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Understanding K–12 teachers' technological pedagogical content knowledge readiness and attitudes toward artificial intelligence education

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Abstract

Artificial intelligence (AI) education is increasingly being recognized as essential at the K–12 level. For better understanding teachers' preparedness for AI education and effectively developing relevant teacher training programs, teachers' technological pedagogical content knowledge (TPACK) readiness and attitudes toward AI teaching must be determined. However, limited research has been conducted on this topic. To address this research gap, we recruited 1,664 K–12 teachers to obtain a comprehensive view of teachers' readiness for and attitudes toward teaching AI in K–12 classrooms. These teachers differed in terms of their gender, teaching subject, teaching grade, teaching experience, and experience in teaching AI. The findings of this study indicated that a substantial gap exists in the AI-related content and technological knowledge of the recruited teachers. Moreover, intriguing relationships were found between the teachers' pedagogical knowledge, content knowledge, and attitudes toward teaching AI. The effects of demographic factors on the teachers' TPACK and attitudes were also examined. On the basis of the findings of this study, recommendations were formulated for developing effective teacher professional development programs in the field of AI education.

Keywords AI education · K-12 teachers · TPACK · Attitudes · Teacher professional development

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1 Introduction

The increasing importance of artificial intelligence (AI) in K–12 education has made it crucial for educators to possess the competencies required for effectively teaching young students about AI (Luckin et al., 2022; Wang et al., 2023). However, studies have indicated that teachers may lack the knowledge and skills required to teach AI knowledge effectively (Nazaretsky et al., 2022). Several challenges contribute to teachers' poor attitudes toward and readiness for teaching AI, including the absence of teacher training in AI; evolving curricula for teaching AI; and factors such as inadequate funding, immature teaching resources, and inadequate technical infrastructure (ISTE, 2023).

Technological pedagogical content knowledge (TPACK) is widely recognized as an effective theoretical framework for assessing teachers' competencies related to the integration of technology in science, technology, engineering, and mathematics (STEM) subjects (Chai et al., 2013; Huang et al., 2022). In the field of K–12 AI education, multiple pedagogical approaches have been employed in learning environments enhanced using various technological tools—such as Machine Learning for Kids, conversational robotics, and TensorFlow—to improve students' learning experience. Therefore, teachers' TPACK competencies are crucial to their implementation of effective pedagogical practices in teaching AI. Moreover, teachers' attitudes toward teaching AI are key factors that determine their acceptance of pedagogical practices in new subjects (Baylor & Ritchie, 2002). Teachers' interest in and attitudes toward a particular subject strongly influence the effectiveness of their teaching of the subject (Ingersoll & Strong, 2011).

Understanding teachers' backgrounds is crucial because this information can provide insights into how their experiences and training have shaped their TPACK readiness (e.g., Cheng, 2017; Jang & Chang, 2016; Lau et al., 2020). A teacher's background can include their educational degrees, subject area expertise, teaching experience, and professional teacher training (Lau and Jong, 2023). These factors can influence their familiarity with AI and their confidence in teaching it. By understanding teachers' backgrounds, targeted training programs can be developed that address teachers' needs and build upon their specific knowledge and skills. This approach can help improve teachers' TPACK readiness, thereby ultimately enhancing the quality of AI education in K–12 schools.

Although the teaching of AI concepts and principles at the K–12 level has become more popular, limited research has used the TPACK theoretical framework to understand teachers' readiness for and attitudes toward teaching AI. Furthermore, the effects of teachers' characteristics—such as their gender, teaching experience, teaching grade, and teaching subject—on their readiness for and attitudes toward AI education have rarely been explored (Lindner & Berges, 2020). Understanding the effects of teachers' characteristics on their TPACK readiness and attitudes toward AI education is crucial. Therefore, the present study examined these effects by analyzing data obtained from 1,664 teachers. The research questions (RQs) of this study were as follows:

RQ1. What are teachers' TPACK readiness and attitudes toward AI education?
RQ2. How do teachers' demographic characteristics—such as their gender, teaching subject, teaching grade, teaching experience, and experience in teaching AI—influence their TPACK readiness and attitudes toward AI education?

2 Theoretical framework and related research

2.1 TPACK framework

The TPACK framework is a theoretical framework for incorporating technology into educational contexts. Mishra and Koehler (2006) developed the TPACK framework to provide a cohesive understanding of the various dimensions of teachers' knowledge and the interrelations between these dimensions. This framework integrates content knowledge (CK), pedagogical knowledge (PK), technological knowledge (TK), and the intersections of these three types of knowledge, namely pedagogical CK (PCK), technological PK (TPK), technological CK (TCK), and TPACK. The TPACK framework is widely used for examining teachers' proficiency in employing digital technologies for educational purposes (Chai et al., 2013; Hew et al., 2019; Voogt et al., 2013). Based on the examination, the framework is used to design professional development activities for enhancing their TPACK (Chai et al., 2013).

Several theoretical models have been proposed for conceptualizing the incorporation of AI education into the TPACK framework. For instance, Ng et al. (2021) revised the TPACK framework to understand teachers' competencies and how AI can influence teachers' teaching and learning. On the basis of an analysis of AI curricula and resources that was conducted using the TPACK framework, Kim et al. (2021) proposed the most crucial teacher competencies for the effective teaching and learning of AI in K–12 education. Sun et al. (2023) designed a professional development program based on the TPACK framework to improve the AI teaching competency of in-service computer science teachers, including their AI knowledge, teaching skills, and teaching self-efficacy. Celik (2023) proposed the Intelligent-TPACK framework for effectively integrating AI into education, and they emphasized the importance of teachers' AI-specific ethical knowledge. The aforementioned transformative TPACK models enable definition of intersections between key components, such as content, pedagogy, AI, ethics, self-efficacy, AI teaching efficacy beliefs, and AI teaching outcomes. These models conceptualize AI, pedagogy, and content as unique bodies of knowledge, thereby facilitating connections between different areas of teacher knowledge.

Although the TPACK framework has been used to examine the AI knowledge required for the successful teaching and learning of AI concepts, further exploration is required to understand the relationship between AI-specific TPACK and attitudes and also the influences of teachers' characteristics on their TPACK readiness and attitudes toward AI education. Considering the aforementioned relationship and influences in the development of targeted teacher training programs can enhance the quality of AI education in K–12 schools. We modified the TPACK framework for the subject of AI; the modified framework has the following components:

1. TK: TK refers to knowledge regarding how to use technologies in teaching and learning AI, including knowledge regarding various technological tools and platforms available for AI education as well as their features, functionalities, and limitations.
2. PK: PK refers to general knowledge regarding instruction related to AI, including instructional principles, student psychology, classroom management, and teaching strategies.
3. CK: CK refers to knowledge regarding the subject matter of AI, including its core concepts, principles, techniques, and applications.
4. TCK: TCK refers to knowledge regarding the relationship between AI and the content being taught, such as how AI can be used to simulate or model the concepts being taught in an AI course.
5. TPK: TPK refers to knowledge regarding how to use AI technologies to support effective teaching and learning strategies, such as using AI-based adaptive learning systems to personalize instruction.
6. PCK: PCK refers to knowledge regarding how to teach AI concepts effectively, including presenting AI content in a manner that is understandable and engaging for students.
7. TPACK: TPACK refers to comprehensive knowledge regarding how to integrate AI technology, pedagogy, and content to facilitate effective teaching and learning, including leveraging technological tools to teach AI content effectively by using appropriate pedagogical strategies.

To implement AI education successfully, a teacher must apply appropriate teaching strategies to demonstrate AI concepts by using technological tools (Dai et al., 2023; Kim et al., 2021). The aforementioned seven knowledge components reveal the professional expertise that teachers require to successfully integrate technology into AI education. The TPACK framework developed in this study can be used to understand how teachers' knowledge interacts meaningfully in the context of AI education.

2.1.1 Teachers' characteristics and TPACK readiness

Demographic factors—such as age, gender, teaching experience, and teaching subject—influence teacher professional development (TPD) and teaching quality. For example, gender affects a person's behavior and habits, including those related to technology. Several studies have indicated that male teachers rate themselves higher on TPACK than do female teachers (Dominguez Castillo et al., 2018; Mahdi & Al-Dera, 2013; Vitanova et al., 2015). Age affects the teaching ability of teachers because age influences their teaching experience and ability to use technology. In general, the digital or information and communications technology skill level of teachers is inversely related to their age (Anzari et al., 2021; Saikkonen & Kaarakainen, 2021); thus, younger teachers are generally more confident in using technology. Teaching experience affects teaching effectiveness and teacher performance (Rahida Aini et al., 2018). Higher teaching experience correlated with higher teaching capability, thereby enabling teachers to design and implement curricula effectively (Irvine, 2019; Kini & Podolsky, 2016). Compared with young teachers, senior teachers can improve students' learning skills (Nyagah & Gathumbi, 2017) and learning effectiveness to a greater extent because senior teachers have more classroom management experience (Zafer & Aslihan, 2012).

