RESEARCH ARTICLE

Journal of Pedagogical Sociology and Psychology
Onlinefirst Article, e47606
https://doi.org/10.33902/JPSP.202647606

The effect of the AI-supported lesson planning process on science teacher candidates' technological pedagogical content knowledge and AI readiness

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Submitted: 30 June 2026 Revised: 13 August 2026 Accepted: 15 August 2026

Abstract

The rapid integration of generative artificial intelligence [AI] into educational settings has increased the need for teacher candidates not only to be prepared for AI but also to develop the competencies required to integrate it into their teaching practices meaningfully. Despite growing interest in AI-supported instruction, there is limited empirical evidence regarding whether teacher candidates' participation in AI-supported lesson planning simultaneously contributes to their technological-pedagogical content knowledge and AI readiness. This study investigated the effects of AI-supported lesson planning on pre-service teachers' AI readiness and maker technological-pedagogical content knowledge. The study employed a single-group pretest-posttest quasi-experimental design with 41 second-year pre-service teachers. Over a 14-week intervention period, participants designed curriculum-aligned lesson plans by integrating productive AI tools into their instructional planning activities. Data were collected using the Artificial Intelligence Readiness Scale and the Maker Technological Pedagogical Content Knowledge Scale. Paired-sample t-tests were conducted to compare pretest and posttest scores. The findings revealed significant improvements in overall AI readiness and in the cognitive, skill, and perception dimensions, while no significant change was observed in maker technological-pedagogical content knowledge. These findings suggest that AI-supported lesson planning can enhance pre-service teachers' confidence and readiness in using AI; however, developing integrated pedagogical technology competencies requires longer-term, practice-oriented interventions. By distinguishing between AI readiness and pedagogical technology integration competencies, this study is expected to contribute to the emerging literature on AI integration in teacher education.

Keywords: Artificial intelligence; AI readiness; Lesson planning; Pre-service teachers; Technological pedagogical content knowledge

1. Introduction

Learning is a dynamic process that continually evolves and is influenced by innovations; in this regard, teachers are among its most significant influencers (Santos & Castro, 2021). Teachers are expected to use technology both to achieve pedagogical goals and to adapt and enhance their teaching strategies in line with digital transformation (Guggemos & Seufert, 2021). AI has become increasingly integrated into educational settings, with applications extending to lesson planning, instructional support, feedback, assessment, and human–AI collaborative learning (Danişman, 2026; Okanya & Asogwa, 2026). As these applications expand, teachers' readiness to engage with AI becomes an important condition for its pedagogically meaningful integration. Readiness and confidence in teaching AI are closely related to teachers' intentions to incorporate AI into educational practice, while more recent evidence indicates that technopedagogical competence is also associated with teachers' acceptance of AI (Ayanwale et al., 2022; Çakır & Güner, 2026). Thus, effective AI integration requires more than willingness to adopt new technologies; teachers need the knowledge and pedagogical competence required to evaluate AI tools, incorporate them purposefully into instruction, and reflect critically on their affordances and limitations (Simiyu et al., 2026; Yanar & Ergene, 2025). This need is particularly salient because teachers may perceive considerable educational potential in AI while still possessing limited knowledge of how AI works or how it can support their professional practice (Chounta et al., 2022). Accordingly, teacher preparation and professional development should address AI-related competencies alongside pedagogical judgment, reflective practice, and human-centred approaches to technology integration (Danişman, 2026; Okanya & Asogwa, 2026; Simiyu et al., 2026).

This concern has led to growing attention to AI readiness in education, which extends beyond familiarity with AI technologies to include the knowledge, abilities, perspectives, and ethical considerations required for their meaningful use in educational contexts (Luckin et al., 2022; Wang et al., 2023). Empirical research has examined in-service teachers' readiness and intentions to teach or integrate AI (Ayanwale et al., 2022), while an increasing body of research has focused specifically on pre-service teachers, addressing their acceptance of AI (Zhang et al., 2023), readiness to integrate AI-based tools through a TPACK perspective (Bautista et al., 2024), and preparedness for AI-integrated teaching (Lucas et al., 2025). Research focusing specifically on pre-service science teachers further indicates that AI-related knowledge, perceived usefulness, and other individual and contextual factors are associated with their intentions to use generative AI in inquiry-based teaching (Ramnarain et al., 2025). These studies suggest that AI readiness should be regarded as a profession-specific aspect of teacher preparation rather than merely as a general disposition toward an emerging technology. During initial teacher education, pre-service teachers are expected to make pedagogical decisions about when, why, and how emerging technologies should be used while simultaneously developing their technological, pedagogical, and content knowledge through coursework and practicum experiences. Evidence from pre-service physical science teacher education indicates that structured practice, modelling, feedback, authentic classroom exposure, and practical lesson planning can strengthen preparation for digital pedagogy (Mohafa et al., 2026). Therefore, providing structured opportunities to engage with AI in authentic pedagogical tasks may be particularly important for their professional preparation. From this perspective, AI-supported lesson planning provides a meaningful context for examining whether hands-on engagement with AI can contribute to science teacher candidates' AI readiness alongside their technological pedagogical content knowledge.

It is argued that educational technologies will increase learning efficiency, prepare individuals to adapt to the evolving digital age, and enable students to acquire technology-based competencies for their professional lives (Seufert et al., 2021). The development of pre-service teachers' TPACK is crucial for them to effectively use digital technologies to enhance student learning (Wekerle & Kollar, 2022). Pre-service teachers need opportunities to develop the professional knowledge required to integrate technology meaningfully into teaching and learning rather than merely learning how to operate technological tools (Lachner et al., 2021). This capacity is commonly conceptualized through technological pedagogical content knowledge [TPACK], which emphasizes the interconnected roles of technological, pedagogical, and content knowledge in the design of instruction (Mishra & Koehler, 2006). Evidence from teacher education indicates that TPACK can be strengthened through structured courses, technology-integration experiences, and practice-oriented instructional design activities (Aktaş & Özmen, 2020; Lachner et al., 2021; Lim et al., 2024).

