RQ2. How are teachers' AI readiness associated with their perceived threats from AI, AI-enhanced innovation, and job satisfaction?

RQ3. How do teachers from different demographic backgrounds vary in AI readiness, perceived threats from AI, AI-enhanced innovation, and job satisfaction?

2. Literature review and hypotheses development

2.1. Prior research on AI readiness

The concept of AI readiness is relatively new, as highlighted in recent studies (Jöhnk et al., 2021; Luckin et al., 2022). Most of the research on AI readiness has been conducted in the business field, where AI has been adopted more widely than in education (Luckin et al., 2022). However, the components of AI readiness are still developing and may differ depending on the specific fields of application.

In the early days of technological readiness research, Parasuraman (2000) proposed a concept of technological readiness and defined it as individuals' inclination to adopt and use new technologies for completing tasks at home and work. Technology readiness was related to mental enablers and inhibitors that determined people's purchase decisions about new technologies. According to Parasuraman (2000), individuals' tendency to use new technologies was caused by the interplay between readiness enablers, including optimism toward technologies and innovativeness for their work, and readiness inhibitors, including discomfort and insecurity resulting from distrust of technologies. However, the technology readiness concept was developed for the service industry to improve customer satisfaction by identifying factors that decrease customers' frustration when interacting with new technologies and encourage their purchase intention. Compared with customers' readiness of using new technologies, educators' readiness of using AI is related to not only themselves but also their students. In addition, AI is different from conventional technologies in that it simulates some degree of human reasoning and learning while conventional technologies acquiesced full control to human beings (Damerji & Salimi, 2021). Therefore, the concept of AI readiness has to be reconsidered and redefined, particularly for educators.

Jöhnk et al. (2021) conceptualized organizational AI readiness based on interviews with 25 AI experts. It comprised 18 factors along five categories, including strategic alignment (aligning organizational needs with AI's potential), resources (finances, personnel, and IT infrastructure allocated for AI implementation), knowledge (AI awareness, skills, and ethics), culture (innovativeness, collaboration, and change management), and data (availability and quality of data for building valid AI models). Nonetheless, the AI readiness framework was developed for the industry sector and mainly reflected the views of the management staff. The 18 factors within five categories were obtained through qualitative analysis of experts' views and were not validated empirically through quantitative studies, thus leading to doubtful generalization to a broad population and other fields.

In education, Luckin et al. (2022) gave a more comprehensive introduction of AI readiness and highlighted contextualization when applying AI readiness to the educational sector. They proposed an AI readiness training framework comprising seven steps, involving engaging with the idea of AI readiness, pinpointing challenges in education to be solved, identifying and collecting data to address the challenges, applying AI techniques for data analysis, learning from the AI results, and iterating the framework if needed. However, Luckin et al.'s (2022) AI readiness framework was developed based on Cross-Industry Standard Process for Data Mining in the business sector, focusing on AI-supported data mining, instead of AI-enhanced teaching practice. In addition, applying the a priori framework from the business sector directly to the field of education may not well address educational challenges facing students and educators.

To prepare medical students for new roles and tasks in AI-enhanced healthcare, Karaca et al. (2021) developed an AI readiness scale for them, which comprised four components, including cognition (cognitive readiness regarding students' basic knowledge of AI), ability (students' competence in using AI for learning), vision (students' critical understanding of AI), and ethics (legal and ethical norms for responsible use of AI). However, Karaca et al. (2021)'s AI readiness scale was developed for specific healthcare student population and the empirical relationships between AI readiness and factors related to AI-enhanced learning were not reported. Despite these, among the prior studies examining AI readiness, Karaca et al. (2021)'s scale is particularly relevant to the research on AI readiness for educators, as their conceptualization of AI readiness is comprehensive and empirically validated.

In short, prior studies (e.g., Holmström, 2022; Luckin et al., 2022) have generally agreed on the importance of AI readiness for individual and organizational use of AI. Nevertheless, the studies on AI readiness are mostly conceptual, theorizing on its definition and factors comprising it. Though AI is gradually becoming a part of education (Brouillette, 2019), limited attention has been given to teachers who normally oversee the design and implementation of AI-enhanced education (Felix, 2020). Few studies have been conducted to empirically examine or validate the concept of AI readiness and its implications for teachers' work (Bhargava et al., 2021; Luckin et al., 2022).

2.2. Hypotheses development

Drawing on Karaca et al. (2021), teachers' AI readiness consists of four components: cognition, ability, vision, and ethics. Aligned with the current research context, the component of cognition refers to teachers' cognitive readiness, involving knowledge about the functions of AI, importance of AI for education, and relationships between AI and human teachers. The ability component is related to teachers' competence and skills in the use of AI for teaching, for instance, selecting AI technologies appropriate for different activities, and designing and refining AI pedagogy for better education. Vision is concerned with teachers' perceptions of strengths and limitations of AI for education and insights into opportunities and challenges involved. Compared with cognitive readiness which emphasizes teachers' knowledge of AI for education, vision is more focused on their ability to envision and explore the potential and boundaries of AI in education. The component of ethics refers to teachers' compliance with ethical and legal norms and regulations related to the use of AI for education.

Even though the ethical issue has been attracting increasing attention (Hagendorff, 2020), limited is known about what may contribute to individuals' ethical knowledge and practice. While external regulations such as ethical guidelines are important, research suggests that they may be insufficient in influencing individuals' ethical decision-making (Hagendorff, 2020; Mittelstadt, 2019). Therefore, it is essential to explore whether teachers' internal factors, such as their cognition, ability, and vision in the use of AI, may predict their ethical use of AI in education. By considering both external regulations and internal factors that influence ethical decision-making, we can take a more comprehensive approach to promoting teachers' ethical use of AI in education. Thus, the following hypotheses are proposed:

Teachers' cognition (H1a), ability (H1b), and vision (H1c) in the educational use of AI are positively associated with their ethical use of AI.

As AI is likely to cause great changes to people's lives in the foreseeable future, its expansion in the field of education appears to be threatening for some educators across different levels of schools (Chounta et al., 2022; Walia & Kumar, 2022). Teachers' perceptions of AI threats are manifested in different ways, such as unsafe feelings about their identities in education, job insecurity, and disruptions to their conventional work (Mirbabaie et al., 2022). However, those who demonstrate higher readiness for the use of AI may embrace AI with more confidence and are likely to adopt innovative behaviors, such as risk-taking, experimentation with new pedagogy, and problem-solving (Jöhnk et al., 2021; Microsoft, 2020). In this sense, AI-enhanced innovation goes beyond introducing more advanced technologies into more classrooms (Popenici & Kerr, 2017). Teachers with high AI readiness can reinvent approaches to teaching in order to better prepare students for the future society (Schleicher, 2015). Therefore, the following hypotheses are developed:

Teachers' cognition (H2a), ability (H2b), vision (H2c), and ethics (H2d) in the use of AI are positively associated with their AI-enhanced innovation.

Teachers' cognition (H3a), ability (H3b), vision (H3c), and ethics (H3d) in the use of AI are negatively associated with their perceived threats from AI.

AI can free teachers from monotonous administrative and teaching work and assist them to focus on innovative work such as developing students' higher-order thinking skills (Belpaeme et al., 2018). Teachers can add humanity to the deployment of AI in education by designing and implementing AI pedagogy and offering social and emotional care (Felix, 2020). The symbiotic interaction between teachers and AI may form a positive complementarity and strengthen teachers' innovation at work, eventually leading to increased job satisfaction (Nazareno & Schiff, 2021), which refers to a positive emotional state attained from one's appraisal of his/her job performance (Locke, 1976).

Although AI is expected to revolutionize learning and teaching in education (Zawacki-Richter et al., 2019), many educators are apprehensive about the possibility of being replaced or having their skills become obsolete (Celik et al., 2022; Chounta et al., 2022). This sense of threat posed by AI may discourage educators from taking risks, ultimately hampering their ability to innovate in teaching with AI (Jöhnk et al., 2021; Kim & Kim, 2022). In addition, perceived threats from AI may lead to a sense of job insecurity and cause anxiety in teachers (Bhargava et al., 2021), thereby eventually undermining their job satisfaction. Informed by the analyses above, the following hypotheses are proposed:

H4. AI-enhanced innovation is positively associated with teachers' job satisfaction.

