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Research Article

A New Scale Development Study on Preservice Teachers' Attitudes toward Artificial Intelligence

Öğretmen Adaylarının Yapay Zekâya Yönelik Tutumlarını Belirlemeye Yönelik Yeni Bir Ölçek Geliştirme Çalışması

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Abstract: The purpose of this study is to develop the "Attitude Scale for Preservice Teachers' Use of AIED (Artificial intelligence in education)" to measure preservice teachers' attitudes toward the use of artificial intelligence in education. This quantitative study was conducted with 278 pre-service teachers enrolled in faculties of education, who were selected through convenience sampling. The data were analyzed through content validity, exploratory factor analysis (EFA), confirmatory factor analysis (CFA), reliability evaluation, and item-total correlations. The EFA results identified a three-factor structure- cognitive, affective, and behavioral attitudes that accounted for 53.40% of the variance. The CFA confirmed this structure with acceptable to good fit indices (x^2/df = 2.045, RMSEA = .061, NNFI = .989, NFI = .981, CFI = .990, GFI = .990, SRMR = .052). Reliability analysis indicated high internal consistency, with Cronbach's α values of .917 for the cognitive, .749 for the affective, .799 for the behavioral sub-dimensions, and .887 for the overall scale. Factor loadings varied between .487 and .913, while item-total correlations ranged from .319 to .758, suggesting strong discrimination levels. The affective dimension showed relatively lower reliability compared to the other dimensions. The overall mean score of 4.311 reflected high levels of positive attitudes toward artificial intelligence among pre-service teachers. In conclusion, the developed scale is a valid and reliable instrument for assessing pre-service teachers' attitudes toward artificial intelligence. Future studies are recommended to replicate CFA with larger and more diverse samples, to further examine the scale's predictive validity. In addition, it is recommended to associate the scale with various socio-demographic variables and to support the affective dimension with qualitative data. This study emphasizes the importance of understanding pre-service teachers' attitudes for the effective integration of artificial intelligence technologies in education and is expected to contribute not only to the literature but also to teacher education practices. For example, by using the AI attitude scale developed in this study, pre-service teachers' attitudes before and after their participation in AI-related educational programs can be measured, and the changes in their attitudes can be scientifically demonstrated through an experimental design.

Keywords: Artificial intelligence, Attitude, Scale development, Validity, Reliability.

Özet: Bu çalışma, öğretmen adaylarının eğitimde yapay zekâ kullanımına yönelik tutumlarını ölçmek amacıyla "Öğretmen Adaylarının Eğitimde Yapay Zekâ Kullanımına (AIED) Yönelik Tutum Ölçeği"nin geliştirilmesini hedeflemektedir. Nicel araştırma yöntemiyle gerçekleştirilen araştırmada, eğitim fakültelerinde öğrenim gören 278 öğretmen adayı uygun örnekleme yöntemiyle seçilmiştir. Veriler kapsam geçerliği, açımlayıcı faktör analizi (AFA), doğrulayıcı faktör analizi (DFA), güvenirlik analizleri ve madde-toplam korelasyonları ile değerlendirilmiştir. AFA sonuçlarına göre ölçek, bilişsel, duyuşsal ve davranışsal olmak üzere üç faktörlü bir yapı sergilemiş ve toplam varyansın %53.40'ını açıklamıştır. DFA sonuçları, modelin kabul edilebilir ve iyi uyum değerlerine sahip olduğunu göstermiştir (x^2/sd = 2.045, RMSEA = .061, NNFI = .989, NFI = .981, CFI = .990, GFI = .990, SRMR = .052). Güvenirlik analizleri, bilişsel boyut için .917, duyuşsal boyut için .749, davranışsal boyut için .799 ve tüm ölçek için .887 Cronbach alfa katsayılarıyla yüksek iç tutarlılık göstermiştir. Ölçek maddelerinin faktör yükleri .487 ile .913 arasında, madde-toplam korelasyon değerleri ise .319 ile .758 arasında değişmiş, bu da maddelerin ayırt edicilik düzeyinin güçlü olduğunu ortaya koymuştur. Duyuşsal boyutun güvenirliği diğer boyutlara kıyasla görece düşük bulunmuştur. Ölçeğin genel puan ortalaması 4.311 olarak hesaplanmış ve öğretmen adaylarının yapay zekâya yönelik olumlu tutumlarının yüksek düzeyde olduğu belirlenmiştir. Sonuç olarak, geliştirilen ölçek, öğretmen adaylarının yapay zekâ kullanımına yönelik tutumlarını değerlendirmek için geçerli ve güvenilir bir araç olarak önerilmektedir. Gelecekte yapılacak çalışmalarda, ölçeğin farklı ve daha geniş

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örneklemlerde DFA ile tekrar test edilmesi, yordayıcı geçerliğinin incelenmesi önerilmektedir. Ayrıca ölçeğin farklı sosyo-demografik değişkenlerle ilişkilendirilmesi ve duyuşsal boyutun nitel verilerle desteklenmesi önerilmektedir. Bu araştırma, eğitimde yapay zekâ teknolojilerinin etkili entegrasyonu için öğretmen adaylarının tutumlarının anlaşılmasının önemini vurgulamakta ve alan yazına olduğu kadar öğretmen eğitimi uygulamalarına da katkı sağlayacağı düşünülmektedir. Örneğin, bu çalışmada geliştirilen yapay zekâ tutum ölçeği kullanılarak öğretmen adaylarının yapay zekâ ile ilgili eğitsel programlara katılımları öncesi ve sonrasındaki tutumları ölçülebilir ve tutumlarındaki değişimler bilimsel olarak deneysel bir desenle ortaya konulabilir.

Anahtar Kelimeler: Yapay Zeka, Tutum, Ölçek Geliştirme, Geçerlik, Güvenirlik.