Research has indicated that some demographic factors may influence teachers' TPACK. For example, compared with male teachers, female teachers might have higher levels of PK (Lin et al., 2013) and CK (Cheng, 2017) but may have lower confidence in their technology-related knowledge, such as TK and TCK (Cheng, 2017; Koh et al., 2014; Roig-Vila et al., 2015). Age and teaching experience may affect teachers' TPACK understanding. More experienced teachers generally have higher levels of CK and PK (Jang & Chang, 2016). By contrast, older and more experienced teachers tend to have lower levels of knowledge related to technology (Lee & Tsai, 2010; Yaghi, 2001). Lee and Tsai (2010) concluded that teachers with more years of experience had lower competence in using Web technology and in incorporating Web technology into teaching. In the field of AI education, few studies have explored how teachers' demographic characteristics—such as their gender, teaching experience, and subject matter expertise—influence their TPACK readiness to teach AI; thus, research is required in this area.

2.1.2 Teacher attitudes and TPACK

Teachers' attitudes toward teaching AI considerably affect their instructional methods and, eventually, students' learning outcomes. Pajares (1992) emphasized that teachers' beliefs play a direct role in shaping their instructional decisions and classroom practices. When teachers perceive a subject (such as AI) as valuable, they often craft more robust and stimulating learning experiences that nurture higher-order thinking and problem-solving abilities, which are essential for AI literacy. Research has indicated that a teacher's enthusiasm for a subject can amplify their effectiveness in teaching it. Interest can motivate teachers to keep pace with the latest advancements in AI education, thereby ensuring that their knowledge remains fresh and applicable (Ingersoll & Strong, 2011). Such passion often leads to more vibrant and engaging classroom interactions, which can pique students' interest and foster more effective learning (Kunter et al., 2008). However, in addition to positive attitudes, teachers need relevant content knowledge and technological skills if they are to teach technology-related subjects successfully (Voogt et al., 2015). Research has indicated that teachers hold a negative attitude toward technology-related teaching when they have limited disciplinary knowledge and lack teaching strategies (Van Driel et al., 2014). Thus, TPACK and attitudes may reinforce each other.

Studies have highlighted the role of teachers' attitudes toward technology integration in the development of TPACK. Teachers who express a positive attitude toward technology are more likely to provide high ratings for their perceptions regarding TPACK dimensions (Raygan & Moradkhani, 2022; Tondeur et al., 2020; Voithofer et al., 2019). However, limited investigations have been performed on attitudes toward teaching technology subjects. Although a crucial relationship exists between TPACK and attitudes toward teaching technology subjects, few studies have examined this relationship. Furthermore, even fewer studies have investigated the relationship between TPACK and attitudes toward AI teaching, where AI serves as the technological tool and subject matter. Continued research in this field may provide valuable insights that can enhance teacher education programs, guide TPD, and ultimately elevate the overall quality of AI education.

3 Methods

3.1 Respondents

This study recruited K–12 teachers with various backgrounds from different provinces in Mainland China and explored their perceptions of teaching AI. A total of 1,831 teachers, who had registered to participate in a large-scale online seminar on educational technology, were invited to participate in this study through completing an online questionnaire on a voluntary basis. The online questionnaire-based survey was conducted one week before the day of the seminar. After invalid questionnaires were eliminated, 1,664 valid samples remained. The demographic background of the respondents who provided valid responses is presented in Table 1..

Of the respondents who provided valid responses, 30.29% were female. The respondents' teaching experience ranged from 1 year to over 16 years. In terms of teaching level, 72.60% of the respondents were primary school teachers, 23.80% were secondary school teachers, and the remaining were extracurricular teachers and preservice teachers who planned to teach K–12 students. The respondents taught a wide range of subjects, including science, technology, mathematics, history, Chinese, and English.

Table 1. Respondents' demographic background

Demographic background		*N*
Gender	Male	1,160
	Female	504
Teaching subjects	Technology only	941
	Science and/or Tech	524
	Non-tech involved	199
Teaching levels	Primary	1,208
	Secondary	396
	Other	60
Teaching experience	< 3 years	685
	3 – 6 years	455
	> 6 years	524
Experience in teaching AI	Yes	1,228
	No	436

3.2 Instruments

We developed two questionnaires to evaluate the teachers' TPACK readiness and attitudes toward learning about AI. The first questionnaire was a self-reported AI-specific TPACK questionnaire, the items of which were modified versions of the items used in the short version of the TPACK questionnaire for teachers (Schmid et al., 2020) that was originally developed by Schmidt et al. (2009). The short version targets secondary teachers who teach various subjects and have different levels of experience. Terms such as "teaching subjects" from the short version of the aforementioned questionnaire were modified to be AI-specific. For example, the item "I have sufficient knowledge about my teaching subjects" was changed to "I have sufficient knowledge about AI."

The second questionnaire was used to assess the respondents' attitudes toward AI education. This questionnaire comprised items that were modified versions of those from the questionnaire developed by Nordlöf et al. (2019) for examining technology teachers' attitudes. In the second questionnaire, teachers' attitudes were conceptualized into two factors: (1) perceived importance of teaching AI and (2) interest in teaching AI. The wording of the items of Nordlöf et al. (2019) was modified to be AI-specific. For example, the item "Technology is an important subject" was changed to "AI is an important subject."

In addition to the questionnaire data, the respondents' demographic data—including their gender, teaching subject, teaching level, teaching experience, and experience in teaching AI—were collected.

3.3 Validity and reliability of the adopted questionnaires

Schimd et al. (2020) successfully validated their shortened questionnaire among 117 secondary school teachers, and Nordlof et al. () successfully validated their questionnaire among 1,163 teachers. The aforementioned questionnaires are frequently applied in the field of technology education (e.g., Marek et al., 2021; Xu et al., 2020).

3.3.1 AI-specific TPACK questionnaire

The validity and reliability of the first questionnaire used in this study were evaluated through confirmatory factor analysis (CFA), which was conducted using Mplus 8.1. Subsequently, correlational analysis was performed to examine the correlations between the questionnaire constructs. Multiple criteria—including the ratio of chi-square to the degrees of freedom (χ^2/df), the comparative fit index (CFI), the root mean square error of approximation (RMSEA), and the standard root mean square residual (SRMR)—were employed to evaluate the fit between the developed model and the collected data. The criterion χ^2/df was adopted instead of χ^2 because χ^2 is excessively sensitive to the sample size (Hu & Bentler, 1999). Acceptable fit between the developed model and the collected data is indicated by a χ^2/df value of ≤ 5 (Carmines & McIver, 1981; Iacobucci, 2010), a CFI of > 0.90 (Russell, 2002), an RMSEA of < 0.08 (Marsh et al., 2004), and an SRMR of < 0.08 (Hooper et al., 2008).

The results of CFA [$\chi^2/df = 3.04$, $p < 0.01$; RMSEA = 0.035; CFI = 0.984; Tucker–Lewis index (TLI) = 0.981; and SRMR = 0.023] indicated that the developed model had a good fit to the collected data. The Cronbach's alpha values for the constructs of the first questionnaire were between 0.83 and 0.93, indicating good reliability for the constructs (Gliem & Gliem, 2003). The factor loadings of the items were significant, ranged between 0.616 and 0.879, and were strongly associated with each other. Table 2 presents the reliability results and factor loadings for the AI-specific TPACK questionnaire.

