Artificial Intelligence Awareness Scale for Pre-Service Teachers

Assoc.Prof. Dr. Mustafa ERSOY
Sivas Cumhuriyet University - Türkiye
ORCID: 0000-0002-7320-8844
mersoy@cumhuriyet.edu.tr

Assoc.Prof. Dr. Ahmet YILDIZ
Sivas Cumhuriyet University - Türkiye
ORCID: 0000-0002-9149-5859
ahmet.yildiz@cumhuriyet.edu.tr

Abstract

This study aimed to create a valid and reliable measurement tool to evaluate the awareness of artificial intelligence (AI) among pre-service teachers. Although AI technologies are progressively being integrated into educational contexts, the literature review shows that comprehensive instruments that reveal the teachers' multidimensional awareness, including positive orientations and concerns, are still missing. Generally, existing scales are mainly focused on technical knowledge or attitudes, thus a gap in measuring holistic AI awareness among prospective teachers has remained unfilled. The research was a scale development study that used a quantitative survey design. The researchers gathered data from 300 pre-service teachers, who volunteered and were enrolled at a state university during the 2024-2025 academic year. They used convenience sampling. Initially, 71 items were pooled based on an extensive literature review and expert evaluations. Content validity was secured through an expert panel, and construct validity was verified by means of Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA). Internal consistency reliability was measured through Cronbach's alpha coefficients. According to the EFA results, two factors with 39 items after the exclusion of the items were identified. These factors were interpreted as AI Acceptance (26 items) and AI Avoidance (13 items). The two-factor model accounted for about 47.68% of the total variance. CFA results verified that the model had good fit indices. The overall scale, as well as the two sub-dimensions, had very good internal consistency, as indicated by the Cronbach's alpha values of more than .89, which were confirmed by reliability analyses. The study findings provide evidence that the developed instrument is a psychometrically valid tool for assessing the awareness of AI among pre-service teachers. The scale includes not only the positive acceptance but also the critical avoidance aspects reflecting the multidimensional nature of the AI awareness. It is suggested that subsequent research uses diverse samples to validate the scale and implement it as an instrument to facilitate teacher education programs committed to the promotion of the responsible and effective use of AI in education.

Keywords: *Artificial intelligence awareness, Pre-service teachers, Scale development, Educational technology*

E-International Journal of Educational Research

Vol: 16, No: 2, pp. 155-171

Research Article

Received: 28.10.2025
Accepted: 16.12.2025

This paper was checked for plagiarism using iThenticate during the preview process and before publication.

Suggested Citation

Ersoy, M. & Yıldız, A. (2025). Artificial intelligence awareness scale for pre-service teachers, *E-International Journal of Educational Research, 16* (2), 155-171. DOI: https://doi.org/10.19160/e-ijer.1812597

INTRODUCTION

Artificial intelligence is attracting attention as a technology with widespread use in social, scientific, and educational fields. Artificial intelligence can be defined as the ability of computer systems to perform human-like cognitive processes, such as collecting and analyzing data, solving problems, making decisions, and learning (Kaplan & Haenlein, 2019). The term "artificial intelligence" was first used by John McCarthy in the 1950s (Dick, 2019). Since the early 21st century, it has become an indispensable part of daily life as well as industry, healthcare, the arts, and education (Hasan & Khidhir, 2023).

The effective use of artificial intelligence applications in education has significant potential primarily in terms of individualizing teaching/learning processes, increasing students' academic achievement, and reducing teachers' workload (Chiu, 2021; Darayseh, 2023; Xia et al., 2023). With artificial intelligence applications, students' performance can be monitored and learning deficiencies can be identified; individualized content can be presented according to their pace and needs (Mahmoud, 2020; Nuangchalerm & Prachagool, 2023). Artificial intelligence-supported teaching applications provide teachers with data-driven feedback about students, support them in classroom management, and thus strengthen teachers' pedagogical decisions (Chiu et al., 2022; İşler & Kılıç, 2021).

The increased prominence of distance learning applications during extraordinary circumstances such as pandemics and earthquakes highlights the importance of artificial intelligence in education (Özutku & Başboğaoğlu, 2022; Darayseh, 2023). In such periods, teachers' digital competencies, awareness of artificial intelligence applications, and their ability to use them become even more crucial (Williamson & Eynon, 2020). Successful use of artificial intelligence applications requires teachers to not only master these applications but also understand their pedagogical value (Holmes et al., 2022).

It is crucial for the successful integration of AI technology into education (Mahmoud, 2020). Awareness is a combination of individuals' knowledge, perception, and attention to a topic. In the context of education, awareness refers to the extent to which an educational stakeholder is familiar with various elements related to education and how they can use them pedagogically (Çetindamar et al., 2022).

Prospective teachers' awareness of AI encompasses the competencies of recognizing these technologies, knowing their own abilities and limitations, and using them for pedagogical purposes within the context of ethical rules (Kong et al., 2023). Prospective teachers with high AI awareness can provide personalized learning opportunities for students, increase students' interest and motivation, use applications in line with pedagogical goals, and, as a result, make teaching processes more effective (Çetindamar et al., 2022; Kong et al., 2023; Wang et al., 2022). Furthermore, increasing prospective teachers' awareness of AI has a significant impact on developing students' AI literacy (Lee et al., 2021).

There are many studies on the use of artificial intelligence in education. How and Hung (2019) stated that artificial intelligence applications help teachers provide meaningful learning experiences for students. Zhao et al. (2019) found that instruction supported by artificial intelligence helped students remember vocabulary, thereby increasing their academic achievement. Deveci Topal et al. (2021) determined that artificial intelligence-supported science instruction increased students' academic performance by stimulating their learning motivation. Akkaya et al. (2021) stated that a significant portion of undergraduate students have various reservations about the use of artificial intelligence.

There are limited studies in literature examining the awareness of teachers and prospective teachers regarding artificial intelligence. While existing literacy scales typically focus on measuring individuals' knowledge levels or technical competencies, attitude scales tend to prioritize affective orientations by assessing emotional tendencies or evaluations toward artificial intelligence. The AI awareness scale developed in this study transcends these limitations by offering a multidimensional construct that integrates elements such as knowledge accumulation, perception, and attention. In this context, AI awareness is defined as the ability to meaningfully interpret information regarding the existence, functionality, application areas, and effects of the technology. Consequently, it encompasses a holistic understanding that is not limited to technical knowledge but also includes ethical, social, and cultural implications. Previous studies have found that prospective teachers are aware of the potential benefits of artificial intelligence but lack sufficient knowledge and skills to use it (Çam et al., 2021; Yılmaz et al, 2021). Ferikoğlu and Akgün (2022) found that teachers have a general interest in artificial intelligence but lack sufficient experience in its use. These results may prevent teachers and prospective teachers from fully utilizing the potential of artificial intelligence in the classroom. Tekin (2023) found that prospective teachers are familiar with artificial intelligence tools but lack sufficient experience in their application. Based on these studies, identifying and developing prospective teachers' awareness of artificial intelligence is critical to the successful implementation of artificial intelligence in education. These findings support the development of a reliable and valid scale that can measure prospective teachers' awareness of artificial intelligence.