H5a. Perceived threats from AI are negatively associated with AI-enhanced innovation.

H5b. Perceived threats from AI are negatively associated with teachers' job satisfaction.

Overall, the hypotheses of this study are visualized in Fig. 1.

3. Methodology

3.1. Participants and research contexts

The participants of this study were recruited from 19 cities in eastern China. To respond to the call from MOE of China to modernize school education using AI (Yan & Yang, 2021), the educational bureaus of these cities have been working to deploy AI for education following the top-down approach by assisting primary and secondary schools to collaborate with technology vendors or help them develop AI applications based on their talent resources.

This study utilized convenience sampling for the participant selection. With the assistance of the educational bureaus of these cities, primary school teachers who were involved in this scheme were approached through an online survey platform, as primary schools normally face less pressure from entrance examinations than secondary schools and thus were active in adopting new technologies for improving and diversifying education. This phenomenon is supported by Celik et al. (2022) who found in their review of teachers' use of AI that primary education was the domain where AI was most frequently used by teachers. Moreover, teachers with prior experience using AI may possess a strong appreciation for the importance of AI readiness and its impact on their professional responsibilities.

As the researchers had no access to information about the total number of the teachers who were invited to participate, the response rate could not be calculated. After excluding invalid responses, the present study retained valid responses from 3164 out of 3950 participants. These valid responses included 1264 teachers from downtown areas, 943 teachers from town areas, and 957 teachers from village areas. Among the participants, 432 were males and 2732 were females, with an average age of 36.82 (SD = 8.10). The participating teachers taught courses ranging from Year 1 to Year 6, including literacy, mathematics, English as a foreign language (EFL), chemistry, music, and so on. Those teaching EFL made up the majority of the participants (N = 2236), followed by those teaching literacy (N = 392), mathematics (N = 323), and other courses (N = 213). The popularity of AI in EFL is probably due to the widespread adoption of AI-powered language learning applications thanks to the advances in natural language processing technologies (Wang et al., 2023; Randall, 2019). AI technologies such as chatbots have also been adopted by teachers to teach literacy and Chinese vocabulary (Chen et al., 2020). As for mathematics learning, many primary school teachers start to use intelligent tutoring systems for automated grading (Hwang & Tu, 2021).

3.2. Instrumentation

Besides the items gathering participants' demographic information, the 31-item survey instrument comprised seven variables, including the four variables of AI readiness (cognition, ability, vision, and ethics), AI-enhanced innovation, perceived threats from AI, and job satisfaction (see Appendix A). The items were rated on a five-point Likert scale where 1 indicated "strongly disagree" and 5 "strongly agree". The four variables of AI readiness were adapted from Karaca et al. (2021). Five

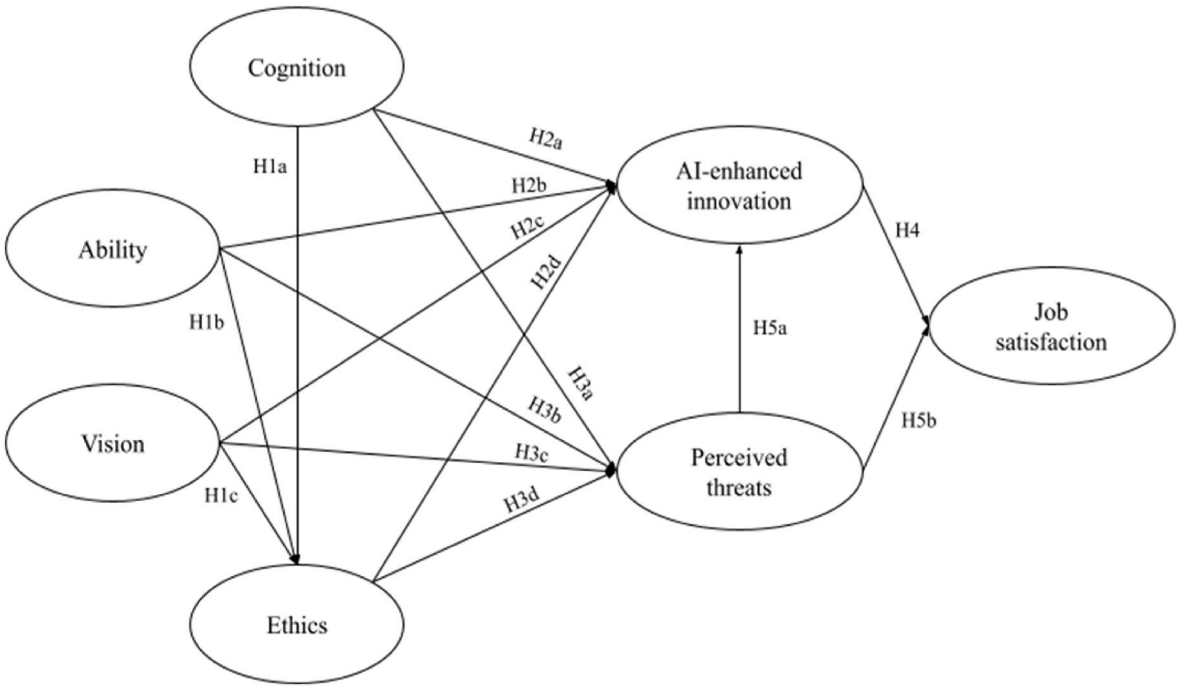

Fig. 1. Hypothesize AI readiness model.

items were used to represent the concept of cognition in the use of AI, for instance, "I understand how AI technologies are trained and function in education." Six items represented the ability to use AI for teaching, for instance, "I can optimize and reorganize the teaching process with the help of AI technologies." There were three items indicating the concept of vision in the use of AI for teaching, for example, "I foresee the opportunities and challenges that AI technologies entail for education." There were four items measuring ethics in the educational use of AI, for example, "I use the data of teachers and students generated by AI systems following legal and ethical norms." The Cronbach's alpha values of cognition, ability, vision, and ethics in this study were 0.93, 0.97, 0.90, and 0.93, respectively (see Table 1 in Section 4).

The variable of perceived AI threats was developed from Mirbabaie et al. (2022) and consisted of five items, for instance, "I think AI

Table 1
Descriptive statistics, item loadings, reliability, and average variance extracted (AVE).

Variables	Indicators	M (SD)	Factor loadings	Cronbach's alpha	Composite reliability	AVE
Cognition	CO1	4.17 (0.83)	0.85	0.93	0.95	0.77
	CO2	4.14 (0.81)	0.90			
	CO3	3.89 (0.91)	0.89			
	CO4	3.87 (0.92)	0.88			
	CO5	4.14 (0.84)	0.86			
Ability	AB1	3.91 (0.88)	0.90	0.97	0.98	0.87
	AB2	3.91 (0.86)	0.94			
	AB3	3.95 (0.85)	0.95			
	AB4	4.01 (0.83)	0.94			
	AB5	3.94 (0.86)	0.94			
	AB6	4.01 (0.86)	0.92			
Vision	VI1	3.87 (0.85)	0.91	0.90	0.94	0.84
	VI2	3.72 (0.89)	0.92			
	VI3	3.88 (0.86)	0.92			
Ethics	ET1	3.90 (0.88)	0.89	0.93	0.95	0.82
	ET2	4.06 (0.84)	0.93			
	ET3	3.99 (0.87)	0.92			
	ET4	4.13 (0.84)	0.89			
Perceived threats	PT1	2.63 (1.13)	0.85	0.94	0.96	0.81
	PT2	2.79 (1.17)	0.91			
	PT3	3.01 (1.16)	0.90			
	PT4	2.91 (1.18)	0.93			
	PT5	2.83 (1.20)	0.92			
AI-enhanced innovation	INN1	3.76 (0.83)	0.92	0.94	0.96	0.89
	INN2	3.88 (0.78)	0.96			
	INN3	3.86 (0.79)	0.96			
Job satisfaction	JS1	3.50 (0.88)	086	0.93	0.94	0.77
	JS2	3.47 (0.92)	0.83			
	JS3	3.72 (0.86)	0.92			
	JS4	3.82 (0.89)	0.89			
	JS5	3.69 (0.89)	0.91			

Note. n.a = not applicable.

technologies could undermine the importance of teachers in education." The Cronbach's alpha value was 0.94. AI-enhanced innovation was developed from Popenici and Kerr (2017) and was measured by three items with a Cronbach's alpha value of 0.94, for example, "AI technologies enable me to organize teaching innovatively." Job satisfaction came from Ragu-Nathan et al. (2008) and was represented by five items with a Cronbach's alpha value of 0.93, such as "In most ways, my job is close to my ideal."

