



# An analysis of science teachers' use of artificial intelligence in education from a Technological Pedagogical Content Knowledge perspective

Gasangusein I. Ibragimov <sup>1\*</sup>

 0000-0002-3506-0754

Elena N. Kolomoets <sup>2</sup>

 0000-0002-4632-6757

Alla A. Filippova <sup>3</sup>

 0000-0002-0295-4751

Elmira R. Khairullina <sup>4</sup>

 0000-0002-2125-4283

Natalya Y. Garnova <sup>3</sup>

 0000-0002-6685-9761

Julia V. Torkunova <sup>5,6</sup>

 0000-0001-7642-6663

<sup>1</sup> Kazan (Volga region) Federal University, Kazan, RUSSIA

<sup>2</sup> Moscow Aviation Institute (National Research University), Moscow, RUSSIA

<sup>3</sup> Sechenov First Moscow State Medical University (Sechenov University), Moscow, RUSSIA

<sup>4</sup> Kazan National Research Technological University, Kazan, RUSSIA

<sup>5</sup> Kazan State Power Engineering University, Kazan, RUSSIA

<sup>6</sup> Sochi State University, Sochi, RUSSIA

\* Corresponding author: [guseinibragimov@yandex.ru](mailto:guseinibragimov@yandex.ru)

**Citation:** Ibragimov, G. I., Kolomoets, E. N., Filippova, A. A., Khairullina, E. R., Garnova, N. Y., & Torkunova, J. V. (2025). An analysis of science teachers' use of artificial intelligence in education from a Technological Pedagogical Content Knowledge perspective. *Online Journal of Communication and Media Technologies*, 15(3), e202523. <https://doi.org/10.30935/ojcmr/16594>

## ARTICLE INFO

Received: 6 Jan 2025

Accepted: 29 May 2025

## ABSTRACT

The aim of the study is to evaluate science teachers' use of artificial intelligence (AI) within the context of Technological Pedagogical Content Knowledge (TPACK). The study examines teachers' AI Competence Self-Efficacy and their TPACK according to demographic variables, investigates the relationship between these two variables, and determines the predictive effect of AI competence self-efficacy on TPACK. Quantitative research method was used at research and relational survey model used. The sample of the study consists of 296 science teachers in 13 different middle schools during the February–March 2025 period. Data were collected by *Teacher AI Competency Self-Efficacy Scale (TAICS)* and the *AI Technological Pedagogical Content Knowledge (AI-TPACK) Scale*. For data analysis, *Independent Samples t-test*, *ANOVA*, *Pearson Correlation Analysis*, and *Structural Equation Modeling (SEM)* were used. According to the results, the overall mean scores of both AI-TPACK and TAICS were found to be medium level. According to gender analysis, female teachers scored higher than male teachers in the sub-dimensions of both AI-TPACK and TAICS. Teachers with fewer years of experience had higher scores in the technology-related components of AI-TPACK, whereas those with more teaching experience had higher averages in dimensions such as Pedagogical Knowledge (PK), Content Knowledge (CK), and Pedagogical Content Knowledge (PCK). In terms of TAICS, teachers with lower experience also had higher average scores. Overall, there were positive and significant correlations between the dimensions of TAICS and AI-TPACK. Finally, the TAICS construct significantly predicted AI-TPACK. Based on these findings, recommendations were given for future research to focus on the active use of AI

---

within the TPACK framework and to include qualitative research designs aimed at exploring the challenges encountered in the process of AI integration.

**Keywords:** artificial intelligence in education, science teachers, technological pedagogical content knowledge, AI pedagogy, technology integration

## INTRODUCTION

---

The rapid development of digital technologies today has directly affected educational practices and directed teachers to adopt new tools and approaches in their instructional processes. Among these technologies, artificial intelligence (AI) stands out as a transformative tool with the potential to personalize learning processes, support assessment practices, and enhance instructional strategies (Hewitt, 2008; Luckin et al., 2016). The effective integration of AI into educational process is not only to technical knowledge but also to pedagogical understanding and content knowledge (CK) (Maghsudi et al., 2021). Technological Pedagogical Content Knowledge (TPACK) framework is a highlighted model used to evaluate teachers' ability to effectively integrate technology within their educational process (Chai et al., 2010; Fieding & Gilbert, 2006; Koehler & Mishra, 2009; Li et al., 2025).

This study aims to examine science teachers' use of AI within the context of TPACK, as they play a critical role in fostering scientific thinking and technological literacy. By investigating the relationship between teachers' AI self-efficacy levels and their TPACK competencies, this research seeks to identify the factors that influence the effective integration of AI in science education.

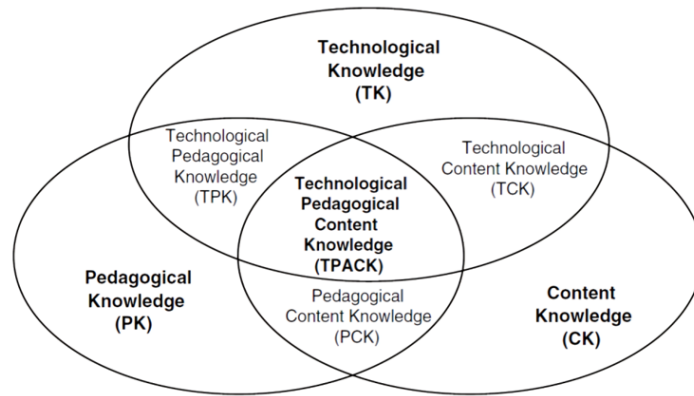
## THEORETICAL FRAMEWORK

---

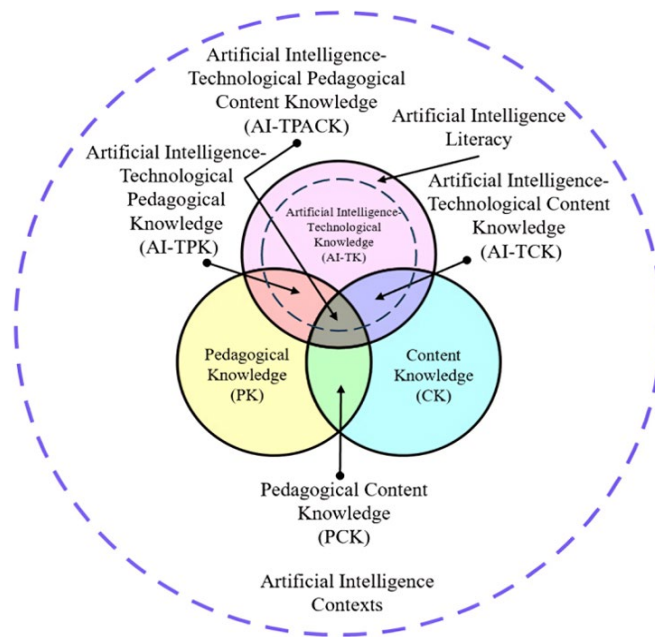
### TPACK and AI-TPACK

The teachers' role, who are directly engaged in the teaching process, on the education technology integration process is crucial. The issues primarily researched by educational researchers are; focused on different models. In this sense, models are placed under two general approaches, technology centered or pedagogy centered; technology centered models target teachers' knowledge (Almithqal & John, 2025) and skills development for technological use, while pedagogy centered models address the integration of teachers' use of technology with pedagogical knowledge (PK) in the teaching process (Chai et al., 2010; Koehler & Mishra, 2005; Koh et al., 2013; Sulistiani et al., 2024.). The foremost pedagogy focused model about the integration of technology in education is TPACK model. TPACK model has taken its final form by integrating "technology" dimension to Pedagogical Content Knowledge (PCK), which was a model addressing teachers' ability to use their content and pedagogy knowledge together (Bwalya et al., 2024; Koehler & Mishra, 2009; Koh et al., 2010).