In summary, this study aims to develop a scale to determine teacher candidates' awareness of artificial intelligence. It is expected that the scale will increase prospective teachers' digital competence and support the widespread use of artificial intelligence applications in education.

METHOD

1-Research Model

This study, which aims to develop a valid and reliable scale to determine prospective teachers' awareness levels of artificial intelligence, was conducted using a survey model, a type of quantitative research. Quantitative research aims to analyze measurable phenomena and events using numerical data and make generalizations (Creswell, 2014). A survey model, on the other hand, examines individuals' perceptions, attitudes, and awareness on a specific topic (Büyüköztürk, 2024). Within this framework, prospective teachers' awareness of artificial intelligence was measured through the participants' own perceptions.

2-Sample

In determining the sample, convenience sampling, a purposive sampling method commonly used in scale development studies, was selected. Researchers who use this method tend to select the most easily accessible individuals, objects, and methods in the sample (Patton, 2002). In this context, a total of 300 volunteer prospective teachers, 229 females (76%) and 71 males (24%), who were receiving pedagogical formation training at the education faculty of a state university and at other faculties of the same university in the 2024-25 academic year participated in the study. Field (2018) describes a sample size of 300 as "good" in scale development studies. In this context, it can be said that the sample size of 300 reached in the study is at an acceptable level for conducting factor analyses (EFA and CFA).

3-Development of the Data Collection Tool

In line with the purpose of the research, the measurement tool developed to determine the awareness levels of prospective teachers towards artificial intelligence was created by following a systematic process.

In the first phase of the process, a conceptual framework was created. By reviewing the literature, the importance of the concept of artificial intelligence awareness on education stakeholders, especially pre-service teachers, was determined (Luckin et al., 2016). In order to create the item pool, scale development studies focusing on artificial intelligence were examined (Çağal, & Keskin, 2024; Ferikoğlu, & Akgün, 2022; Grassini, 2023; Süleymanoğulları et al., 2024). As a result of the review, 77 draft items were created. The item pool was developed by considering the conceptual dimensions of AI awareness: ethical (data privacy, bias), pedagogical (integration into teaching processes), technological competence, and social awareness. This approach aligns with the literature (Chen et al., 2025; Endsley & Jones, 2024; Holmes et al., 2022; Owsley & Greenwood, 2024) which recognizes that awareness is not limited to technical knowledge alone, but is a multi-layered construct consisting of cognitive, behavioral, and critical components. These items consist of statements aimed at measuring pre-service teachers' artificial intelligence awareness. The items were prepared as a 6-point Likert -type scale. The 6-point Likert -type technique is preferred to allow participants to express their opinions more clearly by avoiding the midpoint (Preston & Colman, 2000). Participants could express their opinions on each item on a scale of 1 to 6, ranging from "1 Strongly Disagree," "2 Disagree," "3 Somewhat Disagree," "4 Somewhat Agree," "5 Agree," and "6 Strongly Agree.". To ensure the content validity of the item pool during the initial phase of scale development, opinions were sought from 5 Subject Matter Experts (SMEs) specializing in Artificial Intelligence and Educational Technologies. These experts evaluated the extent to which the items reflected the theoretically identified dimensions of AI awareness (Practical Knowledge, Belief-Attitude, Association Ability, and Theoretical Knowledge), prior to any factor-analytic testing. To provide quantitative evidence for content validity, expert opinions were analyzed using Lawshe's Technique. The analysis revealed that the Content Validity Ratio (CVR) values for the items exceeded the minimum acceptable threshold of 0.99 established by Lawshe (1975). This process ensured that the scale encompasses not only theoretical knowledge but also ethical, pedagogical, and technical competence domains.

4-Data Collection Process

The data collection process was conducted in accordance with the research's ethical guidelines. Participants were informed in writing about the purpose of the study and the principles of voluntary participation, and they were informed that the data would be used solely for scientific purposes. Data were collected via an online form. Participants were given sufficient time to complete the form completely, and incomplete or incorrectly completed forms were excluded from the analysis.

5-Data Analysis

In the analysis of the collected data, data cleaning, missing data analysis, and descriptive statistics were performed. Exploratory factor analysis and confirmatory factor analysis were conducted to test the construct validity of the data obtained from the measurement tool. SPSS 26 was used to explore the underlying factor structure of the scale through exploratory factor analysis. Items with factor loadings below 0.40 or with high loadings on more than one factor were removed from the scale. The number of factors was determined using the Kaiser-Meyer-Olkin (KMO) test and the Bartlett test. It was determined based on the results of the Sphericity Test (Field, 2018). Confirmatory factor analysis The fit of the scale's theoretical factor structure to the data was tested using the AMOS program. The internal consistency of the scale was also tested using Cronbach's Alpha. Furthermore, structural validity was supported by calculating the average variance explanation for each factor. During the data analysis process, Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) were conducted sequentially on the dataset consisting of 300 participants to examine the construct validity of the scale. Although splitting the dataset is recommended in the literature for large samples, the analyses were performed on a single holistic dataset due to the sample size and data collection constraints in the current study. The suitability of the dataset for these analyses was evidenced by a 'perfect' level KMO coefficient (0.929) and a significant Bartlett's test ($p<0.01$). Despite the use of a single dataset, the goodness-of-fit indices obtained from the CFA (RMSEA = 0.086, CFI = 0.904) confirmed that the emerging two-factor structure is psychometrically robust and falls within acceptable limits.

6-Limitations

A methodological limitation of this study is that the sample size (N=300) was not sufficient to split the data into two independent subgroups (split-half method) for EFA and CFA analyses. Therefore, the factor structure and model fit of the scale were tested on the same dataset. Although the fit indices were at acceptable levels, it is recommended for future studies to re-test the scale through cross-validation studies on different and independent sample groups to enhance the generalizability of the results.

FINDINGS

To determine whether the data obtained were suitable for factorization, the Kaiser-Meyer-Olkin sampling adequacy measure and the Bartlett Test of Sphericity were used. The results of these measurements are presented in Table 1.

