An Investigation into the Effect of Teaching Science Topics Supported by Artificial Intelligence on Pre-service Teachers' Technological and Pedagogical Content Knowledge of Artificial Intelligence

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Abstract: This study investigated the effect of artificial intelligence (AI)-supported science instruction on pre-service science teachers' Artificial Intelligence Technological Pedagogical Content Knowledge (AI-TPACK) levels. An explanatory sequential mixed-methods design was employed. In the quantitative phase, a quasi-experimental pretest–posttest matched control group design was used. The study was conducted with a total of 32 pre-service teachers (experimental group, n = 18; control group, n = 14) enrolled at a public university in Ankara during the 2025–2026 academic year. While the existing intelligence games curriculum was implemented in the control group, AI-supported science activities were conducted in the experimental group for 10 weeks. Data were collected using the Artificial Intelligence Technological Pedagogical Content Knowledge Scale and analyzed through paired-samples t-tests, independent-samples t-tests, and the Wilcoxon signed-rank test. Within-group analyses showed significant improvements in the experimental group in the dimensions of Content Knowledge, Artificial Intelligence Technological Knowledge, and Artificial Intelligence Technological Content Knowledge; however, no significant improvement was observed in most pedagogical dimensions. In the control group, significant increases were identified across all dimensions of AI-TPACK. In the between-group posttest comparisons, a statistically significant difference was found only in the Pedagogical Content Knowledge dimension, whereas no significant differences were identified in the other AI-TPACK dimensions or in the overall AI-TPACK score. In the qualitative phase, open-ended survey interviews conducted with 18 pre-service teachers selected from the experimental group were analyzed using thematic analysis. The participants stated that AI facilitated access to information, supported the visualization of science concepts, and enhanced the efficiency of the learning process. Nevertheless, they also expressed concerns regarding the accuracy of AI-generated information, excessive dependence on AI, and the limited pedagogical integration of AI. In conclusion, AI-supported instruction contributed to the development of competencies related to content and technology; however, systematic guidance and explicitly structured instructional practices are needed in teacher education programs to ensure the pedagogically effective integration of AI.

Keywords: Artificial intelligence, intelligence games, technological pedagogical content knowledge (TPACK), science education

Received: 26 March 2026 | Revised: 04 June 2026 | Accepted: 04 June 2026

Cite : Yüksel, İ., Nazlı, N. and Akgöz, E.E. (2026). An Investigation into the Effect of Teaching Science Topics Supported by Artificial Intelligence on Pre-service Teachers' Technological and Pedagogical Content Knowledge of Artificial Intelligence. *Journal of Artificial Intelligence and Human Sciences*, *3*(1), 36-51. Doi: 10.5281/zenodo.21462888

1. Introduction

In recent years, rapid developments in artificial intelligence (AI) technologies have led to significant transformations in education and reshaped the nature of teaching and learning. AI applications have the potential to transform every aspect of education, from the design of educational materials to the assessment of student skills (Zhai & Krajcik, 2024). For approximately 30 years, AI applications in education have been the subject of research (Zawacki-Richter et al., 2019). Baker and Smith (2019) classified AI tools in education into those aimed at students, teachers, and the system. Alam (2021) has stated that artificial intelligence can assist with routine tasks in the educational process and help determine what type of education is required for a specific subject within the educational environment. Recent evidence also indicates that research on artificial intelligence in education has expanded rapidly in Türkiye during the last five years, reflecting increasing scholarly interest in AI-supported teaching, learning, assessment, and teacher education. Bibliometric findings demonstrate that educational AI research has become one of the fastest-growing fields within Turkish educational research (Gündoğdu & Benzer, 2024).

Science education is, by its very nature, a multimodal process that requires the interaction of multiple forms of representation and meaning-making. Consequently, the process of learning and teaching science topics is not limited to verbal or written explanations alone. When making sense of science-related concepts and the relationships between them, students engage with various forms of representation, such as reading texts, interpreting graphs and diagrams, constructing models, analysing data, and visualising information (Bewersdorf et al., 2025). This interaction may be incorporated into application processes guided by, supported by, or enhanced by artificial intelligence in education. The rapid development of the internet, wireless communication, and computer technologies has also accelerated the use of AI-supported applications in classrooms (Ouyang & Jiao, 2021).

Research into the applications and impacts of AI in the classroom is developing rapidly; however, teachers are only just beginning to discover the ways in which AI applications can support their students (Zawacki-Richter et al., 2019). One of the most critical factors for the full integration of artificial intelligence technologies into the education system in Türkiye is the ability of teachers to adapt to these new technologies and develop their digital skills. In particular, fully capitalising on the opportunities offered by artificial intelligence depends not only on the availability of technological tools, but also on the development of teaching staff capable of using these tools effectively (Aydım, 2021). This growing interest is also reflected in the national research landscape, where studies increasingly focus on teacher competencies, AI literacy, instructional applications, and educational policy issues surrounding artificial intelligence (Gündoğdu & Benzer, 2024).

Before the integration of technology into education, Shulman (1986) argued that there are three types of knowledge that teachers should possess: subject-matter content knowledge, pedagogical content knowledge, and curriculum knowledge. In subsequent years, the technological dimension was added to this framework, giving rise to Technological Pedagogical Content Knowledge (TPACK) (Koehler & Mishra, 2008). The TPACK model identifies seven distinct categories of knowledge that teachers need to possess (Graham et al., 2009). Within this framework, content knowledge refers to the specific subject matter being taught or intended to be taught (Koehler & Mishra, 2005). TPACK provides a robust theoretical foundation to guide the integration of technology into education by bringing together the variables arising from this integration and revealing the complex relationships between them. Furthermore, it presents the essential dimensions to be systematically included in teacher training programs (Akkoç et al., 2011). Consequently, TPACK encompasses the holistic professional knowledge base required by pre-service teachers.