Since the survey items were originally adapted from English studies, a back-translation approach was used to reduce the discrepancies between the English and the Chinese versions. Prior to administering the survey instrument to the participants, three experts specializing in AI-enhanced education were consulted regarding the face validity of the instrument. The improved survey was sent to eight primary school teachers to check their understanding of the survey items. Those causing confusion were reworded and refined. In addition, Harman's single-factor test was conducted to identify possible common method bias (Podsakoff et al., 2012). After loading all indicators on a single factor, the variance explained by the factor was 47.63%, which is below 50% and thus implies a low possibility of committing common method bias.

3.3. Data analysis

To address the first and second research questions, partial least squares structural equation modelling (PLS-SEM) was employed to assess the relationships among AI readiness components, perceived threats from AI, innovation, and job satisfaction. PLS-SEM was utilized based on two factors: (a) the exploratory nature of this study; and (b) PLS-SEM's primary focus on prediction and exploration, with the aim of maximizing the variance explained in the dependent variables (Willaby et al., 2015). As such, this analytical technique is well-suited to the objective of the current study. The PLSPM package (version 0.4.9; Sanchez, 2013) in R software was utilized to analyze the data. Ordinary least squares estimator was used to estimate the model parameters (Sanchez, 2013). To address the third research question, second-step cluster analysis was first used to categorize teachers based on AI readiness levels. Second-step cluster analysis can automatically identify the optimal number of clusters based on clustering criteria for multiple solutions rather than arbitrary decisions (Benassi et al., 2020), making it one of the most reliable approaches for cluster analysis (Gelbard et al., 2007; Kent et al., 2014). Subsequently, multigroup comparisons were performed on teachers with different levels of AI readiness and from distinct demographic backgrounds.

4. Research results

This section first reported the PLS-SEM results (see Appendix B for the R codes). Then, the findings of cluster analysis based on teachers' AI readiness were presented, followed by the results of multigroup comparisons according to teachers' demographics.

4.1. PLS-SEM findings

4.1.1. The measurement model

Item reliability was examined by assessing items' loadings with their latent constructs, which are expected to exceed 0.70 (Hair et al., 2014). Table 1 shows that all items' loadings ranged from 0.83 to 0.96, implying that item reliability was satisfied.

To assess the convergent validity of the measurement model, two criteria were consulted: internal consistency which can be determined by the latent variables' composite reliability, and the average variance extracted (AVE) of the variables (Fornell & Larcker, 1981). As indicated in Table 1, the composite reliability values were all above 0.70, suggesting that the latent variables were internally consistent. Table 1 also shows that the AVE varied from 0.88 to 0.94, which are greater than the minimum value of 0.50 (Hair et al., 2011).

The discriminant validity of the model was assessed based on the square roots of the latent variables' AVE, which should be greater than the correlation values between the corresponding variable and other variables (Chin, 1998). As shown in Table 2, the square roots of AVE ranged from 0.88 to 0.93, which all exceeded the correlation values between different variables.

Overall, the quality of the measurement model was confirmed.

4.1.2. Structural model

To evaluate the structural model, the path coefficients, the endogenous variables' explanatory power, and the model's goodness-of-fit (GoF) were examined. The bootstrapping approach was used to validate the structural model (Hair et al., 2014). Table 3 presents the bootstrapped results of the structural model, which were illustrated in Fig. 2.

As shown in Table 3 and Fig. 2, among the four components of AI readiness, cognition, ability, and vision in the educational use of AI technologies were positively associated with ethics, with vision manifesting the greatest path coefficient on ethics. Therefore, H1a, H1b, and H1c were substantiated. The four components of AI readiness (cognition, ability, vision, and ethics) were all significantly positively associated with AI-enhanced innovation in teachers' work, thereby, supporting H2a, H2b, H2c, and H2d. Cognition in the use of AI negatively predicted perceived threats from AI, while ability and ethics did not, hence supporting H3a but not H3c and H3d. Contrary to expectations, vision was positively associated with perceived threats from AI. Thus, H3b was not supported. Teachers' perceptions of AI threats negatively predicted AI-enhanced innovation but did not significantly affect their job satisfaction. Therefore, H4a was substantiated while H4b was not. Finally, AI-enhanced innovation in teachers' work was significantly positively associated with their job satisfaction, hence supporting H5.

As PLS-SEM aims to maximize the variance explained in the endogenous variables, an important criterion for determining the quality of the structural model is the R^2 values of these variables (Henseler et al., 2009). According to Cohen (1988), an R^2 value of 0.02, 0.13, and 0.26 suggests a small, medium, and large effect size, respectively. As shown in Fig. 2, the R^2 values of ethics in the educational use of AI, AI-enhanced innovation, perceived threats from AI, and job satisfaction were 0.73, 0.33, 0.01, and 0.30, mostly implying large effect sizes.

In addition, Tenenhaus et al. (2004) proposed a global criterion of goodness-of-fit ($0 < \text{GoF} < 1$) to measure the overall quality of the structural model, with 0.10, 0.25, and 0.36 suggesting small, medium, and large GoF values. In the present study, the GoF value was 0.53, which was substantially high. On the whole, the structural model was acceptable.

4.2. Cluster analysis findings

Two-step cluster analyses were performed on the four components of

Table 2
Correlations between variables and the square roots of AVE.

Constructs	1	2	3	4	5	6	7
1. Cognition	**0.88**						
2. Ability	0.85	**0.93**					
3. Vision	0.75	0.81	**0.91**				
4. Ethics	0.76	0.77	0.82	**0.91**			
5. Perceived threats	−0.09	−0.07	−0.03	−0.06	**0.90**		
6. AI-enhanced innovation	0.51	0.53	0.51	0.52	−0.13	**0.94**	
7. Job satisfaction	0.39	0.41	0.41	0.40	−0.08	0.55	**0.88**

Note. The bold values in the diagonal row show the square roots of the variables' AVE.

Table 3
Bootstrapped results of the structural model.

Hypotheses		Path coefficients	Standard error	Percentile 0.025	Percentile 0.975
H1a	Cognition - > Ethics	0.23***	0.02	0.18	0.28
H1b	Ability - > Ethics	0.16***	0.02	0.10	0.21
H1c	Vision - > Ethics	0.53***	0.01	0.47	0.58
H2a	Cognition - > AI-enhanced innovation	0.12***	0.03	0.06	0.18
H2b	Ability - > AI-enhanced innovation	0.20***	0.03	0.12	0.25
H2c	Vision - > AI-enhanced innovation	0.11**	0.03	0.04	0.18
H2d	Ethics - > AI-enhanced innovation	0.18***	0.03	0.12	0.24
H3a	Cognition - > Perceived threats	−0.14***	0.04	−0.19	−0.08
H3b	Ability - > Perceived threats	−0.02 n.s.	0.04	−0.09	0.04
H3c	Vision - > Perceived threats	0.12***	0.04	0.06	0.18
H3d	Ethics - > Perceived threats	−0.05 n.s.	0.03	−0.10	0.001
H4	AI-enhanced innovation - > Job satisfaction	0.55***	0.02	0.51	0.57
H5a	Perceived threats - > AI-enhanced innovation	−0.10***	0.01	−0.12	−0.07
H5b	Perceived threats - > Job satisfaction	−0.01 n.s.	0.02	−0.04	0.01

Note. $^{***}p < 0.001$; n.s = nonsignificant.