Table 1. *KMO and Bartlett Test Results of the Scale*

KMO sampling adequacy measurement		.929
Bartlett 's Sphericity Test	X^2	14904.950
	df	2485
	p	.000

When Table 1 is examined, it is seen that KMO is the result of the analysis. It is seen that the value is .929. Since this value is greater than .90, it can be said that the sampling adequacy is "perfect" (Field, 2018; Kalaycı, 2010; Karagöz, 2016). In addition, the result of the Bartlett test of sphericity is significant (X^2 (2485) = 14904.950 and p <.05). These two results show that the data obtained are suitable for factor analysis (Kalaycı, 2010).

Based on principal components analysis, followed by direct oblique rotation. This is because the principal components method is the most frequently and easily used method in practice, while direct oblique rotation is used when a relationship between factors is suspected (Büyüköztürk, 2024). In the first stage, the number of factors was determined without any limitation. However, three criteria were used to determine the final number of factors: eigenvalues, a line graph of the eigenvalues, and the proportion of variance explained.

Graphs drawn according to the eigenvalues of the factors can be used to determine the number of factors (Thompson, 2004). The line graph of the eigenvalues for the 71 items in the draft scale is shown in Figure 1.

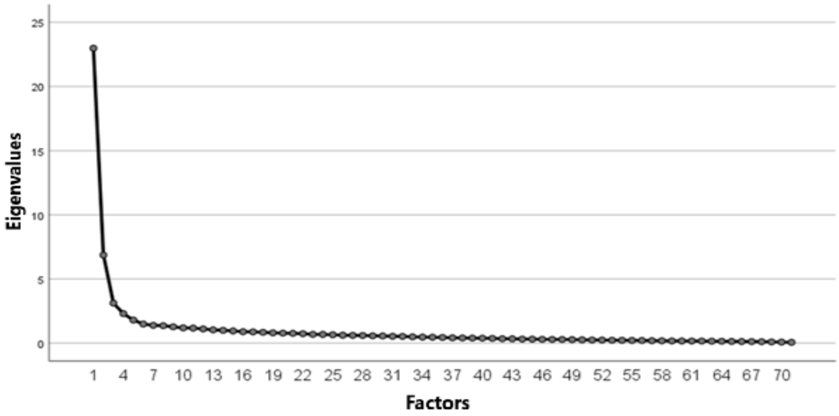

Figure 1. *Line graph of factor eigenvalues related to the scale*

The sharp drops in the slope plot and the beginning of the horizontal line are taken into account when determining the number of factors (Büyüköztürk, 2024). Examining Figure 1, it is seen that there is a rapid decrease after the second factor, and that the graph continues horizontally after the fourth factor. However, the number of factors has not yet been determined. Factors with eigenvalues of one or greater are considered stable (Köklü, 2002). The analysis identified 14 factors with eigenvalues greater than 1. The eigenvalues of each of these factors and their unique contributions to the total explained variance are presented in Table 2.

Table 2. *Eigenvalues of the factors and the variance ratios they explain*

Factors	Eigenvalues	Explained Variance (%)	Total Variance (%)
1	22.976	32.360	32.360
2	6.864	9.668	42.028
3	3.121	4.396	46.424
4	2.303	3.243	49.667
5	1.805	2.542	52.209
6	1.493	2.102	54.311
7	1.393	1.962	56.273
8	1.363	1.920	58.193
9	1.274	1.795	59.987
10	1.194	1.681	61.668
11	1.176	1.656	63.324
12	1.112	1.566	64.890
13	1.039	1.463	66.354
14	1.000	1.409	67.762

For factors to be significant, their individual variance explained must be at least 5% (Karaman, 2023). When Table 2 is examined, it is seen that the unique contributions of the factors, excluding the first two factors, to the explained variance ratio are less than 5%. Therefore, the possibility of a two-factor structure is strengthened. To clarify the number of factors, the explained variance ratio was also considered and it was found that the total variance explained by the first two factors was 42.028%. The explained variance ratio must be greater than 30% (Büyüköztürk, 2024). Considering the eigenvalues of the factors, the line graph of the eigenvalues, and the total variance explained ratios, the number of factors for the developed scale was determined to be two, and all subsequent operations were performed on the two-factor structure.

The next stage of the scale development study involved removing items that did not measure the same construction. As a first criterion, items with a common variance ratio of less than 0.30 were removed from the scale. As a second criterion, it was decided to retain items with factor loadings of 0.45 and above (Büyüköztürk, 2024). As a result of the processes carried out by taking all these criteria and the overlapping of items, 32 items were removed from the 71-item draft scale. As a result of the factor analysis conducted for the remaining 39 items, it was determined that the first factor contributed 32.989% and the second factor 14.686%, a total of 47.675% of the common variance. This rate is sufficient for multifactor designs (Tavşancıl, 2014).

Variance ratios, factor loadings, and factor-related eigenvalues for these items are presented in Table 3.

Table 3. *Statistical information for the first factor*

Item No	Initial Item No	Awareness Clause	Factor Loadings	Factor Variance
1	29	Artificial intelligence applications increase students' motivation.	0.624	0.383
2	41	Artificial intelligence could provide new economic opportunities for this country.	0.625	0.408
3	60	Artificially intelligent systems can outperform humans.	0.610	0.364
4	80	Artificial intelligence applications increase student participation in classes.	0.650	0.412
5	82	Artificial intelligence applications make the learning process easier for students.	0.707	0.496
6	90	Artificial intelligence applications can guide teachers.	0.678	0.460
7	97	Artificial intelligence can have positive impacts on human well-being.	0.725	0.526
8	98	Artificial intelligence is exciting.	0.711	0.511
9	99	Artificial intelligence could provide new economic opportunities for this country.	0.703	0.484
10	100	AI applications can outperform humans.	0.610	0.368
11	102	I like artificial intelligence.	0.730	0.563
12	114	I look forward to further developments in artificial intelligence.	0.672	0.470
13	115	Artificial intelligence offers solutions to many world problems.	0.607	0.360
14	126	Artificial intelligence is fun.	0.740	0.563
15	127	Artificial intelligence is interesting.	0.705	0.488
16	136	Artificial intelligence for education, service and research purposes.	0.703	0.497
17	137	I think more class time should be devoted to artificial intelligence in schools.	0.714	0.516
18	138	Artificial intelligence should be taught in school.	0.787	0.621
19	140	Artificial intelligence in my life in the future.	0.747	0.561
20	141	Artificial intelligence is necessary for everyone.	0.655	0.431
21	142	Artificial intelligence can make everything better.	0.615	0.394
22	143	As a teacher, I can accept artificial intelligence.	0.676	0.504
23	145	I can be a good friend with artificial intelligence.	0.605	0.429
24	146	I think it would be interesting to work in the field of artificial intelligence.	0.659	0.451
25	151	Lessons about artificial intelligence should be taught in school.	0.749	0.558
26	152	Every student should learn about AI in school.	0.749	0.553
	Eigenvalue	12,866		
Variance explained		32.99%		

An examination of Table 3 reveals that the factor loadings of the items in the first factor range from .605 to .787. The eigenvalue of the first factor is 12.866, contributing 32.99% of the total variance explained. It can be said that the items in the first factor are grouped under the heading **"AI**

Acceptance" The second factor of the scale consists of 13 items. The common variance ratios, factor loadings, and eigenvalues for this factor are presented in Table 4.