Lesson planning has consequently become an important context for examining how pre-service teachers translate technology-related knowledge into pedagogical decisions. Previous studies have analyzed technology integration through lesson plans, compared the planning of pre-service and in-service teachers, and examined how different forms of technological and pedagogical support shape technology-infused instructional design (Janssen & Lazonder, 2016; Janssen et al., 2019; Wekerle & Kollar, 2022). Lesson plans have also been used to examine enacted or applied TPACK across different teacher-education contexts (Hasançebi & Baydaş, 2020; Kwangsawad, 2016; Muslu et al., 2022; Yiğit Koyunkaya & Tataroğlu Taşdan, 2019). More intervention-oriented research suggests that developing and collaboratively revising technology-integrated lesson plans can contribute to pre-service teachers' TPACK development and their ability to connect technological choices with pedagogical and content-related considerations (Guo et al., 2026; Saralar-Aras & Türker-Biber, 2024). Taken together, this literature positions lesson planning not simply as a product for assessing technology use but as a practice-oriented space in which technological, pedagogical, and content knowledge can be coordinated.

The emergence of generative AI has extended this challenge by introducing technologies whose outputs must themselves be interpreted, evaluated, adapted, and pedagogically situated. Research on AI and TPACK indicates that traditional TPACK and AI-related TPACK competencies are closely connected, while technopedagogical competence is also associated with teachers' acceptance of AI (Çakır & Güner, 2026; Karataş & Ataç, 2025). Effective AI integration therefore requires more than familiarity with AI tools; teacher candidates need to determine whether AI-generated content is instructionally appropriate, adapt outputs to disciplinary and learner needs, and make informed decisions about when and how AI should contribute to teaching (Simiyu et al., 2026; Yanar & Ergene, 2025). This emphasis is consistent with evidence from science teacher preparation showing that structured practice, modelling, feedback, and authentic lesson-planning experiences can strengthen preparation for digitally mediated pedagogy (Mohafa et al., 2026). AI-supported lesson planning provides a particularly relevant setting for examining these competencies. Thus, authentic engagement with AI can potentially move teacher preparation beyond general awareness of AI toward the practical problem of integrating AI into disciplinary pedagogy.

Against this background, AI readiness and TPACK-related competence are better viewed as complementary rather than competing dimensions of professional preparation. AI readiness concerns teachers' preparedness to engage with AI appropriately and responsibly, whereas TPACK concerns the integration of technology with pedagogy and disciplinary content in instructional practice. Existing research has examined TPACK development through technology-integrated lesson planning and has increasingly investigated AI acceptance, AI-TPACK, and GenAI-supported instructional design (Çakır & Güner, 2026; Karataş & Ataç, 2025). However, within the literature reviewed here, considerably less attention has been given to whether a structured AI-supported lesson-planning experience is associated simultaneously with changes in pre-service science teachers' AI readiness and Maker-TPACK. Examining these constructs together may therefore provide a more integrated account of whether authentic AI-supported instructional design is associated with both preparedness to work with AI and the capacity to coordinate technology, pedagogy, and disciplinary knowledge in maker-oriented science teaching.

Rapid advances in AI have intensified the ongoing digital transformation of education, increasing the need to integrate emerging technologies in ways that are pedagogically meaningful, human-centred, and supported by appropriate professional competencies (Simiyu et al., 2026). In Türkiye, the Türkiye Yüzyılı Maarif Modeli [TYMM], which began phased implementation in Grade 5 in the 2024–2025 academic year, explicitly incorporates digital literacy into the science curriculum and encourages the use of digital resources in learning activities and, where appropriate, assessment processes (Ministry of National Education [MoNE], 2024). These curricular expectations place increasing importance on teachers' capacity to select and integrate technological tools purposefully. Recent evidence indicates that technopedagogical competence is positively associated with teachers' acceptance of AI, while insufficient technological competence can constrain the effective integration of digital technologies in science classrooms (Antwi, 2026; Çakır & Güner, 2026).

Technology integration, however, should not be treated as an educational goal in itself. Technology is most educationally valuable when it supports meaningful learning objectives and provides learners with opportunities to engage in authentic and cognitively demanding tasks (Herrington & Kervin, 2007). Similarly, supportive learning environments, high-quality instructional feedback, and purposeful technology integration are associated with stronger problem-solving performance (Davor et al., 2026). These considerations become particularly important when AI is introduced into science education. Teachers implementing AI-integrated science instruction may encounter difficulties related to AI content knowledge, confidence, and curriculum adaptation, highlighting the importance of appropriate resources and sustained professional preparation (Park et al., 2023).

Accordingly, initial teacher education should provide pre-service teachers with structured opportunities to integrate technology and AI through authentic pedagogical tasks. Evidence from pre-service science teacher education highlights the value of structured practice, modelling, feedback, classroom exposure, and practical lesson planning for strengthening preparation for digital pedagogy (Mohafa et al., 2026). AI-supported lesson planning provides one such context. Pre-service teachers have been shown to use generative AI for developing instructional ideas, learning activities, materials, pedagogical approaches, and assessment components while also encountering limitations that require careful prompting, critical evaluation, and informed pedagogical judgment (Yanar & Ergene, 2025). Similarly, AI-supported practicum experiences involving AI-integrated lesson plans can contribute to pedagogical decision-making, reflective and metacognitive reasoning, responsiveness to learner needs, and professional development (Danişman, 2026).

