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Artificial Intelligence Convergence Teaching Expertise Scale for Pre-service Teachers in Korea: A Validity and Reliability Study

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***Abstract*—Artificial intelligence (AI) drives changes in various areas, including industry, society, and the economy, through technological innovation. In education, AI advancements are leading to innovations in teaching, learning, content, and assessment. Integrating AI into educational practices necessitates developing a tool to measure instructors' AI convergence teaching expertise, which is essential for implementing AI convergence education effectively. This study aimed to develop an assessment tool to measure pre-service teachers' AI convergence teaching expertise. A comprehensive and rigorous approach was adopted, involving a literature review, Delphi survey, exploratory factor analysis, and confirmatory factor analysis. The assessment tool was constructed by applying AI as a technological component within the Technological Pedagogical Content Knowledge (TPACK) framework to define AI convergence teaching expertise and derive relevant items. These items were administered to a sample of 202 pre-service teachers in Korea to validate their reliability and validity. The developed tool comprises 33 self-reported items across eight distinct factors, robustly measuring AI convergence teaching expertise. The Cronbach's α for the tool ranged from 0.822 to 0.922, indicating high reliability. The significance of this study is its potential application within educational settings to determine pre-service teachers' AI convergence teaching expertise. Furthermore, this study offers valuable implications for designing pre-service teacher education programs and ongoing professional development for in-service teachers. By accurately measuring and addressing AI convergence teaching expertise, this tool can contribute to advancing educational practices in the era of AI.**

***Keywords*—AI convergence teaching expertise; pre-service teacher; TPACK; scale development.**

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I. INTRODUCTION

Artificial intelligence (AI) is being utilized in various fields to solve existing problems or bring about efficient innovations. As AI's influence increases in computer science and traditional academic disciplines and industries, the capability to integrate AI to solve problems has grown in importance [1], [2]. Particularly with the development of generative AI, these innovations are rapidly progressing, and AI's disruptive impact is increasing as it merges with robotics [3].

In education, the application of AI has brought about rapid changes. Goals previously pursued in traditional education, such as learning analytics, personalized learning, and adaptive learning, are now being realized through AI [4], [5]. Consequently, there has been rapid advancement in AI-based courseware, programs, and platforms [5]. In Korea, various educational policies have been established to address the increasing use of AI in education, and initiatives such as AI convergence education graduate programs and AI education support projects are being implemented [6]–[9]. In addition, the 2022 revised curriculum centers on 'Digital and AI literacy,' making AI education mandatory in elementary and middle schools [10]. Furthermore, there are plans to develop AI-based digital textbooks and distribute them to schools by 2025 [11].

As AI is introduced into school settings, various educational policies and programs for learners and instructors are being implemented. However, teachers and pre-service teachers still need to be adequately prepared to utilize AI in education [6]–[9]. Therefore, courses aimed at developing the capability to integrate AI into teaching practices are being offered to both teachers and pre-service teachers [10], [12]–[14]. Despite these efforts, there are challenges in developing assessment tools to evaluate the capability of pre-service teachers to integrate AI into their teaching practices [12]–[14].

In Korea, AI convergence education, which integrates AI with subjects other than computer science, is being implemented in schools. AI convergence education is defined as “innovative education that aims to solve given problems by integrating AI with various subjects;” however, researchers have diverse definitions [12], [15]. In school settings, this ambiguity in the definition of AI convergence education leads to its confusion with AI education, AI utilization education, and AI value education [6], [12], [14], [16], [17]. Consequently, the capabilities required for pre-service teachers to practice AI convergence education also vary among researchers [6], [16]–[18]. This situation causes discrepancies in the content taught in AI convergence education courses for pre-service teachers, hindering the achievement of educational goals [15], [19].

To overcome these limitations, this study defines the capability to practice AI convergence education for pre-service teachers as AI convergence teaching expertise. It researches to develop an assessment tool to measure this expertise [15]. Although similar studies have been conducted, they still need to adequately consider the aspects necessary for integrating new technology, such as AI [8], [12], [14], [15]. Therefore, based on the Technological Pedagogical Content Knowledge (TPACK) framework, which relates to technology integration teaching expertise, this study developed an AI convergence education assessment tool. Research was also conducted to analyze the validity and reliability of the AI convergence education assessment tool for pre-service teachers.