Table 4. *Statistical information for the second factor.*

Item No	Initial Item No	Awareness Clause	Factor Loadings	Factor Variance
1	77	I think that if artificial intelligence is used increasingly, people like me will be harmed.	0.667	0.440
2	103	Artificial intelligence poses a threat to people's job security.	0.645	0.407
3	104	I'm worried about AI applications collecting my personal data.	0.611	0.363
4	105	I feel uncomfortable when I think about the future uses of artificial intelligence.	0.729	0.525
5	107	Artificial intelligence is dangerous.	0.859	0.736
6	108	AI applications make many mistakes.	0.601	0.363
7	109	Artificial intelligence scary.	0.798	0.661
8	110	Instinctively dislike AI.	0.657	0.523
9	116	I prefer technologies that do not involve artificial intelligence.	0.550	0.325
10	117	I’m afraid of artificial intelligence.	0.799	0.679
11	119	Artificial intelligence creates problems instead of solving them.	0.622	0.404
12	123	I prefer to avoid technologies that rely on artificial intelligence.	0.595	0.401
13	124	AI applications will increase unemployment by putting people out of work.	0.636	0.396
	Eigenvalue	5,727		
Variance explained		14.69%		

An examination of Table 4 reveals that the factor loadings of the items in the second factor range from .550 to .859. The eigenvalue of the first factor is 5.727, contributing 14.69% of the total variance explained. It can be said that the items in the second factor are grouped under the heading "AI Avoidance".

1- Findings Regarding Reliability

Cronbach's alpha reliability test was conducted to test the reliability of the scale. The reliability value for the entire scale was calculated as 0.892, 0.954 for AI Acceptance factor, and 0.903 for AI Avoidance. These results, all greater than 0.70, indicate that the scale, including its two factors (AI Acceptance and AI Avoidance), is a reliable measurement tool (Büyüköztürk, 2024; Dunn et al., 2014).

The significant difference between the top 27% and bottom 27% groups, based on the total scores obtained from the scale, was also examined. The analysis was conducted using an independent samples t-test, and the results are shown in Table 5.

Table 5. *T-test for the scale and its factors*

	Groups	N	Avg.	ss	t	df	p
First factor	Upper group	81	130.47	8.56	26.216	160	.000
	Subgroup	81	82.00	14.27			
Second factor	Upper group	81	56.77	7.31	32.774	160	.000
	Subgroup	81	24.81	4.86			
The entire scale	Upper group	81	172.87	13.34	24.418	160	.000
	Subgroup	81	121.12	13.64			

Table 5 is examined, it is seen that there is a significant difference between the groups in favor of the upper group, both in the entire scale and in two factors ($p<0.05$). A significant difference between the groups indicates that the internal consistency of the scale is high (Büyüköztürk, 2024).

2- Confirmatory Factor Analysis

To determine the fit values of the scale, which consists of a total of 39 items and two factors, a CFA was conducted using the AMOS program after the EFA. The path diagram of the CFA is shown in Figure 2.

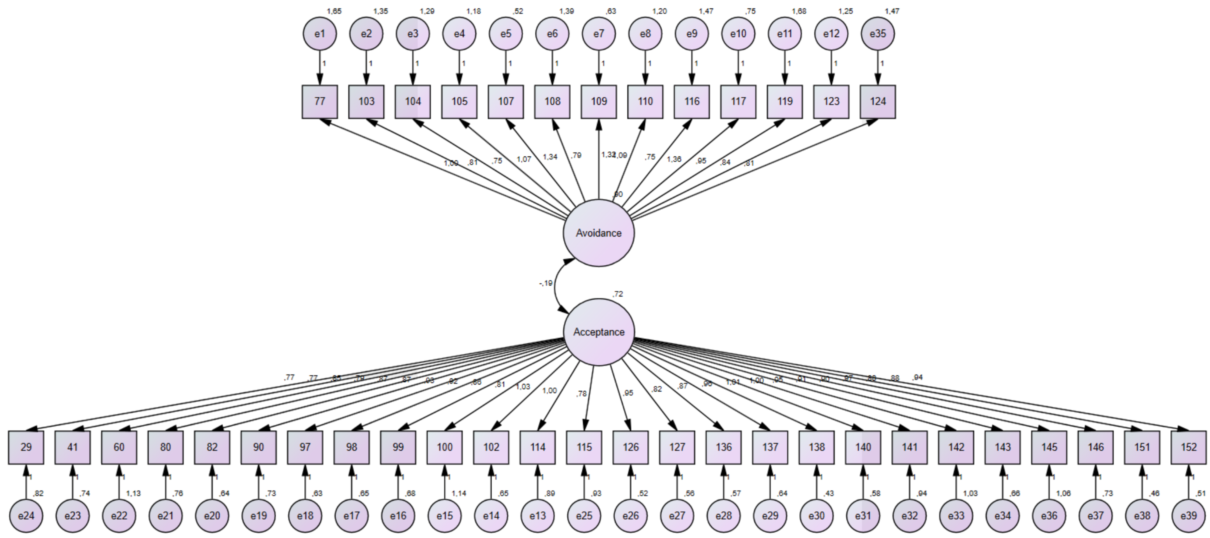

Figure 2. *Factor structure of the developed scale*

An examination of Figure 2 reveals that the factor loadings and error variance values of the items in the developed measurement tool are at acceptable levels. The fit values obtained from the CFA analysis are also presented in Table 6.

Table 6. *Fit index reference values and CFA results*

Fit Index	Estimate	Good Fit	Acceptable Fit	Conclusion
χ2/df	3,217	0≤ χ2/df<2	2≤ χ2/df<5	Acceptable
GFI	0.909	0.95 ≤GFI≤ 1.00	0.90 ≤GFI< 0.95	Acceptable
NFI	0.907	0.95≤NFI≤1.00	0.90 ≤NFI< 0.95	Acceptable
CFI	0.907	0.95 ≤CFI≤ 1.00	0.90 ≤CFI< 0.95	Acceptable
TLI	0.904	0.95 ≤ CFI ≤ 1.00	0.90 ≤ CFI ≤ 0.95	Acceptable
RMSEA	0.086	0≤RMSEA<0.05	0.05≤RMSEA≤0.10	Acceptable

An examination of Table 6 reveals that all fit values obtained for the prospective teachers' artificial intelligence awareness scale are at acceptable levels. Thus, the two-factor structure of the measurement tool was confirmed.