Against this background, the present study aims not merely to increase pre-service teachers' awareness of technological and AI applications but to develop their competence in preparing TYMM-aligned science lesson plans that integrate these technologies meaningfully. The study therefore examines changes in pre-service teachers' technological pedagogical content knowledge [TPACK] and AI readiness. The science-education literature on TPACK has expanded considerably, and intervention studies indicate that structured TPACK development experiences can strengthen pre-service science teachers' capacity to coordinate technological, pedagogical, and content knowledge in practice (Aktaş & Özmen, 2020; Bin Amiruddin et al., 2024). Evidence from Indonesia further indicates that participation in the Teacher Professional Education programme is associated with stronger TPACK development among pre-service science teachers (Chang et al., 2025). Nevertheless, within the literature reviewed here, considerably less empirical attention has been given to whether a structured, AI-supported and TYMM-aligned science lesson-planning experience is associated simultaneously with changes in pre-service teachers' TPACK and AI readiness. Examining these two outcomes together may therefore provide a more specific contribution to understanding how teacher education can prepare future science teachers for pedagogically meaningful technology and AI integration.

1.1. Research Questions

The present study sought to examine the effects of AI-supported instructional planning on science teacher candidates' AI readiness and production-based technological pedagogical content knowledge. To this end, the following research questions were addressed:

RQ 1) Is there a significant difference in science teacher candidates' AI readiness before and after AI-supported instructional planning?

RQ 2) Is there a significant difference in science teacher candidates' production-based technological pedagogical content knowledge before and after AI-supported instructional planning?

2. Method

2.1. Research Design

A single-group pretest-posttest quasi-experimental design was adopted for the study. This design allows for the determination of changes in participants before and after the intervention. It is widely used, particularly in situations where it is difficult to establish a control group in educational settings. As there was no second study group with the same characteristics, the study was designed accordingly. However, potential threats to internal validity (history, maturation, and test effects) were considered, and care was taken to ensure that the implementation was conducted by the same researcher for all participants (Anderson-Cook, 2005).

2.2. Study Group

Participants were selected using an appropriate sampling method and volunteered for the study. The participants consisted of 41 science teacher candidates enrolled in their second year of study. Eight of the teacher candidates are male, and 33 are female. Their ages range from 18 to 22. All participants are taking the lesson planning course for the first time. Ethical committee approval was obtained before the start of the study, and informed consent was obtained from all participants.

2.3. Data Collection

The study was conducted over 14 weeks during the spring semester of the 2024–2025 academic year. In this study, we use two scales.

2.3.1. Production-Based Technological Pedagogical Content Knowledge Scale

Production-Based Technological Pedagogical Content Knowledge Scale (Maker-TPACK) adapted into Turkish by Akçay et al. (2023). The Maker-TPACK consists of 27 items across 7 subdimensions, and its reliability coefficient was .948. In this study, the reliability coefficients for the Maker-TPACK pretest and posttest were calculated as summarized in Table 1.

Table 1
Reliability Analysis Results for Maker-TPACK Used in the Study

Variable and Time of measurement	*Cronbach's alpha*
Maker-TPACK	
Pretest	.885
Posttest	.931

2.3.2. Artificial Intelligence Readiness Scale

The Artificial Intelligence Readiness Scale for Teacher Candidates [AIRS], adapted into Turkish by Özüdoğru and Yıldız Durak (2024). The AI Readiness Scale for Teacher Candidates consists of 18 items across 4 subdimensions, and its reliability coefficient was reported to be .967. In this study, the reliability coefficients for the AIRS pretest and posttest were calculated as in Table 2.

Table 2
Reliability Analysis Results for AIRS Used in the Study

Variable and Time of measurement	*Cronbach's alpha*
AIRS	
Pretest	.887
Posttest	.901

The reliability of the scales used in this study was calculated, and they were found to be highly reliable. Cronbach's alpha values greater than .70 indicate that the scales used are reliable. This also demonstrates that the scales used in the study have good internal consistency. These reliability coefficients indicate that the tests are suitable for use in this study.

2.4. Implementation Process

During implementation, pretests were administered in the first week, and basic training on using generative AI tools in education was provided in the second week. Over the following eleven weeks, teacher candidates prepared lesson plans in accordance with the Maarif Model using generative AI tools such as ChatGPT, Gemini, and Copilot, received structured feedback, and revised their plans. Posttests were administered during the fourteen weeks. Figure 1 summarizes the process. Details of the lesson plans prepared by the trainee teachers over 11 weeks are set out in Table 3.

2.5. Data Analysis

The data obtained in the study were analyzed using SPSS 25. Descriptive statistics, including frequencies, percentages, minimum and maximum values, mean, and standard deviation, were used to analyze the data. The data were tested for normality. Compliance with a normal distribution can be examined using a Q-Q plot (Chan, 2003). Additionally, for the data to follow a normal distribution, the skewness and kurtosis values must fall within ±3 (Shao, 2002). The normality assessment was conducted using both Q-Q plots and Skewness and Kurtosis values. Since the assumptions of the parametric tests were met, the paired-sample *t*-test was preferred. Effect sizes were interpreted according to Cohen's (2013) criteria.