AI readiness. Bayesian Information Criterion (BIC), BIC changes, and the ratio of distance measures were considered to determine the optimal cluster solution while balancing model complexity and accrued information generated by more clusters (Vrieze, 2012). As shown in Appendix C, the three-cluster solution was found to be optimal. It had a lower BIC value (3558.05), a higher BIC change (−1623.46), and the highest ratio of distance measure (3.33).

Table 4 shows the specific composition of the three clusters of teachers, including C1-high levels of AI readiness ($N = 859$, 27.15%), C2-intermediate levels of AI readiness ($N = 1301$, 41.12%), and C3-low levels of AI readiness ($N = 1004$, 31.73%). The three clusters were visualized in Fig. 3. Teachers with an intermediate level of AI readiness accounted for the majority while those with a high level made up the smallest population group.

One-way multivariate analysis of variance (MANOVA) was conducted to assess possible differences among the three clusters in terms of AI readiness components, perceived threats from AI, AI-enhanced innovation, and job satisfaction. Significant differences were identified, Wilks's $\Lambda = 0.15$, $F(14, 6310) = 721.99$, $p < 0.01$. The multivariate η^2 based on Wilks's Λ was 0.62, which was substantial. Follow-up tests to the MANOVA were performed. As given in Table 4, the ANOVA on all seven variables was statistically significant with high values of η^2. Pairwise comparisons showed that, overall, teachers with high AI readiness tended to demonstrate the lowest perceived threats, highest AI-enhanced innovation, and greatest job satisfaction than the other two clusters of teachers.

4.3. Group comparisons based on demographic information

To evaluate whether demographic variables including socioeconomic areas and genders had effects on teachers' AI readiness, their perceptions of AI threats, AI-enhanced innovation, and job satisfaction, one-way MANOVA and *t*-test were conducted.

As for socioeconomic areas, no significant difference was found among teachers from downtowns, towns, and villages, Wilks's $\Lambda = 0.99$, $F(14, 6310) = 1.46$, $p = 0.12$. The multivariate η^2 based on Wilks's Λ was 0.003, which was minimal. Table 5 presents the mean values, standard deviations, and the follow-up ANOVA results. As shown in the table, the ANOVA results for all seven variables were nonsignificant, with minimal values of η^2. The multigroup comparison results were visualized in Fig. 4, which indicates that regardless of the areas where the teachers came from, they demonstrated similar levels of AI readiness, perceived similar levels of threats from AI, and had similar AI-enhanced innovation and job satisfaction.

With regard to genders, independent *t*-tests were conducted. As shown in Table 6, there was only a significant difference between female and male teachers in perceived threats from AI, $t(3162) = 3.79$, $p < 0.001$. Males ($M = 3.01$; $SD = 1.11$) perceived slightly more threats from AI than females ($M = 2.81$; $SD = 1.04$), with a small effect size (Cohen's $d = 0.20$). The 95% confidence interval for the difference in means ranged from 0.09 to 0.31. No significant differences were found in AI readiness, AI-enhanced innovation, and job satisfaction. Fig. 5 displays graphically the differences between female and male teachers, whose lines almost converged on all variables except perceived AI threats.

5. Discussion

Although AI has been increasingly utilized in education and has been found to be beneficial and powerful for student learning (Smakman et al., 2021; Xia et al., 2022), little attention has been paid to the needs and challenges faced by teachers in AI-enhanced teaching (Celik et al., 2022; Langran et al., 2020). Teachers are seen as one of the crucial stakeholders in AI-enhanced education (Celik et al., 2022; Seufert et al., 2021). Therefore, their perspectives, needs, and experiences are vital to the successful integration of AI in school settings (Holmes et al., 2022). In order to effectively implement AI in the classroom, teachers must be prepared in terms of cognition, ability, vision, and ethical considerations related to the use of AI in education (Luckin et al., 2022). This study therefore aimed to empirically examine the concept of AI readiness among 3164 primary school teachers who had experiences using AI technologies in their work. In what follows, we discuss the important findings of this study by relating them to previous research on similar topics.

The significantly positive relationships between ethics and the other three components of AI readiness echo Kish-Gephart et al.'s (2010) meta-analysis of unethical decisions at work, in which individuals' characteristics and experiences, which are internal to them, were found to have a great influence on their ethical decision-making. Ethical guidelines often have no or limited enforcement mechanisms which can strictly monitor and appraise people's use of AI (Hagendorff, 2020). Considering that huge amounts of resources are devoted to the development and use of AI by organizations or individuals while ethical concerns are mostly for public relations, the incentives of people abiding by ethical guidelines may not be substantially strong when the tension between private and public interests occurs (Boddington, 2017; Hagendorff, 2020). Therefore, when AI technologies are used in education which has high societal significance, it may be more effective for teachers to develop strong ethical concerns inherently than merely enforcing external ethical policies. As long as teachers have an adequate knowledge of how AI functions and how to use it effectively and a deep insight into AI's strengths and weaknesses, they may stand in a better position of using AI with personal accountability.

The significantly positive relationships between the four components

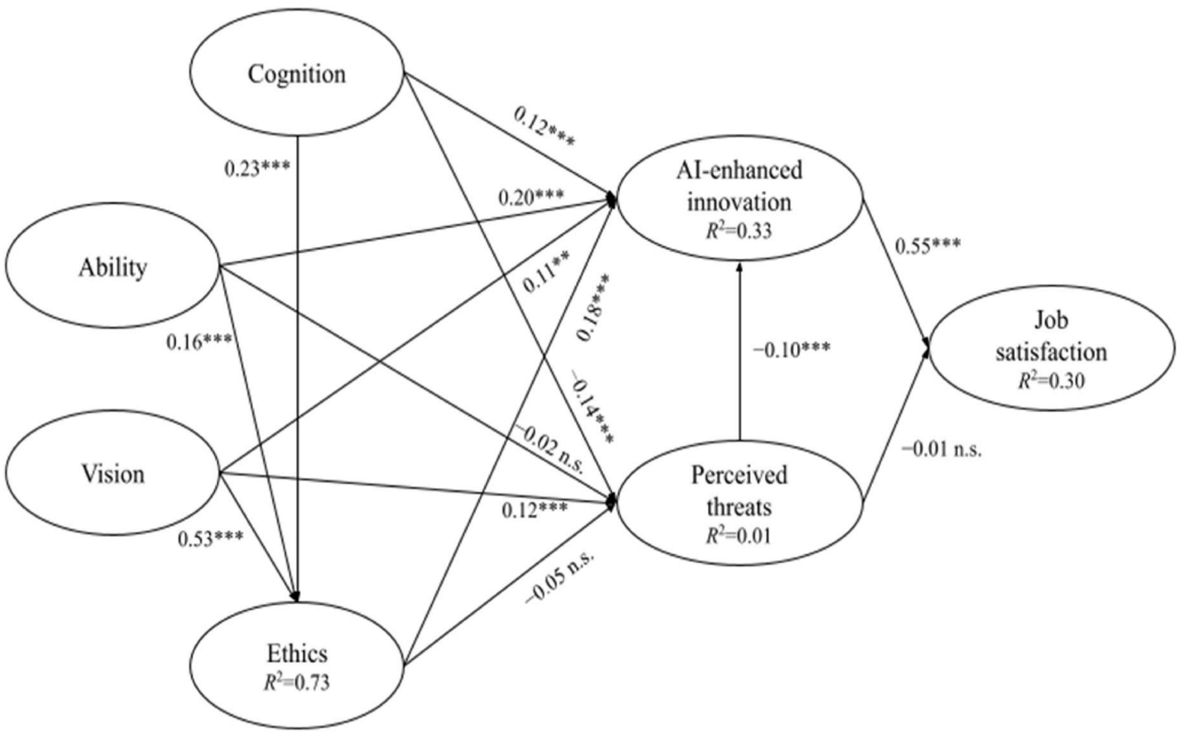

Fig. 2. Validated research model.

Table 4
Distinct clusters of AI readiness and summarized pairwise comparisons using MANOVA.