DISCUSSION, CONCLUSION AND RECOMMENDATIONS

In this study, a 39-item scale was developed to measure preservice teachers' awareness of artificial intelligence. The scale consists of two factors representing the main dimensions of AI awareness: AI Acceptance (26 items) and AI Avoidance (13 items). During the scale development process, a literature review was conducted, an item pool was created, and the measurement tool was finalized in light of the opinions of field experts. The main results obtained regarding the construct validity and reliability of the scale can be summarized as follows.

The suitability of the data for factor analysis was confirmed by the KMO sampling adequacy measure (.929) and the Bartlett test of sphericity (χ^2 = 14.904,950; df = 2485; p = .000). The KMO value was above .90, indicating that the sample was "perfectly" adequate for factor analysis (Büyüköztürk, 2024; Field, 2018).

In the first stage, 14 factors with eigenvalues of one or greater were identified; however, eigenvalues, scree plots and original explained variance When the criteria were evaluated together, it was concluded that the most appropriate structure was two-factor. At the end of the elimination process from the first 71-item draft, 32 items were removed; in the analyses conducted on the remaining 39 items, the first factor was determined as 26 items and the second factor as 13 items. Factor loadings on the first factor were observed to range from .605 to .787, and .550 to .859 for the second factor. These two factors were interpreted as "AI Acceptance" and "AI Avoidance" respectively. It was calculated that the two factors together explained 47.68% of the common variance, with 32.99% accounted for by the AI Acceptance factor and 14.69% by the AI Avoidance factor. In addition, the eigenvalue of AI Acceptance factor was calculated as 12.866, and the eigenvalue of AI Avoidance factor was calculated as 5.727. These values show that the two-factor structure successfully reveals the latent structure of the scale (Tavşancıl, 2014).

The findings indicate that pre-service teachers exhibit both AI Acceptance and AI Avoidance attitudes toward artificial intelligence (AI), reflecting a complex and multidimensional awareness of AI applications. This multidimensional structure aligns with the framework proposed by Nazaretsky et al. (2022), who examined teachers' confidence in and attitudes toward AI through a similarly multifaceted lens. AI awareness is defined as an individual's knowledge of the existence, functioning, application areas, and effects of AI technologies, as well as the ability to interpret this information meaningfully in daily life (Owsley & Greenwood, 2024). This awareness extends beyond technical knowledge and requires a holistic understanding that encompasses ethical, social, and cultural implications (Owsley & Greenwood, 2024). The developed scale conceptualizes AI awareness through two core dimensions, operationalised as two factors: AI Acceptance and AI Avoidance. Enabling pre-service teachers to evaluate both the benefits and the potential risks or ethical concerns of AI is essential for fostering conscious and effective technology use. Accordingly, educational programs should be designed to incorporate content addressing both positive and negative aspects of AI (Luckin, 2018; Teo et al., 2015).

Scale scores show that individuals with high levels of AI Acceptance demonstrate positive attitudes toward the usefulness of AI in education and emphasize the importance of its conscious use. In contrast, those with high AI Avoidance scores highlight potential risks, biases, and issues related to control. The literature further indicates that pre-service teachers' and students' interest in AI is directly associated with their usage knowledge and perceived usefulness (Banaz & Demirel, 2024).

The AI Acceptance dimension begins with pre-service teachers' cognitive recognition of AI's educational benefits and potential. This factor captures their interest levels, perceived usefulness, usage knowledge, and conscious attitudes toward AI. Consistent with this, studies on AI literacy and attitude scales show that teachers perceive AI as a tool that supports learning processes, which in turn enhances technology adoption (Gökçe-Tekin, 2025; Demirdağ et al., 2025). The factor also reflects the development of positive attitudes toward AI (e.g., finding it exciting or enjoyable), which is directly linked to emotional awareness—defined as conscious attention to one's internal states (Chen et al., 2025; Endsley & Jones, 2024). Positive emotional awareness facilitates acceptance and adoption. The items additionally relate to individuals' cognitive understanding of what AI is and how it works (Dolgikh, 2024), as acceptance typically follows recognition of AI's benefits (e.g., economic opportunities, increased student motivation). This supports the view that awareness fundamentally involves possessing knowledge about an object and cognitively processing this information to derive meaning (Dolgikh, 2024).

The AI Avoidance dimension, on the other hand, represents a deeper and more critical aspect of AI Awareness, constituting its critical component (Chen et al., 2025). This dimension reflects pre-service teachers' anxieties, risk perceptions, and evaluations of the potential negative effects of AI. Avoidance is based not only on technical knowledge but also on a holistic understanding of the ethical, social, and cultural impacts of AI (Owsley & Greenwood, 2024). Pre-service teachers exhibit anxiety and avoidance tendencies because they can evaluate the social consequences of AI, such as unemployment, personal data collection, and the possibility of errors (Chen et al., 2025). These findings show that pre-service teachers are aware of issues such as ethics, data privacy, bias, and social impacts (Bayram, 2025; Çam et al., 2021). Moreover, warnings exist that uncontrolled use of AI may exacerbate labor-related and ethical problems (Akkaya et al., 2021; Holmes et al., 2022). This critical evaluation triggers the conscious attention (Situational Awareness) individuals develop toward environmental stimuli (AI risks) (Chen et al., 2025; Endsley & Jones, 2024) and leads to negative emotional reactions such as anxiety or fear

(Emotional Awareness), ultimately resulting in avoidance behavior. In conclusion, the Acceptance and Avoidance dimensions successfully reflect the multidimensional structure of AI Awareness, which encompasses not only technical knowledge (Cognitive) (Dolgikh, 2024) but also emotional/attitudinal acceptance of the opportunities offered by AI and critical/emotional reactions (avoidance) to potential risks (Chen et al., 2025).

Internal consistency of the scale Tested with Cronbach's Alpha, α = .892 for the entire scale; α = .954 for AI Acceptance factor and α = .903 for AI Avoidance factor. These values indicate a high level of internal consistency for both the overall scale and its two factors (AI Acceptance and AI Avoidance) (Büyüköztürk, 2024; DeVellis & Thorpe, 2021). The "Artificial Intelligence Readiness Scale," developed by Ramazanoğlu and Akın (2024), also provides high reliability values and effectively measures teachers' preparedness levels for artificial intelligence applications.