Figure 1
Implementation Process

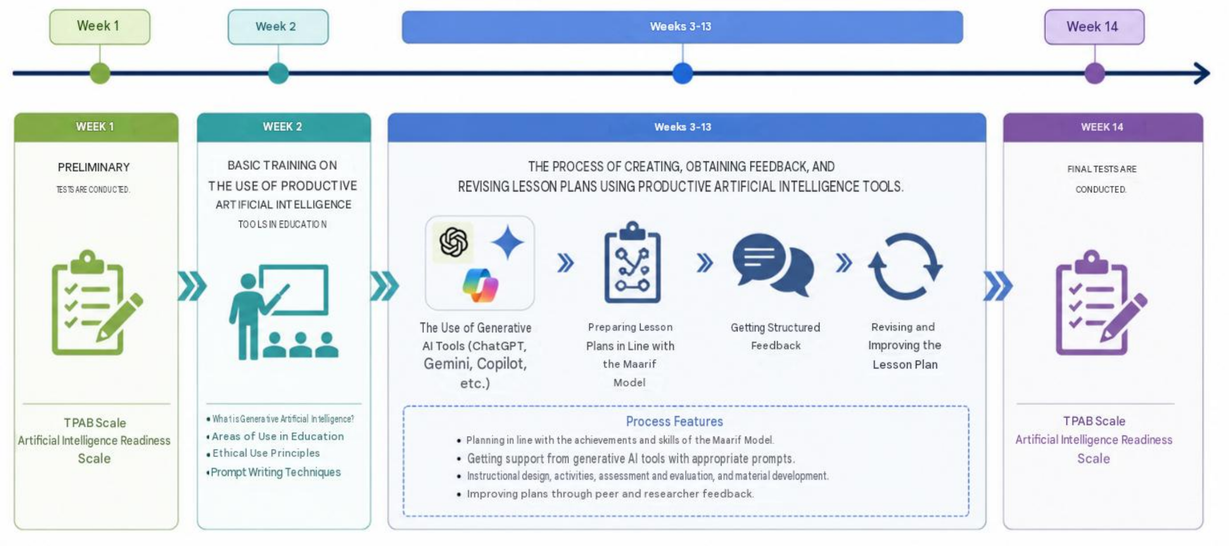

Table 3
Pre-service Teachers' Weekly Lesson Plans

Week	*Lesson plan*	*Week*	*Lesson plan*
1	Our neighbors in the sky and us (Year 5) The solar system and eclipses (Year 6)	7	The world of light (Year 5) Reflection of light and colors (Year 6) Refraction of light and lenses (Year 7) The world of sound (Year 8)
2	The space age (Year 7) Seasons and climate (Year 8)	8	A journey into the structure of living organisms (Year 5) Systems in living organisms (Year 6)
3	Nature of matter (Year 5) Distinctive properties of matter (Year 6)	9	Systems in the human body (Year 7) The mystery of life (Year 8)
4	A journey into the nature of matter (Year 7) The periodic table and the interaction of matter (Year 8)	10	Electricity in our lives (Year 5) The conduction of electricity and resistance (Year 6)
5	Let us learn about force (Year 5) Motion under the influence of force (Year 6)	11	Electricity (Year 7) The journey of electricity (Year 8)
6	Let us explore force and energy (Year 7) Force that makes life easier (Year 8)		

The results of the normality analysis of the variables used in the study are presented in Table 4. The fact that the Skewness and Kurtosis values fall within ±3 indicates that the data follow a normal distribution. For data following a normal distribution, the paired-sample *t*-test was applied to compare quantitative data in a two-dependent-stage comparison.

2.6. Validity and Reliability

To enhance internal validity in this study, the same researcher implemented the study for all participants, and the same lesson plan development process was followed throughout implementation. Data collection conditions were standardized for both the pretest and posttest administrations; all participants were given the same instructions, and the assessment tools were administered in the same setting. In quasi-experimental studies, standardizing the implementation process helps reduce the effects of the implementer and procedural differences that threaten internal validity (Anderson-Cook, 2005).

Table 4
Results of the Normality Analysis for the Scales Used in the Study

Variables	*Time of measurement*	*Skewness*	*Kurtosis*	*Status*
Cognition	Pretest	0.812	1.000	Normal
	Posttest	0.563	0.688	Normal
Ability	Pretest	−0.422	1.489	Normal
	Posttest	−0.324	1.125	Normal
Vision	Pretest	0.103	−0.113	Normal
	Posttest	0.084	0.432	Normal
Ethics	Pretest	0.298	0.286	Normal
	Posttest	−1.077	2.177	Normal
AIRS	Pretest	0.314	0.594	Normal
	Posttest	0.672	0.953	Normal
Content information	Pretest	−0.316	-0.361	Normal
	Posttest	−0.699	0.979	Normal
Pedagogical knowledge	Pretest	0.613	1.064	Normal
	Posttest	0.163	1.538	Normal
Technical information	Pretest	−0.595	1.099	Normal
	Posttest	−0.303	0.311	Normal
Pedagogical content knowledge	Pretest	0.229	0.524	Normal
	Posttest	0.532	1.117	Normal
Technological field knowledge	Pretest	−0.683	2.419	Normal
	Posttest	0.642	0.832	Normal
Technological-pedagogical knowledge	Pretest	0.000	0.407	Normal
	Posttest	−0.427	0.339	Normal
Technological and pedagogical content knowledge	Pretest	0.476	0.715	Normal
	Posttest	−0.772	2.917	Normal
Maker-TPACK	Pretest	0.598	0.572	Normal
	Posttest	0.197	1.060	Normal