	C1 (*N* = 859)	C2 (*N* = 1301)	C3 (*N* = 1004)				
Variables	M (SD)	M (SD)	M (SD)	*F*	*p*	Bonferroni Post-hoc*	η^2
Cognition	4.90 (0.22)	4.09 (0.36)	3.24 (0.57)	3760.62	<.001	C1>C2>C3	0.70
Ability	4.92 (0.21)	3.99 (0.31)	3.09 (0.55)	5205.33	<.001	C1>C2>C3	0.77
Vision	4.74 (0.41)	3.86 (0.34)	2.99 (0.51)	4022.91	<.001	C1>C2>C3	0.72
Ethics	4.88 (0.27)	4.08 (0.36)	3.21 (0.62)	3360.33	<.001	C1>C2>C3	0.68
Perceived threats	2.68 (1.45)	2.86 (0.94)	2.93 (0.72)	13.79	<.001	C1<C2, C1<C3	0.01
AI-enhanced innovation	4.39 (0.71)	3.85 (0.59)	3.34 (0.64)	625.19	<.001	C1>C2>C3	0.28
Job satisfaction	4.09 (0.79)	3.65 (0.67)	3.25 (0.69)	325.86	<.001	C1>C2>C3	0.17

Note. C1 = High readiness; C2 = Intermediate readiness; C3 = Low readiness; F = Fisher's F; η^2 = partial et-square; *Mean differences should be significant at the 0.007 level.

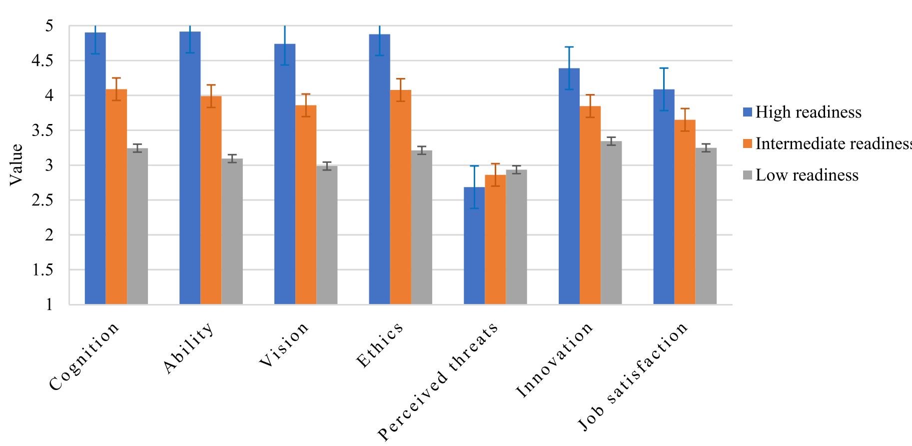

Fig. 3. The visualized distribution of the three AI readiness clusters across the seven variables. *Note*. High Readiness (*N* = 859), Intermediate Readiness (*N* = 1301), Low Readiness (*N* = 1004).

of AI readiness and AI-enhanced innovation corroborate the previous research (e.g., Luckin et al., 2022; Vazhayil et al., 2019) on the important effects of AI readiness on innovating educators' teaching practice. Teachers with high levels of AI readiness are likely to be more capable of deploying AI technologies to support their teaching work (Luckin et al., 2022). They tend to have a comprehensive knowledge of AI for

Table 5
Teachers from different socio-economic areas and summarized pairwise comparisons using MANOVA.

	Downtown ($N = 1264$)	Town ($N = 943$)	Village ($N = 957$)				
Variables	M (SD)	M (SD)	M (SD)	F	p	Bonferroni Post-hoc	η^2
Cognition	4.06 (0.75)	4.03 (0.74)	4.03 (0.79)	0.64	0.53	n.a.	0.00
Ability	3.97 (0.81)	3.96 (0.76)	3.94 (0.81)	0.33	0.72	n.a.	0.00
Vision	3.81 (0.80)	3.82 (0.78)	3.83 (0.80)	0.20	0.82	n.a.	0.00
Ethics	4.04 (0.77)	3.99 (0.76)	4.02 (0.80)	0.95	0.39	n.a.	0.001
Perceived threats	2.81 (1.02)	2.85 (1.07)	2.86 (1.08)	0.87	0.42	n.a.	0.001
AI-enhanced innovation	3.85 (0.75)	3.81 (0.74)	3.84 (0.78)	0.83	0.44	n.a.	0.001
Job satisfaction	3.64 (0.78)	3.60 (0.75)	3.68 (0.80)	2.46	0.09	n.a.	0.002

Note. F = Fisher's F; η^2 = partial et-square; n.a. = not available.

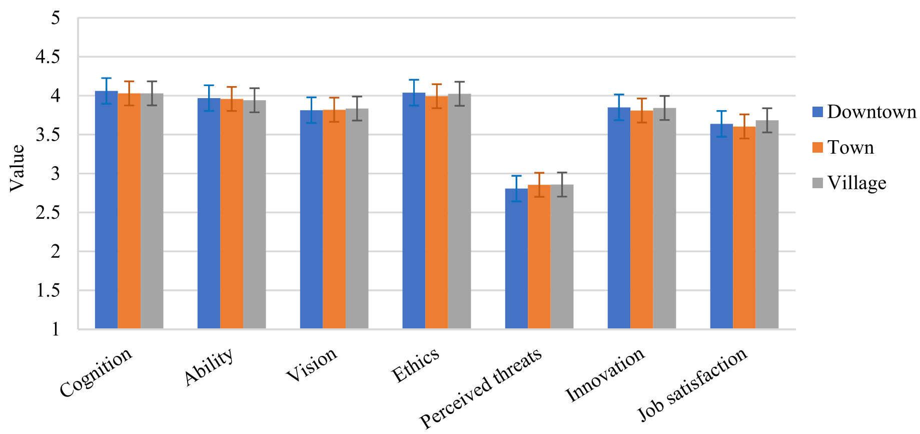

Fig. 4. The visualized distribution of the teachers from distinct socio-economic areas across the seven variables. N*ote*. Downtown ($N = 1264$), Town ($N = 943$), Village ($N = 957$).

Table 6
Teachers of different genders and summarized comparisons using independent *t*-tests.

	Male ($N = 432$)	Female ($N = 2732$)				
Variables	M (SD)	M (SD)	t	p	Bonferroni Post-hoc*	Cohen's d
Cognition	4.01 (0.83)	4.05 (0.75)	−0.85	0.39	n.a.	0.05
Ability	3.95 (0.82)	3.96 (0.79)	−0.19	0.85	n.a.	0.01
Vision	3.88 (0.82)	3.81 (0.79)	1.58	0.11	n.a.	0.09
Ethics	4.01 (0.83)	4.02 (0.76)	−0.35	0.72	n.a.	0.01
Perceived threats	3.01 (1.11)	2.81 (1.04)	3.79	<0.001	Male > Female	0.20
AI-enhanced innovation	3.88 (0.83)	3.83 (0.74)	1.31	0.19	n.a.	0.06
Job satisfaction	3.71 (0.88)	3.63 (0.76)	1.69	0.09	n.a.	0.10

Note. n.a. = not available; *Mean differences should be significant at the 0.007 level.

education and know when, where, and how to apply AI, thereby being able to make informed decisions on pedagogical strategies and enhance their teaching practice (Nazaretsky et al., 2022).

Among the four components of AI readiness, cognition was negatively associated with perceived threats from AI while vision positively predicted the latter. Threatening feelings essentially result from the lack of knowledge of AI and uncertain prospects of what and how the inclusion of AI will impact their work (Celik et al., 2022; Mirbabaie et al., 2022). Individuals who have limited knowledge of AI for education may make insensible decisions about what and how AI can do for education, either overestimating or underestimating AI's role in education (Russell, 2021). The significantly negative association between cognition and perceived threats from AI suggests that a comprehensive knowledge of AI can help minimize the ambiguities and illusions about the role of AI in education.