TPACK model was considered within the framework of PCK model and two types of technology integration, namely integrative and transformative, were suggested (Lee & Tsai, 2010; Lim & Chai, 2008; Schmidt et al., 2009) ([Figure 1](#)). Pierson (1999) explained TPACK in its simplest form as the combination of content knowledge, pedagogic knowledge, and technologic knowledge or the integration of technology. Following the TPACK definition of Pierson (2001), Keating and Evans (2001) developed a wider definition for TPACK, emphasizing that the technology used in the education process should also fit the content. According to Keating and Evans (2001) TPACK provide the opportunity to present content knowledge in the most suitable way by using technology. TPACK concept, which was defined as pedagogic content knowledge of technology by Margerum-Lays and Marks (2003), is expressed as an applicable knowledge, derived from teaching-learning situation in which educational technology was used. According to the researchers, a teacher who owns this knowledge knows how to use particular technologies in education; how much time is required for performing the education with these technologies; how to solve students' probable problems with particular technologies; and how to organize teaching and learning according to technologic facilities (Ay et al., 2015; Margerum-Lays & Marx, 2003). This teacher has the ability to use technology rationally and (s)he is aware of the impact of technology in learning the concepts that students have to.



**Figure 1.** TPACK framework (Source: Koehler et al., 2014 and <https://tpack.org>)



**Figure 2.** AI-TPACK structural diagram (Source: Ning et al., 2024, p. 5)

With the increasing integration of artificial intelligence into educational processes, it is seen that new contexts are being loaded into the TPACK framework (Mishra & Koehler, 2006). In addition, the integration of AI technologies into the TPACK framework will lead to different innovations in teaching methods, learning environments and other educational variables (Ning et al., 2024). Determining the relationships between technology, pedagogical knowledge and content knowledge has brought about an original TPACK framework based on the age of AI. In this framework, technology is positioned as the most dynamic element compared to pedagogical and content knowledge elements. It can be said that as the knowledge and awareness levels of teachers about AI technology increase, these knowledge areas will also transform in parallel. In particular, TPK will transform into AI-TPK over time, and TCK will transform into AI-technological pedagogical knowledge (AI-TCK); lastly, TPACK evolved into AI Technological Pedagogical Content Knowledge (AI-TPACK), which includes cognitive components called AI literacy (Çelik, 2023). In this context, the new theoretical framework of AI-TPACK has been presented in [Figure 2](#).

The AI-TPACK represents a specific and detailed type of three core domains: CI (disciplinary expertise), PK (instructional methods and strategies), and TK specifically related to AI. This type of knowledge is different from the expertise of subject matter experts and AI technology experts. It composed teaching styles that involve the use of AI technology, which go beyond general pedagogical knowledge and take a specific approach to certain disciplines. AI-TPACK enables educators or AI tools that function as educators to have a level of knowledge comparable to human teachers. This knowledge enables them to carry out teaching tasks independently or collaboratively with human educators (Ning et al., 2024).

This is important in the current AI era, where AI technology has moved beyond being merely a tool for teaching and learning. Instead, a new focus is emerging on how human teachers and AI tools (AI teachers) can effectively collaborate. This collaborative aspect forms an integral part of the AI-TPACK framework (Çelik, 2023). Therefore, the interactive relationships between AI technology, subject content, and teaching methods are of critical importance in the AI-TPACK framework. These relationships form the core of AI-TPACK from the perspective of human-computer collaborative thinking. This perspective emphasizes the importance of integrating AI technology not only as a complementary tool but as an integral component of the teaching and learning process; thus, how educational content is presented and understood is being reshaped in the AI era (Ning et al., 2024).

The integration of AI technology into the TPACK framework can revolutionize teaching methods, learning process, and other educational stakeholders. Therefore, the development of an AI-enriched TPACK model (AI-TPACK) is becoming an important area of research and investigation. The AI-TPACK framework has had an impact on research and practice in the fields of teacher professional development, leading to extensive academic reviews and research.

### Teacher AI Competence

Digital competence is the knowledge, skills, and dispositions required to use and interact with digital technology critically, creatively, and responsibly in a variety of contexts (Hatlevik et al., 2015; Janssen et al., 2013). Individuals who possess high levels of digital competence possess a good understanding of the contribution of digital technology to society currently and a positive disposition towards the contribution of the technology. They can use technologies consciously, responsibly, and healthily (Ilomäki et al., 2016). Teacher digital competence refers to a teacher's capacity to plan, organize, implement, and evaluate learning activities using digital technologies; the ability to develop students' digital competences, and their participation in professional learning (Chiu et al., 2024).

AI competence self-efficacy refers to individuals' beliefs concerning their capability for successfully understanding, using, and implementing AI technologies in various scenarios. This skill entails problem-solving confidence, confidence in decision-making, and utilizing AI in occupational or daily practices (Yılmaz et al., 2023). AI competence self-efficacy is the individual's self-evaluation of human capacity to employ AI technologies. Following Bandura's self-efficacy theory, this concept measures individuals' belief in their capability to successfully perform certain tasks. Implementations of AI in learning, positive attitudes of educators towards their own AI capacities are central to the successful adoption of these technologies in the classroom (Bandura, 2005).

TPACK can be thought of as a teacher's capacity to make effective decisions when designing and implementing teaching and learning practices enhanced by digital tools. However, the framework doesn't explicitly address the implications of emerging technologies such as AI, particularly concerning issues like disinformation, fake news, and ethical or moral considerations. But these aspects are essential for the responsible integration of modern digital Technologies which educators are expected to provide not only effective but also safe and healthy learning environments for their students (Chiu et al., 2024; Falloon, 2020). According to Angeli and Valanides (2009), defining the individual components of TPACK remains challenging due to the inherently blurred and ambiguous boundaries between its constructs. This issue is similarly evident in the literature related to AI-TPACK (Ning et al., 2024).