While numerous studies have investigated pre-service and in-service teachers' TPACK, there remains a critical gap in the literature regarding the specific integration of AI. Existing literature contains only a limited number of studies aimed at developing pre-service teachers' knowledge within a concrete technological framework rather than mere abstract guidelines. To address this gap, the primary purpose of this study is to investigate the effect of AI-supported science instruction on pre-service science teachers' Artificial Intelligence Technological Pedagogical Content Knowledge (AI-TPACK). According to Canbazoğlu Bilici et al. (2024), AI-TPACK is conceptualised across seven distinct sub-dimensions: Content Knowledge (CK), Pedagogical Knowledge (PK), AI-Technological Knowledge (AI-TK), Pedagogical Content Knowledge (PCK), AI-Technological Content Knowledge (AI-TCK), AI-Technological Pedagogical Knowledge (AI-TPK), and AI-Technological Pedagogical Content Knowledge (AI-TPACK). Considering these dimensions, the rapid advancement of AI and its near-universal accessibility necessitate a clear definition of its role in science teacher education. Although the volume of AI-related educational research has increased considerably in Türkiye, bibliometric evidence suggests that empirical studies examining AI-supported pedagogical competencies among pre-service teachers remain relatively limited, indicating the need for intervention-based research in this area (Gündoğdu & Benzer, 2024).

The primary purpose of this study is to investigate the effect of AI-supported science instruction on pre-service science teachers' Artificial Intelligence Technological Pedagogical Content Knowledge (AI-TPACK). To evaluate the effectiveness of integrating AI into science education, specifically within the structure of an "Intelligence Games" course, this study addresses the following research questions:

Research Question 1 (RQ1): Is there a statistically significant difference between the pre-test and post-test scores of the control group regarding the overall AI-TPACK scale and its individual sub-dimensions?

Research Question 2 (RQ2): Is there a statistically significant difference between the pre-test and post-test scores of the experimental group regarding the overall AI-TPACK scale and its individual sub-dimensions?

Research Question 3 (RQ3): Is there a statistically significant difference between the post-test scores of the control and experimental groups regarding the overall AI-TPACK scale and its individual sub-dimensions?

Research Question 4 (RQ4): How do pre-service teachers experience AI-supported instructional processes in science education?

Research Question 5 (RQ5): How do the qualitative findings explain and support the quantitative results regarding the changes in pre-service teachers' AI-TPACK levels?

2. Methodology

This study employed an explanatory sequential mixed-methods design, in which quantitative data were collected and analysed in the first phase, followed by qualitative data collection and analysis to further explain and elaborate on the quantitative findings. This design enables a more comprehensive understanding of the research problem by integrating numerical results with participants' in-depth perspectives.

2.1. Quantitative Phase

In the first phase of the study, a quasi-experimental pre-test and post-test matched control group design, one of the quasi-experimental designs, was utilised (Büyüköztürk, Kılıç Çakmak, Akgün, Karadeniz, Demirel, 2022). In this design, matched groups are assigned to experimental and control groups, where the experimental group receives the treatment while the control group continues with the existing instructional process.

The study was conducted with a total of 32 pre-service teachers (experimental group: n=18; control group: n=14) studying in the Department of Mathematics and Science Education at a state university in Ankara during the 2025–2026 academic year. While the control group followed the existing "intelligence games" course within the science education curriculum, the experimental group participated in science activities supported by artificial intelligence. The implementation lasted for 10 weeks.

Data were collected using the Artificial Intelligence Technological Domain Knowledge Scale, adapted into Turkish by Canbazoğlu Bilici, Tanrısevdi, Yıldız Durak, and Çakıroğlu (2024), based on the AI-TPAB scale developed by Ning et al. (2024). Confirmatory Factor Analysis (CFA) confirmed the seven-factor structure of the 39-item, 5-point Likert-type scale. The overall Cronbach's Alpha coefficient was 0.980. Reliability coefficients for the sub-dimensions were reported as follows: subject knowledge (0.873), pedagogical knowledge (0.885), AI-technological knowledge (0.954), pedagogical subject knowledge (0.928), AI-technological subject knowledge (0.973), AI-technological pedagogical knowledge (0.970), and AI-TPAB (0.946) (Canbazoğlu Bilici et al., 2024).

Quantitative data were analysed using Jamovi statistical analysis software. Normality (Shapiro-Wilk) and homogeneity (Levene) tests were conducted to determine the suitability of parametric analyses. Accordingly, paired samples t-tests, independent samples t-tests, and non-parametric tests were employed.

2.2. Qualitative Phase

In the second phase, qualitative data were collected to explain the quantitative findings in greater depth. A purposive sampling strategy was used to select participants from those involved in the quantitative phase, ensuring that they had direct experience with AI-supported instructional practices.

Data were collected using an open-ended questionnaire developed by the researchers. The questions focused on the participants' views regarding the use of artificial intelligence in science education, its role in integrating science topics with brain games, its impact on learning processes, and the advantages and limitations of artificial intelligence. The open-ended questionnaire allowed participants to freely express their perspectives while maintaining consistency. The qualitative phase was conducted with a total of 18 pre-service teachers selected via purposive sampling exclusively from the experimental group (n=18), ensuring they had direct, hands-on experience with the 10-week AI-supported science instructional processes.

Interviews were conducted online following the quantitative phase. All sessions were recorded and transcribed verbatim to ensure accuracy.

The qualitative data were analysed using thematic analysis. The analysis process included familiarisation with the data, initial coding, categorisation, and the identification of overarching themes. Both inductive and deductive approaches were employed; while some themes emerged directly from the data, others were interpreted within the AI-TPACK framework.