II. Materials and Method

A. Research Procedure

This study aimed to measure pre-service teachers' AI convergence teaching expertise by developing and validating assessment items through item development and factor analysis. A Delphi study with experts based on the TPACK framework created items for AI convergence teaching expertise [20], [21]. Prior research on TPACK and AI convergence education and prior studies on TPACK assessment tools were analyzed. This process led to the initial extraction of items to measure pre-service teachers' AI convergence teaching expertise by factor. Expert reviews and exploratory and confirmatory factor analyses were performed to ensure the validity of the extracted items.

B. Development of Preliminary Items

1) Literature Analysis: To develop an assessment tool to measure the AI convergence teaching expertise of pre-service teachers, prior research related to AI education was analyzed to define AI convergence education. Using TPACK to measure teaching expertise was deemed appropriate according to the definition of AI convergence education [15]. By incorporating AI as a technological tool within TPACK and integrating content knowledge (CK) and pedagogical knowledge (PK), it was believed that TPACK development would enhance AI convergence teaching expertise, enabling the effective use of AI in instructional content and teaching-learning processes [21]–[27]. Consequently, prior studies on TPACK, AI convergence education, and TPACK assessment tools were analyzed. This analysis led to the extraction of items for each specific factor of TPACK, resulting in 58 items. Five AI education experts reviewed the extracted items, and 7 items deemed redundant or irrelevant were removed.

2) Delphi Survey: In this study, the Delphi method was used to develop items to measure pre-service teachers' AI convergence teaching expertise. The Delphi method involves repeated anonymous feedback from an expert panel to reach a consensus in a field that lacks a theoretical framework [28], [29]. The expert panel consisted of 14 members, including professors, teachers, and researchers with expertise in AI convergence education and AI education. The Delphi survey was conducted twice, from December 2022 to March 2023. The initial Delphi survey, which typically begins with open-ended questions, was skipped, and the first round focused on using a 5-point Likert scale to evaluate the appropriateness and validity of the factors and the 51 items initially derived. Feedback was collected on the factors and items to improve them. The second Delphi survey revised items with low content validity based on the first round and modified items according to expert feedback. The same expert panel then used a 5-point Likert scale to evaluate the revised items for appropriateness and validity [30]. This process led to the extraction of items to measure pre-service teachers' AI convergence teaching expertise. Overlapping items were integrated, and four items deemed inappropriate for pre-service teachers were removed. Consequently, 47 items were derived through the Delphi process.

3) Preliminary Survey: Using the items derived from the Delphi survey, a preliminary survey was conducted in June 2023 with 20 pre-service teachers. The pre-service teachers were first- and second-year students at a university in Korea. The purpose of the preliminary survey was to assess the clarity and comprehensibility of the items and the appropriateness and ease of the response formats. Pre-service teachers read the items and used a 5-point Likert scale to indicate their level of understanding. Items with an average score of 2 or lower were selected, and interviews were conducted with pre-service teachers regarding items with low comprehensibility. Based on the interview results, two items deemed inappropriate for pre-service teachers were removed.

C. Validation of AI Convergence Teaching Expertise Items

1) Research Subjects: A questionnaire was conducted to validate the AI convergence teaching expertise items finalized through the Delphi and preliminary surveys, targeting pre-service teachers. This survey was conducted with pre-service teachers attending colleges of education and teacher training colleges in Korea, and 222 responses were collected. Among these, data from 13 pre-service teachers were excluded from the validation process due to insincere responses. Consequently, data from 209 pre-service teachers validated the AI convergence teaching expertise items. Approximately 60% of the pre-service teachers were male, and 40% were female. Regarding year level, approximately 60% were first-year students, 30% were second-year students, and 10% were third- and fourth-year students. The majors included a wide range of subjects, such as Korean, English, Mathematics, Science, and Social Studies, and computer education related to AI. Due to the nature of the pre-service teacher training system in Korea, there were also pre-service teachers majoring in elementary education. Based on the survey results of the pre-service teachers, exploratory factor analysis, reliability analysis, and confirmatory factor analysis were conducted to validate the items.