The aim of the study is to explore how science teachers use AI within the framework of TPACK. The research investigates teachers' levels of AI use and TPACK according to demographic variables, examines the relationship between these two constructs, and identifies how AI influences the integration of TPACK in educational practices. In line with this aim, the study seeks to answer the following research questions:

1. What is the overall level of science teachers' AI-TPACK proficiency?
2. Do science teachers' AI-TPACK scores change according to demographic characteristics?
3. What is the level of science teachers' AI competence self-efficacy?
4. Do science teachers' AI competence scores differ based on demographic characteristics?
5. Is there a statistically significant relationship between science teachers' AI-TPACK and AI competence self-efficacy scores?

**Table 1.** Demographic data of the participants

						Total
Gender	Frequency (n)	Male	Female			296
	Percentage (%)	41.6	58.4			100
Class stages	Frequency (n)	5. class	6. class	7. class	8. class	13
	Percentage (%)	23.2	30.7	23.2	23.2	100
Age range	Year	21–30	31–40	41–50	51 or above	
	Frequency (n)	80	104	82	30	296
	Percentage (%)	27.1	35.1	27.7	10.1	100
Career year	Year	1–10	11–20	21–30	31 or above	
	Frequency (n)	121	76	68	31	296
	Percentage (%)	40.9	25.6	23.0	10.5	100

6. To what extent do AI competence scores and components of AI-TPACK influence the overall AI-TPACK score?

## MATERIAL AND METHODS

### Research Design

The research was organized according to the correlational method, which is one of the non-experimental quantitative research methods. Correlational model is the form of study where the researcher seeks a relationship between two or more variables that happen to interact with each other (McMillian & Schumacher, 2004). The goal of the study is to obtain a decision or a model from a study of the relationship between variables. Thus, this study is built upon the *Explanatory Correlational Design* (Creswell, 2005).

### Participants

This research was conducted with 319 Science teachers of 13 purposefully selected schools. The first requirement of the participants was teachers' and schools' willingness for management. The second was the number of variety students in class. And the third was the teachers' variety class stages. The information gathered from 23 teachers are highly likely to adversely affect the validity of the study and were removed before the analysis (these teachers provided the same score to all of the items). Therefore, the information gathered from 296 participants was used in the study. Information about the demographic characteristics of the participant group is presented within [Table 1](#).

### Data Collection Tools

#### Teacher AI competence self-efficacy scale

*Teacher AI competency self-efficacy scale (TAICS)* was used for teachers' AI competence. The *TAICS* was developed by Chiu et al. (2025). The *TAICS* is a 24-item instrument designed to measure AI competency across six dimensions, with each dimension consisting of four items. The scale demonstrates high reliability, with Cronbach's alpha values exceeding 0.87. Responses are collected using a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree).

The first dimension, AI Knowledge (AIK), demonstrates teachers' ability to differentiate between AI-based and traditional tools, ensuring effective integration into educational settings. AI Pedagogy (AIP) evaluates how teachers use AI tools to enhance both content delivery and student engagement. AI Assessment (AIA), third dimension, focuses on leveraging AI for student evaluations, enabling teachers to monitor progress and facilitate self-assessment. The fourth dimension, AI Ethics (AIE), examines teachers' understanding of ethical considerations related to AI, such as privacy, security, and responsible AI use in educational environments. Human-Centered Education (HCE) emphasizes a critical approach to AI integration, assessing both its advantages and potential risks, including issues related to bias and equity. Lastly, Professional Engagement (PEN) measures teachers' commitment to ongoing learning and collaboration in AI-driven education, including their participation in professional development activities.

**Table 2.** Skewness and kurtosis values of tools

	N	Skewness		Kurtosis	
		Statistic	Standard error	Statistic	Standard error
AI knowledge (AIK)	296	-.430	.172	-.930	.313
AI pedagogy (AIP)	296	-.537	.172	-.605	.313
AI assessment (AIA)	296	-.293	.172	-.892	.313
AI ethics (AIE)	296	-.436	.172	-.593	.313
Human-centered education (HCE)	296	-.430	.172	-.843	.313
Professional engagement (PEN)	296	-.603	.172	-.580	.313
TAICS total mean	296	-.598	.172	-.511	.313
Pedagogical knowledge (PK)	296	-.641	.172	-.374	.313
Content knowledge (CK)	296	-.467	.172	-.930	.313
AI-technological knowledge (AI-TK)	296	-.430	.172	-.705	.313
Pedagogical content knowledge (PCK)	296	-.725	.172	-.252	.313
AI-technological pedagogical knowledge (AI-TCK)	296	-.364	.172	-.785	.313
AI-technological content knowledge (AI-TPK)	296	-.610	.172	-.588	.313
AI-TPACK	296	-.537	.172	-.605	.313

**Table 3.** Science teachers' AI-TPACK levels

AI-TPACK	N	Mean	Standard deviation
PK	296	3.63	.897
CK	296	3.42	1.17
AI-TK	296	3.44	1.09
PCK	296	3.37	1.02
AI-TCK	296	3.40	1.05
AI-TPK	296	3.42	1.08
AI-TPACK	296	3.46	.878

### Teachers' AI-TPACK scale

The *AI-TPACK scale* was developed by Ning et al. (2024). The *AI-TPACK scale* was used for teachers' AI based technological pedagogical content knowledge competence. The *AI-TPACK scale* is a 39-item instrument designed to AI-TPACK competency across seven dimensions. The *AI-TPACK scale* composes seven sub-dimensions: PK, CK, AI-Technological Knowledge (AI-TK), PCK, AI-TCK, AI-Technological Content Knowledge (AI-TPK), and AI-TPACK. Cronbach's alpha values for the sub-dimensions ranged from 0.806 to 0.945, with an overall scale value of 0.957. The *AI-TPACK scale* which 5-point Likert scale, ranging from 1 (strongly non-conformant) to 5 (strongly conformant). There are no negative items and high score demonstrate optimum AI based TPACK.

### Determining the Analysis Type

In order to analyze the data, scales were initially transferred to Excel and then to IBM SPSS 25.0 program after appropriate coding. Skewness and kurtosis values were examined for the sub-dimensions of the *TAICS* and *teachers' AI-TPACK scale*. The skewness and kurtosis values of the data collection tools and their sub-dimensions were examined, and it was observed that the values were within the  $\pm 1.5$  range. According to Sharma and Ojha (2019). data within this range can be considered normally distributed. For the analysis of the independent variables in terms of scale scores, *independent sample t-test*, *one-way analysis of variance (ANOVA)*, and Tukey (Dunnnett C if homogeneity not assumed) post-hoc test were utilized. A significance level of  $p < .05$  was considered in the data analysis. The relationship between independent variables was examined using *Pearson correlation coefficient (r)*. *Structural equation modeling (SEM)* is used for test causal relationship models. **Table 2** shows the skewness and kurtosis values of tools.

## FINDINGS

This section presents the findings obtained from the analysis of the data. The findings related to the first research question, which aims to determine the AI-TPACK levels of science teachers, are presented in **Table 3**. According to **Table 3**, the AI-TPACK levels of science teachers, the highest mean score was observed in the PK dimension, with a value of 3.63. The lowest mean score was found in the PCK dimension, with a value of 3.37.