To ensure trustworthiness, several strategies were applied. Credibility was enhanced through prolonged engagement and the use of direct quotations. Transferability was supported through detailed descriptions of the research context. Dependability and confirmability were ensured by maintaining an audit trail throughout the data collection and analysis processes.

2.3. Integration of Phases

The study followed a sequential structure (QUAN → QUAL), in which qualitative findings were used to explain and interpret the quantitative results. This integration enabled a deeper understanding of why certain AI-TPACK dimensions improved while others did not, thereby strengthening the overall validity and interpretability of the findings.

2.4. Limitations of the Study

In this study, while the experimental group engaged in an AI-supported science curriculum, the control group followed the existing 'intelligence games' course curriculum. This curricular divergence was due to institutional administrative scheduling and fixed course availabilities during the relevant academic term. This situation poses a potential limitation for the study's internal validity, as the difference in course content may influence the outcomes independently of the AI treatment. Future research should employ control groups that follow identical science content without AI support to isolate the unique variance explained solely by AI integration.

3. Findings

The first sub-question of the study was as follows: "Is there a statistically significant difference between the control group's pre-test and post-test scores on the subdimensions of the Artificial Intelligence Technological Domain Knowledge Scale?" To determine whether the control group's pre-test and post-test scores differed significantly, a normality test was first conducted. The results are presented in Table 1.

Table 1. Shapiro-Wilk Normality Test Results for the Control Group's AI-TPACK Subdimensions

Sub-dimensions	W	p
Content Knowledge	0.965	0.803
Pedagogical Knowledge	0.981	0.982
AI-Technological Knowledge	0.960	0.725
Pedagogical Content Knowledge	0.915	0.184
AI-Technological Content Knowledge	0.976	0.944
AI-Technological Pedagogical Knowledge	0.961	0.735
AI-Technological Pedagogical Content Knowledge	0.953	0.613

According to Table 1, all Shapiro-Wilk test results for the AI-TPACK sub-dimensions and the overall AI-TPACK scale were non-significant ($p > .05$), indicating that the assumption of normality was not violated. Therefore, parametric analyses were considered appropriate, and paired-samples t-tests were conducted to examine the differences between the pre-test and post-test scores of the control group. The t-test values for the sub-dimensions of the control group's artificial intelligence technological pedagogical content knowledge are presented in Table 2.

Table 2. Paired-Samples t-Test Results for the Control Group's Technological Pedagogical Content Knowledge Subdimensions

Sub-dimensions	t	df	p	Cohen's d
Subject Knowledge	-2.55	13.0	0.024	-0.68
Pedagogical Knowledge	-2.21	13.0	0.045	-0.59
Artificial Intelligence- Technological Knowledge	-3.27	13.0	0.006	-0.87
Pedagogical Content Knowledge	-2.32	13.0	0.037	-0.62
Artificial Intelligence - Technological Subject Knowledge	-4.04	13.0	0.001	-1.08
Artificial Intelligence- Technological Pedagogical	-4.29	13.0	0.001	-1.15
Artificial Intelligence - Technological Pedagogical Content Knowledge	-2.83	13.0	0.014	-0.76
Overall AI-TPACK Scale	-3.95	13	0.002	**-1.06**

According to the findings in Table 2 of the study, when examining the pre-test and post-test total scores of the control group, a significant ($p<0.05$) difference emerged across all sub-dimensions.

According to Table 3, based on the control group's pre-test and post-test mean scores, the post-test mean score for each sub-dimension is higher than the pre-test score.

The second sub-question of the study was as follows: "Is there a statistically significant difference between the experimental group's pre-test and post-test scores on the subdimensions of the Artificial Intelligence Technological Pedagogical Content Knowledge Scale?" To determine whether the experimental group's pre-test and post-test mean scores differed significantly, a normality test was first conducted. The results are presented in Table 4.

Table 3. Statistical Values for the Control Group's Artificial Intelligence Technological Pedagogical Content Knowledge Subdimensions

Sub-dimensions	N	Mean	Median	SD
Subject Knowledge Pre-test	14	15.9	15.0	3.11
Subject Knowledge Post-test	14	17.9	18.0	1.99
Pre-test on Pedagogical Knowledge	14	21.6	21.0	3.82
Pedagogical Knowledge Post-test	14	24.2	24.5	2.69
Artificial Intelligence - Technological Knowledge Pre-test	14	15.1	15.5	4.09
Artificial Intelligence- Technology Knowledge Post- test	14	18.2	18.0	2.78
Pre-test on Pedagogical Content Knowledge	14	20.4	21.0	5.94
Pedagogical Content Knowledge Post-test	14	23.9	23.0	3.45
Artificial Intelligence- Technological Subject Knowledge Pre-test	14	17.1	16.0	4.00
Artificial Intelligence- Technological Subject Knowledge Post- test	14	21.6	21.0	3.93
Artificial Intelligence- Technological Pedagogical Knowledge Pre-test	14	17.1	16.5	3.96
Artificial Intelligence- Technological Pedagogical Knowledge Post-test	14	22.3	22.0	3.47
Artificial Intelligence- Technological Pedagogical Content Knowledge Pre-test	14	15.6	16.0	3.20
Artificial Intelligence- Technological Pedagogical Content Knowledge Post-test	14	18.5	18.5	2.88

According to the Shapiro-Wilk normality test results presented in Table 4, the distributions of Subject Matter Knowledge ($W = 0.898$, $p = 0.053$), Pedagogical Knowledge ($W = 0.950$, $p = 0.421$), Pedagogical Content Knowledge ($W = 0.935$, $p = 0.237$), Artificial Intelligence-Technological Subject Matter Knowledge ($W = 0.946$, $p = 0.373$), and Artificial Intelligence-Technological Pedagogical Content Knowledge ($W = 0.974$, $p = 0.863$) did not significantly deviate from normality, as their p-values were greater than .05. Therefore, the null hypothesis of normality was not rejected.