The positive relationship between the vision of AI and perceived AI threats seems to be counterintuitive. Though it has been repeatedly stressed that human teachers will not be replaced and the social and innovative parts of their work will be demanded more than ever in AI-enhanced education (Celik et al., 2022; Felix, 2020), AI developers are taking serious efforts to completely automate education by closing the social-emotional gap and displacing human teachers (Schiff, 2021). The increased use of social robots may exemplify such effort (Papadopoulos et al., 2020; Smakman et al., 2021). Even if AI cannot replace human teachers, the job market for human teachers can be encroached on by highly advanced AI (Schiff, 2021), thereby posing real threats to human teachers. Therefore, the clearer the vision of AI one could have, the more threats he/she may perceive from it.

AI-enhanced innovation was positively associated with teachers' job satisfaction. This finding makes much sense. AI can bring innovation as well as uncertainties to teachers' work. Those struggling with uncertainties related to the implementation of AI may suffer from reduced job satisfaction (Brougham & Haar, 2018). Nonetheless, those who appreciate the innovative benefits associated with AI tend to experience enhanced job satisfaction (Bhargava et al., 2021). In education, teachers who embrace AI and are ready to apply AI in their work can enjoy benefits that are rarely provided by other technologies (Luckin et al.,

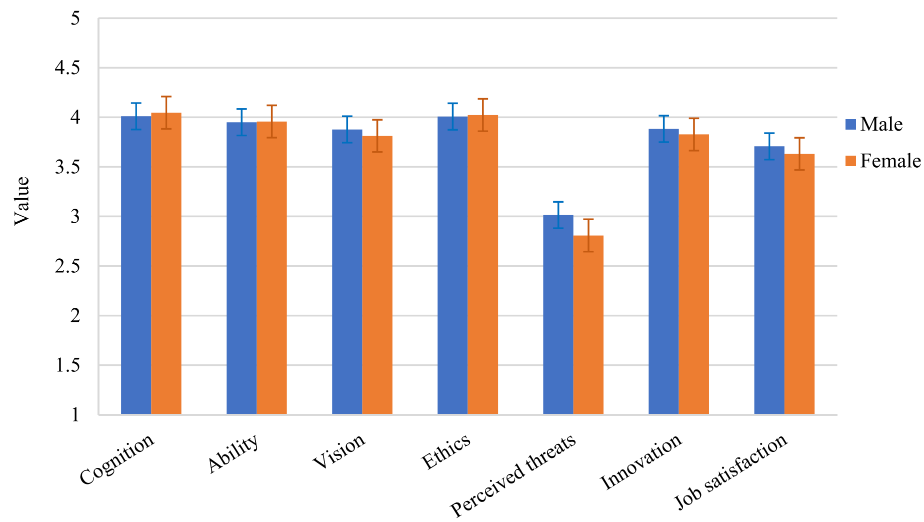

Fig. 5. The visualized distribution of male and female teachers across the seven variables. N*ote*. Male (*N* = 432), Female (*N* = 2732).

2022). For instance, teachers can use chatbots to automatically answer students' questions and rely on intelligent learning management systems to schedule learning activities and provide adaptive feedback to every student (Celik et al., 2022). As a result, teachers can be freed from routine tasks and focus on orchestrating innovative ways of developing students' higher-order thinking, thereby experiencing augmented teaching competence and enhanced positive emotional state (Luckin et al., 2022).

Perceived threats from AI negatively affected AI-enhanced innovation. This could be because that teachers who have low readiness levels for the use of AI may perceive AI as threatful in that it may disrupt their work habits, render their established teaching experience obsolete, and possibly replace them someday (Chounta et al., 2022; Mirbabaie et al., 2022). As argued by Damerji and Salimi (2021) in their study of individuals' adoption of AI for accounting using the reasoned action theory, those who held negative attitudes toward AI were not likely to have strong intentions of using it, let alone integrating AI to change their established ways of working. Similarly, teachers perceiving intense threats from AI may not be engaged in innovative endeavors, such as risk-taking and experimenting with uncertainties related to AI-supported pedagogy (Jöhnk et al., 2021).

The perceived threats from AI did not negatively affect teachers' job satisfaction. This is largely in line with Bhargava et al. (2021) who found that knowledge workers in business sectors, such as accounting, finance, and consulting, often do not perceive considerable threats from AI as they know AI can help upgrade their skillsets and strengthen their employability, thereby likely experiencing great job satisfaction. Likewise, teachers who understand AI and have a proper vision of AI for education are not likely to feel threatened by it as they know that AI cannot replace them in doing creative and emotional tasks, which are essential for students' growth (Bhargava et al., 2021; Celik et al., 2022). Instead, they may feel empowered by AI to achieve higher teaching performance (Luckin et al., 2022).

With regard to the findings of cluster analysis and subsequent group comparisons, the high AI readiness clusters of teachers tended to experience the lowest threats from AI while reporting the highest levels of innovation and job satisfaction. This finding is generally consistent with prior studies (Luckin et al., 2022; Vazhayil et al., 2019) about the importance of AI readiness for educators' work. As Luckin et al. (2022) suggested, high readiness for the use of AI for education may reduce possibly daunting feelings caused by AI, decrease the difficulty of deploying AI in teaching practice, and increase the benefits AI could bring to education.

Even though males and socioeconomically advantaged individuals have often been reported to display higher competence in mastering digital technologies than females and socioeconomically disadvantaged people (Beaunoyer et al., 2020; Park et al., 2019), almost no difference was identified between them in AI readiness and AI-enhanced innovation in this study. The largely insignificant differences between educators of different genders and among those from different socioeconomic regions could be due to the decreasing costs of accessing AI, which are made possible by the rapid advancements in AI technologies (Gardner et al., 2021). This result could also be caused partly by the government policies and national AI schemes that ardently support the use of AI to innovate education and promote equity in education across different socioeconomic areas and population groups in recent years (Knox, 2020; Yan & Yang, 2021).

6. Contributions and implications

The findings of this study carry the following contributions to theories and practices related to AI-enhanced education from the educators' perspectives.

First, though the problem of relatively slow, albeit growing, application of AI in education has been articulated by educational practitioners and researchers (Luan et al., 2020; Luckin et al., 2022), few have considered the underlying reasons of the problem from the perspective of teachers. Inadequate AI readiness can hinder the integration of AI in the classroom (Chounta et al., 2022). This study conceptualized the concept of AI readiness for teachers from four components, including cognition, ability, vision, and ethics, and empirically validated that teachers with distinct levels of AI readiness tend to vary in their attitudes toward AI and innovation and satisfaction at work. Therefore, the framework of AI readiness not only offers a viable way of preparing teachers for AI-enhanced learning, but also provides a new solution to problems hampering the successful implementation of AI in education.

Second, this study investigated the interrelationships among the four components of AI readiness, highlighting the importance of sufficient knowledge of AI (cognition), competence and skills in the use of AI (ability), and a critical view of AI (vision) in forging teachers' ethical awareness in the responsible use of AI, which has been drawing considerable attention from almost all sectors that have adopted AI (Hagendorff, 2020; Ng et al., 2021). In addition, this study examined the relationships between teachers' AI readiness and factors such as perceived threats from AI, innovation, and job satisfaction, thereby empirically substantiating the importance of AI readiness in improving teachers' work efficiency and experience (Luckin et al., 2022).

Third, this study for the first time empirically tested the variance and invariance of AI readiness across different demographic factors, including genders and socio-economical situations. Compared with previously often-reported disparities of individuals with different genders and socioeconomic statuses in the proficiency of using information technologies (Wang & Wong, 2019; Park et al., 2019), the invariance of AI readiness in these factors implies that increased accessibility and enhanced ease of use of AI technologies (Gardner et al., 2021; Luan et al., 2020) may bridge the gap between individuals from distinct demographic backgrounds.

The present study could have the following implications for AI-enhanced education. First, current AI education is more focused on teaching people to learn AI in technical terms by programming and developing AI applications (Luckin et al., 2022). As AI is a rapidly growing area where new algorithms are developed frequently, it is neither practical nor necessary for human teachers to be programmers. Instead, they have to be savvy consumers who can select appropriate AI applications and algorithms to support them in innovating their work and increasing their job satisfaction. As such, it is critical for human teachers to be equipped with adequate knowledge, skills, and vision as well as ethics, that is, AI readiness, so as to make informed decisions about what AI to use and how to use AI appropriately.