**Table 4.** AI-TPACK score differences of science teachers according to gender variable

Variable	Gender	Mean	Standard deviation	df	t	p	Direction of difference
PK	Female	3.72	.920	294	2.47	.014*	Female > male
	Male	3.45	.829				
CK	Female	3.58	1.13	294	3.17	.002*	Female > male
	Male	3.13	1.19				
AI-TK	Female	3.60	1.05	294	3.40	.001*	Female > male
	Male	3.15	1.11				
PCK	Female	3.51	1.02	294	3.44	.001*	Female > male
	Male	3.09	.970				
AI-TCK	Female	3.55	1.00	294	3.45	.001*	Female > male
	Male	3.12	1.07				
AI-TPK	Female	3.58	1.03	294	3.47	.001*	Female > male
	Male	3.13	1.10				
AI-TPACK	Female	3.60	.857	294	3.78	.000*	Female > male
	Male	3.21	.864				

**Table 5.** Science teachers' AI-TPACK score differences according to seniority variable

Variable	Seniority	N	Mean	Standard deviation	F	p	Direction of difference
PK	1-10 year	76	3.46	.816	4.46	.004*	1-10 year < 21-30 year 1-10 year < 31 year and above
	11-20 year	121	3.60	.954			
	21-30 year	68	3.90	.884			
	31 year and above	31	3.92	.689			
CK	1-10 year	76	3.25	1.08	3.76	.011*	1-10 year < 31 year and above
	11-20 year	121	3.34	1.27			
	21-30 year	68	3.72	1.14			
	31 year and above	31	3.88	0.61			
AI-TK	1-10 year	76	3.89	1.11	3.14	.025*	31 year and above < 1-10 year
	11-20 year	121	3.68	1.13			
	21-30 year	68	3.34	1.08			
	31 year and above	31	3.29	.532			
PCK	1-10 year	76	3.23	1.03	2.98	.032*	1-10 year < 21-30 year 1-10 year < 31 year and above
	11-20 year	121	3.27	1.13			
	21-30 year	68	3.60	.871			
	31 year and above	31	3.74	.569			
AI-TCK	1-10 year	76	3.77	1.11	2.33	.075*	
	11-20 year	121	3.53	1.13			
	21-30 year	68	3.41	.860			
	31 year and above	31	3.40	.589			
AI-TPK	1-10 year	76	3.89	1.11	2.36	.071*	
	11-20 year	121	3.56	1.13			
	21-30 year	68	3.44	.998			
	31 year and above	31	3.38	.587			
AI-TPACK	1-10 year	76	3.85	.849	4.93	.002*	31 year and above < 1-10 year 21-30 year < 1-10 year
	11-20 year	121	3.72	.940			
	21-30 year	68	3.32	.812			
	31 year and above	31	3.36	.405			

The overall AI-TPACK mean was calculated as 3.46, indicating that the teachers' integrated PK regarding AI is at a moderate level.

According to the results of the independent samples t-test, the gender variable led to statistically significant differences across all sub-dimensions (Table 4). Female science teachers scored significantly higher than male teachers in PK [ $t(294) = 2.47, p = .014$ ], CK [ $t(294) = 3.17, p = .002$ ], AI-TK [ $t(294) = 3.40, p = .001$ ], PCK [ $t(294) = 3.44, p = .001$ ], AI-TCK [ $t(294) = 3.45, p = .001$ ], AI-TPK [ $t(294) = 3.47, p = .001$ ], and overall AI-TPACK scores [ $t(294) = 3.78, p < .001$ ].

According to ANOVA test results, there are some differences in AI-TPACK and dimensions based on science teachers' years of experience (Table 5). Significant differences were found in PK [ $F(3,292) = 4.46, p = .004$ ], CK [ $F(3,292) = 3.76, p = .011$ ], and PCK [ $F(3,292) = 2.98, p = .032$ ], with scores increasing as teaching experience

**Table 6.** TAICS levels of science teachers

TAICS	N	Mean	Standard deviation
AIK	296	3.43	1.12
AIP	296	3.37	1.11
AIA	296	3.26	1.06
AIE	296	3.38	1.02
HCE	296	3.45	1.06
PEN	296	3.47	1.03
TAICS total	296	3.39	.925

**Table 7.** Analysis of science teachers' TAICS levels in terms of gender variable

Variable	Gender	Mean	Standard deviation	df	t	p	Direction of difference
AIK	Female	3.63	1.03	294	4.31	.000*	Female > Male
	Male	3.06	1.18				
AIP	Female	3.49	1.08	294	2.41	.017*	Female > Male
	Male	3.16	1.13				
AIA	Female	3.37	1.02	294	2.51	.012*	Female > Male
	Male	3.05	1.11				
AIE	Female	3.46	.980	294	1.87	.062*	
	Male	3.23	1.08				
HCE	Female	3.54	1.01	294	1.86	.064*	
	Male	3.30	1.14				
PEN	Female	3.60	.994	294	2.87	.004*	Female > Male
	Male	3.24	1.06				
TAICS total	Female	3.51	.883	294	3.07	.002*	Female > Male
	Male	3.17	.964				

grew. However, in AI-related sub-dimensions, significant differences were identified in AI-TK [ $F(3,292) = 3.14$ ,  $p = .025$ ] and the overall AI-TPACK score [ $F(3,292) = 4.93$ ,  $p = .002$ ], where teachers with 1–10 years of experience scored higher than with more than 21 years of experience. There are not any statistically significant differences in AI-TCK [ $F(3,292) = 2.33$ ,  $p = .075$ ] and AI-TPK [ $F(3,292) = 2.36$ ,  $p = .071$ ]. These findings suggest that early-career teachers demonstrate effective technology integration in AI-related dimensions, while more experienced teachers tend to perceive themselves as more competent in traditional pedagogical and CK domains.

According to findings, science teachers' highest TAICS score is PEN [mean ( $M$ ) = 3.47, standard deviation ( $SD$ ) = 1.03] and HCE ( $M$  = 3.45,  $SD$  = 1.06) dimensions (Table 6). These are followed by AIK ( $M$  = 3.43,  $SD$  = 1.12), AIE ( $M$  = 3.38,  $SD$  = 1.02), AIP ( $M$  = 3.37,  $SD$  = 1.11) and AIA ( $M$  = 3.26,  $SD$  = 1.06) dimensions. Total TAICS score is calculated  $M$  = 3.39 ( $SD$  = .925). This result shows that teachers' perceptions of TAICS components are at a medium level.