The Artificial Intelligence Readiness Scale and the Production-Based Technological Pedagogical Content Knowledge Scale used in the study are assessment tools that were previously adapted into Turkish and subjected to validity and reliability studies. In addition, within the scope of the present study, the reliability coefficients of the scales were recalculated, and it was determined that the Cronbach's alpha coefficients ranged from .887 to .901 for the Artificial Intelligence Readiness Scale and from .885 to .931 for the Maker-TPACK Scale. Alpha coefficients above .70 indicate that the scales possess an adequate level of internal consistency, while values above .80 indicate high reliability (Taber, 2018). These findings support the reliability of the measurement tools used in the study for the current sample. To enhance the reliability of the study's statistical results, the assumptions of parametric tests were examined in detail prior to analysis. The normality of the data was assessed not only using Skewness and Kurtosis coefficients but also by considering Q-Q plots. Since the Skewness and Kurtosis values fell within acceptable limits and the graphical analyses supported a normal distribution, the paired t-test was used. Furthermore, in addition to reporting significance levels, Cohen's d effect size coefficients were calculated to highlight the practical importance of the intervention. Reporting effect sizes is an important requirement of current reporting standards, as it allows evaluation of the intervention's actual effect size in addition to statistical significance (Cohen, 2013; Field, 2024).

To support the study's external validity, the characteristics of the study group, the intervention process, data collection tools, and data analysis methods were described in detail. The aim was to ensure that the study could be replicated with similar samples and that findings could be compared. However, because the study employed a single-group pretest-posttest quasi-experimental design, caution is warranted when generalizing the findings to other samples. For this reason, the study's methodological process was reported in detail to enhance transparency and reproducibility (Anderson-Cook, 2005).

3. Findings

In this section, the data obtained during the research are analyzed and presented in line with the research objectives and questions. The findings have been systematically examined using data from the collection tools and are supported by the relevant tables and figures. First, the findings on teacher candidates' AI readiness before and after AI-supported instructional planning are presented in Table 5.

Table 5
Comparison of Participants' Pretest and Posttest Scores for AIRS and Its Dimensions

	Min	*Max*	*Mean*	*SD*	*t*	*p*	*Cohen's d*
Cognition							
Pretest	16.00	25.00	19.29	1.99	−2.469	.018*	.386
Posttest	16.00	25.00	20.02	2.20			
Skill							
Pretest	16.00	29.00	22.90	2.48	−2.038	.048*	.318
Posttest	15.00	30.00	23.78	3.21			
Vision							
Pretest	8.00	15.00	11.27	1.61	−2.090	.043*	.326
Posttest	9.00	15.00	11.83	1.22			
Ethics							
Pretest	12.00	20.00	15.51	1.98	−0.383	.704	.060
Posttest	7.00	20.00	15.66	2.34			
AIRS							
Pretest	53.00	86.00	68.98	6.64	−2.204	.033*	.344
Posttest	58.00	90.00	71.29	7.07			

Note. *$p < .05$.

According to the results of the comparison of pre- and posttest AI readiness levels among the teacher candidates participating in the study, statistically significant increases were found in favor of the posttest for the Cognition, Ability, and Vision subscales as well as the total AI Readiness Scale score ($p < .05$). In contrast, no significant change was observed in the Ethics subscale ($p > .05$).

The mean score for the Cognition subscale was 19.29 ± 1.99 on the pretest and 20.02 ± 2.20 on the posttest. The difference between the pretest and posttest scores is statistically significant [$t = -2.469$; $p = .018$]. The effect size was Cohen's $d = .386$, indicating that the training had a small effect on the cognitive dimension. The mean score for the skill subscale was 22.90 ± 2.48 on the pretest and 23.78 ± 3.21 on the posttest. A significant increase was observed between the pretest and posttest scores [$t = -2.038$; $p = .048$]. The calculated Cohen's $d = .318$ indicates that the intervention had a small effect on the ability dimension. The mean score for the vision subscale was 11.27 ± 1.61 on the pretest and 11.83 ± 1.22 on the posttest. The difference between the pretest and posttest scores is significant [$t = -2.090$; $p = .043$]. Cohen's $d = .326$ indicates that the training had a small effect on the vision dimension. The mean score for the ethics subscale was calculated as 15.51 ± 1.98 on the pretest and 15.66 ± 2.34 on the posttest. No statistically significant difference was found between the pretest and posttest scores [$t = -0.383$; $p = .704$]. Furthermore, the Cohen's d value of .060 indicates that the intervention had a negligible effect on the ethical dimension. The total AIRS score was 68.98 ± 6.64 on the pretest and 71.29 ± 7.07 on the posttest. A statistically significant increase was determined between the pretest and posttest scores [$t = -2.204$; $p = .033$]. The Cohen's d value of .344 indicates that the training had a small effect on general AI readiness.

The findings related to the teacher candidates' production-based technological pedagogical content knowledge before and after AI-supported instructional planning are presented in Table 6.

Table 6
Comparison of Participants' Pretest and Posttest Scores for AI Readiness and Its Dimensions

	Min	*Max*	*Mean*	*SD*	*t*	*p*	*Cohen's d*
Content information							
Pretest	6.00	13.00	10.07	1.60	−1.086	.284	.170
Posttest	5.00	14.00	10.34	1.76			
Pedagogical knowledge							
Pretest	13.00	20.00	15.88	1.42	−0.477	.636	.075
Posttest	11.00	20.00	16.27	1.78			
Technical information							
Pretest	8.00	23.00	16.56	2.89	−0.477	.636	.075
Posttest	9.00	24.00	16.73	3.10			
Pedagogical content knowledge							
Pretest	12.00	20.00	16.07	1.65	−0.411	.683	.064
Posttest	12.00	20.00	16.20	1.78			
Knowledge of technology							
Pretest	13.00	25.00	19.51	1.98	−1.427	.161	.223
Posttest	15.00	25.00	20.10	2.31			
Technological pedagogical knowledge							
Pretest	5.00	10.00	7.00	1.07	0.000	1.000	.000
Posttest	4.00	10.00	7.00	1.30			
Technological and pedagogical content knowledge							
Pretest	12.00	20.00	15.39	1.92	−0.925	.361	.144
Posttest	9.00	20.00	15.66	2.00			
Maker-TPACK							
Pretest	83.00	121.00	100.49	8.42	−1.507	.140	.235
Posttest	76.00	129.00	102.29	10.67			

Note. $^{*}p < .05$

A paired samples *t*-test was conducted to compare the Maker-TPACK levels of the teacher candidates participating in the study before and after the training. According to the analysis results, no statistically significant difference was found between the pretest and posttest scores in any of the scale's subscales or in the total score ($p > .05$). Furthermore, the calculated Cohen's *d* values indicate a negligible or small effect size for all variables.