Table 4. Shapiro–Wilk Normality Test Results for the Experimental Group's Artificial Intelligence Technological Pedagogical Content Knowledge Scale Subdimensions

Sub-dimensions	W	p
Subject Knowledge	0.898	0.053
Pedagogical Knowledge	0.950	0.421
Artificial Intelligence - Technological Knowledge	0.867	0.016
Pedagogical Content Knowledge	0.935	0.237
Artificial Intelligence- Technological Subject Knowledge	0.946	0.373
Artificial Intelligence- Technological Pedagogical Knowledge	0.813	0.002
Artificial Intelligence- Technological Pedagogical Content Knowledge	0.974	0.863

Accordingly, the experimental group's pre-test and post-test scores for these five subdimensions were analyzed using paired-samples t-tests. In contrast, the distributions of Artificial Intelligence-Technological Knowledge (W = 0.867, p = 0.016) and Artificial Intelligence-Technological Pedagogical Knowledge (W = 0.813, p = 0.002) significantly deviated from normality, as their p-values were less than .05. Therefore, the normality assumption was not met for these subdimensions, and the pre-test and post-test scores were analyzed using the nonparametric Wilcoxon signed-rank test.

Table 5. Paired-Samples t-Test Results for the Experimental Group's Artificial Intelligence–Technological Pedagogical Content Knowledge Subdimensions

Sub-dimensions	t	df	p
Subject Knowledge	-2.79	17	0.012
Pedagogical Knowledge	-1.82	17	0.087
Pedagogical Content Knowledge	-1.36	17	0.193
Artificial Intelligence-Technological Subject Knowledge	-2.71	17	0.015
Artificial Intelligence-Technological Pedagogical Content Knowledge	-1.64	17	0.120

According to Table 5, there was a significant difference ($p < 0.05$) in the experimental group's subject knowledge and artificial intelligence-technological subject knowledge sub-dimensions. There was no significant difference ($p > 0.05$) in the pedagogical knowledge, pedagogical subject knowledge, and artificial intelligence-technological pedagogical subject knowledge sub-dimensions.

As the artificial intelligence - technological knowledge and artificial intelligence-technological pedagogical knowledge sub-dimensions did not exhibit a normal distribution, the Wilcoxon signed-rank test was conducted among these sub-dimensions.

Table 6. Wilcoxon Signed-Rank Test Results for the Experimental Group's Artificial Intelligence–Technological Pedagogical Content Knowledge Subdimensions

Sub-dimensions	W	Z	p
Artificial Intelligence-Technological Knowledge	25.0	-1.98	0.048
Artificial Intelligence-Technological Pedagogical Knowledge	36.5	-1.88	0.060

According to Table 6, the Wilcoxon signed-rank test was conducted for the sub-dimensions that did not meet the normality assumption. The results demonstrated a statistically significant difference between the pre-test and post-test scores in the Artificial Intelligence-Technological Knowledge sub-dimension ($W = 25.0$, $p = 0.048$, $p < 0.05$). Conversely, no statistically significant difference was found in the Artificial Intelligence-Technological Pedagogical Knowledge sub-dimension ($W = 36.5$, $p = 0.060$, $p > 0.05$), despite an increase in the mean scores.

Table 7. Descriptive Statistics for the Experimental Group's Artificial Intelligence–Technological Pedagogical Content Knowledge Subdimensions

Sub-dimensions	N	Mean	Median	SD
Subject Knowledge Pre-test	18	16.9	16.0	3.39
Subject Knowledge Post-test	18	18.8	19.0	2.66
Pre-test on Pedagogical Knowledge	18	20.5	19.0	5.20
Pedagogical Knowledge Post-test	18	23.2	23.0	3.11
Artificial Intelligence - Technological Knowledge Pre-test	18	15.9	15.0	4.02
Artificial Intelligence-Technology Knowledge Post- test	18	17.4	17.0	3.90
Pre-test on Pedagogical Content Knowledge	18	19.6	20.0	4.23
Pedagogical Content Knowledge Post-test	18	21.2	22.0	3.47
Artificial Intelligence- Technological Subject Knowledge Pre-test	18	18.7	18.0	4.85
Artificial Intelligence- Technological Subject Knowledge Post-test	18	21.8	21.5	4.22
Artificial Intelligence- Technological Pedagogical Knowledge Pre-test	18	19.9	19.5	5.39
Artificial Intelligence- Technological Pedagogical Knowledge Post-test	18	21.7	21.5	5.14
Artificial Intelligence- Technological Pedagogical Content Knowledge Pre-test	18	16.1	16.0	3.46
Artificial Intelligence- Technological Pedagogical Content Knowledge Post-test	18	17.9	18.5	4.28

According to Table 7, based on the mean pre-test and post-test scores of the experimental group, the post-test mean score for each sub-dimension is higher than the pre-test score.

The third sub-question of this study is: "Is there a statistically significant difference between the post-test mean scores of the control and experimental groups on the sub-dimensions of the artificial intelligence technological domain knowledge scale?" To determine whether there is a statistically significant difference between the pre-test and post-test scores of the artificial intelligence technological domain knowledge scale for the control and experimental groups, a normality test was first conducted. The findings are presented in Table 8.