1. Introduction

In the 21st century, we live in the era of globalization, where any innovation can reach the ends of the earth at great speed. It is known that there has been a breakthrough in technological developments and digital transformation, particularly in areas such as artificial intelligence (AI), robotics, autonomous systems, and augmented reality (Günay & Çalık, 2019). One of the most innovative breakthroughs in these contemporary technological fields is artificial intelligence. Ng (2017) argues that artificial intelligence is the new electricity of this age. Artificial intelligence can be defined as the ability of machines or software systems to learn, adapt, and make decisions based on past experience using algorithms and data models for tasks that would normally require human intervention, and in this context, the goal of artificial intelligence is to enable machines to perform complex tasks efficiently and autonomously by mimicking human intelligence (Toro-Espinoza et al., 2023).

Due to the wide range of uses of artificial intelligence technology and its potential contributions in many different fields, it has taken a central position today. While the concept of artificial intelligence was once limited to the realm of science fiction, it has become integrated into our daily routines, and these technologies have found their place in every aspect of society, from autonomous vehicles to smart homes and digital assistants (Southworth et al., 2023). Furthermore, new technological advancements are altering how we communicate, connect, socialize, and search for and obtain information (Vuorikari, Kluzer, & Punie, 2022). Artificial intelligence has become a game-changing technology in business, industry, and society due to concurrent advancements in digitalization, processing power, and data availability (Holmes, Bialik, & Fadel, 2019).

The rapid advancement of technology has significantly altered how societies function, but it has also raised interest in artificial intelligence and made current technologies more prominent in education (Li & Wang, 2023; Turkaya & Özdemir, 2024). The need to transition to distant learning from preschool to university in many nations has led to a major growth in the importance and application of artificial intelligence, particularly in light of the COVID-19 pandemic (Huang et al., 2020; Savaş, 2021). Following this process, it became clear that using artificial intelligence was both necessary and inevitable. Using AI technologies or application programs to support teaching, learning, or decision-making in educational settings is known as AIED (Artificial intelligence in education) (Hwang et al., 2020). According to related literature, various AI technologies are employed in education, including chatbots, intelligent tutoring systems, face recognition software, recommendation systems, automatic assessment systems, intelligent content delivery, and learning analytics within the context of personalized learning systems (Iqbal, 2023; Akgun & Greenhow, 2022; Hwang et al., 2020).

The development of AI-enhanced educational technologies is transforming the roles of human teachers and creating new pedagogical possibilities. Telli Yamamoto and Karaman (2011) argue that robot teachers will be able to process multimedia materials, use video and audio resources, and thereby enrich the learning experience. They also emphasize that such teachers may not only be physical robots but also software programs operating on computers and mobile devices systems that never become ill or tired of providing guidance. This perspective aligns with the systematic review by Xu and Ouyang (2022), who classify the functions of AI in education into three categories: simulating human behavior through decision-making likesocial robots, acting as an educational intermediary like smart teachers, and supporting the learning process as a complementary assistant. As a natural outcome of this multifaceted structure, the most widely used AIED applications today are recommendation systems, adaptive learning environments, and intelligent tutoring systems (Akdeniz & Özdinç, 2021).

According to Vivar & Peñalvo (2023), experts state that the mission of AI in teaching is to help plan, personalize, visualize and facilitate the learning process. AIED reduces the workload of teachers by automating their time-consuming tasks, making it possible for them to focus on higher-level responsibilities such as curriculum development and student advising (Chan & Tsi, 2023). In addition, the development of AI technology helps to improve the physical environment of educational activities in the direction of flexibility and hierarchy, encourages the assessment of students to move in a comprehensive direction, and students' performance in the learning process is added to the assessment (Huang, Shen, & Ren, 2021).

The use of AI-supported technologies in education is increasing day by day and is expected to continue. Sánchez Vera (2023) also states that the global education market is expected to be based on artificial intelligence. However, the attitudes of teachers and pre-service teachers, who are the cornerstone of education, towards the use of AI-supported technologies in education are of great importance. Upon reviewing the literature, it was discovered that there aren't many studies on artificial intelligence for pre-service teachers. Studies that examined pre-service teachers' attitudes toward their subject areas (Banaz & Maden, 2024; Mart & Kaya, 2024; Eyüp & Kayhan, 2023) and in-service subject teachers' attitudes and perspectives toward artificial intelligence (Zormanová, 2024; Fissore et al., 2024; Yetişensoy, 2024; Küçükkara, Ünal, & Sezer, 2024) accounted for a sizable amount of the reviewed studies. In addition, in a study, teachers expressed the need for more confidence in their AI skills, although they are not highly concerned about the gradual spread of AI at various levels (Fissore et al., 2024). Meanwhile, some educators and aspiring educators consider AI essential and benefit from its potential, whereas others do not wish to live in a future dominated by AI regulations (Haseski, 2019).

On the other hand, most teachers today do not have a basic understanding of artificial intelligence (Yetişensoy, 2024). Moreover, they find it difficult to effectively integrate and utilize AI technologies into their educational processes (Kim & Kwon, 2023). There are a number of studies that support this situation. For instance, Lindner and Berges (2020) stated that German teachers possess only a basic understanding of AI, and their perceptions tend to be rather general. Likewise, Chounta et al. (2022) examined Estonian K-12 teachers and observed that, despite their positive attitudes toward integrating AI into education, their knowledge about AI remained limited. Moreover, they lacked a comprehensive understanding of its potential and applications in the educational context.