When teachers' TAICS levels were examined according to gender, there is a significant differences were found in favor of female teachers in terms of AIK [ $t(294) = 4.31$ ,  $p = .000$ ], AIP [ $t(294) = 2.41$ ,  $p = .017$ ], AIA [ $t(294) = 2.51$ ,  $p = .012$ ], PEN [ $t(294) = 2.87$ ,  $p = .004$ ] and TAICS total score [ $t(294) = 3.07$ ,  $p = .002$ ] (Table 7). However, there is no significant difference in terms of AIE [ $t(294) = 1.87$ ,  $p = .062$ ] and HCE [ $t(294) = 1.86$ ,  $p = .064$ ].

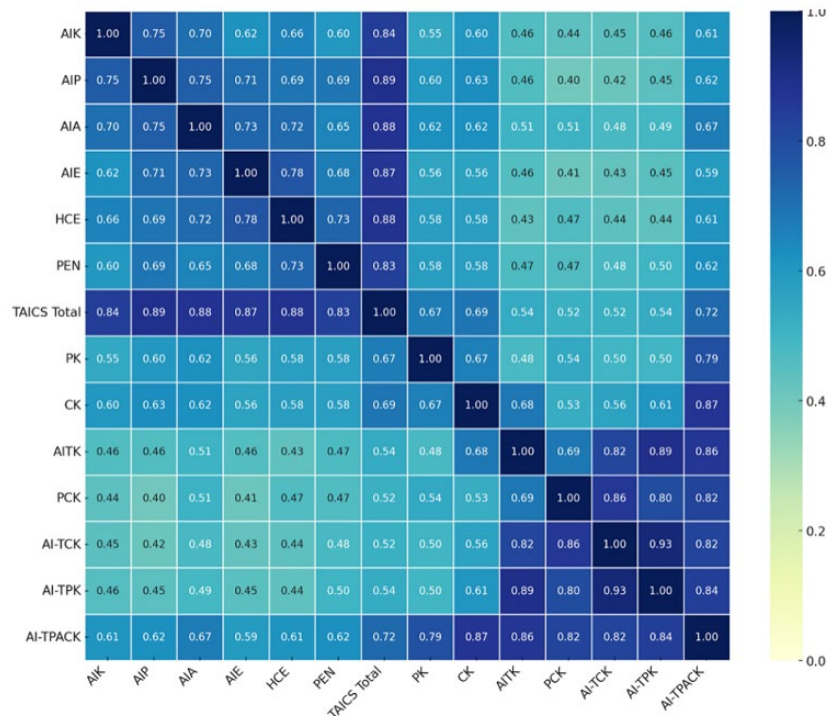
According to the seniority variable, teachers' TAICS levels change significantly in the HCE [ $F(3, 292) = 5.31$ ,  $p = .001$ ], PEN [ $F(3, 292) = 2.75$ ,  $p = .043$ ] dimensions and TAICS total score [ $F(3, 292) = 2.99$ ,  $p = .031$ ] (Table 8). These differences indicate that teachers with 31 years or more of experience significantly lower score than with 1–10 years and 11–20 years of experience. However there is not significant differences according to another dimensions: AIK [ $F(3, 292) = 1.24$ ,  $p = .293$ ], AIP [ $F(3, 292) = 1.78$ ,  $p = .150$ ], AIA [ $F(3, 292) = 1.91$ ,  $p = .128$ ], and AIE [ $F(3, 292) = 2.51$ ,  $p = .058$ ] based on years of seniority.

According to the correlation analysis, there are generally positive and significant relationships between TAICS and AI-TPACK. The highest correlation is between AI-TPK and AITK ( $r = .891^{**}$ ) and AI-TCK ( $r = .931^{**}$ ). While the lowest correlations are between PCK and AIP ( $r = .400^{**}$ ) and AIK and PCK ( $r = .441^{**}$ ). According to findings the relationship between composite structures containing AI components and TAICS dimensions is high (see Figure 3).



**Table 8.** Analysis of science teachers' TAICS levels in terms of seniority variable

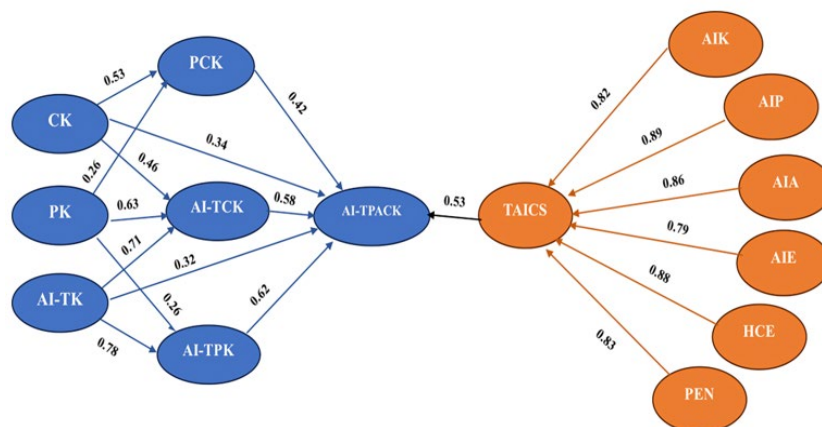
Variable	Seniority	N	Mean	Standard deviation	F	p	Direction of difference
AIK	1-10 year	76	3.65	1.08	1.24	.293	
	11-20 year	121	3.60	1.12			
	21-30 year	68	3.32	1.23			
	31 year and above	31	3.41	.932			
AIP	1-10 year	76	3.80	1.13	1.78	.150	
	11-20 year	121	3.49	1.11			
	21-30 year	68	3.37	1.13			
	31 year and above	31	3.25	.896			
AIA	1-10 year	76	3.57	.994	1.91	.128	
	11-20 year	121	3.38	1.10			
	21-30 year	68	3.11	1.13			
	31 year and above	31	3.34	.845			
AIE	1-10 year	76	3.75	1.02	2.51	.058	
	11-20 year	121	3.52	1.05			
	21-30 year	68	3.43	1.01			
	31 year and above	31	3.22	.702			
HCE	1-10 year	76	3.87	.943	5.31	.001*	31 year and above < 1-10 year
	11-20 year	121	3.72	1.18			
	21-30 year	68	3.61	.971			
	31 year and above	31	3.19	.608			
PEN	1-10 year	76	3.92	.941	2.75	.043*	31 year and above < 1-10 year
	11-20 year	121	3.60	1.14			
	21-30 year	68	3.52	.968			
	31 year and above	31	3.32	.665			
TAICS total	1-10 year	76	3.76	.835	2.99	.031*	31 year and above < 1-10 year
	11-20 year	121	3.50	.993			
	21-30 year	68	3.48	.931			
	31 year and above	31	3.24	.581			

**Figure 3.** Correlation heat map (Source: Produced by the authors with analysis program)

LISREL software was used for SEM analysis and fit statistics were analyzed using *maximum likelihood method*. Based on the obtained result, the value that doesn't exceed theoretical limits has been identified [ $\chi^2 = 666.71$ ,  $df = 362$ ,  $p < .01$ ] (Table 9). Moreover, other goodness of fit parameters (GFI = 0.92, AGFI = 0.89, PGFI

**Table 9.** Fit parameters of the SEM analysis

Fit parameters	Coefficient
GFI	.92
AGFI	.89
PGFI	.85
RMSEA	.06
CFI	.90
NFI	.89
Df	362
$\chi^2$	666.71
$\chi^2/df$	1.84

**Figure 4.** Path diagram (Source: Produced by the authors)

= 0.85, RMSEA = 0.06, CFI= 0.90, NFI = 0.89) showed that the model proposed for the scale was appropriate. According to this result, it can be said that the analysis of the values obtained for the model under standard fit indices confirmed the modeled factor structure. It has been found that GFI, AGFI, CFI, and PGFI values varied between 0 and 1. Even though there is no consensus in the literature, obtaining a coefficient higher than 0.85 is accepted as a good fit (Anderson & Gerbing, 1984).