Second, the relationships between ethics and cognition, ability, and vision in the use of AI can inspire the development of strategies aiming to improve individuals' ethical decision-making. Though stipulating ethical guidelines and policies is necessary, albeit limited in effectiveness, for guiding the responsible use of AI (Hagendorff, 2020), increasing people's knowledge of AI and how it functions for education and enhancing their competence and skills may be more important. Particularly, given that the vision of the educational use of AI makes up the biggest predictor of ethics, it may be highly rewarding to deepen teachers' insights into what AI can or cannot do for education and what is needed from humans to effectively harness AI's capabilities while mitigating potential risks.

Third, educators should have a proper vision of AI for education. While there may be concerns about AI encroaching on the job market for educators, their job cannot be entirely replaced. Instead, the evolution of AI technologies requires more from teachers in terms of their humanity and social and emotional care (Felix, 2020). Undoubtedly, there are many issues that need to be addressed when applying AI in education. However, it is essential for educators to initially focus on understanding what and how AI can offer them and how they can adapt to AI-enhanced education to enhance their innovation at work and improve their teaching efficiency (Hrastinski et al., 2019).

And fourth, given the insignificant differences between educators from distinct demographic backgrounds in AI readiness, strategies about the implementation of AI in education can take less consideration of possible disparities caused by demographical factors and focus more on how to probe into educators' actual needs and concerns about AI so as to improve their AI readiness and increase the success rate of AI-enhanced education.

7. Limitations and future research

First, the study participants were limited to primary school teachers with similar socio-cultural backgrounds. As a result, it is unclear if the research findings can be applied to wider and more diverse teacher groups. Future studies are suggested to validate the research findings by including teachers with varying levels of experience in using AI for education and from different school levels and countries. Second, as the research on AI readiness is still in its early stage, researchers have not achieved a consensus on its conceptualization across different fields. More efforts and attention are needed to further theorize and validate the concept of AI readiness to better facilitate the implementation of AI in education. Third, while AI readiness is crucial for successfully implementing AI-enhanced education, this study only examined its relationship with few factors relevant to teachers' work. Consequently, our understanding of the impact of AI readiness on teachers' work remains limited. To fill this gap, future studies are advised to investigate the relationship between AI readiness and additional factors related to teachers' work, such as work stress, turnover intention, and work performance resulting from the use of AI. Fourth, the research findings of this study relied on survey data, which may be susceptible to response biases. As such, researchers are suggested to draw on more data sources such as interviews with teachers and their yearly work appraisals to triangulate with survey data so as to strengthen the arguments related to AI readiness and its importance for AI-enhanced education.

Credit author statement

Xinghua Wang: Conceptualization, Investigation, Methodology, Software, Formal analysis, Writing-original draft; **Linlin Li**: Data curation, Writing-review & editing; **Seng Chee Tan**: Conceptualization, Writing-review & editing **Lu Yang**: Resources, Data curation, Methodology; **Jun Lei:** Conceptualization, Methodology, Writing-review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chb.2023.107798.

References

Albacete, P., Jordan, P., Katz, S., Chounta, I. A., & McLaren, B. M. (2019). The impact of student model updates on contingent scaffolding in a natural-language tutoring system. In S. Isotani, E. Millán, A. Ogan, P. Hastings, B. M. McLaren, & R. Luckin (Eds.), *Proceedings of the 20th international conference on artificial intelligence in education* (pp. 37–47). Springer.

Beaunoyer, E., Dupéré, S., & Guitton, M. J. (2020). COVID-19 and digital inequalities: Reciprocal impacts and mitigation strategies. *Computers in Human Behavior, 111*, Article 106424.

Belpaeme, T., Kennedy, J., Ramachandran, A., Scassellati, B., & Tanaka, F. (2018). Social robots for education: A review. *Science Robotics, 3*(21), eaat5954.

Benassi, M., Garofalo, S., Ambrosini, F., Sant'Angelo, R. P., Raggini, R., De Paoli, G., … Piraccini, G. (2020). Using two-step cluster analysis and latent class cluster analysis to classify the cognitive heterogeneity of cross-diagnostic psychiatric inpatients. *Frontiers in Psychology, 11*, 1085.

Bhargava, A., Bester, M., & Bolton, L. (2021). Employees' perceptions of the implementation of robotics, artificial intelligence, and automation (RAIA) on job satisfaction, job security, and employability. *Journal of Technology in Behavioral Science, 6*(1), 106–113.

Boddington, P. (2017). *Towards a code of ethics for artificial intelligence*. Springer.

Brougham, D., & Haar, J. (2018). Smart technology, artificial intelligence, robotics, and algorithms (STARA): Employees' perceptions of our future workplace. *Journal of Management and Organization, 24*(2), 239–257.

Brouillette, M. (2019). AI added to the curriculum for doctors-to-be. *Nature Medicine, 25*(12), 1808–1809.

Celik, I., Dindar, M., Muukkonen, H., & Järvelä, S. (2022). The promises and challenges of artificial intelligence for teachers: A systematic review of research. *TechTrends, 66*, 616–630.

Chen, H.-L., Vicki Widarso, G., & Sutrisno, H. (2020). A chatbot for learning Chinese: Learning achievement and technology acceptance. *Journal of Educational Computing Research, 58*(6), 1161–1189.

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. *Modern Methods for Business Research, 295*(2), 295–336.

Chounta, I.-A., Bardone, E., Raudsep, A., & Pedaste, M. (2022). Exploring teachers' perceptions of Artificial Intelligence as a tool to support their practice in Estonian K-