Insufficient knowledge in this area might contribute to the development of negative attitudes in educational settings (Yetişensoy, 2024). Chiu et al. (2023) conducted a systematic review of the literature and highlighted that certain students and teachers experienced anxiety and demonstrated lower self-confidence in AI-assisted learning processes. This situation may make it more challenging for teachers to effectively integrate AI technologies into their teaching cycles (Chiu et al., 2023). To overcome this challenge, it would be useful to know the attitudes of teachers and pre-service teachers. Because teachers, as the main force of AI education, play an important role in effectively integrating AI tools into classroom instruction (Pan, Wang, & Wang 2023). Considering these factors, understanding preservice teachers' attitudes towards artificial intelligence is both essential and significant, as they are set to play key roles in future educational processes.

Attitude is one of the fundamental concepts in social psychology and can be defined as a psychological tendency in which an individual evaluates a specific situation, object, or abstract phenomenon positively or negatively (Albarracin & Shavitt, 2018; Allport, 1935; Howe & Krosnick, 2017). Attitude is considered a multidimensional construct consisting of three components: affective, cognitive, and behavioral (Garcia-Santillan et al., 2012; Svenningsson et al., 2022). The affective component of attitude emphasizes positive or negative feelings toward a situation or object (Ibuot, 2020; Janakiraman et al., 2021), while the cognitive component highlights beliefs, thoughts, and opinions (Ibuot, 2020; Svenningsson et al., 2022). On the other hand, the behavioral component denotes the typical ways in which an individual responds to a given object or phenomenon (Ibuot, 2020; Zhang, Zhang, & Zhou, 2021).

Current research (Cicero et al., 2025; Şahin & Yıldırım, 2024) primarily focuses on individuals' general attitudes toward artificial intelligence. However, the lack of a comprehensive and psychometrically sound scale that can assess pre-service teachers' general attitudes creates a significant gap in this area. This situation makes it difficult to accurately assess pre-service teachers' tendencies to integrate artificial intelligence into educational processes. The research question addressed in this study is whether preservice teachers' attitudes towards the use of artificial intelligence may be measured with a scale to be developed, and whether there is a need for such a scale. Considering the integration of technology in education and classroom teaching (Wang et al., 2024), artificial intelligence is expected to play an increasingly important role. Therefore, the aim of the research is to develop a scale that measures pre-service teachers' attitudes towards artificial intelligence, which is rapidly taking its place in the future education world.

It will be highly significant to obtain information about the attitudes of pre-service teachers, who will play a vital role in the teaching process, in order to effectively

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utilize the potential of artificial intelligence technology in educational settings. The development of positive attitudes toward artificial intelligence among pre-service teachers and educators may facilitate the alignment of AI with individual student needs in classroom settings, its use in research, communication, and feedback processes, as well as support students in autonomously modeling their learning. It can also enable decisions on which knowledge and skills to present based on past performance, and on students' levels of understanding and educational progress. Consequently, this may contribute not only to the enhancement of students' creativity but also to the development of their cognitive, emotional, and behavioral learning processes (Arslan, 2020; Baltezarević & Baltezarević, 2024; Güneyli et al., 2024). Consequently, developing a valid and reliable scale that can measure pre-service teachers' attitudes toward artificial intelligence will not only fill a gap in the literature but also contribute to the design of teacher training programs, educational policies, and curriculum development efforts. In this context, the study is expected to make significant contributions to both the literature and practice.

2. Method

2.1. Research Model

This study was designed as scale development research to assess candidate teachers' attitudes toward the integration of AIED. The study employed an applied and descriptive research model within a quantitative framework (Şata, 2020). Descriptive research typically involves examining large groups as they naturally exist, without introducing any intervention or manipulation..

2.2. Population and Sample

The target group of this study includes teacher candidates enrolled in the faculty of education, while the sample comprises 278 individuals selected through a convenient sampling approach, which is a type of non-random sampling. Participation in the study was voluntary. As inclusion criteria, individuals pursuing studies at an education faculty were considered, while as exclusion criteria, those not pursuing their studies at an education faculty were considered as well. While cleaning and analyzing the data, it was found that there were no missing values or unassigned values. In addition, an extreme value analysis was performed and it was determined that there were no extreme values. Within the scope of the research, it was determined that pre-service teachers studying in fifteen different teaching programs participated in the study. Table 1 presents the descriptive statistics of the socio-demographic variables of the pre-service teachers involved in the study.

Table 1. Frequency and Percentage Values of Socio-Demographic Characteristics of Pre-Service Teachers

Variables	Variable level	F	%
Gender	Male	74	26.6
	Female	204	73.4
Grade level	1st grade	22	7.9
	2nd grade	94	33.8
	3rd grade	140	50.4
	4th grade	22	7.9
Socio-economic status	Low	37	13.3
	Medium	230	82.7
	High	11	4.0
Age level	20 years and under	39	14.0
	21 years	62	22.3
	22 years	77	27.7
	23 years	41	14.7
	24 years and above	59	21.2
Mother's education level	Illiterate	66	23.7
	Literate	22	7.9
	Primary school	110	39.6
	Secondary school	29	10.4
	High school	32	11.5
	Associate's degree	7	2.5
	Bachelor's degree and above	12	4.3
Father's education level	Illiterate	27	9.7
	Literate	85	30.6
	Primary school	57	20.5
	Secondary school	66	23.7
	High school	10	3.6
	Associate's degree	33	11.9
	Bachelor's degree and above	27	9.7
	Total	278	100.0

An analysis of Table 1 reveals that the number of female pre-service teachers is three times higher than that of male pre-service teachers. It was found that the majority of students in the second and third years were in the majority, and most perceived their socio-economic status as being at the middle level. When the age distribution is examined, it is seen that the maximum age is 22 years and the minimum age is 20 years and below. When the education levels of mother and father were analyzed, it was determined that higher education was less and primary education was more.