Table 8. Shapiro-Wilk Normality Test Results for the Artificial Intelligence-Technological Pedagogical Content Knowledge Scale Subdimensions in the Control and Experimental Groups

Sub-dimensions	W	p
Subject Knowledge	0.974	0.630
Pedagogical Knowledge	0.974	0.601
Artificial Intelligence - Technological Knowledge	0.975	0.661
Pedagogical Content Knowledge	0.970	0.508
Artificial Intelligence- Technological Subject Knowledge	0.964	0.356
Artificial Intelligence- Technological Pedagogical Knowledge	0.974	0.615
Artificial Intelligence- Technological Pedagogical Content Knowledge	0.975	0.661

According to the Shapiro-Wilk normality test results presented in Table 8, the scores for all subdimensions of the Artificial Intelligence–Technological Pedagogical Content Knowledge Scale were normally distributed across the control and experimental groups. The p-values for Subject Matter Knowledge ($W = 0.974$, $p = 0.630$), Pedagogical Knowledge ($W = 0.974$, $p = 0.601$), Artificial Intelligence–Technological Knowledge ($W = 0.975$, $p = 0.661$), Pedagogical Content Knowledge ($W = 0.970$, $p = 0.508$), Artificial Intelligence–Technological Subject Matter Knowledge ($W = 0.964$, $p = 0.356$), Artificial Intelligence-Technological Pedagogical Knowledge ($W = 0.974$, $p = 0.615$), and Artificial Intelligence-Technological Pedagogical Content Knowledge ($W = 0.975$, $p = 0.661$) were all greater than .05. Therefore, the null hypothesis of normality was not rejected, indicating that the normality assumption was met for all subdimensions. Consequently, parametric independent samples t-tests were utilised to compare the post-test scores between the control and experimental groups.

Following the within-group analyses presented in Tables 5 and 6, the third research question examined whether the post-test scores differed between the experimental and control groups. After confirming the normality assumption (Table 8), independent samples t-tests were conducted. The results are presented in Table 9.

Table 9. Post-test Scores for the Sub-dimensions of Artificial Intelligence Technological Pedagogical Content Knowledge in the Control and Experimental Groups, and Independent t-Test Values

Sub-dimensions	t	df	p	Cohen's d
Subject Knowledge	1.143	30.0	0.262	0.41
Pedagogical Knowledge	-1.001	30.0	0.325	-0.36
Artificial Intelligence - Technological Knowledge	-0.670	30.0	0.508	-0.24
Pedagogical Content Knowledge	-2.192	30.0	0.036	-0.78
Artificial Intelligence- Technological Subject Knowledge	0.130	30.0	0.897	0.05
Artificial Intelligence- Technological Pedagogical Knowledge	-0.386	30.0	0.702	-0.14
Artificial Intelligence- Technological Pedagogical Content Knowledge	-0.459	30.0	0.650	-0.16
Overall AI-TPACK Scale	-0.812	30	0.423	-0.29

According to Table 9, a statistically significant difference between the experimental and control groups was observed only in the Pedagogical Content Knowledge (PCK) sub-dimension ($t(30) = -2.192$, $p = .036$, Cohen's $d = -0.78$). Examination of the descriptive statistics (Table 10) indicates that this difference favored the control group ($M = 23.9$, $SD = 3.45$) over the experimental group ($M = 21.2$, $SD = 3.47$). No statistically significant differences were found in the remaining AI-TPACK sub-dimensions or in the overall AI-TPACK score ($p > .05$).

Table 10. Descriptive Statistical Values of Post-test Scores for the Control and Experimental Groups Across AI-TPACK Sub-dimensions

Sub-dimensions	Groups	N	Mean	Median	SD
Subject Knowledge	Control Group	14	17.9	18.0	1.99
	Experimental Group	18	18.8	19.0	2.66
Pedagogical Knowledge	Control Group	14	24.2	24.5	2.69
	Experimental Group	18	23.2	23.0	3.11
Artificial Intelligence - Technological Knowledge	Control Group	14	18.2	18.0	2.78
	Experimental Group	18	17.4	17.0	3.90
Pedagogical Content Knowledge	Control Group	14	23.9	23.0	3.45
	Experimental Group	18	21.2	22.0	3.47
Artificial Intelligence - Technological Subject Knowledge	Control Group	14	21.6	21.0	3.93
	Experimental Group	18	21.8	21.5	4.22
Artificial Intelligence - Technological Pedagogical Knowledge	Control Group	14	22.3	22.0	3.47
	Experimental Group	18	21.7	21.5	5.14
Artificial Intelligence - Technological Pedagogical Content Knowledge	Control Group	14	18.5	18.5	2.88
	Experimental Group	18	17.9	18.5	4.28

Table 10 presents the descriptive statistics, including sample size (N), mean scores, medians, and standard deviations (SD), of the post-test scores obtained by the pre-service teachers in both the control ($n = 14$) and experimental ($n = 18$) groups. When analysing the post-test mean scores, the experimental group achieved slightly higher descriptive performance in Subject Knowledge ($M = 18.8$, $SD = 2.66$) and Artificial Intelligence - Technological Subject Knowledge ($M = 21.8$, $SD = 4.22$) compared to the control group. Conversely, the control group exhibited higher post-test mean scores in dimensions such as Pedagogical Knowledge ($M = 24.2$, $SD = 2.69$), Artificial Intelligence - Technological Knowledge ($M = 18.2$, $SD = 2.78$), and Pedagogical Content Knowledge ($M = 23.9$, $SD = 3.45$). These descriptive metrics lay the foundation for inferential statistical comparisons conducted to verify if these observed differences carry statistical significance.

Theme 1: AI as a Facilitator of Learning

Participants frequently described artificial intelligence as a tool that facilitates learning processes, saves time, and provides quick access to information. AI was perceived as a supportive assistant, particularly in generating ideas, summarising content, and preparing instructional materials.