Comparisons between the "Top 27%" and "Bottom 27%" groups, which were created by taking into account the scores from the entire scale, were conducted using independent samples t-tests; significant differences were found in favor of the top group for both each factor and the total scale ($p < .05$). This result supports the discriminatory power of the scale (Büyüköztürk, 2024). Comparisons of the top and bottom groups demonstrate the scale's ability to distinguish differences between individuals at different levels. This result increases the scale's usability in educational assessments. Furthermore, a systematic review by Lintner (2024) discusses the discriminatory properties of scales measuring teachers' knowledge and attitudes toward artificial intelligence, highlighting the importance of such tools.

The findings of the developed scale are consistent with existing research on AI awareness in the literature. Previous studies have generally evaluated teachers' and students' attitudes toward AI at two extremes: "positive view of technology" and "anxiety/negative perceptions" (Bayram, 2025; Gökçe-Tekin, 2025). The scale developed within this framework comprehensively measures both advantages and risks through its positive and negative view dimensions. When considered together, these results demonstrate that the 39-item scale is an effective tool for assessing pre-service teachers' awareness of AI. The positive view dimension measures participants' perceptions of the benefits of AI in education and daily life, their adaptation to technological innovations, and their interest in AI applications. Participants who scored high on this dimension indicate a positively developed awareness of AI.

Research findings indicate that prospective teachers' awareness of artificial intelligence has developed to varying degrees across cognitive and affective dimensions. A significant correlation was observed between positive and negative views, indicating that prospective teachers are able to evaluate artificial intelligence with a more conscious and critical perspective. Furthermore, the scale's validity and reliability analyses support the scientific credibility of the results.

Based on the findings of this research, the following recommendations can be offered:

- - Develop structured AI-focused courses at both undergraduate and graduate levels that introduce preservice teachers to foundational AI concepts, practical applications, and the broader ethical landscape surrounding emerging technologies.
- Implement school-based professional learning initiatives and psycho-educational programs designed to cultivate responsible AI use, reduce misconceptions, and strengthen teachers' confidence in navigating AI-supported learning environments.
- - Integrate specialized modules such as “AI Ethics, Data Protection, and Algorithmic Fairness” into teacher education curricula and in-service training to address heightened anxiety in the Avoidance dimension, particularly concerns related to privacy, surveillance, and job displacement.
- - Offer practice-oriented workshops on “AI Integration in Instructional Design and Classroom Practice” to channel the strong motivation observed in the Adoption dimension into concrete pedagogical skills and hands-on experimentation.
- - Conduct cross-validation studies with diverse and independent samples from various regions and subject areas to overcome the single-dataset limitation and reinforce the structural validity and generalizability of the scale.

- - Employ mixed-method research designs that combine quantitative results with qualitative insights—including interviews, focus groups, or reflective narratives—to uncover the underlying drivers of teachers' perceptions. In-depth interviews with individuals scoring high on the Avoidance dimension would be especially valuable for identifying sources of resistance.

REFERENCES/KAYNAKÇA

Akkaya, B., Özkan, A., & Özkan, H. (2021). Artificial intelligence anxiety (AIA) scale: Adaptation to Turkish, validity and reliability study. *Alanya Academic View*, *5*(2), 1125–1146. https://doi.org/10.29023/alanyaakademik.833668

Banaz, E., & Demirel, O. (2024). Examining the artificial intelligence literacy of Turkish teacher candidates according to different variables. *Dokuz Eylül University Buca Faculty of Education Journal*, (60), 1516–1529. https://doi.org/10.53444/deubefd.1461048

Bayram, V. (2025). Artificial intelligence ethics: A scale development study. *International Journal of Economic and Administrative Academic Research*, *5*(1), 123–148.

Büyüköztürk, Ş. (2024). *Data analysis handbook for social sciences*. Pegem Publishing.

Chen, X., Chen, R. R., Wei, S., & Davison, R. M. (2025). Herd behavior in social commerce: Understanding the interplay between self-awareness and environment-awareness. *Internet Research*, *35*(3), 947–980. https://doi.org/10.1108/INTR-05-2022-0359

Chiu, T. K. (2021). A holistic approach to the design of artificial intelligence (AI) education for K-12 schools. *TechTrends*, *65*(5), 796–807. https://doi.org/10.1007/s11528-021-00637-1

Chiu, T. K., Xia, Q., Zhou, X., Chai, C. S., & Cheng, M. (2022). Systematic literature review on opportunities, challenges, and future research recommendations of artificial intelligence in education. *Computers and Education: Artificial Intelligence*, *4*, 100118. https://doi.org/10.1016/j.caeai.2022.100118

Creswell, J. W. (2014). *Research design: Qualitative, quantitative, and mixed methods approaches*. SAGE Publications.

Çağal, M. T., & Keskin, Y. M. (2024). Development of artificial intelligence and robot technology perception scale. *Journal of Reasoning*, *7*(2), 138–157. https://doi.org/10.33817/muhakeme.1507672

Çam, M. B., Çelik, N., Turan Güntepe, E., & Durukan, Ü. G. (2021). Determining the awareness of prospective teachers about artificial intelligence technologies. *Mustafa Kemal University Journal of Social Sciences Institute*, *18*(48), 263–285.

Çetindamar, D., Kitto, K., Wu, M., Zhang, Y., Abedin, B., & Knight, S. (2022). Explicating AI literacy of employees at digital workplaces. *IEEE Transactions on Engineering Management*, *71*, 810–823. https://doi.org/10.1109/TEM.2021.3138503

Darayseh, A. (2023). Acceptance of artificial intelligence in teaching: Science teachers' perspective. *Computers and Education: Artificial Intelligence*, *4*, 100132. https://doi.org/10.1016/j.caeai.2023.100132

Demirdağ, S., Ünver, A. K., & Gürez, I. (2025). Development of a teacher artificial intelligence attitude scale: A validity and reliability study. *Asian Studies*, *9*(33), 1–22. https://doi.org/10.31455/asya.1712885

DeVellis, R. F., & Thorpe, C. T. (2021). *Scale development: Theory and applications*. SAGE Publications.

Deveci Topal, A., Dilek Eren, C., & Kolburan Geçer, A. (2021). Chatbot application in a 5th grade science course. Education and Information Technologies, 26(5), 6241-6265. https://doi.org/10.1007/s10639-021-10627-8

Dick, S. (2019). Artificial Intelligence. *Harvard Data Science Review, 1*(1). https://doi.org/10.1162/99608f92.92fe150c

Dolgikh, S. (2024). Self-awareness in natural and artificial intelligent systems: A unified information-based approach. *Evolutionary Intelligence*, *17*(5), 4095–4114. https://doi.org/10.1007/s12065-024-00974-z

Dunn, T. J., Baguley, T., & Brunsden, V. (2014). From alpha to omega: A practical solution to the pervasive problem of internal consistency estimation. *British Journal of Psychology*, *105*(3), 399–412.