Table 2. Artificial Intelligence Tools Used by Pre-Service Teachers

Variable		F	%1	%2
	ChatGPT	175	48.9	62.9
	Copilot	27	7.5	9.7
	Gemini	47	13.1	16.9
AI tools	Cladue	11	3.1	4.0
	Other	18	5.0	6.5
	None	80	22.3	28.8
	Total	**358**	**100.0**	**128.8**

1%= percentage of total number of people 2% = percentage of total responses

When Table 2 is examined, it is seen that the artificial intelligence tool that pre-service teachers use the most is ChatGPT and the least is Claude. In addition, approximately 22% of the pre-service teachers do not use any artificial intelligence tool. As shown in Table 2, a total of 358 responses were recorded from 278 participants, since pre-service teachers were allowed to indicate more than one AI tool. Therefore, the total number of responses exceeded the number of participants. Accordingly the percentages in the first column (%1) represent the proportion of the total participants (N=278), whereas the percentages in the second column (%2) refer to the proportion of the total responses (N=358).

2.3. Development of the Data Collection Tool

In line with the aim of the study, the development stages of the measurement tool designed to assess pre-service teachers' attitudes toward artificial intelligence were carried out through a systematic process. First, a literature review was conducted to determine whether an appropriate measurement tool already existed. As a result of the literature review, it was determined that there are attitude scales towards artificial intelligence for different segments of the society, but there is no measurement tool directly for pre-service teachers. In addition, it was determined that the institutional structures of other attitude scales towards artificial intelligence were weak and that they were not intended to measure all dimensions of attitude. In the second stage, the theoretical structure of the concept of attitude was examined, and the sub-dimensions of the scale were determined by considering the attitude components, which include the affective, cognitive, and behavioral dimensions of attitude (Svenningsson et al., 2022; Verplanken, Hofstee, & Janssen, 1998).

In the third stage, an item pool was created by writing items to adequately represent each sub-dimension of attitude. First, 43 items were written and then it was reduced to 39 items by determining that there were items with similar meanings. The draft form was sent to eight experts, including 4 Psychological Counseling and Guidance experts, 2 Turkish Language experts and 2 Measurement and Evaluation experts, to collect evidence of the content validity of the items. Expert opinion was conducted using the Lawshe technique (Lawshe, 1975). In the Lawshe technique, the threshold value of each item for eight experts was determined to be .693 (Wilson, Pan, & Schumsky, 2012) and items below this threshold value were removed from the draft form. Content validity rate was calculated for each item and it was determined that the content validity rates of twelve items were lower than the threshold value of .693 and they were removed from the measurement tool. In addition, in line with the expert opinions, two items that were deemed necessary but should be corrected were corrected. As a result, the draft form sent to the experts as 39 items was reduced to 27 items and finalized before the application. After the development process of the measurement tool was completed, the data collection process started.

2.4. Data Collection

First, the study was evaluated and deemed ethically appropriate in terms of its purpose, methodology, and implementation by the Van Yüzüncü Yıl University Social and Human Sciences Publication Ethics Board. After obtaining ethics committee approval, the data collection process was initiated.The measurement instrument developed by the researchers was administered online, leveraging the various advantages provided by this platform. One of the primary reasons for choosing online data collection was the target audience's ability to adapt to online surveys. This method offers significant flexibility in terms of time and location, allowing participants to complete the survey at their convenience. Additionally, online surveys enable researchers to reach a broad audience beyond geographical limitations, making the data collection process more inclusive.

From a cost perspective, online surveys are more economical compared to traditional methods, eliminating additional expenses such as printed materials and mailing. The data collection and analysis process is also accelerated, as digitally collected data can be analyzed in real-time. Moreover, participants can respond anonymously, which encourages more honest and objective answers. Online platforms also allow for quick updates and modifications to survey content, enhancing the flexibility of the data collection process. For these reasons, an online method was preferred for data collection in this study. The data collection process lasted approximately two weeks.

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2.5. Data Analysis

First, descriptive statistics measures were used in data analysis. Then, the content validity ratio was used to assess the content validity of the data obtained from the measurement tool. Exploratory factor analysis was conducted to support the construct validity of the data collected through the measurement tool. To assess the reliability of the data collected from the measurement tool, Cronbach's alpha and McDonald's Omega coefficients were calculated. Finally, the item-total score correlation coefficients and the discrimination of the items were analyzed.

Before examining the factor structure of the developed measurement tool with factor analytic methods, some assumptions to be met were tested. First, Kaiser-Meyer-Olkin (KMO) and Barlett's sphericity test were performed to determine whether the items of the developed scale could be grouped under one factor. According to the analysis, it was determined that the scale items were factorizable (KMO = .930; Bartlett test $\chi 2$ (sd) = 4309.686 (351); p $^{<}$ .001). According to these findings, it is seen that the scale items have a factorizable structure. Because the KMO value was .50 and above and Barlett's test was statistically significant (Field, 2009; Büyüköztürk, 2012).

To determine the number of factors, eigenvalues, the scree plot, parallel analysis, expert opinions, and the conceptual content of the items were all taken into account. A factor loading threshold of 0.400 was adopted, which is commonly regarded as an indicator of the strength of the relationship between each item and its corresponding factor (Tabachnick & Fidell, 2013). The item-total correlation coefficient value of .20 and above indicates that the item works in harmony with the overall scale (Crocker & Algina, 2006). Finally, since it was stated that there should be at least five participants per item for adequate sample size (27 items x 5 = 135 participants), it was determined that this assumption was also met. In addition, a sample size of 200 is considered sufficient for testing non-complex models (Brown, 2015; Bentler & Chou, 1987). SPSS (version 25) and JASP (version 0.18.3.0) package programs were used for data analysis.

3. Findings

In order to establish the construct validity of the measurement tool designed for the study, exploratory factor analysis was initially conducted. According to the exploratory factor analysis, it was determined that there were four factors with factor eigenvalues greater than 1.00 and explained 52.20% of the total variance. In the first factor analysis, it was determined that two items (m1 and m11) did not load under any factor and the loading value was lower than .40, so the analyses were repeated by removing both items in turn. The scatter plot for the first analysis is given in Figure 1.