3.3.2 AI-specific teacher attitude questionnaire

CFA was performed again to evaluate the second questionnaire (i.e., the teacher attitude questionnaire). The results of CFA (i.e., $\chi^2/df = 2.44$, $p < 0.01$;

Table 2 Reliability results and factor loadings for the AI-specific TPACK questionnaire

Factors	Items	Factor loading	Cronbach's alpha
CK	CK1	0.737	0.857
	CK2	0.804	
	CK3	0.772	
	CK4	0.784	
PK	PK1	0.826	0.933
	PK2	0.859	
	PK3	0.879	
	PK4	0.873	
	PK5	0.852	
TK	TK1	0.818	0.832
	TK2	0.813	
	TK3	0.616	
	TK4	0.728	
TPK	TPK1	0.851	0.893
	TPK2	0.851	
	TPK3	0.874	
TCK	TCK1	0.754	0.837
	TCK2	0.827	
	TCK3	0.803	
PCK	PCK1	0.833	0.858
	PCK2	0.844	
	PCK3	0.781	
TPACK	TPACK1	0.817	0.856
	TPACK2	0.811	
	TPACK3	0.820	

Table 3 Reliability results and factor loadings for the AI-specific teacher attitude questionnaire

Factors	Item	Factor loading	Cronbach's alpha
IMP	A1	0.680	0.804
	A2	0.688	
	A3	0.741	
	A4	0.736	
INT	A5	0.703	0.641 → 0.800[1]
	A6[1]	0.095[1]	
	A7	0.705	
	A8	0.715	
	A9	0.708	

[1]Notes: After deleting item A6, the Cronbach's alpha for INT was 0.800

RMSEA = 0.029; CFI = 0.993; TLI = 0.990; and SRMR = 0.018) indicated that the developed model had a good fit to the collected data. After one item from the "interest in teaching AI" factor (item A6) had been deleted, the Cronbach's alpha value for this factor increased from 0.641 to 0.800, which indicated high reliability (Gliem & Gliem, 2003). The factor loadings of the remaining items were significant, ranged between 0.680 and 0.741, and exhibited strong associations with each other. Table 3 presents the reliability results and factor loadings for the AI-specific teacher attitude questionnaire.

Factor loadings of all items were between 0.616 and 0.879.

3.3.3 Correlation analysis

A Pearson's correlation test was conducted to determine the relationships between the dependent variables of this study (Field, 2013). The coefficients of the correlations between the examined constructs had magnitude of less than 0.85 (Table 4). Strong correlations existed among all factors related to TPACK (i.e., CK, PK, TK,

Table 4 Correlations between the factors related to TPACK and attitudes

	CK	PK	TK	TPK	TCK	PCK	TPACK	IMP	INT
CK	1								
PK	0.495**	1							
TK	0.613**	0.607**	1						
TPK	0.598**	0.681**	0.715**	1					
TCK	0.640**	0.547**	0.692**	0.791**	1				
PCK	0.579**	0.665**	0.668**	0.791**	0.768**	1			
TPACK	0.628**	0.600**	0.674**	0.765**	0.781**	0.786**	1		
IMP	0.436**	0.087**	0.345**	0.333**	0.451**	0.319**	0.444**	1	
INT	0.530**	0.300**	0.453**	0.509**	0.584**	0.487**	0.603**	0.722**	1

IMP: perceived importance of teaching AI; INT: interest in teaching AI.

TPK, TCK, PCK, and TPACK), and attitudes of the perceived importance of teaching AI as well as interest in teaching AI. Specifically, the coefficients of the correlations between the factors related to TPACK varied from 0.547 (between TCK and PK) to 0.791 (between TCK and TPK). The coefficients of the correlations between the factors related to TPACK and attitudes ranged from 0.087 (between perceived importance and PK) to 0.603 (between interest and TPACK).

3.4 Data collection and analysis

The data of this study was collected through an online survey and imported into SPSS 27.0 and RStudio for descriptive and clustering analyses. Levene's test was used to assess the homogeneity of variances (Table 5); this assessment is a precondition for parametric tests such as clustering analyses, analyses of variance (ANOVAs), and t-tests (Cuevas et al., 2004; Lakens, 2013). The skewness of the data ranged from − 0.657 to − 0.002, and the kurtosis ranged from − 0.672 to 0.349. For a large sample (N = 1,664 in this study), a distribution is considered approximately normal if the skewness or kurtosis (excess) of the data is between − 1 and 1. Therefore, the data of this study had a normal distribution.

To address the potential common method bias (CMB), Harman's single-factor test was applied to the collected data, encompassing fourteen variables. These variables included the five demographic, seven TPACK variables, and two related to attitudes, chosen to capture the multidimensional aspects of our research model comprehensively. The test involves conducting an exploratory factor analysis (EFA) on all these variables without rotation. This approach can be used to assess if a predominant portion of the total variance can be attributed to a single factor, indicative of CMB (Podsakoff et al., 2003). The EFA results revealed that a single factor accounted for 41.073% of the total variance. This percentage is below the commonly cited threshold of 50% for severe common method variance, suggesting that while CMB cannot be entirely ruled out, its impact does not overshadow the data multidimensionality (ibid.). This outcome supports the presence of diverse factors and constructs significantly contributing to the observed variance, thereby reinforcing the robustness and interpretability of the research results.

Table 5 Results obtained in the test of normality

Factors	Skewness	Kurtosis
CK	-0.582	0.329
PK	-0.544	0.147
TK	-0.002	-0.237
TPK	-0.429	-0.297
TCK	-0.553	-0.271
PCK	-0.563	0.273
TPACK	-0.557	-0.307
IMP	-0.503	-0.672
INT	-0.657	-0.008

To answer RQ1, descriptive analysis was conducted to examine the teachers' perceived TPACK readiness and attitudes toward AI education, following which cluster analysis was performed. The cluster analysis for factors related to TPACK and attitudes was conducted in two steps (Clatworthy et al., 2005; Hair et al., 2010; Mooi & Sarstedt, 2011). First, hierarchical cluster analysis was performed to determine the optimal number of clusters. This step helped to identify the natural groupings or patterns within the data. Subsequently, k-means cluster analysis was conducted to obtain the final clustering solution. After performing k-means clustering, we conducted repeated-measures ANOVA and a paired-samplesss t-test to explore the differences between the clusters further.

To answer RQ2, one-way ANOVA and t-tests were performed to examine the effects of the teachers' demographic characteristics on their perceived TPACK readiness and attitudes toward AI education. Furthermore, multinomial logistic regression was performed to explore the patterns of clusters based on different demographic factors.

4 Results

4.1 Results obtained for RQ1

4.1.1 Teachers perceived TPACK readiness and attitudes

Table 6 presents the overall results obtained for the surveyed teachers' TPACK readiness for and attitudes toward AI education. The teachers rated their TPACK abilities above average across all categories, with the mean scores ranging from 3.284 to 3.604. Repeated-measures ANOVA was conducted to examine the differences between the scores assigned to the seven factors related to TPACK readiness. The results indicated significant differences between the scores for these factors [$F(6, 8397.84) = 97.58$, $p < 0.001$, partial $\eta^2 = 0.06$]. Pairwise comparisons with Bonferroni adjustments for multiple tests revealed that the average perceived PK of the respondents [M = 3.604, standard deviation (SD) = 0.812] was significantly higher

Table 6 Teachers' perception of their TPACK readiness and their attitudes toward AI education

	Mean	SD	95% CI	
CK	3.284	0.860	3.243	3.325
PK	3.604	0.812	3.565	3.643
TK	3.292	0.735	3.256	3.327
TPK	3.413	0.836	3.373	3.453
TCK	3.365	0.892	3.322	3.407
PCK	3.512	0.782	3.474	3.550
TPACK	3.380	0.890	3.337	3.423
IMP	3.953	0.769	3.916	3.990
INT	3.885	0.708	3.851	3.919

than their perceived levels of all other TPACK-related factors. By contrast, the average perceived CK (M = 3.284, SD = 0.860) and TK (M = 3.292, SD = 0.735) of the respondents were significantly lower than their perceived levels of all other TPACK-related factors.

The teachers provided high scores for the importance of teaching AI (M = 3.953, SD = 0.769) and interest in teaching AI (M = 3.885, SD = 0.708). Moreover, a paired-samples t-test revealed a significant difference between the scores of these two factors ($t = 5.013$, $p < 0.001$).

4.1.2 Pattern of the teachers' perceptions

Hierarchical cluster analysis was conducted to determine the optimal number of clusters. The dendrogram determined using Ward's linkage revealed the presence of three, five, or six distinct clusters in the data (Fig. 1). We then used the elbow method to determine the elbow point in the dendrogram, which refers to the point at which the within-cluster sum of squares starts decreasing linearly or relatively slowly. As displayed in Fig. 2a, the results obtained using the elbow method indicated that the optimal number of clusters was 5 or 6. The Bayesian information criterion (BIC) was also used to determine the optimal number of clusters (Fig. 2b). The maximum BIC value was obtained for five clusters; thus, the optimal number of clusters was 5.