2) Exploratory Factor Analysis: Factor analysis was conducted to extract factors from the items during the item development process. Factor analysis analyzes the relationships between items or variables to group those with correlations into a single factor, thus assigning meaning to the extracted factors to reveal the structure within the items or variables [31]. Exploratory factor analysis (EFA) identifies statistically significant factors by analyzing the results of the items from the assessment tool to find latent factors within the data [12], [31]. EFA is beneficial when developing assessment tools in areas with few reference tools or without a theoretical framework. Therefore, EFA was conducted based on the results of the new AI convergence teaching expertise assessment tool. The principal component extraction method was used, with a Varimax rotation for orthogonal rotation and the Kaiser method for determining the number of factors. To verify the construct validity in the EFA, the Kaiser–Meyer–Olkin (KMO) measure and Bartlett's test of sphericity were conducted. Factors with eigenvalues greater than 1 were extracted, and items with communality and factor loadings less than 0.500 were removed.

3) Reliability and Correlation Analysis: The reliability of the factors and items derived through the EFA was analyzed. This process verified the consistency of the items for each factor and removed items that lowered reliability. However, in this study, no items were removed during the reliability analysis because no items lowered the reliability of each factor. Based on previous research, a correlation analysis was conducted to examine the relationships between the factors derived through the TPACK framework for AI convergence teaching expertise.

4) Confirmatory Factor Analysis:

To test the researcher's hypotheses, a confirmatory factor analysis (CFA) was conducted to pre-establish relationships between variables before performing a factor analysis [12], [14], [31]. This process verified the construct validity of the items measuring pre-service teachers' AI convergence teaching expertise. It assessed the fit of the AI convergence teaching expertise model derived from TPACK. Although χ^2 is used for this purpose, it is sensitive to sample size, making it unsuitable for empirical research in the social sciences; thus, other fit indices were additionally analyzed [12], [31].

To assess fit, the values of χ^2 divided by degrees of freedom (CMIN/DF), comparative fit index (CFI), Tucker–Lewis index (TLI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR) were used. A model was considered a good fit if CMIN/DF was below 3, CFI and TLI were above 0.800, and RMSEA and SRMR were below 0.080 [32].

Furthermore, the convergent validity of the latent variables was verified. Convergent validity, which indicates that a factor accurately measures what it is supposed to measure, is established when the covariances among the measurement variables within the same construct are high. Discriminant validity, which indicates that a factor is distinctly different from other factors, is established when the covariances among the measurement variables of different constructs are relatively low. Convergent validity is considered achieved when construct reliability (CR) is above 0.700, and the average variance extracted (AVE) is above 0.500 [31], [32].

III. Results and Discussion

A. Development of Preliminary Items

1) Literature Analysis and Item Development:

Prior research related to AI convergence education was analyzed to develop an assessment tool for measuring pre-service teachers' AI convergence teaching expertise. Convergence education in Korea aims to cultivate problem-solving skills through integrating multiple subjects, and it has been researched in various forms, starting with STEAM education [33]–[35]. Consequently, AI convergence education, such as 'AI + X' or 'X + AI,' is being studied to incorporate AI into existing subjects effectively. However, there are limitations due to the ambiguous definition of AI convergence education, which is often conflated with AI education and AI utilization education [16]–[18], [36]. Furthermore, the definition of convergence itself is ambiguous, leading to different perspectives among researchers on AI convergence education [16]–[36].

Notably, in Kim and Lee [8], the TPACK framework was approached from the CK perspective, using existing technology as a tool for teaching AI [15]. Similarly, Kim, Ryu and Han [18] and Choi [36] indicated a hierarchy among AI education, AI utilization education, and AI convergence education. These studies suggest that the difficulties experienced in technology integration within traditional TPACK education will also be present in AI convergence education [37], [38]. Lim, Jin and Lim [39] argued that since the principles and concepts of AI are both CK and technological knowledge (TK), it is challenging to introduce AI as a technological tool in TPACK . However, the concepts and principles of AI as CK (content to be taught) and AI as TK (use and application of AI) differ from a teaching-learning perspective. In the TK domain, AI is already being introduced through advanced technologies, such as learning analytics and generative AI, focusing on understanding how to utilize these technologies effectively in teaching and educational content [15], [25], [27]. In contrast, CK focuses on the concepts and principles of AI, emphasizing how AI operates in real-life applications.