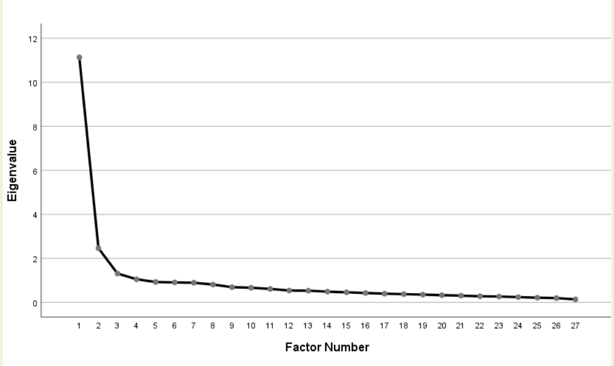

Figure 1. Scatter Plot of the Factor Structure of the Developed Measurement Tool

Figure 1 shows that the line flattens after the third factor. Accordingly, parallel analysis was performed considering both the scatter plot and the theoretical structure and the number of factors was decided. According to the parallel analysis, it was decided that the structure had three factors. The scatter plot obtained as a result of parallel analysis is given in Figure 2.

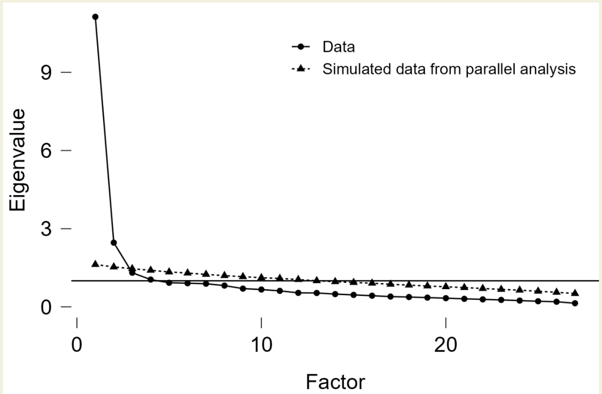

Figure 2. Scatter Plot Obtained as a Result of Parallel Analysis

An examination of Figure 2 reveals that the empirical data line intersects with the data line derived from parallel analysis at the third factor. This result shows that the measurement tool has a three-factor structure. After deciding the number of factors, the factor loadings of the items were examined and it was determined that five items (m8, m10, m14, m25 and m27) had low factor loadings and two items (m12 and m18) had overlapping factor loadings and were removed from the measurement tool. Each item was removed in turn and the

Table 3. EFA Analysis

F1 (Cognitive)			F2 (Affactive)			F3 (Behavioral)		
Previous Item Number	New Item Number	Factor loading	Previous Item Number	New Item Number	Factor loading	Previous Item Number	New Item Number	Factor Loading
M2	M01	.662	M16	M10	.872	M20	M13	.697
M3	M02	.680	M17	M11	.686	M21	M14	.587
M4	M03	.766	M19	M12	.586	M22	M15	.487
M5	M04	.705				M23	M16	.532
M6	M05	.681				M24	M17	.780
M7	M06	.913						
M9	M07	.627						
M13	M08	.663						
M15	M09	.640						
Eigenvalue		7.224			1.116		2.108	
Explained Variance (%)		39.90			3.60		9.80	
Total Explained Variance (%)					53.30			

Note: Factor loadings of the excluded item: M01: .377, M08: .344, M10: .318, M14: .360, M25: .382, M27: .379

analyses were repeated. As a result, a measurement tool consisting of 17 items and three factors was obtained. The EFA results of the final version of the measurement tool are given in Table 3.

An analysis of Table 3 reveals that the three identified factors account for 53.40% of the total variance. Accordingly, 53% of the variation in candidates' attitudes toward artificial intelligence is explained by the developed measurement tool. In addition, it was determined that the cognitive dimension of attitude had the highest variance and the lowest variance was in the affective dimension. The factor loadings of the items were analyzed and found to range between 0.487 and 0.913, exceeding the minimum threshold of 0.40. Consequently, support for the construct validity of the developed measurement tool was established. Additionally, Cronbach's alpha and McDonald's Omega coefficients were computed to assess the reliability of the measurements, and the results are presented in Table 4.

Table 4. Reliability Values of the Measurements Obtained from the Measurement Tool

Factor	Number of Items	Cronbach α (%95 GA)	McDonald ω (%95 GA)
Cognitive	9	.917 (.901-.931)	.918 (.904-.933)
Affective	3	.749 (.694-.797)	.766 (.720-.812)
Behavioral	5	.799 (.758-.834)	.804 (.767-.840)
The Whole Scale	17	.887 (.866-.905)	.894 (.876-.912)

Table 5. Item-Total Score Correlations

Item Number	Mean Score of Item ()	Adjusted Item-Total Correlation (r)	Item Number	Mean Score of Item ()	Adjusted Item-Total Correlation (r)
M1	4.284	.600	M10	4.406	.498
M2	4.637	.570	M11	4.396	.420
M3	4.090	.675	M12	4.342	.319
M4	3.795	.523	M13	4.687	.581
M5	4.421	.712	M14	4.608	.577
M6	4.263	.718	M15	4.004	.450
M7	4.342	.700	M16	3.935	.576
M8	4.424	.758	M17	4.320	.668
M9	4.342	.750			
Overall Scale Item Mean				: 4.311	
Scale-Wide Item-Total Correlation Values				: .594	

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Table 4 indicates that the reliability coefficients computed for both the sub-factors and the overall scale are .70 or higher. Accordingly, the results derived from the instrument demonstrated high reliability (Salvucci et al., 1997). After providing evidence for the validity and reliability of the measurements obtained from the measurement tool, the item-total score correlation coefficients were examined and the findings are given in Table 5.