The results of hierarchical cluster analysis indicated that the optimal number of clusters was 5. Next step, the k-means cluster analysis was performed. The five

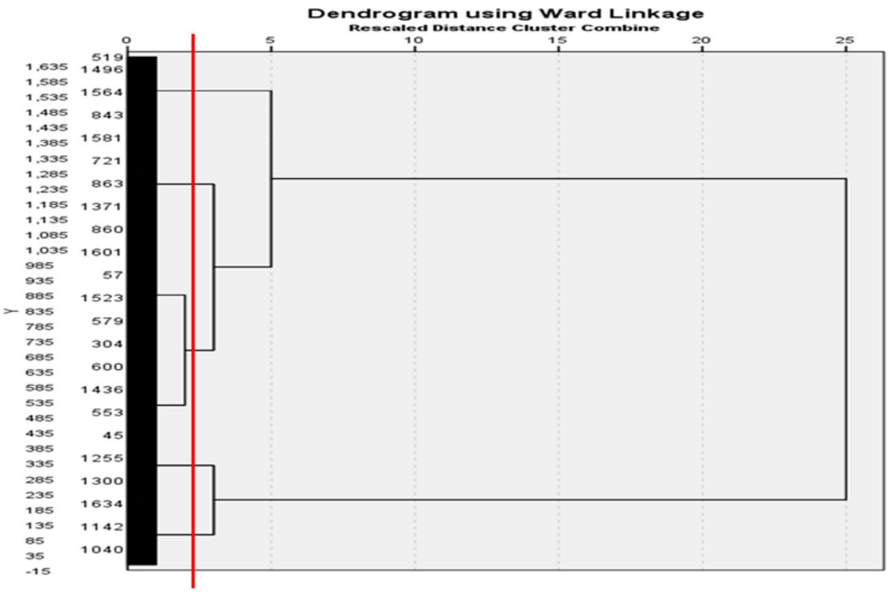
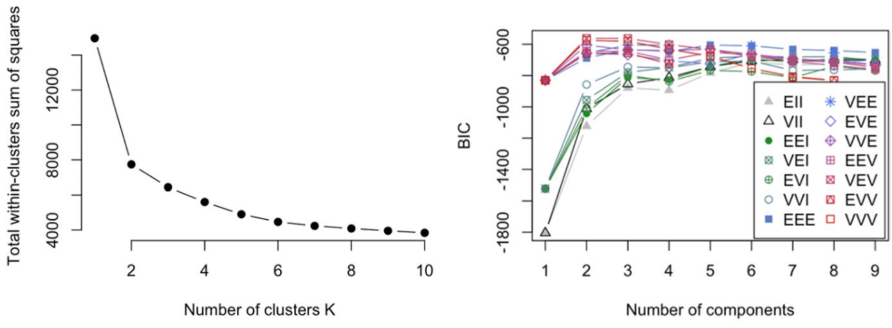


Fig. 1 Dendrogram obtained through hierarchical cluster analysis



(a) (b)

Fig. 2 Results obtained using the (a) elbow method and (b) BIC

cluster centers for each factor are presented in Table 7, and a visual representation of these clusters is displayed in Fig. 3.

The five identified clusters were labeled as follows: (1) high readiness–high attitudes (HR–HA), (2) above-average readiness–high attitudes (AR–HA), (3) above-average readiness–average attitudes (AR–AA), (4) low readiness–high attitudes (LR–HA), and (5) low readiness–low attitudes (LR–LA). One-way ANOVA revealed significant differences between all seven TPACK-related factors across the five clusters.

The HR–HA cluster ($N=226$) comprised respondents who rated themselves highly on all seven TPACK-related factors ($M>4.30$). They also perceived AI education as crucial ($M=4.48$) and expressed strong interest in teaching AI ($M=4.41$). No significant differences were found between the scores for the seven TPACK-related factors within this cluster.

The AR–HA ($N=580$) and AR–AA ($N=470$) clusters contained respondents who rated themselves as above average on all seven TPACK-related factors, with the mean scores ranging from 3.37 to 4.06. However, their attitudes toward AI education

Table 7 Five cluster centers for each factor

Cluster	HR–HA	AR–HA	AR–AA	LR–HA	LR–LA
Sample (*N*)	226	580	470	214	174
CK	4.30	3.44	3.49	2.53	1.83
PK	4.43	3.52	4.06	2.34	3.14
TK	4.30	3.37	3.43	2.32	2.51
TPK	4.38	3.57	3.72	2.16	2.36
TCK	4.36	3.68	3.56	2.12	2.04
PCK	4.40	3.68	3.75	2.27	2.67
TPACK	4.40	3.69	3.58	2.11	2.06
IMP	4.48	4.58	3.45	3.93	2.54
INT	4.41	4.36	3.73	3.51	2.49

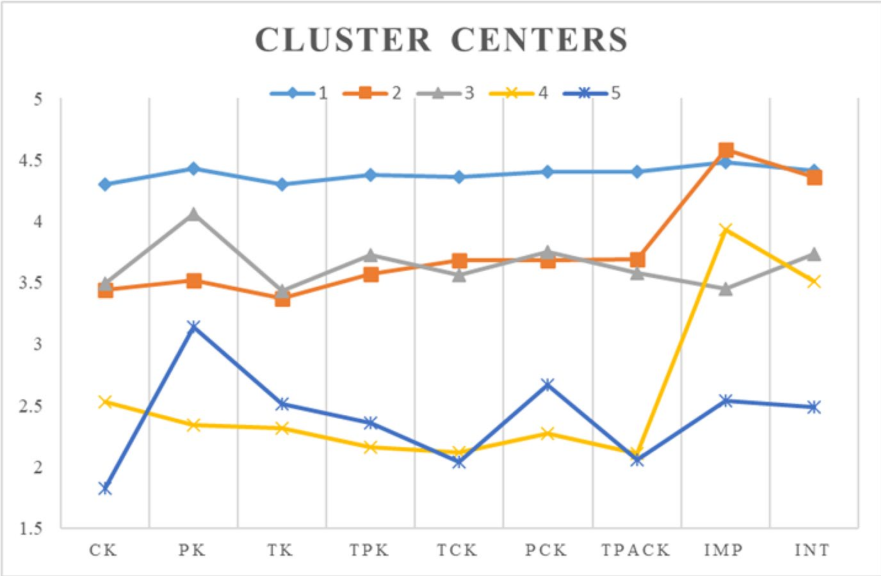


Fig. 3 Five cluster centers for each factor. Remarks: (1) HR–HA, (2) AR–HA, (3) AR–AA, (4) LR–HA, and (5) LR–LA

varied significantly. The AR–HA group exhibited marginally higher scores for perceived importance of teaching AI and interest in teaching AI than the HR–HA group; however, this difference was nonsignificant. Moreover, the AR–AA group had moderate scores for perceived importance in teaching AI (M = 3.45) and interest in teaching AI (M = 3.73). Interestingly, the AR–AA group had a significantly higher score for PK than did the AR–HA group.

The LR–HA (N = 214) and LR–LA (N = 174) clusters comprised respondents who exhibited low readiness in AI-specific TPACK. In both clusters, scores were below average in almost all TPACK-related factors, with the variance (PK vs. CK) between the factors being greatest for the LR–LA cluster. Attitudes toward AI teaching also varied within these clusters. The LR–HA group perceived AI education as fairly important (M = 3.93) and showed interest in it (M = 3.51), whereas the LR–LA group had low scores for importance of teaching AI (M = 2.54) and interest in AI teaching (M = 2.49).