One participant stated:

"Artificial intelligence is a tool that makes our work easier. I use it to get examples and create drafts."

Another participant emphasised:

"It provides quick access to information and helps us save time in our studies."

These findings suggest that AI contributes to efficiency and accessibility in learning environments.

Theme 2: Contribution to Concretisation and Visualisation

A prominent theme was the role of AI in making abstract concepts more concrete through visualisations, simulations, and examples. Participants highlighted that AI-supported tools enhance understanding, especially in science topics that are difficult to grasp.

For example:

"I would use AI tools to make difficult concepts more concrete through visuals and simulations."

Another participant noted:

"Students can understand topics more easily when supported with simulations and visual materials."

This indicates that AI plays an important role in supporting conceptual understanding.

Theme 3: Limitations and Concerns about AI Use

Despite its advantages, participants expressed several concerns about AI. The most frequently mentioned issues were incorrect or incomplete information, limitations in solving complex problems, and over-reliance on AI.

One participant stated:

"Sometimes AI gives incorrect answers, so I feel the need to check other sources."

Another participant remarked:

"I think AI is insufficient in solving some types of questions."

Additionally, concerns about reduced creativity and dependency were highlighted:

"It makes things easier, but I think it can make people lazy over time."

These findings reveal that participants approach AI critically and do not fully trust its outputs.

Theme 4: Impact on Learning and Individual Differences

Participants emphasised that AI can support individualised learning by adapting to students' needs and allowing them to learn at their own pace. AI was described as a potential "learning assistant" that can provide repeated explanations and personalised support.

One participant explained:

"Students can ask AI questions freely and repeatedly without hesitation."

Another participant added:

"AI can provide learning opportunities suitable for each student's level and needs."

However, some participants also noted that improper use might negatively affect students' critical thinking skills.

3.3. Integration of Quantitative and Qualitative Findings

The integration of quantitative and qualitative findings provides a deeper understanding of the results obtained in this study.

Quantitative findings indicated that while some AI-TPACK sub-dimensions showed statistically significant improvements, others, particularly pedagogical dimensions, did not demonstrate significant differences.

Qualitative findings help explain this pattern. Participants' concerns about the accuracy of AI-generated information, its limitations in problem-solving, and their lack of prior training in AI use suggest that they may not fully integrate AI into pedagogical practices. This may account for the lack of significant improvement in pedagogical knowledge-related dimensions.

Furthermore, although participants acknowledged the benefits of AI in visualisation and content support, they tended to use it primarily as a support tool for information access and material preparation, rather than as a pedagogically integrated instructional strategy. This limited use may explain why improvements were more evident in content-related dimensions than in pedagogical ones.

Additionally, participants' concerns about dependency and reduced critical thinking may have influenced their cautious use of AI, thereby limiting its potential impact on deeper pedagogical competencies.

Overall, the qualitative findings complement the quantitative results by suggesting possible explanations for the observed changes in AI-TPACK. While participants reported that AI supported content learning, visualisation, and access to information, the post-test comparisons indicated only limited differences between the experimental and control groups. The qualitative evidence therefore suggests that participants perceived AI as a useful learning support rather than as a tool that produced substantially greater pedagogical gains than the existing instructional approach.

4. Discussion

The present study aimed to examine the impact of AI-supported science instruction on pre-service teachers' AI-TPACK levels and to explain these effects through participants' experiences and perceptions. The findings revealed that both groups showed improvements in several AI-TPACK sub-dimensions over time; however, post-test comparisons indicated only limited differences between the experimental and control groups. The integration of qualitative findings provides important insights into these results.

First, the improvement observed in content- and technology-related dimensions is consistent with previous research indicating that AI tools can effectively support access to information, content generation, and visualisation (Zhai & Krajcik, 2024; Ouyang & Jiao, 2021). Participants in the present study emphasised that AI facilitated learning by providing quick access to information and enabling the visualisation of abstract scientific concepts. This aligns with the literature suggesting that AI-enhanced environments can support conceptual understanding through multimodal representations (Holmes et al., 2019). These findings are consistent with recent trends reported in the Turkish AI in education literature, where empirical research has increasingly shifted from conceptual discussions toward classroom-based applications and teacher competencies (Gündoğdu & Benzer, 2024). This trend also indicates a gradual shift from descriptive AI research toward intervention-based studies examining instructional effectiveness.

However, the lack of significant improvement in pedagogical dimensions may be explained by several factors. Qualitative findings indicated that participants tended to use AI primarily as a support tool rather than as an integrated pedagogical component. This result is consistent with studies showing that teachers often adopt new technologies at a surface level before fully integrating them into their instructional practices (Ertmer & Ottenbreit-Leftwich, 2010). In this sense, the development of technological knowledge may precede pedagogical transformation.

Another important finding relates to participants' concerns about the accuracy and reliability of AI-generated information. Similar concerns have been highlighted in the literature, where issues such as misinformation, lack of transparency, and limited contextual understanding are identified as barriers to effective AI integration in education (Zawacki-Richter et al., 2019). These concerns may have limited participants' willingness to rely on AI for deeper pedagogical decision-making, thereby affecting their development in pedagogical knowledge domains.

Furthermore, the findings suggest that a lack of prior experience and training in AI-supported instruction may have constrained participants' ability to use AI tools pedagogically. This is in line with the TPACK framework, which emphasises that effective technology integration requires not only technological knowledge but also the ability to align technology with pedagogy and content (Koehler & Mishra, 2009). Without sufficient training, teachers may struggle to move beyond basic usage toward meaningful integration.

The qualitative findings also revealed a tension between the perceived benefits of AI (e.g., efficiency, personalisation, and accessibility) and concerns about over-reliance and reduced critical thinking. This dual perspective reflects broader discussions in the literature regarding the ethical and pedagogical implications of AI in education (Holmes et al., 2021). While AI has the potential to support individualised learning, its misuse may hinder the development of higher-order thinking skills if not carefully guided.