In the Content Knowledge subscale, the mean pretest score was 10.07 ± 1.60, and the mean posttest score was 10.34 ± 1.76. No statistically significant difference was found between the pretest and posttest scores [$t = -1.086$; $p = .284$]. The Cohen's *d* value of .170 indicates that the intervention had a negligible effect on content knowledge. In the Pedagogical Knowledge subscale, the mean pretest score was 15.88 ± 1.42, and the mean posttest score was 16.27 ± 1.78. No significant difference was found between the pretest and posttest scores [$t = -1.327$; $p = .192$]. The Cohen's *d* value of .207 indicates that the program had a small effect on pedagogical knowledge. In the Technological Knowledge subscale, the mean pretest score was 16.56 ± 2.89, and the mean posttest score was 16.73 ± 3.10. No statistically significant difference was found between the pretest and posttest scores [$t = -0.477$; $p = .636$]. The Cohen's *d* value of .075 indicates that the intervention had a negligible effect on technological knowledge. In the Pedagogical Content Knowledge subscale, the mean pretest score was 16.07 ± 1.65, and the mean posttest score was 16.20 ± 1.78. No significant difference was found between the pretest and posttest scores [$t = -0.411$; $p = .683$]. The Cohen's d value of .064 indicates that the intervention had a negligible effect on this dimension. In the "Technological Domain Knowledge" subscale, the mean pretest score was 19.51 ± 1.98, and the mean posttest score was 20.10 ± 2.31. No statistically significant difference was found between the pretest and posttest scores [$t = -1.427$; $p = .161$]. The Cohen's *d* value of .223 indicates that the intervention had a small effect on technological content knowledge. In the Technological Pedagogical Content Knowledge subdimension, the mean pretest and posttest scores were both 7.00. The analysis revealed no difference between the pretest and posttest scores. The Cohen's d value indicates that the intervention did not affect this dimension. In the Technological Pedagogical Content Knowledge subdimension, the mean pretest score was 15.39 ± 1.92, and the mean posttest score was 15.66 ± 2.00. No significant difference was found between the pretest and posttest scores [$t = -0.925$; $p = .361$]. The Cohen's d value of .144 indicates that the intervention had a negligible effect on this dimension.

The total Maker-TPACK score was 100.49 ± 8.42 on the pretest and 102.29 ± 10.67 on the posttest. The difference between the pretest and posttest Maker-TPACK scores is not statistically significant [$t = -1.507$; $p = .140$]. The Cohen's d value of .235 indicates that the intervention had a small effect on overall production-based technological pedagogical content knowledge.

4. Discussion and Conclusion

This study examined changes in pre-service teachers' artificial intelligence readiness and Maker-Based Technological Pedagogical Content Knowledge [Maker-TPACK] following a 14-week AI-focused training program. The findings revealed a significant increase in overall AI readiness, whereas no statistically significant change was observed in the Maker-TPACK total score or any of its subdimensions. This divergent pattern should not be interpreted as evidence that AI readiness and Maker-TPACK are independent competencies. Rather, it suggests that the two constructs may respond differently to an AI-focused educational experience. This interpretation is consistent with evidence showing that technopedagogical competence is associated with AI acceptance and that AI-related readiness and TPACK-related knowledge are interconnected while representing different aspects of teachers' professional preparation (Bautista et al., 2024; Çakır & Güner, 2026).

One of the most notable findings was the significant increase in the overall AI readiness score and in the cognition, competence, and vision dimensions. These changes suggest that, following the training, participants perceived themselves as more knowledgeable about AI, more capable of engaging with AI applications, and better prepared to consider the potential role of AI in their future professional practice. Similar patterns have been reported in intervention research. Laupichler et al. (2022), for example, found that an AI-focused flipped classroom course significantly increased medical students' self-perceived AI readiness, with particularly pronounced gains in vision, followed by ability and cognition. Although their participants were medical rather than teacher-education students, the findings indicate that structured exposure to AI can contribute to changes in perceived readiness. In teacher education, authentic engagement with generative AI during lesson planning has likewise enabled pre-service teachers to explore its instructional affordances and limitations, while AI-supported practicum experiences have provided opportunities for pedagogical decision-making and reflective engagement with AI-generated suggestions (Danişman, 2026; Yanar & Ergene, 2025).

Nevertheless, the magnitude of the observed changes should be interpreted cautiously. Cohen's d values of approximately .30–.40 represent modest effects when considered against conventional benchmarks. Thus, statistical significance should not be interpreted as evidence of a large practical change in AI readiness. The findings instead suggest that the training was associated with detectable but relatively limited changes in participants' perceived preparedness. Structured practice, modelling, feedback, and authentic pedagogical experiences may be important for strengthening technology-related self-efficacy and professional preparation among pre-service teachers (Mohafa et al., 2026). Similarly, research on AI-supported lesson planning shows that experience with generative AI allows pre-service teachers to move from general familiarity with the technology toward evaluating its usefulness and limitations within specific instructional tasks (Yanar & Ergene, 2025).