Therefore, this study defines AI convergence teaching expertise as the knowledge (TPACK) required to effectively integrate AI into teaching, with AI as a technological tool in the TPACK framework. This includes the development of technological content knowledge (TCK), technological pedagogical knowledge (TPK), and technological pedagogical content knowledge (TPACK) based on TK, and leveraging educational contexts (conteXtual knowledge [XK]) to teach subject content (CK) effectively in teaching-learning situations (PK) [15], [40]. Unlike previous studies that extracted components such as 'basic, design, implementation, evaluation' or 'AI literacy, AI utilization/convergence' or 'AI knowledge, AI education knowledge, subject convergence knowledge, AI convergence education design, operation, support, AI ethics, AI openness, and AI teacher efficacy,' this study derived factors based on the TPACK framework [6], [12], [14].

In this study, AI was introduced as a technological tool in the TPACK framework, considering the AI convergence TPACK framework to be the integration of AI with subjects, teaching, and educational contexts, as in technology integration. Consequently, an AI-integrated TPACK framework was proposed based on Mishra [40] (see Fig. 1) [15]. To measure pre-service teachers' AI convergence teaching expertise, items related to CK, PK, TK, XK, pedagogical content knowledge (PCK), TCK, TPK, and TPACK were derived based on Koehler and Mishra [26] TPACK framework. Previous studies on TPACK evaluation were referenced to derive these items [25], [41]–[44]. A total of 51 items were extracted for each factor.

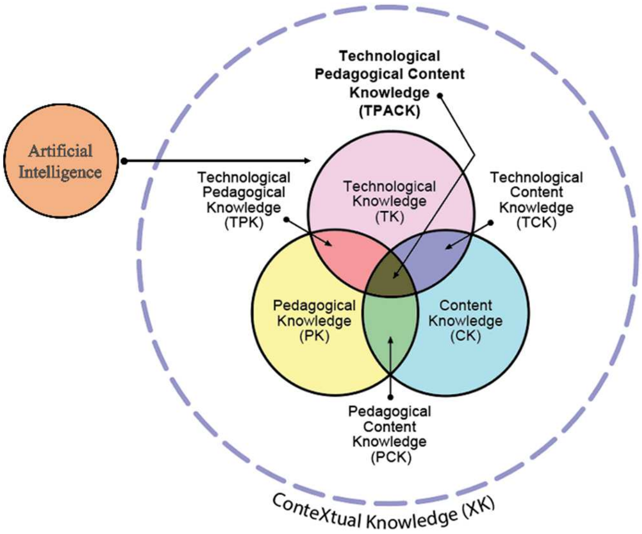

Fig. 1 Bringing AI to TPACK's Technology Tools

2) Delphi Survey:

A Delphi survey was conducted to validate whether the items derived from the literature analysis were appropriate for measuring pre-service teachers' AI convergence teaching expertise. Among the total items, 26 did not meet the content validity ratio (CVR) 0.571. Items that did not meet the CVR were either revised or deleted, and items that needed modification based on expert feedback were revised [30].

As a result, 22 of the 51 items were retained, 25 were revised, and four were deleted. The revised items needed to align with the AI convergence TPACK framework or were difficult for pre-service teachers to understand. For example, the item "I can appropriately use AI to promote student learning during lessons" was modified based on expert feedback, as pre-service teachers, depending on their grade level, might not have had any teaching experience. Consequently, the item was revised to suit pre-service teachers.

Four items with low CVR were removed because they were deemed ambiguous and unsuitable for developing the assessment tool based on conflicting expert opinions. For example, "I know the administrative support necessary for teaching the subject" was considered more appropriate for in-service teachers than pre-service teachers. Therefore, based on expert opinions, it was determined that pre-service teachers could ambiguously interpret this item, and it was thus deleted. Through the process of revision and deletion, 47 items were derived from the original 51 items. The second round of the Delphi survey involved some item revisions; overall, the CVR improved, and the content validity of the developed items was confirmed.

3) Preliminary Survey:

The items reviewed by experts were administered to pre-service teachers to check their comprehension. A survey of 20 pre-service teachers assessed their understanding of the items, and adjustments were made to explain complicated terms or modify expressions. Specifically, TK-related items involving AI platforms or programming languages were sometimes incomprehensible, depending on the pre-service teachers' grade level or AI experience. Therefore, these items were either revised or deleted if revision was impossible (2 items). Through the preliminary item development process, 45 items were finalized to measure AI convergence teaching expertise (see Table 1).