Overall, the integration of quantitative and qualitative findings suggests that AI-supported instruction contributed to improvements in several AI-TPACK dimensions within the experimental group. However, similar improvements were also observed in the control group, and the post-test comparisons revealed only one significant between-group difference, favouring the control group in the Pedagogical Content Knowledge dimension. These findings indicate that the additional contribution of AI-supported instruction beyond the existing instructional approach was limited under the conditions of the present study. This highlights the importance of designing teacher education programs that not only introduce AI tools but also explicitly model their pedagogical integration. The limited improvement in pedagogical dimensions may be attributed to several factors. First, participants primarily used AI as a supportive tool rather than integrating it into instructional design. Second, concerns about the accuracy and reliability of AI-generated content may have reduced their willingness to rely on these tools pedagogically. Finally, the lack of prior training in AI-supported instruction likely constrained their ability to use AI in a pedagogically meaningful way.

5. Conclusion and Implications

Among the strategic recommendations are leveraging AI for personalised learning, integrating AI-focused instructional models, and ensuring that AI serves as a complement rather than a replacement for teacher-student interactions. The findings emphasise the necessity of AI literacy for both educators and students in order to mitigate its potential negative effects. By providing a structured framework to evaluate the impact of artificial intelligence and proposing actionable strategies for its effective implementation in secondary education, this study contributes to the ongoing debate on the role of AI in education (Şahin & Teke, 2025). This study investigated the effects of AI-supported science instruction on pre-service teachers' AI-TPACK levels using an explanatory sequential mixed-methods design. The findings showed that both instructional approaches were associated with improvements in several AI-TPACK dimensions over time. Although the experimental group demonstrated significant within-group gains in selected content- and technology-related dimensions, the post-test comparisons between the experimental and control groups revealed only limited differences, with a significant advantage for the control group only in the Pedagogical Content Knowledge dimension. These findings suggest that the additional contribution of AI-supported instruction should be interpreted cautiously and that effective pedagogical integration of AI may require more comprehensive instructional design and sustained teacher preparation.

The integration of qualitative findings provided important insights into this pattern. While participants recognised the benefits of AI in facilitating access to information, enhancing visualisation, and supporting learning processes, they tended to use AI tools primarily as supplementary resources rather than as integral components of pedagogical design. Concerns regarding the accuracy of AI-generated information, limited experience with AI tools, and lack of structured guidance were identified as key factors limiting deeper pedagogical integration.

These findings suggest that the mere inclusion of AI tools in educational settings is not sufficient to ensure meaningful instructional transformation. Instead, effective integration requires a pedagogically grounded approach that explicitly connects AI technologies with instructional strategies and content knowledge. In this respect, the study highlights the importance of moving beyond surface-level technology use toward a more holistic and reflective integration aligned with the AI-TPACK framework. This study contributes to the literature by demonstrating that AI integration in education does not inherently lead to pedagogical development. Instead, it highlights the necessity of explicitly designed instructional support that connects AI tools with pedagogical practices. At the same time, expanding AI integration in education requires greater attention to legal responsibility, institutional governance, algorithmic transparency, and accountability and accountability mechanisms. As AI becomes increasingly embedded in educational decision-making, teacher education should also address the legal and ethical implications of AI use alongside pedagogical competencies (Değirmenci & Mengüç, 2025).

5.1. Implications

The findings of this study offer several important implications for teacher education and educational practice.

First, teacher education programs should incorporate structured training on AI-supported pedagogy, rather than focusing solely on technical skills. Pre-service teachers need opportunities to develop not only familiarity with AI tools but also the ability to integrate them effectively into teaching and learning processes.

Second, instructional designs should include guided and practice-based experiences that model how AI can be used to support pedagogical decision-making, student engagement, and assessment. Without such guidance, teachers may remain at a basic usage level and fail to realise the full potential of AI in education.

Third, educational policymakers and curriculum developers should consider developing AI integration frameworks and guidelines that support teachers in aligning AI use with pedagogical goals. This is particularly important in contexts where AI adoption is still emerging.

Finally, addressing teachers' concerns about trust, accuracy, and ethical use of AI is essential. Providing critical AI literacy and promoting reflective practices can help teachers use AI tools more confidently and responsibly. In addition, teacher education programmes should familiarise future teachers with emerging legal and regulatory discussions surrounding artificial intelligence so that AI can be used responsibly and in accordance with ethical standards (Değirmenci & Mengüç, 2025).

5.2. Limitations and Future Research

Despite its contributions, this study has several limitations that should be acknowledged. First, the study was conducted with a limited sample of pre-service teachers within a specific context, which may affect the generalizability of the findings. Future studies could include larger and more diverse samples to enhance external validity. Second, the duration of the intervention may not have been sufficient to observe long-term changes in pedagogical knowledge and practices. Longitudinal studies are needed to examine how AI-TPACK develops over time with sustained exposure to AI-supported instruction. Third, the study relied on self-reported data and perceptions in the qualitative phase, which may be subject to bias. Future research could incorporate classroom observations and performance-based assessments to provide a more comprehensive understanding.

Finally, future studies should explore different instructional models, subject areas, and AI tools to better understand how contextual factors influence the integration of AI into teaching practices. Future research may also investigate how legal regulations, ethical awareness, and institutional governance influence teachers' willingness to adopt AI-supported instructional practices (Değirmenci & Mengüç, 2025).

Authors contributions

İbrahim Yüksel, Nazike Nazlı and Ersin Eren Akgöz contributed equally to this work.

Statements and Declarations

Ethical Considerations

Not applicable.