The absence of a statistically significant change in the ethics dimension deserves particular attention. However, this finding does not necessarily indicate that ethical competence is inherently more difficult or slower to develop than other aspects of AI readiness. A useful comparison is provided by Laupichler et al. (2022), whose AI course produced positive changes across all four readiness dimensions, but whose ethics dimension showed the smallest comparative self-assessment gain at 40.8%, compared with 55.1% for cognition, 57.3% for ability, and 67.1% for vision. The authors attributed the comparatively limited ethics gain to the absence of a dedicated, in-depth ethics module. This pattern is relevant to the present findings because it suggests that ethical preparedness may require explicit instructional attention rather than emerging automatically from increased familiarity with AI tools (Laupichler et al., 2022). Such explicit attention is increasingly important because responsible educational use of generative AI involves issues extending beyond technical proficiency, including algorithmic bias, transparency, accountability, data governance, and the critical evaluation of AI-generated outputs (Holmes & Tuomi, 2022; Simiyu et al., 2026). Current frameworks for AI integration similarly argue that professional development should extend beyond technical skills to encompass pedagogical integration, ethical considerations, and critical evaluation of AI outputs (Simiyu et al., 2026). Future training programs could therefore incorporate case-based ethical dilemmas, analysis of problematic AI outputs, discussions of bias and transparency, and scenario-based decision-making activities. Such activities would allow pre-service teachers to move beyond awareness of ethical principles toward applying those principles when making pedagogical decisions.

The second major finding was the absence of statistically significant change in either the Maker-TPACK total score or its subdimensions. This finding is theoretically plausible because technological familiarity alone does not constitute TPACK. TPACK concerns the coordinated use of technological, pedagogical, and content knowledge when making context-sensitive instructional decisions (Mishra & Koehler, 2006). Preparing pre-service teachers for this type of integration therefore requires more than exposure to technological tools; the teacher-education literature emphasizes learning technology through design, authentic technology-integration experiences, modelling, and opportunities to connect technological choices with pedagogy and disciplinary content (Tondeur et al., 2012). Technology-integration experience is also one of the factors associated with pre-service teachers' capacity to integrate technology into instruction (Farjon et al., 2019). The nature of the outcome measure is especially important in interpreting this result. Maker-TPACK operationalizes the TPACK framework specifically within maker-oriented contexts and digital production technologies. The Turkish adaptation used with pre-service science teachers retains the seven dimensions of CK, PK, TK, PCK, TCK, TPK, and TPACK, but situates them within the maker movement and the use of digital production tools (Akçay et al., 2023). Therefore, if the present intervention concentrated primarily on learning to use AI applications and preparing AI-supported lesson plans, without sustained engagement in maker-oriented design and production activities, the instructional experience may not have been sufficiently aligned with the competencies assessed by the Maker-TPACK instrument. From this perspective, the absence of significant Maker-TPACK gains may reflect the specificity of the construct and the instructional experiences provided rather than simply an insufficient duration of training. The 14-week duration of the intervention should not by itself be treated as the explanation for the nonsignificant Maker-TPACK findings. Duration may matter, but the intensity, focus, and alignment of learning activities with the targeted construct may be equally or more important. Longer interventions may be useful when they provide repeated cycles of technology-supported instructional design, implementation, feedback, reflection, and revision. Evidence from teacher education similarly emphasizes authentic and scaffolded technology experiences rather than exposure alone as a basis for developing meaningful technology integration (Mohafa et al., 2026; Tondeur et al., 2012).

The use of a self-report Maker-TPACK measure should also be considered when interpreting the null findings. A lack of significant change in perceived competence does not necessarily demonstrate that no development occurred in participants' actual instructional performance. Performance-based approaches using lesson plans, teaching episodes, design tasks, or other instructional artefacts can provide information that is not captured by self-report scales. Valtonen et al. (2020), for example, used technology-integrated lesson plans to examine pre-service teachers' confident and challenging TPACK areas and noted that performance-oriented assessments can provide deeper insight into the nature of TPACK than survey measures alone. Likewise, research on AI-supported lesson planning has successfully combined lesson plans, AI interaction transcripts, and interviews to examine how AI use is translated into pedagogical design (Yanar & Ergene, 2025). Future studies could therefore triangulate Maker-TPACK scales with lesson-plan rubrics, evaluations of maker or digital artefacts, AI interaction records, and classroom observations. Finally, although the posttest means for the Maker-TPACK total score and several subdimensions were higher than their corresponding pretest means, these nonsignificant differences should be described as directional trends rather than evidence that the intervention was partially effective. Small effect-size estimates in TCK, PK, and TPACK may warrant further investigation, particularly with confidence intervals and adequately powered designs, but they do not establish the presence of a reliable intervention effect. Future research could examine whether more intensive and explicitly maker-aligned AI-supported instructional experiences produce stronger changes in Maker-TPACK, while larger samples could provide greater statistical power and more precise estimates of potentially small effects. Overall, the present findings suggest that increasing pre-service teachers' perceived readiness to engage with AI may be more readily achieved through focused AI training than developing the broader, context-dependent capacity to integrate emerging technologies within maker-oriented pedagogy.