TABLE I
CONSTRUCTING PRELIMINARY TEST QUESTIONS FOR THE AI CONVERGENCE TEACHING EXPERTISE

Factor	N	Factor	N
CK	4	TCK	3
TK	6	PCK	6
PK	7	TPK	6
XK	7	TPACK	6
Total			45

B. Validation of AI Convergence Teaching Expertise Items

1) EFA:

A preliminary survey was conducted with 209 pre-service teachers enrolled in teacher training colleges (secondary pre-service teachers) and education colleges (elementary pre-service teachers) in Korea. Fundamental statistical analysis and EFA were performed on the collected data. The descriptive statistics of the items showed that the means ranged from 2.406 to 3.737, with standard deviations between 0.748 and 1.033. The absolute values of skewness were less than 2, and the absolute values of kurtosis did not exceed 7. The overall reliability of the items was Cronbach's $\alpha = 0.965$, and no items were found to affect reliability upon removal adversely. Therefore, all 45 items derived from the preliminary survey were used in the EFA.

The EFA results showed that the KMO measure of sampling adequacy was 0.940, indicating that the data were suitable for factor analysis since KMO values above 0.800 are considered appropriate. Bartlett's test of sphericity results was $\chi^2 = 6686.629$ ($p < 0.000$), confirming that the data were independent. Following the Kaiser method, eight factors with eigenvalues greater than 1.000 were extracted, explaining 68.138% of the total variance. However, some items did not meet the initial development criteria for factor loadings and communality values. These items were removed to explore the optimal factor structure.

The factor analysis identified 33 items to measure pre-service teachers' AI convergence teaching expertise. The KMO value in the EFA was 0.934, and Bartlett's test of sphericity result was $\chi^2 = 4747.591$ ($p < 0.000$), both statistically significant. The final assessment tool comprised eight factors: CK (4 items), TK (6 items), PK (7 items), XK (7 items), TCK (3 items), PCK (6 items), TPK (6 items), and TPACK (6 items), with a cumulative variance of 73.212%. The results of the EFA for the AI convergence teaching expertise items are shown in Table 2.

TABLE II
THE RESULTS OF EFA AND RELIABILITY OF AI CONVERGENCE TEACHING EXPERTISE

Factor	Variable	Factor analysis				Cronbach α
		Factor loadings	Communality	Eigenvalues	Explained variance (%)	
CK	CK1	0.827	0.786	3.276	9.928	0.922
	CK2	0.817	0.778			
	CK3	0.807	0.786			
	CK4	0.710	0.727			
TK	TK1	0.742	0.657	2.694	8.164	0.850
	TK3	0.623	0.700			
	TK4	0.605	0.715			
	TK5	0.584	0.690			
	TK6	0.532	0.690			
PK	PK1	0.760	0.674	3.477	10.536	0.891
	PK2	0.728	0.808			
	PK3	0.717	0.808			
	PK5	0.657	0.838			
XK	XK1	0.738	0.696	1.960	5.941	0.863
	XK2	0.703	0.777			
	XK3	0.562	0.764			
TCK	TCK1	0.769	0.720	2.996	9.079	0.884
	TCK2	0.734	0.698			
	TCK3	0.675	0.684			
PCK	PCK2	0.766	0.822	3.099	9.392	0.822
	PCK3	0.755	0.811			
	PCK4	0.714	0.680			
	PCK5	0.569	0.718			
	PCK6	0.496	0.623			
TPK	TPK2	0.688	0.702	1.912	5.794	0.836
	TPK3	0.679	0.639			
	TPK6	0.556	0.609			
TPACK	TPACK1	0.777	0.825	4.745	14.378	0.827
	TPACK2	0.769	0.796			
	TPACK3	0.764	0.740			
	TPACK4	0.753	0.774			
	TPACK5	0.658	0.761			
	TPACK6	0.655	0.664			

2) Reliability and Correlation Analysis: Reliability testing was conducted to examine the internal consistency of the items. The overall Cronbach's α was 0.956. For each factor, the Cronbach's α values ranged from 0.822 to 0.922 (see Table 2). Additionally, no items were found that would increase the Cronbach's α value if removed. This confirms that the AI convergence teaching expertise assessment tool for pre-service teachers is highly reliable. The correlation between factors within the assessment tool was analyzed. The subfactors of the AI convergence teaching expertise assessment tool exhibited significant correlations with each other. Therefore, the subfactors derived from the factor analysis are organically related and form a single latent construct. The results of the correlation analysis for the assessment tool are presented in Table 3.