An analysis of Table 5 reveals that the item averages in the measurement tool range from 3.795 to 4.687. The overall mean score was calculated as 4.311, indicating high attitude levels. An examination of the item-total score correlation values showed that they ranged between .319 and .758, indicating a moderate to strong association with the total score, in other words, their discrimination levels were high.

Analysis of the correlations among the sub-dimensions of the measurement tool revealed a strong positive association between the cognitive and behavioral dimensions ($r = .70$, $p < .05$). However, no significant correlation was observed between the cognitive and affective dimensions ($r = -.02$, $p > .05$), and the relationship between the behavioral and affective dimensions was not statistically significant ($r = .04$, $p > .05$). In this scale, the cognitive dimension, consistent with the cognitive component of attitude theory (Ibuot, 2020), includes items related to preservice teachers' thoughts and beliefs about the use of artificial intelligence in education, such as "The individual feedback provided by artificial intelligence can improve student achievement". The affective dimension addresses emotional states such as anxiety, concern, and fear regarding the use of artificial intelligence in education. The behavioral dimension, on the other hand, consists of items measuring preservice teachers' behavioral tendencies such as "I would participate in training seminars and activities related to artificial intelligence" toward the use of artificial intelligence in educational contexts.

In order to provide evidence for the construct validity of the measurements obtained from the instrument, a confirmatory factor analysis (CFA) was conducted, and the findings are presented in Table 6.

The confirmatory factor analysis was conducted to evaluate the construct validity of the measurement model. The model fit indices indicated that the tested model achieved an acceptable to good fit with the data. Specifically, the ratio of chi-square to degrees of freedom was 2.045, which falls within the acceptable range ($2 \leq \chi^2/df \leq 5$). The RMSEA value was .061 (90% CI = .050–.073), which is also within the acceptable range (< .08) and close to the threshold for good fit (< .05). In addition, incremental fit indices demonstrated strong model performance: NNFI = .989, NFI = .981, CFI = .990, and GFI = .990, all of which exceed the .95 cutoff, suggesting a good fit. Finally, the SRMR value was .052, which is slightly above the strict .05 criterion but still within the acceptable fit range (< .08).

Table 6. Confirmatory Factor Analysis (CFA) Results, Measurement Model Tested for the Instrument

Fit Indices	Good Fit Range	Acceptable Fit Range	Parameter Estimates
χ^2 /df	$0 \leq \chi^2/df < 2$	$2 \leq \chi^2/df \leq 5$	2.045
RMSEA (%90 GA)	0≤RMSEA<0.05	0.05≤RMSEA≤0.10	0.061 (0.050-0.073)
NNFI	0.95≤NNFI≤1.00	0.90 ≤NNFI< 0.95	0.989
NFI	0.95≤NFI≤1.00	0.90 ≤NFI< 0.95	0.981
CFI	0.95 ≤CFI≤ 1.00	0.90 ≤CFI< 0.95	0.990
GFI	0.95 ≤GFI≤ 1.00	0.90 ≤GFI< 0.95	0.990
SRMR	0≤ SRMR <0.05	0.05≤ SRMR ≤0.10	0.052

4. Discussion, Conclusion and Limitations

It was determined that the whole of the "Attitude Scale for Preservice Teachers' Use of AIED" developed by the researchers of this article and its "cognitive", "affective" and "behavioral" sub-factors provided valid and reliable measurements. Cognitive, affective and behavioral attitudes are included in this study in which participants' attitudes towards artificial intelligence are examined. When the literature is examined, there are different scales or questionnaires developed to examine pre-service teachers' thoughts, feelings or perceptions about AIED. Üzüm, Elçiçek, & Pesen (2024), who developed the scale of teachers' perception of the use of AIED, found that the scale with three sub-factors, namely "learning perception", "teaching perception" and "ethical perception", was a valid and reliable scale. Ayanwale et al. (2022) stated in their research that they adapted the 33-item scale of teachers' readiness and behavioral intention to use AIED by adapting it from the scale studies in the literature and that it is an eight-subdimensional scale with sub-factors such as "attitudes towards using artificial intelligence", "readiness for artificial intelligence", "perceived usefulness". The researchers found the reliability coefficient of the "attitudes towards using artificial intelligence" sub-factor as .93 and its variance as .82 with high validity and reliability. The researchers stated that with their study, teachers' behavioral intentions regarding the use of artificial intelligence in educational settings can be examined in the future.

Al Darayseh (2023) conducted a study to investigate how science teachers accept the use of AIED. The 32-item scale designed by Al Darayseh (2023) assessed various dimensions related to "confidence in one's abilities," "emotional concerns," "anticipated benefits," "perceived user-friendliness," "views on AI applications," and "future use intention.". The researcher stated that science teachers' acceptance of artificial intelligence is high and that their "attitudes toward integrating AI into education" influence their behavioral intention to adopt this technology in teaching (Al Darayseh, 2023). In this context, it can be said that cognitive attitudes toward integrating artificial intelligence into education are effective in the realization of behaviors related to AI adoption in teaching (Sanusi, Ayanwale, & Tolorunleke, 2024). As a matter of fact, among the sub-factors of the scale developed in this study, a high correlation was found between the "cognitive dimension" and the "behavioral dimension" regarding the integration of artificial intelligence into education. In this study, while an innovative scale was developed to assess pre-service teachers' perspectives on the application of artificial intelligence, a study was also conducted on the development, validity, and reliability of the Medical Artificial Intelligence Readiness Scale (MAIRS-MS) for medical students (Karaca, Çalışkan, & Demir, 2021). The researchers highlighted that this scale, designed to assess readiness for integrating artificial intelligence into medical education, is vital for addressing future AI-related needs of pre-service doctors and for advancing subsequent research in this field (Karaca, Çalışkan, & Demir, 2021).