When the findings are considered collectively, the intervention appears to have influenced the two areas of professional preparation differently. The improvement in AI readiness suggests that structured engagement with AI can strengthen pre-service teachers' knowledge of AI, confidence in using AI-related technologies, and perceptions of their future educational relevance. In contrast, the absence of statistically significant change in Maker-TPACK suggests that developing the capacity to integrate emerging technologies into pedagogically and contentually meaningful instructional designs may require more sustained and practice-embedded learning experiences. This interpretation is consistent with research showing that effective AI integration in teacher education extends beyond technical familiarity and requires technological, pedagogical, content-related, and ethical knowledge to be developed in an interconnected manner (Rui et al., 2025; Simiyu et al., 2026). Accordingly, AI preparation in teacher education should not be organized primarily around learning individual tools. Instead, pre-service teachers need opportunities to use AI in authentic instructional-design processes, including lesson planning, material development, assessment, differentiation, and the critical evaluation and adaptation of AI-generated outputs.

This interpretation is also consistent with emerging Intelligent-TPACK research. Pre-service teachers report needs that extend across technological, pedagogical, content, and ethical dimensions of AI integration, suggesting that AI preparation should be embedded within the broader professional knowledge required for teaching rather than treated as an isolated technological competency (Rui et al., 2025). Furthermore, teachers' TPACK has been found to be positively associated with AI acceptance, reinforcing the connection between readiness to engage with AI and the pedagogical competence required to integrate it meaningfully into instruction (Çakır & Güner, 2026). From this perspective, AI-related learning experiences may be more productive when they are integrated into subject-specific methods courses, lesson-design activities, and practicum experiences rather than offered solely as stand-alone technology training. Evidence from pre-service science teacher preparation similarly highlights the importance of structured practice, modelling, feedback, and practical instructional experiences for developing digital-pedagogical competence. Such experiences provide opportunities to connect technological knowledge with actual pedagogical decisions rather than acquiring these competencies in isolation. In addition, sustainable AI integration requires professional learning that extends beyond technical proficiency to include pedagogical integration, critical evaluation, ethical considerations, and continuing support (Simiyu et al., 2026). Mailizar et al. (2026) provide particularly relevant evidence in this regard. Their semester-long work with pre-service mathematics teachers showed that generative AI, when incorporated into structured and reflective lesson-planning activities, can support the development of TPACK, technological confidence, creativity in lesson planning, and the personalization of learning materials. At the same time, substantial variation in participants' development led the authors to emphasize differentiated support and ongoing training according to prior technological experience, motivation, and self-efficacy (Mailizar et al., 2026). Taken together with the present findings, this evidence suggests that developing AI readiness and pedagogically integrated technology competence may require different intensities and forms of support. Teacher education programs may therefore benefit from progressively moving candidates from AI awareness and tool familiarity toward repeated, subject-specific instructional design, implementation, reflection, feedback, and revision.

This study contributes to the field as one of the few studies that jointly examine the impact of AI education on teacher candidates within the frameworks of AI readiness and Maker-TPACK. The findings indicate that focusing AI content in teacher education programs solely on technical skills is insufficient; pedagogical practices, design-based learning activities, and ethical considerations must also be systematically integrated into the programs. Future research comparing teacher candidates across disciplines, using experimental and control group designs, conducting long-term follow-up studies, and linking classroom teaching performance to observational data will contribute to a more comprehensive understanding of the impact of AI education on teacher competencies.

5. Limitations and Future Directions

The findings of this study should be evaluated in light of certain limitations. First, the study employed a single-group pretest-posttest quasi-experimental design. The absence of a control group makes it difficult to definitively establish that the changes observed during the intervention process stemmed solely from the intervention itself. It has been noted that in such designs, factors threatening internal validity—such as history, maturation, and the testing effect may influence the research results (Anderson-Cook, 2005). The second limitation of the study is that the sample consisted solely of 41 science teacher candidates enrolled at a single public university. Therefore, the findings should not be generalized to other universities, teacher education programs, or sample groups. It is emphasized that sample characteristics are important for interpreting research results in educational research, and that generalizability should be limited to similar study groups (Creswell & Creswell, 2017). Another limitation is that the data used in the study were collected via self-report scales. Participants assessed AI readiness and production-based technological pedagogical content knowledge based on their own perceptions. It has been noted that social desirability bias or individual perceptual differences may influence the results of self-report-based measurements (Podsakoff et al., 2003). Therefore, for future studies, it is recommended that lesson plans be evaluated using rubrics, that classroom observation data be utilized, and that performance-based assessments be incorporated into the research. Finally, the intervention conducted in this study was limited to 14 weeks. Although the AI-supported instructional planning experience was found to facilitate significant development in pre-service teachers' AI readiness, no significant changes were observed in their levels of maker- or TPACK. It is noted that the development of integrated teacher competencies, such as TPACK, requires long-term interventions, repeated teaching experiences, and practice-based professional development (Koehler et al., 2013; Tondeur et al., 2012). Therefore, it is recommended that longer-term, controlled, and mixed-methods studies be conducted.

Author contributions: Conceptualization, methodology, investigation, data analysis, and writing—review and editing. Ayberk Bostan Sarıoğlan: Conceptualization, methodology, investigation, data analysis, and writing—review and editing. Burcu Akbay: Conceptualization, methodology, investigation, data curation, formal analysis, and writing. All authors contributed to the interpretation of the findings, critically reviewed the manuscript, approved the final version, and agreed to be accountable for all aspects of the work.

Data availability: The data that support the findings of this study are available from the corresponding author upon reasonable request, subject to ethical and confidentiality considerations.

Declaration of interest: The authors declare no competing of interest.

Ethics declaration: The study was conducted in accordance with the ethical principles applicable to research involving human participants. Ethical approval was obtained from the Balıkesir University Ethics Committee for Science and Engineering on 10 April 2025 (approval no. 52899066/050.99/498044).

Funding: This study was supported by the Balıkesir University Scientific Research Projects Unit with project number 2025/067.

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