**Figure 4** shows the standardized coefficients of the SEM analysis result. AI-TPACK is significantly predicted by AI-TCK ( $\beta = 0.58$ ), AI-TPK ( $\beta = 0.62$ ) and PCK ( $\beta = 0.42$ ) dimensions. PK ( $\beta = 0.63$ ), CK ( $\beta = 0.46$ ), and AI-TK ( $\beta = 0.32$ ) make significant contributions to AI-TCK. Similarly, AI-TPK is affected by PK ( $\beta = 0.26$ ) and AI-TK ( $\beta = 0.78$ ) dimensions. TAICS variable is a significant predictor of AI-TPACK ( $\beta = 0.53$ ). The TAICS is highly represented by the sub-dimensions AIP ( $\beta = 0.89$ ), AIA ( $\beta = 0.86$ ), AIE ( $\beta = 0.79$ ), HCE ( $\beta = 0.88$ ), PEN ( $\beta = 0.83$ ) and AIK ( $\beta = 0.82$ ), respectively. Standardized coefficients obtained from SEM analysis, showing the relations of the variables with the items are between 0.32 and 0.89 (see **Figure 4**).

## DISCUSSION AND CONCLUSION

In this study, the levels of science teachers' AI-TPACK and TAICS were examined. The findings show that teachers have high competence especially in the PK dimension. This finding shows that teachers have pedagogical abilities such as instructional designs, material design, teaching methods, classroom management and evaluation (Graham, 2011). Teachers' AI-TPACK is at a medium level which shows that teachers are in the development process of AI-based pedagogical integration.

According to gender variable, there are significant differences in favor of female teachers in all sub-dimensions of AI-TPACK. This finding shows that female teachers are more sensitive to technological developments and more familiar to adopt AI-based teaching practices. Similarly, in TAICS sub-dimensions, female teachers are higher levels of competence than male teachers in AIK, AIP, AIA, PEN, and TAICS Total mean scores. In the analyses conducted according to the professional seniority variable, it was determined that the levels of classical knowledge components, PK, CK and PCK, increased significantly as experience increased. This shows that teachers develop their teacher knowledge application with professional experience

(Archambault & Barnett, 2010). However, the fact that teachers with less experience have higher scores in AI-based components such as AI-TK and AI-TPACK shows that young teachers are more comfortable using digital technologies. Abbitt (2011) stated that the integration of technological, pedagogical and CK is affected by demographic variables. In addition, a study by Scherer et al. (2019) showed that teachers' self-efficacy beliefs in technology use are strong predictors of their technology acceptance and integration behaviors.

The findings according to TAICS scale show that teachers reached the highest averages in the PEN and HCE dimensions. This result reveals that teachers are willing to contribute to the cognitive development and learning processes of students in AI-based educational environments. The lowest average in the AIA dimension suggests that teachers are not yet sufficient to actively use AI in measurement-evaluation processes. When examined in terms of gender differences, significant differences were found in favor of female teachers in the AIP, AIA, PEN, and TAICS Total mean dimensions. However, there is the fact that there was no significant difference in the AIE and HCE dimensions. This result shows that ethical and student-centered approaches are independent of gender. Analyses conducted according to the professional seniority variable show that teachers with 31 years of seniority and above have lower scores in HCE, PEN, and TAICS total mean. This result suggests that teachers with more experience are more reserved towards innovative practices. On the other hand, the lack of significant differences in the dimensions of AIK, AIP, AIA, and AIE shows that these dimensions are shaped by individual motivation and learning tendency rather than professional seniority.

The study by Çelik (2023) shows that teachers are more successful in pedagogically integrating AI technologies. It does not replace traditional teacher roles but rather enhances student learning through personalized feedback and adaptive instruction. This is equal with the findings of Selwyn (2020). In addition, the study conducted by Zhang et al. (2023) is consistent with the significant positive relationships between teachers' technology and AI acceptance. According to these studies, it reinforces the applicability of the TPACK and UTAUT models in understanding teachers' acceptance and integration processes of AI technologies (Tram, 2025).

According to the results of correlation analyses, there are significant and positive relationships between AI-TPACK and TAICS dimensions. A high level of positive correlation was observed between AI-TPK and AI-TK and AI-TCK. This finding reveals the importance of considering technological knowledge and pedagogical integration together in terms of teacher competencies. On the other hand, lower-level relationships were observed between PCK and AIP and AIK. This result shows that the integration of classical knowledge-based competencies with AI-based approaches is limited. According to the SEM results, AI-TPACK structure is significantly predicted by AI-TCK, AI-TPK, and PCK. We can say that teachers need to have both technological knowledge and pedagogical and CK with a holistic approach in order to use AI technologies effectively in the classroom. The fact that AI-TPK is related to AI-TK and PK also emphasizes the need to combine pedagogical practices with technology. Lastly, TAICS structure significantly predicts AI-TPACK. This means that teachers' acceptance levels of AI, pedagogical skills and cognitive awareness are effective in the development of AI-TPACK competencies. TAICS strongly represents AI-TPACK reveals, so cognitive, pedagogical and technological competencies should be evaluated together in order for teachers to use AI technologies effectively.

In the literature, there is not a definitive finding showing that the contribution of TK, CK and PK on TPACK is stronger than TPK, TCK, and PCK's. Using regression analysis, Chai et al. (2010) proved that TK, CK and PK have a direct effect on TPACK and found that PK had the highest effect. Again, Chai et al. (2011) have researched the effect of TK, PK, CK and TPK on TPACK via SEM on Singapore teacher candidates and revealed that the effects of CK, PK and TK on TPACK were lower than TPK. In another study conducted on teachers in Singapore, the significant effect of TK, PK, TPK and TCK on TPACK was mentioned (Koh et al., 2013). The performed scale development and adaptation study has also revealed these relationships partially. According to the results the basic knowledge components CK, PK, and AI-TK have relatively less effect on teachers' AI-TPACK level (Ning et al., 2024). One of the most important findings is the explanatory power difference between technology-related and unrelated knowledge components. The results obtained showed that technology-based knowledge components (AI-TK, AI-TCK, and AI-TPK) included in the teacher AI-TPACK framework have a strong correlation with teachers' AI-TPACK level and have high explanatory power. In contrast, the effect of non-technology components such as CK, PK and PCK on AI-TPACK remains weaker than.