With the EFA analysis conducted in this study, it was found that the cognitive dimension of pre-service teachers' attitudes towards the use of artificial intelligence had the highest variance and the lowest variance was found in the affective dimension. Although it was found to be sufficient in terms of validity, it was concluded that the validity of the affective dimension was lower than the cognitive and behavioral attitude dimension. This finding that pre-service teachers' cognitive and behavioral attitudes toward the use of AIED were at a high level may be related to their openness to the idea of integrating learning with technology. In line with this view, a qualitative study by Adıgüzel, Karalı, and Aydemir (2025) reported that teachers highlighted both the benefits of AI such as making learning more enjoyable, supporting individualized learning, and producing effective outcomes and the challenges, including the risk of replacing classroom interaction and reducing student effort in completing assignments, which are about cognitive and behavioral perspectives.

Teachers' emotional readiness for the use of AIED and their adaptation to AI-supported educational programs are related to their experiences with such programs (Meylani, 2024). In this context, the weakness of the affective attitude dimension among pre-service teachers in this study, as well as the absence of a significant correlation between the affective dimension and the cognitive and behavioral dimensions, may be associated with the limited adaptation and experience in using AI and with the need for curricula addressing the use of AI in education (Kong, Yang, & Hou, 2024). This situation can be explained by the limited emotional awareness of teacher candidates regarding the use of AIED, which results in a lower affective dimension. In their study, Darancik, Kaçar, and Sezik (2025) emphasized the need to enhance pre-service teachers' cognitive and emotional awareness of AI use in education, pointing out that German language teacher candidates may experience moderate anxiety about the use of AI in teaching and learning, and therefore underlining the importance of providing training within the framework of the technology acceptance model.

The use of AI can bring forward cognitive dimensions such as critical thinking and problem-solving, as well as behavioral tendencies toward its use among educators, while also promoting emotional comfort in human-AI interaction and fostering emotional awareness and intelligence in young people (Delello et al., 2025). On the other hand, Pokrivcakova (2023) found that while teacher candidates had positive expectations regarding the use of AI applications, they also expressed emotional concerns that such use could diminish certain teaching skills and make instruction less personal. These findings may provide clues as to why the affective component is weaker.

When examining the literature, it is observed that cognitive elements related to artificial intelligence usage have an impact on behavioral intention. Alzahrani (2023) found that higher education students' intentions to adopt AI technology in learning environments (behavioral attitude dimension) are influenced by their awareness of technology usage, performance expectancy, and perceived risk factors through attitudes. Additionally, ease of use also plays a role in shaping their intention to engage with AI-based tools. Influential factors, including risk perception and the ease of utilizing artificial intelligence, appear to be associated with the cognitive attitude dimension.

A review of the literature indicates that emotional components also play a role in the integration of artificial intelligence into daily life. For instance, integrating smart technologies into the healthcare sector might be considered a natural progression in Japan, a nation recognized

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for its deep-rooted interest in robotics. However, Japanese culture also places significant value on conventional social structures and longstanding institutional norms, particularly in medical services (Ho et al., 2023). To assess how AI technology is perceived in Japan, researchers gathered data from 245 individuals visiting medical facilities in a suburban region and found that older men and women, in particular, expressed reservations about losing control over AI-driven systems (Ho et al., 2023). Kaya et al. (2024) examined how various socio-demographic factors, individual characteristics, and concerns related to AI influence adults' attitudes toward artificial intelligence. Through Hierarchical Multiple Linear Regression analysis, the researchers demonstrated that computer usage level, knowledge of artificial intelligence were significant predictors of positive attitudes toward artificial intelligence. Additionally, negative attitudes toward AI were influenced by compatibility, anxiety about configuring AI, and anxiety regarding AI learning (Kaya et al., 2024). As a result, attitudes towards the use of artificial intelligence are related to cognitive, affective and behavioral attitude dimensions and many different demographic variables.

In this study, construct validity analyses were conducted to establish the validity and reliability of the developed measurement tool. However, the absence of an additional validated instrument that could be used to assess criterion-related validity constitutes a limitation. For example, if the attitudes of prospective teachers toward artificial intelligence had been examined in relation to other instruments for criterion validity, such as the artificial intelligence awareness scale for teachers (Ferikoğlu & Akgün, 2022) or the artificial intelligence anxiety scale (Terzi, 2020), their attitudes could have been evaluated from different perspectives. Moreover, in line with the nature of criterion validity (Kelecioğlu & Şahin, 2014), analyses of the relationship between the attitude construct and related variables such as awareness, related to the cognitive dimension, and anxiety, related to the affective dimension could have contributed to demonstrating the predictive power of this scale through its association with relevant measurement tools. Future research is recommended to address this by including other established scales that are conceptually related to attitudes toward artificial intelligence. In this study, the sample was limited to prospective teachers enrolled in faculties of education. However, teacher candidates participating in pedagogical formation (certificate) programs at universities could also have been included. This is considered another limitation of the study.

5. Recommendations and Implications

Based on the findings of this study and the existing literature on attitudes toward AI in higher education and other educational settings, several suggestions may be offered. The scale developed in this study, which measures attitudes toward integrating artificial intelligence into educational settings, was found to be valid and reliable. It is recommended that researchers interested in exploring attitudes toward the use of AIED employ this scale, and examine these attitudes in relation to socio-demographic variables within their samples.