4.2 Results obtained for RQ2

We explored the effects of five demographic factors—gender, teaching subject, teaching grade, teaching experience, and experience in teaching AI—on the teachers' TPACK readiness and attitudes by conducting t-tests and ANOVAs. We categorized the teachers into three groups in accordance with their teaching subject: the technology group (teachers who exclusively taught technology-related subjects), the science group (teachers who taught subjects such as mathematics, science,

Table 8 Differences in the seven TPACK-related factors between the genders

	Male ($N=1160$) Mean (SD)	Female ($N=504$) Mean (SD)	t	p	95% CI of the difference	
CK	3.33 (0.87)	3.17 (0.83)	3.495	< 0.001	0.070	0.250
PK	3.65 (0.80)	3.49 (0.83)	3.776	< 0.001	0.078	0.248
TK	3.36 (0.74)	3.14 (0.69)	5.381	< 0.001	0.133	0.285
TPK	3.47 (0.82)	3.27 (0.85)	4.476	< 0.001	0.112	0.286
TCK	3.42 (0.89)	3.25 (0.90)	3.565	< 0.001	0.076	0.262
PCK	3.54 (0.79)	3.44 (0.77)	2.441	0.015	0.020	0.183
TPACK	3.42 (0.89)	3.29 (0.89)	2.862	0.004	0.043	0.228

Table 9 Differences in the seven TPACK-related factors between teaching subject groups

	Tech-only ($N=941$) Mean (SD) [95% CI]	Science ($N=524$) Mean (SD) [95% CI]	Non-tech ($N=199$) Mean (SD) [95% CI]	F	p
CK	3.31 (0.86) [3.256, 3.366]	3.29 (0.86) [3.215, 3.362]	3.14 (0.86) [3.025, 3.264]	3.098	0.045
PK	3.63 (0.79) [3.582, 3.683]	3.64 (0.80) [3.573, 3.710]	3.37 (0.92) [3.241, 3.498]	9.483	< 0.001
TK	3.31 (0.73) [3.263, 3.356]	3.31 (0.74) [3.245, 3.372]	3.16 (0.75) [3.057, 3.267]	3.527	0.030
TPK	3.42 (0.83) [3.368, 3.473]	3.46 (0.85) [3.390, 3.536]	3.24 (0.82) [3.130, 3.360]	5.042	0.007
TCK	3.36 (0.90) [3.303, 3.418]	3.40 (0.88) [3.322, 3.473]	3.30 (0.88) [3.175, 3.422]	0.921	0.398
PCK	3.53 (0.78) [3.475, 3.575]	3.52 (0.79) [3.449, 3.584]	3.43 (0.77) [3.329, 3.545]	1.056	0.348
TPACK	3.39 (0.89) [3.336, 3.450]	3.40 (0.88) [3.319, 3.471]	3.27 (0.91) [3.152, 3.407]	1.443	0.237

physics, biology, etc.), and the non-technology group (teachers who taught subjects such as Chinese or English, social sciences and humanities, and history, regardless of whether they also taught science or technology subjects). The effects of gender, teaching subject, teaching grade, teaching experience, and experience in teaching AI are presented in Table 8, 9, 10, 11, 12, 13. and 14..

4.2.1 TPACK readiness

On average, the male teachers rated themselves significantly higher than the female teachers on all seven TPACK-related factors. No significant differences were discovered between the three teaching subject groups in terms of their TCK, PCK, or TPACK scores. However, post-hoc analysis revealed that the non-technology group rated themselves lower on CK, PK, and TK than the technology and science groups. Significant differences were found between teachers from primary versus secondary

Table 10 Differences in the seven TPACK-related factors between teaching grades

	Primary (N = 1208) Mean (SD) [95% CI]	Secondary (N = 396) Mean (SD) [95% CI]	Others (N = 60) Mean (SD) [95% CI]	F	p
CK	3.32 (0.86) [3.271, 3.368]	3.18 (0.88) [3.096, 3.269]	3.24 (0.79) [3.038, 3.445]	3.873	0.021
PK	3.67 (0.80) [3.626, 3.716]	3.42 (0.83) [3.333, 3.498]	3.50 (0.77) [3.300, 3.700]	15.529	< 0.001
TK	3.31 (0.73) [3.271, 3.354]	3.22 (0.75) [3.143, 3.290]	3.37 (0.76) [3.171, 3.563]	2.876	0.057
TPK	3.47 (0.83) [3.423, 3.517]	3.23 (0.85) [3.147, 3.315]	3.47 (0.80) [3.261, 3.672]	12.514	< 0.001
TCK	3.41 (0.89) [3.355, 3.456]	3.22 (0.89) [3.133, 3.308]	3.49 (0.87) [3.264, 3.714]	7.071	< 0.001
PCK	3.55 (0.79) [3.508, 3.598]	3.38 (0.75) [3.304, 3.452]	3.57 (0.69) [3.394, 3.750]	7.716	< 0.001
TPACK	3.44 (0.87) [3.392, 3.491]	3.18 (0.92) [3.092, 3.273]	3.45 (0.84) [3.239, 3.672]	13.003	< 0.001

Table 11 Differences in the seven TPACK-related factors between levels of teaching experience

	< 3 years (N=685) Mean (SD) [95% CI]	3 – 5 years (N=455) Mean (SD) [95% CI]	> 6 years (N=524) Mean (SD) [95% CI]	F	p
CK	3.25 (0.82) [3.190, 3.313]	3.32 (0.87) [3.241, 3.401]	3.29 (0.91) [3.216, 3.372]	0.935	0.393
PK	3.53 (0.82) [3.467, 3.591]	3.71 (0.72) [3.639, 3.773]	3.61 (0.86) [3.538, 3.686]	6.544	0.001
TK	3.27 (0.72) [3.225, 3.332]	3.36 (0.75) [3.292, 3.429]	3.25 (0.74) [3.185, 3.313]	2.994	0.050
TPK	3.41 (0.84) [3.349, 3.475]	3.45 (0.82) [3.378, 3.528]	3.38 (0.85) [3.307, 3.453]	0.929	0.395
TCK	3.39 (0.89) [3.328, 3.461]	3.40 (0.89) [3.313, 3.478]	3.30 (0.90) [3.222, 3.376]	2.070	0.127
PCK	3.51 (0.77) [3.453, 3.569]	3.56 (0.76) [3.487, 3.626]	3.47 (0.82) [3.404, 3.545]	1.348	0.260
TPACK	3.38 (0.88) [3.314, 3.446]	3.43 (0.88) [3.351, 3.512]	3.33 (0.92) [3.257, 3.415]	1.407	0.245

Table 12 Differences in the seven TPACK-related factors between levels of experience in teaching AI

	Yes (N=1228) Mean (SD)	No (N=436) Mean (SD)	t	p	95% CI of the difference	
CK	3.36 (0.86)	3.07 (0.83)	6.031	< 0.001	0.193	0.379
PK	3.72 (0.75)	3.27 (0.89)	9.379	< 0.001	0.360	0.533
TK	3.37 (0.72)	3.07 (0.74)	7.474	< 0.001	0.222	0.380
TPK	3.50 (0.81)	3.18 (0.87)	7.012	< 0.001	0.232	0.412
TCK	3.42 (0.88)	3.21 (0.92)	4.183	< 0.001	0.110	0.304
PCK	3.57 (0.77)	3.35 (0.79)	5.141	< 0.001	0.138	0.307
TPACK	3.45 (0.87)	3.18 (0.93)	5.506	< 0.001	0.174	0.367

schools in terms of all TPACK-related factors except for TK (F=2.876, p=0.057). In general, the primary school teachers reported higher scores for all TPACK-related factors than the secondary school teachers. Teachers with different levels of teaching experience exhibited significant differences in terms of PK (F=6.544, p=0.001) and TK (F=2.994, p=0.050). Post-hoc analysis indicated that the teachers with 3–5 years of teaching experience had higher PK than those with less than 3 years of experience. Experience in teaching AI had a significant effect on the teachers' perceived TPACK. The teachers with prior experience in teaching AI reported higher scores for all seven TPACK-related factors than those without such experience.

4.2.2 Attitudes toward teaching AI

Tables 13. and 14. present the effects of the five demographic factors on the teachers' perceived importance of teaching AI and interest in teaching AI.