This finding is consistent with Ning et al. (2024). Understanding the relationships between the analyzed data and knowledge components revealed the necessity of changing the traditional TPACK framework.

### Limitations and Recommendations of the Study

There are some limitations of the study because of method and model of research. The research data were collected through self-reporting. The responses given by the participants based on their own perceptions may not exactly coincide with real practices. In addition, only quantitative data collection tools were used as a collecting data. A mixed-design study supported by qualitative data collection methods can provide the opportunity to analyze teachers' mindset and experiences in technology use processes in more depth. It would be especially useful to evaluate teachers' classroom practices by class observation. In this way, a more holistic and realistic understanding of the role of AI in education can be developed. The measurement tools used in the study may be limited in reflecting all AI-based teaching competencies; therefore, it would be useful to evaluate different dimensions with more comprehensive scales to be developed in future research.

It is recommended that training programs be provided to school administrators and education policy makers to develop AI literacy and digital pedagogical competencies of older ages and more senior teachers. Awareness studies on the effective use of educational technologies should be increased and technical and pedagogical infrastructure should be provided to support teachers in using these technologies effectively in the classroom. In addition, identifying the difficulties teachers face in the integration of AI-based applications into the education process and developing solutions to these difficulties are of critical importance for a sustainable and effective digital transformation process.

**Author contributions:** All authors contributed equally to all stages of the work. All authors approved the final version of the article.

**Funding:** The authors received no financial support for the research and/or authorship of this article.

**Ethics declaration:** The authors declared that this study was approved by Kazan Federal University. The authors further declared that the research was conducted following academic research and ethical methods and informing the participants.

**Declaration of interest:** The authors declared no competing interest.

**Data availability:** Data generated or analyzed during this study are available from the authors on request.

### REFERENCES

- Abbitt, J. T. (2011). Measuring technological pedagogical content knowledge in preservice teacher education: A review of current methods and instruments. *Journal of Research on Technology in Education*, 43(4), 281–300. <https://doi.org/10.1080/15391523.2011.10782573>
- Almithqal, E. A., & John, T. (2025). Exploring Jordanian university lecturers' TPACK knowledge: Integrating ICT for teaching English pronunciation. *Pedagogical Research*, 10(1), Article em0227. <https://doi.org/10.29333/pr/15588>
- Anderson, J. C., & Gerbing, D. (1984). The effect of sampling error on convergence, improper solutions, and goodness-of-fit indices for maximum likelihood confirmatory factor analysis. *Psychometrika*, 49, 155–173. <https://doi.org/10.1007/BF02294170>
- Angeli, C., & Valanides, N. (2009). Epistemological and methodological issues for the conceptualization, development, and assessment of ICT-TPCK: Advances in technological pedagogical content knowledge (TPCK). *Computers & Education*, 52(1), 154–168. <https://doi.org/10.1016/j.compedu.2008.07.006>
- Archambault, L. M., & Barnett, J. H. (2010). Revisiting technological pedagogical content knowledge: Exploring the TPACK framework. *Computers & Education*, 55(4), 1656–1662. <https://doi.org/10.1016/j.compedu.2010.07.009>
- Ay, Y., Karadağ, E., & Acat, M. B. (2015). The technological pedagogical content knowledge-practical (TPACK-practical) model: Examination of its validity in the Turkish culture via structural equation modeling. *Computers & Education*, 88, 97–108. <https://doi.org/10.1016/j.compedu.2015.04.017>
- Bandura, A. (2005). Guide for constructing self-efficacy scales. In F. Pajares, & T. Urdan (Eds.), *Self-efficacy beliefs of adolescents* (pp. 307–337). Information Age Publishing.

- Bwalya, A., Rutegwa, M., & Mapulanga, T. (2024). Developing pre-service biology teachers' technological pedagogical content knowledge through a TPACK-based course. *European Journal of Educational Research*, 13(1), 263–278. <https://doi.org/10.12973/eu-jer.13.1.263>
- Çelik, I. (2023). Towards intelligent-TPACK: An empirical study on teachers' professional knowledge to ethically integrate artificial intelligence (AI)-based tools into education. *Computers in Human Behavior*, 138, Article 107468. <https://doi.org/10.1016/j.chb.2022.107468>
- Chai, C. S., Koh, J. H. L., & Tsai, C. C. (2010). Facilitating preservice teachers' development of technological, pedagogical, and content knowledge (TPACK). *Educational Technology and Society*, 13(4), 63–73.
- Chai, C. S., Koh, J. H. L., & Tsai, C. C. (2011). Exploring the factor structure of the constructs of technological, pedagogical, content knowledge (TPACK). *The Asia Pacific Education Researcher*, 20(3), 595–603.
- Chiu, T. K. F., Ahmad, Z., & Çoban, M. (2025). Development and validation of teacher artificial intelligence (AI) competence self-efficacy (TAICS) scale. *Education and Information Technologies*, 30, 6667–6685. <https://doi.org/10.1007/s10639-024-13094-z>
- Chiu, T. K. F., Falloon, G., Song, Y. J., Wong, V. W. L., Zhao, L., & Ismailov, M. A. (2024). A self-determination theory approach to teacher digital competence development. *Computers & Education*, 24, Article 105017. <https://doi.org/10.1016/j.compedu.2024.105017>
- Creswell, J. W. (2005). *Educational research: Planning, conducting, and evaluating quantitative and qualitative research*. Pearson.
- Falloon, G. (2020). From digital literacy to digital competence: The teacher digital competency (TDC) framework. *Educational Technology Research and Development*, 68(5), 2449–2472. <https://doi.org/10.1007/s11423-020-09767-4>
- Fieding, J., & Gilbert, N. (2006). *Understanding social statistics*. SAGE. <https://doi.org/10.4135/9781446249406>
- Graham, C. R. (2011). Theoretical considerations for understanding technological pedagogical content knowledge (TPACK). *Computers & Education*, 57, 1953–1960. <https://doi.org/10.1016/j.compedu.2011.04.010>
- Hatlevik, O. E., Guðmundsdóttir, G. B., & Loi, M. (2015). Digital diversity among upper secondary students: A multilevel analysis of the relationship between cultural capital, self-efficacy, strategic use of information and digital competence. *Computers & Education*, 81, 345–353. <https://doi.org/10.1016/j.compedu.2014.10.019>
- Hewitt, J. (2008). Reviewing the handbook of technological pedagogical content knowledge (TPACK) for educators. *Canadian Journal of Science, Mathematics and Technology Education*, 8(4), 355–360. <https://doi.org/10.1080/14926150802506274>
- Illomäki, L., Paavola, S., Lakkala, M., & Kantosalo, A. (2016). Digital competence—An emergent boundary concept for policy and educational research. *Education and Information Technologies*, 21, 655–679. <https://doi.org/10.1007/s10639-014-9346-4>
- Janssen, J., Stoyanov, S., Ferrari, A., Punie, Y., Pannekeet, K., & Sloep, P. (2013). Experts' views on digital competence: Commonalities and differences. *Computers & Education*, 68, 473–481. <https://doi.org/10.1016/j.compedu.2013.06.008>
- Keating, T., & Evans, E. (2001). Three computers in the back of the classroom: Preservice teachers' conceptions of technology integration. In *Proceedings of the Society for Information Technology & Teacher Education International Conference 2001* (pp. 1671–1676). AACE.
- Koehler, M. J., Mishra, P., Kereluik, K., Shin, T. S., & Graham, C. R. (2014). The technological pedagogical content knowledge framework. In J. M. Spector, M. D. Merrill, J. Elen, & M. J. Bishop (Eds.), *Handbook of research on educational communications and technology* (pp. 101–111). Springer. [https://doi.org/10.1007/978-1-4614-3185-5\\_9](https://doi.org/10.1007/978-1-4614-3185-5_9)
- Koehler, M., & Mishra, P. (2005). What happens when teachers design educational technology? The development of technological pedagogical content knowledge. *Journal of Educational Computing Research*, 32(2), 131–152. <https://doi.org/10.2190/0EW7-01WB-BKHL-QDYV>
- Koehler, M., & Mishra, P. (2009). What is technological pedagogical content knowledge? *Contemporary Issues in Technology and Teacher Education*, 9(1), 60–70.
- Koh, J. L., Chai, C. S., & Tsai, C. C. (2010). Examining the technological pedagogical content knowledge of Singapore pre-service teachers with a large-scale survey. *Journal of Computer Assisted Learning*, 26(6), 563–573. <https://doi.org/10.1111/j.1365-2729.2010.00372.x>