Endsley, M. R., & Jones, D. G. (2024). Situation awareness-oriented design: Review and future directions. *International Journal of Human–Computer Interaction*, *40*(7), 1487–1504. https://doi.org/10.1080/10447318.2024.2318884

Ferikoğlu, D., & Akgün, E. (2022). An investigation of teachers' artificial intelligence awareness: A scale development study. *Malaysian Online Journal of Educational Technology*, *10*(3), 215–231. https://doi.org/10.52380/mojet.2022.10.3.407

Field, A. (2018). *Discovering statistics using IBM SPSS statistics*. SAGE Publications.

Gökçe-Tekin, Ö. (2025). Artificial intelligence literacy scale development and validation study. *Western Anatolian Educational Sciences Journal*, *16*(1), 418–434. https://doi.org/10.51460/baebd.1609636

Grassini, S. (2023). Development and validation of the AI attitude scale (AIAS-4): A brief measure of general attitude toward artificial intelligence. *Frontiers in Psychology*, *14*, 1191628. https://doi.org/10.3389/fpsyg.2023.1191628

Hasan, D. F., & Khidhir, A. M. (2023). Towards deep enhancement learning techniques using fuzzy logic: A survey. *International Journal of Electrical and Computer Engineering (IJECE)*, *13*(3), 3041–3055. http://doi.org/10.11591/ijece.v13i3.pp3041-3055

Holmes, W., Porayska-Pomsta, K., Holstein, K., Sutherland, E., Baker, T., & Rodrigo, M. M. T. (2022). Ethics of AI in education: Towards a community-wide framework. *International Journal of Artificial Intelligence in Education*, *31*, 611–631. https://doi.org/10.1007/s40593-021-00239-1

How, M. L., & Hung, W. L. D. (2019). Educing AI-thinking in science, technology, engineering, arts, and mathematics (STEAM) education. *Education Sciences*, *9*(3), 184. https://doi.org/10.3390/educsci9030184

İşler, B., & Kılıç, M. (2021). The use and development of artificial intelligence in education. *New Media Electronics Journal*, *5*(1), 1–11. https://doi.org/10.17932/IAU.EJNM.25480200.2021/ejnm_v5i1001

Kalaycı, Ş. (2010). *Multivariate statistical techniques with SPSS applications*. Asil Publishing Distribution.

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, *62*(1), 15–25.

Karagöz, Y. (2016). *Applied statistical analysis in SPSS 23 and AMOS 23*. Nobel Academic Publishing.

Karaman, M. (2023). Exploratory and confirmatory factor analysis: A conceptual study. *International Journal of Economics and Administrative Sciences*, *9*(1), 47–63.

Kong, S. C., Cheung, W. M. Y., & Zhang, G. (2023). Evaluating an artificial intelligence literacy program for developing university students' conceptual understanding, literacy, empowerment and ethical awareness. *Educational Technology and Society*, *26*(1), 16–30.

Köklü, N. (2002). *Açıklamalı istatistik terimleri sözlüğü*. Nobel.

Lawshe, C. H. (1975). A quantitative approach to content validity. *Personnel Psychology*, *28*(4), 563–575.

Lee, I., Ali, S., Zhang, H., DiPaola, D., & Breazeal, C. (2021, March). Developing middle school students' AI literacy. *In Proceedings of the 52nd ACM Technical Symposium on Computer Science Education* (pp. 191–197).

Lintner, A. (2024). A case study on critical thinking and artificial intelligence in middle school. *Turkish Online Journal of Educational Technology-TOJET*, *23*(4), 1–7.

Luckin, R. (2018). *Enhancing learning and teaching with technology: What the research says*. UCL IOE Press.

Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). *Intelligence unleashed: An argument for AI in education*. Pearson.

Mahmoud, A. (2020). Artificial intelligence applications: An introduction to education development in the light of Corona virus pandemic COVID 19 challenges. *International Journal of Research in Educational Sciences*, *3*(4), 171–224. https://doi.org/10.29009/ijres.3.4.4

Nazaretsky, T., Gökçay, D., & Silva, M. (2022). Preparing educators for an AI-driven world: Strategies for developing AI literacy in schools. *Journal of Digital Learning in Teacher Education*, *38*(3), 223–237. https://doi.org/10.1234/jdlte.2022.38.3.223

Nuangchalerm, P., & Prachagool, V. (2023). AI-driven learning analytics in STEM education. *International Journal of Research in STEM Education*, *5*(2), 77–84.

Owsley, C. S., & Greenwood, K. (2024). Awareness and perception of artificial intelligence operationalized integration in news media industry and society. *AI & Society*, *39*(1), 417–431. https://doi.org/10.1007/s00146-022-01386-2

Özutku, R., & Başboğaoğlu, U. (2022). The scale of online learning perception: The COVID-19 effect on shifting higher education to distance learning in Turkey. *E-Uluslararası Pedandragoji Dergisi*, *2*(1), 17–32.

Patton, M. Q. (2002). *Qualitative research and evaluation methods*. SAGE Publications.

Preston, C. C., & Colman, A. M. (2000). Optimal number of response categories in rating scales: Reliability, validity, discriminatory power, and respondent preferences. *Acta Psychologica*, *104*(1), 1–15.

Ramazanoğlu, M., & Akın, T. (2025). AI readiness scale for teachers: Development and validation. *Education and Information Technologies*, *30*(6), 6869–6897. https://doi.org/10.1007/s10639-024-13087

Süleymanoğulları, M., Özdemir, A., & Tekin, A. (2024). Artificial intelligence scale: A validity and reliability study. *Education Science and Sports*, *6*(1), 13–27.

Tavşancıl, E. (2014). *Tutumların ölçülmesi ve SPSS ile veri analizi*. Ankara, Turkey: Nobel Akademi Publishing.

Tekin, N. (2023). Artificial intelligence in education: A content analysis on the trends of research from Turkey. *Necmettin Erbakan University Ereğli Faculty of Education Journal*, *5*(Special Issue), 387–411. https://doi.org/10.51119/ereegf.2023.49

Teo, T., Fan, X., & Du, J. (2015). Technology acceptance among pre-service teachers: Does gender matter? *Australasian Journal of Educational Technology*, *31*(3).

Thompson, B. (2004). *Exploratory and confirmatory factor analysis: Understanding concepts and applications*. American Psychological Association.

Wang, B., Rau, P., & Yuan, T. (2022). Measuring user competence in using artificial intelligence: Validity and reliability of artificial intelligence literacy scale. *Behaviour and Information Technology*, *42*(9), 1324–1337. https://doi.org/10.1080/0144929x.2022.2072768

Williamson, B., & Eynon, R. (2020). Historical threads, missing links, and future directions in AI in education. *Learning, Media and Technology*, *45*(3), 223–235. https://doi.org/10.1080/17439884.2020.1798995

Xia, Q., Chiu, T. K., & Chai, C. S. (2023). The moderating effects of gender and need satisfaction on self-regulated learning through artificial intelligence (AI). *Education and Information Technologies*, *28*(7), 8691–8713.