Table 13. Effects of demographic factors on the perceived importance of teaching AI

Demographic factors		*N*	Mean	95% CI	SD	*t*/*F*	*p*
Gender	Male	1160	3.944	[3.900, 3.987]	.756	-.718	.473
	Female	504	3.973	[3.903, 4.043]	.798		
Teaching Subjects	Technology only	941	3.930	[3.881, 3.979]	.766	1.213	.297
	Science and/or Tech	524	3.995	[3.929, 4.062]	.773		
	Non-tech involved	199	3.947	[3.840, 4.055]	.770		
Teaching Grade	Primary	1208	3.954	[3.911, 3.997]	.762	.053	.948
	Secondary	396	3.953	[3.875, 4.031]	.790		
	Other	60	3.921	[3.724, 4.117]	.761		
Teaching Exp.	< 3 years	685	3.957	[3.900, 4.013]	.758	.161	.852
	3 – 5 years	455	3.936	[3.864, 4.008]	.780		
	> 6 years	524	3.962	[3.896, 4.029]	.774		
Exp. in teaching AI	Yes	1228	3.961	[3.918, 4.004]	.768	.752	.452
	No	436	3.929	[3.856, 4.002]	.772		

Table 14. Effects of demographic factors on interest in teaching AI

Demographic factors		*N*	Mean	95% CI	SD	*t*/*F*	*p*
Gender	Male	1160	3.898	[3.858, 3.939]	.702	1.194	.233
	Female	504	3.853	[3.790, 3.916]	.722		
Teaching Subjects	Technology only	941	3.873	[3.828, 3.919]	.708	.866	.421
	Science and/or Tech	524	3.917	[3.857, 3.977]	.702		
	Non-tech involved	199	3.853	[3.752, 3.954]	.723		
Teaching Grade	Primary	1208	3.913	[3.874, 3.953]	.693	3.697	.025*
	Secondary	396	3.806	[3.731, 3.880]	.752		
	Other	60	3.825	[3.647, 4.003]	.688		
Teaching Exp.	< 3 years	685	3.880	[3.829, 3.931]	.683	.435	.647
	3 – 5 years	455	3.910	[3.843, 3.977]	.729		
	> 6 years	524	3.869	[3.807, 3.931]	.723		
Exp. in teaching AI	Yes	1228	3.915	[3.876, 3.954]	.696	2.955	
	No	436	3.799	[3.730, 3.868]	.735		

Gender, teaching subject group, teaching grade, and teaching experience did not have significant effects on the perceived importance of teaching AI. Similarly, gender, teaching subject group, and teaching experience did not have significant effects on interest in teaching AI. However, the primary school teachers had marginally higher scores on interest in teaching AI than did the secondary school teachers and teachers belonging to other teaching levels. Furthermore, the teachers with prior experience in AI teaching had significantly higher scores for perceived importance of teaching AI and interest in teaching AI than those who did not have such experience. Thus, practical experience in AI teaching positively influenced attitudes toward AI education.

4.2.3 Demographic factors and clusters

We used multinomial logistic regression to explore the patterns of clusters based on demographic factors. The -2 log likelihood for the final model was 883.23 [$\chi^2(32) = 127.39$, $p < 0.001$], which indicated that this model had a reasonable fit for the data. Table 15 presents the results of likelihood ratio tests, which suggested that only gender and experience in teaching AI were statistically significant predictors of cluster membership. Tables 16 and 17 present the odds ratios and indicate how gender and experience in teaching AI affected the likelihood of belonging to each cluster. The results indicated that the likelihood of the male teachers belonging to the HR–HA cluster was consistently higher than those from a different cluster. Conversely, the likelihood of the female teachers belonging to the AR–HA cluster was marginally higher than that of them belonging to the AR–AA cluster. In addition, the likelihood of the teachers with prior experience in teaching AI belonging to the HR–HA cluster was consistently higher than those from a different cluster.

Table 15 Results of likelihood ratio tests for the five demographic factors

Effect	-2 Log likelihood of reduced model	χ2	df	Sig
Intercept	883.23	/	/	
Gender	912.03	28.80	4	0.000
Teaching Subjects	884.62	1.39	8	0.994
Teaching Grade	893.74	10.50	8	0.231
Teaching Experience	891.39	8.15	8	0.419
Experience in teaching AI	932.82	49.59	4	0.000

Table 16 Odd ratios for clusters by gender (only significant values are displayed)

	HR–HA vs	AR–HA vs	AR–AA vs	LR–HA vs	LR–LA vs
HR-HA	1				
AR-HA	2.78(0.000)	1	1.40(0.016)		
AR-AA	1.99(0.002)		1		
LR-HA	2.55(0.000)			1	
LR-LA	2.53(0.000)				1

Table 17 Odd ratios for clusters by experience in teaching AI (only significant values are displayed)

	HR–HA vs	AR–HA vs	AR–AA vs	LR–HA vs	LR–LA vs
HR-HA	1				
AR-HA	3.75(0.000)	1	1.45(0.017)		
AR-AA	2.59(0.000)		1		
LR-HA	5.54(0.000)	1.48(0.032)	2.14(0.000)	1	
LR-LA	4.44(0.000)		1.72(0.012)		1

Intriguingly, the likelihood of those without prior AI teaching experience belonging to the AR–HA cluster was higher than those from the AR–AA cluster.

5 Discussion

In the present study, we surveyed K–12 teachers' TPACK readiness and attitudes toward AI education. Moreover, we examined how the teachers' demographic characteristics—including their gender, teaching subject, teaching grade, teaching experience, and experience in teaching AI—influenced their TPACK readiness and attitudes toward AI education. The results of this study provide valuable insights into the TPACK readiness and attitudes toward AI education of teachers, thereby enabling the development of tailored professional development programs for teachers from diverse backgrounds. The following text describes the TPACK readiness and attitudes toward AI education of the surveyed teachers, the patterns identified through cluster analysis, and the effects of demographic characteristics on the teachers' TPACK readiness and attitudes toward AI education. Subsequently, suggestions are provided with respect to professional teacher development programs and resources for AI education.

5.1 Teachers' TPACK readiness and attitudes toward teaching AI

In general, the results obtained for RQ1 indicated that the surveyed teachers had fewer perceptions towards their AI-related knowledge (i.e., CK) and AI technological use (i.e., TK) than their AI teaching skills (PK). Thus, the first challenge in AI education involves understanding AI. For example, Lindner and Berges (2020) discovered that educators with a preliminary understanding of AI can explain essential concepts related to AI but not in detail. The field of AI encompasses various complex topics, such as AI and robotics, AI and machine learning, data science, big data and analytics, high-performance computing, and cybersecurity. Because of the extensive, abstract, and intricate nature of AI knowledge, teachers must be given suitable professional training to obtain a comprehensive understanding of AI and AI-related concepts. Furthermore, teacher trainers must ensure that teachers involved in AI education are able to not only grasp AI-related concepts but also use AI technology proficiently. However, most teachers involved in teaching AI have not majored in computer science or received formal prior training (Chiu & Chai, 2020). Such lack of knowledge can lead to misconceptions regarding AI, which negatively affects classroom instruction.

The results of cluster analysis revealed interesting relationships between the teachers' PK and their attitudes toward AI education. In particular, the AR–AA and LR–LA clusters had significantly higher scores for PK than for the other TPACK-related constructs (Fig. 3). Moreover, these clusters had lower scores for perceived importance of teaching AI and interest in teaching AI than did the other clusters. Several possible explanations exist for the aforementioned results. First, this study found that the perceived relevance of AI as a discipline may influence teachers' attitudes toward AI education. In the field of STEM education, attitudes toward STEM are related to beliefs regarding the relevance of STEM to daily life (Thibaut et al., 2018; Weng et al., 2020). An individual's attitude toward a subject is closely associated with their career choices and commitment to their career (Tseng et al., 2013; Huang and Jong, 2020). Considering the diverse subject backgrounds of the surveyed teachers, some may have considered themselves to be proficient in their teaching subject (i.e., high PK) and may have regarded AI to be irrelevant to their lives and career; such beliefs would have resulted in a negative attitude toward AI education. Second, the differences between AI-specific pedagogical approaches and traditional teaching methods may affect teachers' attitudes toward AI education. A previous study found that popular methods of teaching AI—such as a customized-platform-based approach (e.g., Lin et al., 2020), a game-based approach (Priya et al., 2022), project-based learning (Tseng et al., 2021), and experiential learning (Hsu et al., 2022)—differ considerably from traditional direct instruction (Su et al., 2023). Teachers may feel that their teaching experience and skills (i.e., PK) do not transfer well to the AI context (e.g., CK, TK, and PCK). Third, a lack of CK may influence teachers' attitudes toward AI education. For example, two types of low scorers were discovered in this study: the LR–LA cluster and the LR–HA cluster teachers. The teachers from the LR–LA cluster had moderate PK (3.14) but very low CK (1.83), whereas the teachers from the LR–HA cluster had low PK but a relatively higher CK (2.53). Surprisingly, the LR–LA cluster teachers had very low scores for perceived importance of teaching AI and interest in teaching AI. By contrast, the scores of the LR–HA cluster teachers for the aforementioned factors were relatively high, comparable to those of teachers with higher levels of perceived TPACK (e.g., AR–AA). We found that a lack of CK significantly contributed to the teachers lacking confidence and willingness to engage in AI education; this finding is in line with that of previous research. Various scholars have argued that primary teachers with low scientific literacy and negative perceptions of science are more likely to lack motivation to implement science in teaching (Harlen & Holroyd, 1997; Jarvis & Pell, 2004; Tosun, 2000; Yates & Goodrum, 1990).