Consent to Participate

Informed consent was obtained from all participants before data collection.

Consent for Publication

All authors consent to the publication of this manuscript.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding Statement

The author(s) received no financial support for the research, authorship, and/or publication of this article.

Data availability

Not applicable.

References

Akarsu, B., & Güven, E. (2014). Fen ve teknoloji öğretmen adaylarının teknolojik pedagojik alan bilgilerinin incelenmesi. *Gaziantep Üniversitesi Sosyal Bilimler Dergisi, 13*(2), 515–524. https://doi.org/10.21547/jss.256825

Akkoç, H., Özmantar, M. F., Bingölbalı, E., Demir, S., Baştürk, S., & Yavuz, İ. (2011). *Matematik öğretmen adaylarına teknolojiye yönelik pedagojik alan bilgisi kazandırma amaçlı program geliştirme* (TÜBİTAK Proje No. 107K531).

Akkol, S., & Balkan, Z. E. (2024). Artificial intelligence integration in mathematics education: A SWOT-BWM analysis. *International Social Sciences Studies Journal, 10*(10), 1754–1770. https://doi.org/10.5281/zenodo.13990459

Alam, A. (2021, November 26–27). Possibilities and apprehensions in the landscape of artificial intelligence in education [Conference presentation]. *International Conference on Computational Intelligence and Computing Applications (ICCICA)*, Nagpur, India. https://doi.org/10.1109/ICCICA52458.2021.9697272

Aydın, S. (2021). Dijital teknolojilerin eğitimde kullanımı ve öğretmenlerin yeterlilikleri. *Eğitim Teknolojileri Dergisi, 18*(2), 45–67.

Baker, T., & Smith, L. (2019). *Educ-AI-tion rebooted? Exploring the future of artificial intelligence in schools and colleges*. Nesta.

Bewersdorf, A., et al. (2025). Multimodal learning in science education: Representations and meaning-making. *Science Education Review, 34*(2), 145–162.

Büyüköztürk, Ş., Kılıç Çakmak, E., Akgün, Ö. E., Karadeniz, Ş., & Demirel, F. (2022). *Eğitimde bilimsel araştırma yöntemleri*. Pegem Akademi.

Ertmer, P. A., & Ottenbreit-Leftwich, A. T. (2010). Teacher technology change: How knowledge, beliefs, and culture intersect. *Journal of Research on Technology in Education, 42*(3), 255–284.

Değirmenci, O., & Mengüç, S. (2025). *The problem of sanctions applicable to artificial intelligence*. *Journal of Artificial Intelligence and Human Sciences, 2*(1), 22–33. https://doi.org/10.5281/zenodo.16234382

Graham, R. C., Burgoyne, N., Cantrell, P., Smith, L., St Clair, L., & Harris, R. (2009). TPACK development in science teaching: Measuring the TPACK confidence of in-service science teachers. *TechTrends, 53*(5), 70–79.

Gündoğdu, A., & Benzer, S. (2024). *Bibliometric analysis of articles published on artificial intelligence in education during the last five years in Türkiye*. *Journal of Artificial Intelligence and Human Sciences, 1*(1), 22–35. https://doi.org/10.5281/zenodo.14669374

Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial intelligence in education: Promises and implications for teaching and learning*. Centre for Curriculum Redesign.

Holmes, W., Persson, J., Chounta, I.-A., Wasson, B., & Dimitrova, V. (2021). *Artificial intelligence and education: A critical view through the lens of human rights, democracy and the rule of law*. Council of Europe.

Kaya, Z., & Yılayaz, Ö. (2013). Öğretmen eğitimine teknoloji entegrasyonu modelleri ve teknolojik pedagojik alan bilgisi. *Batı Anadolu Eğitim Bilimleri Dergisi, 4*(8), 57–83.

Koehler, M. J., & Mishra, P. (2008). Introducing TPCK. In *Handbook of technological pedagogical content knowledge (TPCK) for educators* (pp. 3–29). Routledge.

Koehler, M. J., & Mishra, P. (2009). What is technological pedagogical content knowledge (TPACK)? *Contemporary Issues in Technology and Teacher Education, 9*(1), 60–70.

Li, A., & Wang, S. (2025). Functional attitudes towards artificial intelligence among university students: Development of a scale and influencing factors. *Higher Education*. https://doi.org/10.1007/s10734-025-01497-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), 978. https://doi.org/10.3390/su16030978

Orhan Göksün, D. (2025). Öğretmen adaylarının yapay zekâ teknolojileri tabanlı teknolojik pedagojik içerik bilgisi durumlarının belirlenmesi. *Adıyaman Üniversitesi Sosyal Bilimler Enstitüsü Dergisi, 50*, 1–35. https://doi.org/10.14520/adyusbd.1688360

Ouyang, F., & Jiao, P. (2021). Artificial intelligence in education: The three paradigms. *Computers and Education: Artificial Intelligence, 2*, 100020. https://doi.org/10.1016/j.caeai.2021.100020

Shulman, L. S. (1986). Those who understand: Knowledge growth in teaching. *Educational Researcher, 15*(2), 4–14.

Şahin, S., & Teke, B. (2025). Matematik eğitiminde yapay zekâ entegrasyonu: Bir SWOT-BWM analizi. *Dijital Çağda Öğrenme ve Öğretme Dergisi, 10*(2), 273–286. https://doi.org/10.53850/joltida.1667650

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – Where are the educators? *International Journal of Educational Technology in Higher Education, 16*(39). https://doi.org/10.1186/s41239-019-0171-0

Zhai, X., & Krajcik, J. (2024). AI in science education: Opportunities and challenges. *Journal of Research in Science Teaching, 61*(2), 123–145.