TABLE III
PEARSON CORRELATIONS BETWEEN SUBFACTORS

	CK	TK	PK	XK	TCK	PCK	TPK
CK	-						
TK	0.567^{***}	-					
PK	0.397^{***}	0.459^{***}	-				
XK	0.426^{***}	0.516^{***}	0.618^{***}	-			
TCK	0.559^{***}	0.642^{***}	0.378^{***}	0.564^{***}	-		
PCK	0.366^{***}	0.437^{***}	0.579^{***}	0.480^{***}	0.397^{***}	-	
TPK	0.403^{***}	0.577^{***}	0.499^{***}	0.575^{***}	0.548^{***}	0.557^{***}	-
TPACK	0.469^{***}	0.610^{***}	0.483^{***}	0.539^{***}	0.564^{***}	0.644^{***}	0.710^{***}

$^{*}p < 0.001$

3) CFA: CFA was conducted to verify the stability of the theoretical factor structure derived from the EFA. A descriptive statistical analysis for each item confirmed that normality was satisfied. Next, examining the model fit indices showed that the CMIN/DF was 1.741, the TLI was 0.913, the CFI was 0.923, the SRMR was 0.057, and the RMSEA was 0.060 (see Table 4). These results indicate that the measurement model derived in this study is appropriate.

TABLE IV
MODEL FIT INDEX OF AI CONVERGENCE TEACHING EXPERTISE TEST TOOL

Index	Value	Criteria	Result
CMIN/df	1.741	< 3.000	Accept
TLI	0.913	≥0.900	Accept
CFI	0.923	≥0.900	Accept
SRMR	0.057	≦0.080	Accept
RMSEA	0.060	≤0.080	Accept

Finally, the convergent validity of the assessment tool was confirmed. The standardized factor loadings for each item developed in this study ranged from 0.588 to 0.901, meeting the minimum criterion of 0.500. The AVE values ranged from 0.521 to 0.676, exceeding the AVE criterion 0.500. The CR values ranged from 0.823 to 0.923, indicating that convergent validity was satisfied [29]. This confirms that this study's AI convergence teaching expertise assessment tool is valid. Table 5 presents the AI convergence teaching expertise assessment tool for pre-service teachers, derived through EFA and CFA.

TABLE V
ARTIFICIAL INTELLIGENCE CONVERGENCE TEACHING EXPERTISE SCALE

Factor	No.	Item
CK	1	I have sufficient knowledge of the subject.
	2	I can be an expert on the subject.
	3	I am confident in teaching the subject.
	4	I have various methods and strategies to understand the subject more deeply.
TK	5	I can quickly learn how to handle and utilize AI.
	6	I have the knowledge needed to use AI effectively.
	7	I can solve problems that arise when using AI on my own.
	8	I understand the concepts and principles of AI.
	9	I can use AI to solve problems encountered in everyday life.
PK	10	I can guide effective discussions among students during group activities.
	11	I can expand students' thinking by presenting challenging tasks.
	12	I can help students control and manage their learning.
	13	I can help students reflect on their learning strategies.
XK	14	I can select equipment to use in the classroom environment.
	15	I can use the classroom environment necessary for teaching the subject.
	16	I can design practical lessons according to the classroom environment.
TCK	17	I can use AI specifically designed to teach the subject content.
	18	I can come up with ways to utilize AI to teach the subject.
	19	I can effectively use AI to teach the subject content to students.
PCK	20	I think I can use various teaching strategies to enhance students' understanding in teaching-learning situations.
	21	I can engage students in project-based learning to solve real-life problems.
	22	I can provide appropriate feedback based on students' assessment results to enhance their understanding of teaching-learning situations.
	23	I can facilitate meaningful discussions among students.
	24	I can propose solutions for complex subject content.
TPK	25	I can explore ways to utilize AI to provide personalized learning based on students' cognitive levels.
	26	I can facilitate student collaboration through AI.
	27	I can devise ways to utilize AI to promote students' self-directed learning.
TPACK	28	I can design inquiry activities that help students understand subject content using AI.
	29	I can create activities that help students construct knowledge in various forms using AI.
	30	I can effectively assess students' academic achievement of the subject content using AI and provide appropriate feedback.
	31	I can design lessons that appropriately combine subjects, AI, technology, and pedagogy for student-centered learning.
	32	I can create activities that allow students to learn subject content knowledge using AI independently.
	33	I can select discussion topics on a subject and facilitate students' online collaboration using appropriate technology.