5.2 Demographic effects

RQ2 examined the possible relationships of teachers' demographic characteristics (gender, teaching subject, teaching grade, teaching experience, and experience in teaching AI) with their TPACK readiness and attitudes toward teaching AI. Of the demographic factors, teaching grade and teaching experience are highlighted in the following text.

The results indicated that the primary school teachers had higher scores for all seven TPACK-related factors than the secondary school teachers. This finding challenges the traditional view that AI is a more suitable subject for older adolescents (Barik et al., 2013). A potential explanation for the aforementioned finding may be the differing objectives and environments of primary and secondary education. Primary education emphasizes broad and foundational learning and often involves exploration-based subjects, such as introductory science. By contrast, secondary education focuses on specialized areas of study to prepare students for tertiary education and future careers (Nusche et al., 2012). Furthermore, compared with secondary school teachers, primary school teachers may have more flexibility to integrate interdisciplinary themes, use varied teaching methodologies, and customize learning on the basis of student needs; by contrast, secondary school teachers may have less autonomy to innovate because of examination pressures and the rigid curriculum structure in secondary schools (Ingersoll, 2003). Therefore, compared with secondary school teachers, primary school teachers may be more open-minded about new teaching areas. In addition, secondary school teachers may believe that a deep understanding of complex concepts is required for teaching AI, which can make them fearful of teaching AI in their classrooms. However, these expectations may not align with the reality of AI education. Age-appropriate technologies and teaching approaches can be used to visualize and simplify AI concepts, thereby making them accessible to students at all levels (Yue et al., 2022).

In this study, teachers of early career (i.e., those with a teaching experience of less than 3 years) tended to give themselves low scores for all TPACK-related factors; however, the scores for these factors did not differ significantly with differing teaching experience. Studies have obtained contrasting results regarding the effects of teaching experience on TPACK-related factors. For example, Cheng (2017) found that teachers with more teaching experience were more confident in their CK, PK, and PCK. Moreover, Jang and Chang (2016) concluded that more experienced teachers generally have higher levels of CK and PK. By contrast, Lee and Tsai (2010) discovered that teachers with more teaching experience had lower confidence in their Web-based TPACK. Similarly, Koh et al. (2014) determined that more experienced teachers had lower perceived TPACK. One possible explanation for the results of Lee and Tsai (2010) and Koh et al. (2014) is that the pedagogical practices of more experienced teachers may have been more strongly shaped by the school system, which is exam-driven and focuses on the dissemination of knowledge and facts (Hogan & Gopinathan, 2008). These teachers may be more rigid in their expertise or in executing fixed teaching routines (Hatano & Inagaki, 1986). Therefore, they may perceive greater barriers in transitioning between pedagogical approaches within the school system, which might explain the effects of teaching experience on teachers' TPACK perceptions.

Experience in teaching AI had a significant effect on the surveyed teachers' perceived TPACK. The teachers with prior experience in teaching AI reported higher scores for all seven TPACK-related factors than did those without such experience. The results of this study indicate that experience in teaching AI has a stronger influence on teachers' perceived AI-related TPACK than does teaching subject or teaching experience. Teachers should be given opportunities to practice AI teaching before formally beginning it.

5.3 Implications for TPD

The research presented in this study makes both theoretical and empirical contributions to the field of AI education for TPD. Theoretical contributions include the examination of teachers' technological pedagogical content knowledge (TPACK) readiness and attitudes toward AI teaching, which provides insights into the preparedness of teachers for integrating AI education and developing AI literacy (Ng et al., 2021). This study addresses a research gap by investigating these aspects, shedding light on the current state of teacher readiness for AI education and the factors that influence it. Empirically, the study recruited a substantial sample size of 1,664 K-12 teachers with diverse backgrounds in terms of gender, teaching subject, teaching grade, teaching experience, and experience in teaching AI. By involving a large and varied group of teachers, the study provides a comprehensive view of the readiness and attitudes of teachers toward teaching AI in K-12 settings.

By understanding teachers' backgrounds, the findings of the study reveal a significant gap in AI-related content and technological knowledge among the recruited teachers. Interesting relationships are identified between teachers' pedagogical knowledge, content knowledge, and attitudes toward teaching AI. The study also examines the influence of demographic factors on teachers' TPACK and attitudes. These empirical findings contribute to the understanding of the current state of teachers' readiness for AI education and provide valuable insights into developing meaningful TPD programs for AI education that positively influence their TPACK and attitudes.

Recently, a global group, the TeachAI Steering Committee (2023), has initiated three seminal guiding directions for empowering educators to teach with and about AI in schooling contexts, namely, (i) "guidance and policy," (ii) "organizational learning," and (iii) "improvement and transformation." The first direction is about developing policies to ensure students' learning will not be undermined by the introduction of AI. The second direction is about providing teachers with ongoing AI-related learning opportunities on an organizational basis. The third direction is about identifying suitable realms where AI can be leveraged so as to improve and transform the education system. Based on the results of the present study and according to the guiding directions initiated by the TeachAI Steering Committee (2023), we further proposed a framework for formulating TPD programs for better preparing K–12 teachers to implement AI education, as illustrated in Fig. 4 and discussed in the following subsections.

5.3.1 Guidance and policy

With respect to the direction of "guidance and policy" (TeachAI Steering Committee, 2023), there are three areas that a TPD program for AI education should address. The first area is "age-appropriate AI content knowledge" (see Fig. 4). It is related to the appropriate selection of CK, the importance of which is indicated by the results of this study. When teachers lack confidence in their AI-related CK, they are relatively uninterested in teaching AI. Currently, AI education training programs for teachers primarily focus on offering basic insights into and practical experience of AI (Xia & Zheng, 2020), or on instructions regarding how to use particular teaching resources (Williams et al., 2021). Although these programs give teachers some relevant knowledge, they may not cover the vast spectrum of AI knowledge. Further, in K–12 education, AI knowledge can be approached in a flexible manner. For example,

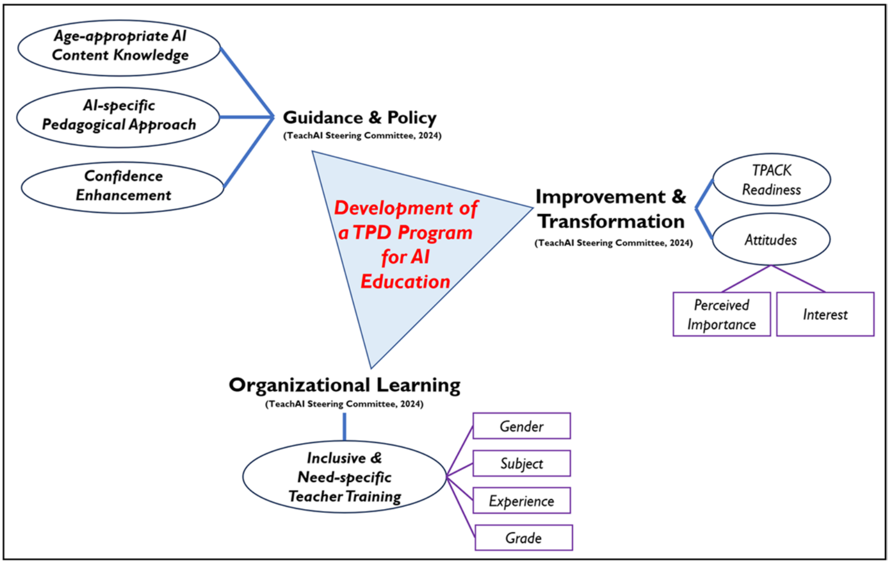


Fig. 4 Framework for the development of a TPD program for AI education

according to Yue et al. (2022), AI learning content can involve understanding AI through playful exploration activities and understanding the basic principles of AI approaches through experiment-based activities. Challenging AI algorithms need not be explained to primary school students. Therefore, the government and universities should establish learning standards, curricula, and guidelines that clearly outline the AI-related concepts that students must learn at each specific age. If teachers are given a clear framework of AI education, they can better understand what AI concepts they need to teach, thereby enabling them to focus their efforts on acquiring the necessary knowledge and skills. TPD programs related to AI education should prioritize equipping teachers with the level-appropriate knowledge, skills, and resources required for them to confidently incorporate AI into their classrooms. These programs should scaffold teachers with not only essential AI-related competencies (i.e., CK and TK) but also confidence in the implementation of AI education.