The data obtained from the scale may guide the design of teacher training programs enriched with AI-supported applications, lessons, and materials. Indeed, Telli and Aydın (2025), in their study, highlight the potential of integrating artificial intelligence into universities to reshape educational processes, while also noting the challenges it presents. Such programs for preservice teachers may include modules on general AI use, student development activities, simulations, gamification, creativity and storytelling-based problem solving, as well as AI-supported practices that provide cognitive, emotional, and behavioral feedback (Er & Batdı, 2024; Kassenkhan, Moldagulova, & Serbin, 2025). Using the AI attitude scale developed in this study to measure pre-service teachers' attitudes before and after participation could enable an experimental design to reveal changes in their attitudes scientifically.

In terms of education policies, determining the attitudes of prospective teachers toward the use of AIED will contribute to the development of national AI strategies. This can support the organization of teacher training programs in a more contemporary and innovative way, with a focus on technology. Overall, the developed scale can provide concrete data and contribute not only to measuring individual attitudes but also to structuring teacher training programs and shaping AI-focused education policies. In future studies, the scale developed in this research may be also used to examine the relationships between prospective teachers' attitudes toward the use of AI technologies and various variables such as their perceptions of AI-related assignments during their college education, their expectations regarding AI, and their intended purposes for using AI in educational settings.

It is also recommended that the scale be administered to a broader audience, including in-service teachers, academics, and decision-makers involved in educational applications of artificial intelligence. Future studies are recommended to replicate CFA with larger and more diverse samples, to further examine the scale's predictive validity. Researchers may complement the quantitative findings from the scale with qualitative methods particularly focusing on the cognitive, affective, and behavioral attitude dimensions as well as incorporating additional questions related to participants' artificial intelligence knowledge and their academic and technological goals within a mixed-methods design. Such an approach may offer a more in-depth understanding of attitudes toward AIED.

Research Ethics

The ethics application for the study was made on 06/08/2024 and the research was carried out with the approval of Van Yüzüncü Yıl University Social and Human Sciences Publication Ethics Board Commission dated 06/09/2024 and numbered 2024/18.

Author Contributions

Conceptualization: [Revşan Calp, Gamze Mukba], Methodology: [Revşan Calp, Gamze Mukba, Mehmet Şata], Investigation: [Revşan Calp, Gamze Mukba], Resources: [Revşan Calp, Gamze Mukba, Mehmet Şata], Scale item development: [Revşan Calp, Gamze Mukba, Mehmet Şata], Data collection: [Revşan Calp], Writing - Original Draft Preparation: [Revşan Calp, Gamze Mukba], Writing - Review & Editing: [Revşan Calp, Gamze Mukba], Data Analysis: [Mehmet Şata], Discussion-Conclusion: [Revşan Calp, Gamze Mukba, Mehmet Şata].

Competing Interests

The authors declare that there is no conflict of interest.

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Data Availability

Not applicable.

Note

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Appendix 1. Attitude Toward Artificial Intelligence Scale (ATAIS) of Preservice Teachers / Yapay Zekaya İlişkin Öğretmen Adaylarının Tutum Ölçeği

Maddeler	Hiç Katılmıyorum	Katılmıyorum	Biraz Katılmıyorum	Biraz Katılıyorum	Katılıyorum	Tamamen Katılıyorum.
1. Yapay zekânın vereceği bireysel geri dönütler öğrenci başarısını arttırabilir.	( )	( )	( )	( )	( )	( )
2. Yapay zekâ destekli eğitim, öğrencilerin iş yükünü azaltabilir.	( )	( )	( )	( )	( )	( )
3. Yapay zekânın öğrenme stilime uyum sağladığını düşünüyorum.	( )	( )	( )	( )	( )	( )
4. Yapay zekâ destekli eğitimin öğrencilerin eleştirel düşünme becerilerini geliştirebilir.	( )	( )	( )	( )	( )	( )
5.Yapay zekânın eğitimde kullanılmasını destekliyorum.	( )	( )	( )	( )	( )	( )
6.Yapay zekâ destekli eğitimin bireysel başarıyı olumlu yönde etkileyeceğini düşünüyorum.	( )	( )	( )	( )	( )	( )
7. Yapay zekâ destekli eğitimin öğrencilerin öğrenme deneyimlerini zenginleştireceğini düşünüyorum.	( )	( )	( )	( )	( )	( )
8. Derslerde yapay zekâ kullanımını eğlenceli buluyorum.	( )	( )	( )	( )	( )	( )
9. Yapay zekâ destekli eğitim öğrenci motivasyonunu arttırır.	( )	( )	( )	( )	( )	( )
10. Yapay zekânın eğitimde kullanımıyla beraber insan etkileşiminin zayıflamasını endişe verici buluyorum.	( )	( )	( )	( )	( )	( )
11. Yapay zekânın eğitimde kullanılmasıyla ileride öğretmenlere ihtiyaç kalmaması gibi durumlardan korkuyorum.	( )	( )	( )	( )	( )	( )
12. Yapay zekâ destekli eğitimde verilerimin gizliliği ve güvenliği konusunda endişe duyuyorum.	( )	( )	( )	( )	( )	( )
13. Yapay zekânın yardımı ile birçok eğitim materyaline kolaylıkla erişim sağlayabilirim.	( )	( )	( )	( )	( )	( )
14. Yapay zekâyı ödevlerimde ve araştırmalarımda rahatlıkla kullanabilirim.	( )	( )	( )	( )	( )	( )
15. Yapay zekâ ile ilgili verilecek olan eğitim seminerlerine ve etkinliklerine katılırım.	( )	( )	( )	( )	( )	( )
16. Yapay zekâ tarafından desteklenen öğrenme deneyimlerini diğer öğrenme deneyimlerine göre tercih ederim.	( )	( )	( )	( )	( )	( )
17. Yapay zekâ destekli eğitim teknolojilerini çevreme öneririm.	( )	( )	( )	( )	( )	( )

Note. Items 1–9: Cognitive Dimension; Items 10–12: Affective Dimension: Items 13–17: Behavioral Dimension