IV. CONCLUSION

With the increasing use of AI in education, the importance of teaching competencies that integrate AI into lessons is growing. Consequently, various policies and research related to AI convergence education are being conducted in Korea. In line with this trend, this study developed an assessment tool to measure pre-service teachers' AI convergence teaching expertise. The study analyzed prior research to derive the factors and initial items for AI convergence teaching expertise based on the TPACK framework to achieve this. Additionally, a Delphi survey was conducted to develop preliminary test items, and then exploratory and confirmatory factor analyses were performed based on the results of the initial test items. The conclusions drawn from this study are as follows:

First, a literature analysis determined that AI convergence teaching expertise for pre-service teachers was defined as the ability to effectively conduct lessons using AI-related technologies by the subject content and teaching-learning situations, considering the educational context. This expertise involves the theoretical and practical capabilities to design, implement, evaluate, and reflect on AI convergence lessons through the interaction of TK, CK, and PK based on XK. This definition integrates AI as a technological tool within the TPACK framework, with subfactors corresponding to TK, CK, PK, XK, PCK, TCK, TPK, and TPACK.

Second, an assessment tool was developed to measure pre-service teachers' AI convergence teaching expertise. A Delphi survey, exploratory factor analysis, and confirmatory factor analysis developed 33 items evaluated on a 5-point Likert scale. The items were designed for pre-service teachers in Korea, with the assessment tool taking approximately 10–15 minutes to complete. The reliability of the assessment tool was 0.956, with subfactor reliability ranging from 0.822 to 0.922. Furthermore, the assessment tool's discriminant, construct, and content validity were verified, confirming its suitability for measuring pre-service teachers' AI convergence teaching expertise.

This study has the following limitations: The research was developed for pre-service teachers; however, practicing teachers also play a crucial role in implementing education in schools. Therefore, further research is needed to analyze the validity of the assessment tool for in-service teachers. Additionally, continuous post-validation is required to ensure the tool’s validity, determine stable utilization methods, and prove the tool’s applicability. Therefore, correlation studies with prior research on AI convergence teaching expertise are needed to verify construct validity.

The assessment tool developed in this study requires further refinement to achieve a precise and singular factor structure. During the development process, many items were deleted, and other factors were revised and supplemented. Future research should use the deleted items to revise and supplement the factors. Given the diverse definitions and perspectives on AI convergence education among researchers, it is essential to consider the different aspects or perspectives each assessment tool aims to measure.

Lastly, while the assessment tool developed in this study contributes to measuring AI convergence teaching expertise, it employs a self-reporting evaluation method. Although this method is convenient, it has limitations in assessing teaching competencies. Evaluations should include various forms, such as performance-based assessments, interviews, and rubric-based evaluations of artifacts. Future research should analyze the correlations with multiple evaluation tools and verify the effectiveness and validity of the assessment tool developed in this study.

The implications of this study are as follows: This study defined the AI convergence teaching expertise of pre-service teachers based on the TPACK framework and developed an assessment tool accordingly. While prior research has focused on defining teacher competencies for AI education, educational environments, and AI utilization education, this study is significant in developing an assessment tool based on the TPACK framework that can be used in school settings.

Second, this study is highly relevant to the current context, in which interest in AI and the demand for AI convergence education are increasing in schools. Generally, assessment tools have been developed to measure attitudes and literacy among elementary and secondary students. This study is significant in that it measures the development of AI convergence teaching expertise of pre-service teachers in line with the activation of AI convergence education in schools. This study presents a cross-disciplinary context for using AI in schools, which will serve as a reference for future research on the subject-specific characteristics of AI convergence education.

Third, the developed assessment tool can contribute to guiding the direction of AI convergence education for pre-service teachers. In Korea, various subjects and courses related to AI convergence education are being established in graduate schools and other educational institutions. However, a lack of clear guidelines for AI convergence education leads to significant variation in the subjects and content taught across schools. This study provides directions regarding what should be taught regarding AI convergence education for pre-service teachers.

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