- Koh, J. L., Chai, C. S., & Tsai, C. C. (2013). Examining practicing teachers' perceptions of technological pedagogical content knowledge (TPACK) pathways: A structural equation modeling approach. *Instructional Science*, 41, 793–809. <https://doi.org/10.1007/s11251-012-9249-y>
- Lee, M., & Tsai, C. (2010). Exploring teachers' perceived self efficacy and technological pedagogical content knowledge with respect to educational use of the world wide web. *Instructional Science*, 38(1), 1–21. <https://doi.org/10.1007/s11251-008-9075-4>
- Li, M., Vale, C., Tan, H., & Blannin, J. (2025). Exploring demographic influences on digital technology integration in Chinese primary mathematics education. *International Electronic Journal of Mathematics Education*, 20(2), Article em0810. <https://doi.org/10.29333/iejme/15814>
- Lim, C. P., & Chai, C. S. (2008). Teachers' pedagogical beliefs and their planning and conduct of computer mediated classroom lessons. *British Journal of Educational Technology*, 39(5), 807–828. <https://doi.org/10.1111/j.1467-8535.2007.00774.x>
- Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). *Intelligence unleashed: An argument for AI in education*. Pearson.
- Maghsudi, S., Lan, A., Xu, J., & van der Schaar, M. (2021). Personalized education in the artificial intelligence era: What to expect next. *IEEE Signal Processing Magazine*, 38(5), 37–50. <https://doi.org/10.1109/MSP.2021.3055032>
- Margerum-Lays, J., & Marx, R. W. (2003). Teacher knowledge of educational technology: A case study of student/mentor teacher pairs. In Y. Zhao (Ed.), *What should teachers know about technology? Perspectives and practices* (pp. 123–159). Information Age Publishing.
- McMillian, J. H., & Schumacher, S. (2004). *Research in education: A conceptual introduction*. Allyn & Bacon.
- Mishra, P., & Koehler, M. J. (2006). Technological pedagogical content knowledge: A new framework for teacher knowledge. *Teachers College Record*, 108(6), 1017–1054. <https://doi.org/10.1111/j.1467-9620.2006.00684.x>
- Ning, Y., Zhang, C., Xu, B., Zhou, Y., & Wijaya, T. T. (2024). Teachers' AI-TPACK: Exploring the relationship between knowledge elements. *Sustainability*, 16(3), Article 978. <https://doi.org/10.3390/su16030978>
- Pierson, M. (1999). *Technology practice as a function of pedagogical expertise* [PhD thesis, Arizona State University].
- Pierson, M. E. (2001). Technology integration practice as a function of pedagogical expertise. *Journal of Research on Computing in Education*, 33(4), 413–430. <https://doi.org/10.1080/08886504.2001.10782325>
- Scherer, R., Siddiq, F., & Tondeur, J. (2019). The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. *Computers & Education*, 128, 13–35. <https://doi.org/10.1016/j.compedu.2018.09.009>
- Schmidt, D. A., Baran, E., Thompson, A. D., Mishra, P., Koehler, M. J., & Shin, T. S. (2009). Technological pedagogical content knowledge (TPACK): The development and validation of an assessment instrument for preservice teachers. *Journal of Research on Technology in Education*, 42(2), Article 27. <https://doi.org/10.1080/15391523.2009.10782544>
- Selwyn, N. (2020). Re-imagining 'Learning Analytics'... a case for starting again? *The Internet and Higher Education*, 46, Article 100745. <https://doi.org/10.1016/j.iheduc.2020.100745>
- Sharma, C., & Ojha, C. S. P. (2019). Statistical parameters of hydrometeorological variables: Standard deviation, SNR, skewness and kurtosis. In R. AlKhaddar, R. K. Singh, S. Dutta, & M. Kumari (Eds.), *Advances in water resources engineering and management: Select proceedings of TRACE 2018* (pp. 59–70). Springer. [https://doi.org/10.1007/978-981-13-8181-2\\_5](https://doi.org/10.1007/978-981-13-8181-2_5)
- Sulistiani, I. R., Setyosari, P., Sa'dijah, C., & Praherdhiono, H. (2024). Technological pedagogical content knowledge of preservice elementary teachers: Relationship to self-regulation and technology integration self-efficacy. *European Journal of Educational Research*, 13(1), 159–170. <https://doi.org/10.12973/eu-jer.13.1.159>
- Tram, N. H. M. (2025). Unveiling the drivers of AI integration among language teachers: Integrating UTAUT and AI-TPACK. *Computers in the Schools*, 42(2), 100–120. <https://doi.org/10.1080/07380569.2024.2441155>
- Yilmaz, H., Maxutov, S., Baitekov, A., & Balta, N. (2023). Student's perception of Chat GPT: A technology acceptance model study. *International Educational Review*, 1(1), 57–83. <https://doi.org/10.58693/ier.114>



Zhang, C., Schießl, J., Plössl, L., Hofmann, F., & Gläser-Zikuda, M. (2023). Acceptance of artificial intelligence among pre-service teachers: A multigroup analysis. *International Journal of Educational Technology in Higher Education*, 20(1), Article 49. <https://doi.org/10.1186/s41239-023-00420-7>