The second area is “AI-specific pedagogical knowledge” (see Fig. 4). It is related to innovative AI-specific pedagogical approaches. The results of this study indicate counterintuitive relationships between PK and other TPACK and attitude factors, especially, this indicates that the pedagogical approach for AI education may be different from the pedagogical approach that teachers are familiar with in a normal classroom. The latest reviews in the field of AI education have suggested that although various pedagogical approaches—such as customized-platform-based approaches, project-based learning, and game-based approaches—have been employed in teaching AI in K–12 classrooms (Yue et al., 2022; Su et al., 2023), new pedagogical approaches must still be developed; examples of such approaches include design-oriented approaches (Yue et al., 2022) and collaborative project-based learning (Dai et al., 2023). Therefore, teachers should be responsible and accountable for pedagogical and educational decision-making processes especially when using AI tools (TeachAI Steering Committee, 2023). TPD programs must introduce innovative AI-specific PK and up-to-date AI teaching resources to teachers to enable them to keep pace with the latest advancements in AI and AI education. Teachers should be given continuous support and growth opportunities to enable them to continually refine their pedagogical approaches and adapt to the evolving landscape of AI.

The third area is "confidence enhancement" (see Fig. 4). It is related to the low confidence levels of secondary school teachers in teaching AI. To address this problem, teachers should be provided specific guidelines, curricula, and resources to enhance their confidence in teaching AI. The guidelines should clarify the goal of teaching AI, such as to foster AI literacy rather than to become a programming expert. The resources should aim to demystify AI and provide practical strategies for integrating AI concepts into the classroom. Understanding appropriate goals and knowledge in AI education can help teachers to overcome their fears associated with AI teaching and to engage with their students confidently in their classes. In addition, TPD programs should encourage all teachers, regardless of their subject area, to learn about AI and incorporate it into their teaching practices. AI is a rapidly evolving field that has the potential to affect various disciplines and industries; thus, all teachers must understand the fundamentals and applications of AI.

5.3.2 Organizational learning

With respect to the guiding direction of "organizational learning" (TeachAI Steering Committee, 2023), a TPD program for AI education should cultivate an inclusive and need-specific training environment for teachers (see Fig. 4). According to our findings, teachers from various backgrounds possess the potential to contribute to AI education. It is crucial to offer professional development opportunities to all teachers of different genders, teaching subjects, teaching experience, and teaching grades. Therefore, recognizing and accommodating the diverse demographic backgrounds of teachers is essential, ensuring that professional development initiatives are inclusive and mindful of different subject perspectives and teaching contexts. Of the demographic factors investigated in this study, experience in teaching AI had the strongest effect on all factors related to TPACK readiness and attitudes toward teaching AI. Yet, there is a notable deficiency in opportunities for teachers to engage in practical teaching experiences, with most AI-related educational initiatives being short-term and small-scale (Yue et al., 2022). This gap highlights the necessity for TPD programs to align more closely with school policies, fostering environments that encourage and facilitate more extensive teaching practices rather than focusing solely on theoretical "teacher development." As highlighted by Darling-Hammond et al. (2017), effective professional development should be deeply integrated with teaching practice and supported by school policies, thereby creating a continuous loop of feedback and improvement. A review conducted by Huang et al. (2022) on STEM TPD programs emphasized the use of the "learning by design" approach, where teachers engage in tasks that they are likely to encounter in their classrooms. This approach aims to enhance teachers' comprehension of student requirements and offers them opportunities to participate in relevant tasks (Quarderer & McDermott, 2018). We suggest that in addition to CK, PK, and knowledge regarding AI-specific pedagogical approaches, TPD programs should give teachers practical teaching experience, such as experience in microteaching with peers. By acquiring authentic experience in teaching AI and reflecting on their teaching practice, teachers can become more confident and better prepared for AI education.

5.3.3 Improvement and transformation

With respect to the guiding direction of “improvement and transformation” (TeachAI Steering Committee, 2023), to facilitate the desirable improvement and effective transformation of teaching practice to take place in schools, a TPD program for AI education should emphasize both TPACK readiness and attitudes towards teaching AI (see Fig. 4). The TPACK readiness involves age-appropriate AI content knowledge, AI-specific pedagogical approaches, and the embrace of AI technologies. The TPD program should provide curriculum guides for age-appropriate teaching topics, such as basic AI knowledge, societal impacts of AI, and AI ethics, to meet the specific curriculum needs and cognitive development of students. Once the teaching contents have been identified, it is crucial to provide pedagogical guidelines and document successful cases for teachers to design their instructional practices in the classroom. Importantly, teaching AI is not limited to STEM or computer science; it can involve different subject areas. For instance, language teachers can engage students in interacting with chatbots to enhance their language acquisition and writing skills (Su et al., 2023). Furthermore, the TPD program should equip teachers with the skills to harness the potential of AI technologies in improving students’ learning experiences and digitally transforming current teaching practices. This enables teachers to effectively integrate AI technologies across various subjects and disciplines, fostering interdisciplinary connections and expanding students’ understanding of AI’s applications. In addition to enhancing TPACK competencies, TPD programs should prioritize fostering positive attitudes towards teaching, including cultivating interest and recognizing the perceived importance of the content being taught. We suggest a particular focus be placed on confidence enhancement. As teachers hold positive attitudes towards teaching AI and become more confident, they are likely to engage more deeply with AI education, thereby improving their TPACK competencies and encouraging a more enthusiastic reception of AI topics among students. This holistic approach to TPD, encompassing both the acquisition of technical competencies and the cultivation of supportive attitudes, is crucial for the successful integration of AI education into the classroom. Through these efforts, education systems can drive positive change and transformation that prepares students for the AI-driven world while empowering educators to become ready and confident in teaching AI.

6 Limitations

This study has several limitations. First, because of its exploratory nature, we employed a convenience sampling approach to collecting the research data in the study. As indicated, the majority of the respondents were male. In fact, this research sample might not represent the general population of teachers in mainland China, and thus, there is a limitation of the generalizability of our findings. Further research into a more diverse sample can be carried out to triangulate or compare our present work.

Secondly, although collecting quantitative data to examine teachers' readiness for and attitudes toward teaching AI can reveal trends in general, qualitative analysis, such as interviews, should be employed in future studies to gain a more detailed insight into what teachers need to be prepared for AI education. Lastly, empirical studies are needed to evaluate the proposed TPD framework.

7 Conclusion

In conclusion, this study comprehensively explored teachers' perceived TPACK readiness and attitudes toward AI teaching as well as the influences of demographic characteristics on these two factors. The teachers surveyed in this study exhibited relatively low perceived CK and TK related to AI. The results of cluster analysis revealed intriguing relationships between PK, CK, and attitudes toward AI education. High confidence in PK related to general teaching does not lead to high confidence or interest in teaching AI. Demographic analysis suggested that more teaching experience does not guarantee a better understanding and implementation of AI education. Instead, the present analysis suggests that teaching practice, especially that involving AI, is a more crucial factor than teaching experience for developing confidence in AI-related TPACK. Furthermore, the results reveal a high potential for teaching AI at the primary school level to provide students with an early introduction to AI.

On the basis of the results of the present study, we have formulated a framework that helps consider demographic characteristics and teacher background for the design of TPD programs related to AI education. We suggest that such programs should consider the various backgrounds, views, assumptions, and AI-education-related expectations of teachers. To enhance teachers' readiness and attitudes to incorporate AI knowledge into their curriculum for fostering students' AI literacy, TPD programs and resources should ensure that teachers are aware of learning standards, the curriculum, guidelines, and resources relevant to AI. Specifically, four directions are proposed in this paper for TPD programs related to AI education: (1) the selection of age- and level-appropriate CK, (2) the development of innovative AI-specific pedagogical approaches, (3) the enhancement of the confidence of secondary school teachers in AI teaching, and (4) the provision of practice related to AI teaching.

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Declarations

Conflicts of interest The authors declare that they have no conflict of interest. The manuscript has not been published previously and is not being simultaneously submitted elsewhere. There are not any real or potential conflicts of interest that could be seen as having an influence on the research.
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