12 education. *International Journal of Artificial Intelligence in Education, 32*(3), 725–755.
Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2 ed.). Lawrence Earlbaum Associates.
Damerji, H., & Salimi, A. (2021). Mediating effect of use perceptions on technology readiness and adoption of artificial intelligence in accounting. *Accounting Education, 30*(2), 107–130.
Felix, C. V. (2020). The role of the teacher and AI in education. In *International perspectives on the role of technology in humanizing higher education*. Emerald Publishing Limited.
Ferguson, R., Brasher, A., Clow, D., Cooper, A., Hillaire, G., Mittelmeier, J., & Vuorikari, R. (2016). Research evidence on the use of learning analytics: Implications for education policy. In R. Vuorikari, & J. Castano-Munoz (Eds.), *Joint research centre science for policy reportA European framework for action on learning analytics* (pp. 1–152).
Fornell, C., & Larcker, D. F. (1981). Structural equation models with unobservable variables and measurement error: Algebra and statistics. *Journal of Marketing Research, 18*(3), 382–388.
Gardner, J., O'Leary, M., & Yuan, L. (2021). Artificial intelligence in educational assessment:'Breakthrough? Or buncombe and ballyhoo? *Journal of Computer Assisted Learning, 37*(5), 1207–1216.
Gelbard, R., Goldman, O., & Spiegler, I. (2007). Investigating diversity of clustering methods: An empirical comparison. *Data & Knowledge Engineering, 63*(1), 155–166.
Hagendorff, T. (2020). The ethics of AI ethics: An evaluation of guidelines. *Minds and Machines, 30*(1), 99–120.
Hair, J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2014). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage.
Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice, 19*(2), 139–152.
Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. *Advances in International Marketing, 20*(1), 277–319.
Holmes, W., Porayska-Pomsta, K., Holstein, K., Sutherland, E., Baker, T., Shum, S. B., & Bittencourt, I. I. (2022). Ethics of AI in education: Towards a community-wide framework. *International Journal of Artificial Intelligence in Education, 32*(3), 504–526.
Holmström, J. (2022). From AI to digital transformation: The AI readiness framework. *Business Horizons, 65*(3), 329–339.
Hrastinski, S., Olofsson, A. D., Arkenback, C., Ekström, S., Ericsson, E., Fransson, G., & Fuentes, A. (2019). Critical imaginaries and reflections on artificial intelligence and robots in postdigital K-12 education. *Postdigital Science and Education, 1*(2), 427–445.
Hwang, G.-J., & Tu, Y.-F. (2021). Roles and research trends of artificial intelligence in mathematics education: A bibliometric mapping analysis and systematic review. *Mathematics, 9*(6), 1–19.
Jöhnk, J., Weißert, M., & Wyrtki, K. (2021). Ready or not, AI comes—an interview study of organizational AI readiness factors. *Business & Information Systems Engineering, 63*(1), 5–20.
Karaca, O., Çalışkan, S. A., & Demir, K. (2021). Medical artificial intelligence readiness scale for medical students (MAIRS-MS)–development, validity and reliability study. *BMC Medical Education, 21*(1), 1–9.
Kent, P., Jensen, R. K., & Kongsted, A. (2014). A comparison of three clustering methods for finding subgroups in MRI, SMS or clinical data: SPSS TwoStep cluster analysis, latent gold and SNOB. *BMC Medical Research Methodology, 14*(1), 113.
Kim, N. J., & Kim, M. K. (2022). Teacher's perceptions of using an artificial intelligence-based educational tool for scientific writing. *Frontiers in Education, 7*, Article 755914.
Kish-Gephart, J. J., Harrison, D. A., & Treviño, L. K. (2010). Bad apples, bad cases, and bad barrels: meta-analytic evidence about sources of unethical decisions at work. *Journal of Applied Psychology, 95*(1), 1–31.
Knox, J. (2020). Artificial intelligence and education in China. *Learning, Media and Technology, 45*(3), 298–311.
Langran, E., Searson, M., Knezek, G., & Christensen, R. (2020). AI in teacher education. In*Society for information technology & teacher education international conference. Association for the Advancement of Computing in Education (AACE)*, 751–756.
Locke, E. A. (1976). The nature and causes of job satisfaction. In M. D. Dunnette (Ed.), *Handbook of industrial and organizational psychology* (pp. 1293–1349). Rand McNally.
Luan, H., Geczy, P., Lai, H., Gobert, J., Yang, S. J., Ogata, H., … Tsai, C.-C. (2020). Challenges and future directions of big data and artificial intelligence in education. *Frontiers in Psychology, 11*, Article 580820.
Luckin, R., Cukurova, M., Kent, C., & du Boulay, B. (2022). Empowering educators to be AI-ready. *Computers & Education: Artificial Intelligence*, Article 100076.
Microsoft. (2020). *Determine how ready your business is for AI*. Retrieved 23 Dec 2022, from.
Mirbabaie, M., Brünker, F., Möllmann Frick, N. R., & Stieglitz, S. (2022). The rise of artificial intelligence–understanding the AI identity threat at the workplace. *Electronic Markets, 32*(1), 73–99.
Mittelstadt, B. (2019). Principles alone cannot guarantee ethical AI. *Nature Machine Intelligence, 1*(11), 501–507.
Nazareno, L., & Schiff, D. S. (2021). The impact of automation and artificial intelligence on worker well-being. *Technology in Society, 67*, Article 101679.
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*, 914–931.
Ng, D. T. K., Leung, J. K. L., Chu, S. K. W., & Qiao, M. S. (2021). Conceptualizing AI literacy: An exploratory review. *Computers & Education: Artificial Intelligence, 2*, Article 100041.
Papadopoulos, I., Lazzarino, R., Miah, S., Weaver, T., Thomas, B., & Koulouglioti, C. (2020). A systematic review of the literature regarding socially assistive robots in pre-tertiary education. *Computers & Education, 155*, Article 103924.
Parasuraman, A. (2000). Technology readiness index (TRI): A multiple-item scale to measure readiness to embrace new technologies. *Journal of Service Research, 2*(4), 307–320.
Park, C., Kim, D.-g., Cho, S., & Han, H.-J. (2019). Adoption of multimedia technology for learning and gender difference. *Computers in Human Behavior, 92*, 288–296.
Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2012). Sources of method bias in social science research and recommendations on how to control it. *Annual Review of Psychology, 63*, 539–569.
Popenici, S. A., & Kerr, S. (2017). Exploring the impact of artificial intelligence on teaching and learning in higher education. *Research and Practice in Technology Enhanced Learning, 12*(1), 1–13.
Ragu-Nathan, T., Tarafdar, M., Ragu-Nathan, B. S., & Tu, Q. (2008). The consequences of technostress for end users in organizations: Conceptual development and empirical validation. *Information Systems Research, 19*(4), 417–433.
Randall, N. (2019). A survey of robot-assisted language learning (RALL). *ACM Transactions on Human-Robot Interaction (THRI), 9*(1), 1–36.
Russell, S. (2021). Human-compatible artificial intelligence. In S. Muggleton, & N. Chater (Eds.), *Human-like machine intelligence* (pp. 3–23). Oxford University Press.
Sanchez, G. (2013). *PLS path modeling with R*. Berkeley: Trowchez Editions.
Schiff, D. (2021). Out of the laboratory and into the classroom: The future of artificial intelligence in education. *AI & Society, 36*(1), 331–348.
Schleicher, A. (2015). *Schools for 21st-century learners: Strong leaders, confident teachers, innovative approaches*. OECD Publishing.
Seufert, S., Guggemos, J., & Sailer, M. (2021). Technology-related knowledge, skills, and attitudes of pre-and in-service teachers: The current situation and emerging trends. *Computers in Human Behavior, 115*, Article 106552.
Smakman, M., Vogt, P., & Konijn, E. A. (2021). Moral considerations on social robots in education: A multi-stakeholder perspective. *Computers & Education, 174*, Article 104317.
Tarus, J. K., Niu, Z., & Mustafa, G. (2018). Knowledge-based recommendation: A review of ontology-based recommender systems for e-learning. *Artificial Intelligence Review, 50*(1), 21–48.
Tenenhaus, M., Amato, S., & Esposito Vinzi, V. (2004). A global goodness-of-fit index for PLS structural equation modelling. In *Proceedings of the XLII SIS scientific meeting* (pp. 739–742). Padova: CLEUP.
Van Leeuwen, A., & Rummel, N. (2020). Comparing teachers' use of mirroring and advising dashboards. In n C. Lang, G. Siemens, A. F. Wise, D. Gasevic, & A. Mercernon (Eds.), *Proceedings of the 10th international conference on learning analytics and knowledge (LAK'20)* (pp. 26–34). SoLAR.
Vazhayil, A., Shetty, R., Bhavani, R. R., & Akshay, N. (2019). Focusing on teacher education to introduce AI in schools: Perspectives and illustrative findings. In *In2019 IEEE tenth international conference on Technology for Education (T4E)* (pp. 71–77). IEEE.
Vrieze, S. I. (2012). Model selection and psychological theory: A discussion of the differences between the akaike information criterion (AIC) and the bayesian information criterion (BIC). *Psychological Methods, 17*(2), 228–243.
Walia, J. S., & Kumar, P. (2022). Tech transition: An exploratory study on educators' AI awareness. *International Journal of Virtual and Personal Learning Environments, 12*(1), 1–17.
Wang, X., & Wong, B. (2019). Bridging knowledge divides utilizing cloud computing learning resources in underfunded schools: Investigating the determinants. *Journal of Educational Computing Research, 57*(3), 591–617.
Wang, X., Liu, Q., Pang, H., Tan, S. C., Lei, J., Wallace, M. P., & Li, L. (2023). What matters in AI-supported learning: A study of human-AI interactions in language learning using cluster analysis and epistemic network analysis. *Computers & Education, 194*, Article 104703.
Willaby, H. W., Costa, D. S., Burns, B. D., MacCann, C., & Roberts, R. D. (2015). Testing complex models with small sample sizes: A historical overview and empirical demonstration of what partial least squares (PLS) can offer differential psychology. *Personality and Individual Differences, 84*, 73–78.
Xia, Q., Chiu, T. K., Lee, M., Sanusi, I. T., Dai, Y., & Chai, C. S. (2022). A self-determination theory (SDT) design approach for inclusive and diverse artificial intelligence (AI) education. *Computers & Education, 189*, Article 104582.
Yan, S., & Yang, Y. (2021). Education informatization 2.0 in China: Motivation, framework, and vision. *ECNU Review of Education, 4*(2), 410–428.
Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education–where are the educators? *International Journal of Educational Technology in Higher Education, 16*(1), 1–27.