Yılmaz, Y., Yılmaz, D. U., Yıldırım, D., Korhan, E. A. & Kaya, D. Ö. (2021). Opinions of health sciences faculty students on artificial intelligence and the use of artificial intelligence in health. *Suleyman Demirel University Journal of Health Sciences*, *12*(3), 297–308.

Zhao, L., Chen, L., Liu, Q., Zhang, M., & Copland, H. (2019). Artificial intelligence-based platform for online teaching management systems. *Journal of Intelligent and Fuzzy Systems*, *37*(1), 45–51. https://doi.org/10.3233/JIFS-179062

Conflict of Interest Declaration: The authors declare no potential conflicts of interest related to the research, authorship and/or publication of this article.

Support/Funding Information: The authors have not received any financial support for the research, authorship and/or publication of this article.

Ethics Declaration: For this research, ethical permission was obtained from the decisions of Sivas Cumhuriyet University, Educational Sciences Research Ethics Board dated 28.11.2025 and numbered 642906. We, as the authors of the study, have produced an original study; the preparation, data collection, analysis and that the principles and rules of scientific ethics have been complied with at all stages, including the presentation of information; this all data and information obtained within the scope of the study are cited and these sources are included in the bibliography that no changes have been made to the data used, that the study was conducted in accordance with the Committee on Publication Ethics (COPE) and declare that ethical duties and responsibilities are respected.

Declaration of Use of Artificial Intelligence: The artificial intelligence system named "Gemini" was utilized to ensure the research's compliance with grammar rules and linguistic consistency.

Öğretmen Adaylarına Yönelik Yapay Zekâ Farkındalık Ölçeği

Doç. Dr. Mustafa ERSOY
Sivas Cumhuriyet Üniversitesi - Türkiye
ORCID: 0000-0002-7320-8844
mersoy@cumhuriyet.edu.tr

Doç. Dr. Ahmet YILDIZ
Sivas Cumhuriyet Üniversitesi - Türkiye
ORCID: 0000-0002-9149-5859
ahmet.yildiz@cumhuriyet.edu.tr

Özet

Bu çalışmanın amacı öğretmen adaylarının yapay zekâ (AI) farkındalığını değerlendirmek için geçerli ve güvenilir bir ölçüm aracı oluşturmaktır. Her ne kadar YZ teknolojileri giderek eğitim bağlamlarına entegre ediliyor olsa da literatür taraması, olumlu yönelimler ve kaygılar da dahil olmak üzere öğretmenlerin çok boyutlu farkındalığını ortaya koyan kapsamlı araçların hala eksik olduğunu göstermektedir. Genel olarak mevcut ölçekler ağırlıklı olarak teknik bilgi veya tutumlara odaklandığından, öğretmen adayları arasında bütünsel YZ farkındalığının ölçülmesine ilişkin bir boşluk doldurulamamıştır. Araştırma nicel tarama modelinin kullanıldığı bir ölçek geliştirme çalışmasıdır. Araştırmacılar, 2024-2025 eğitim-öğretim yılında gönüllü olarak bir devlet üniversitesine kayıt yaptıran 300 öğretmen adayından veri topladı. Kolayda örneklemeyi kullandılar. Başlangıçta, kapsamlı bir literatür taramasına ve uzman değerlendirmelerine dayanarak 71 madde bir araya getirildi. İçerik geçerliliği uzman bir panel aracılığıyla sağlandı ve yapı geçerliliği Açımlayıcı Faktör Analizi (EFA) ve Doğrulayıcı Faktör Analizi (CFA) aracılığıyla doğrulandı. İç tutarlılık güvenirliği Cronbach alfa katsayıları ile ölçülmüştür. EFA sonuçlarına göre maddelerin çıkarılmasının ardından 39 maddelik iki faktör tespit edilmiştir. Bu faktörler Yapay Zekâ Kabulü (26 madde) ve Yapay Zekâdan Kaçınma (13 madde) olarak yorumlandı. İki faktörlü model toplam varyansın yaklaşık %47,68'ini açıklamaktadır. CFA sonuçları modelin iyi uyum indekslerine sahip olduğunu doğrulamıştır. Ölçeğin geneli ve iki alt boyutu, güvenilirlik analizleriyle de doğrulanan, 0,89'un üzerindeki Cronbach alfa değerlerinin gösterdiği gibi çok iyi bir iç tutarlılığa sahipti. Çalışma bulguları, geliştirilen aracın öğretmen adayları arasında YZ farkındalığını değerlendirmek için psikometrik olarak geçerli bir araç olduğuna dair kanıt sunmaktadır. Ölçek yalnızca olumlu kabulü değil, aynı zamanda YZ farkındalığının çok boyutlu doğasını yansıtan kritik kaçınma yönlerini de içermektedir. Sonraki araştırmaların, ölçeği doğrulamak ve eğitimde YZ'nın sorumlu ve etkili kullanımını teşvik etmeye yönelik öğretmen eğitimi programlarını kolaylaştıracak bir araç olarak uygulamak için çeşitli örnekleri kullanması önerilmektedir.

Anahtar Kelimeler: *Yapay zekâ farkındalığı, Öğretmen adayları, Ölçek geliştirme, Eğitim teknolojisi*

E-Uluslararası Eğitim Araştırmaları Dergisi

Cilt: 16, No: 2, ss. 155-171

Araştırma Makalesi

Gönderi: 28.10.2025
Kabul: 16.12.2025

Bu çalışma ön inceleme sürecinde ve yayımlanmadan önce iThenticate yazılımı ile taranmıştır.

Önerilen Atıf

Ersoy, M. ve Yıldız, A. (2025). Artificial intelligence awareness scale for pre-service teachers, E-International Journal of Educational Research, *16* (2), 155-171. DOI: https://doi.org/10.19160/e-ijer.1812597

Genişletilmiş Özet

Problem: Yapay zekâ (YZ) hızla genişleyen bir teknoloji olarak bilgisayar sistemlerinin veri toplama ve analiz etme, problem çözme, karar verme ve öğrenme gibi insana benzer bilişsel süreçleri gerçekleştirebilme kapasitesi sayesinde eğitim ortamları da dâhil birçok alanda etkisini artırmaktadır (Kaplan & Haenlein, 2019; Dick, 2019). Eğitim alanında YZ uygulamalarının öğretim/öğrenme süreçlerini bireyselleştirme, akademik başarıyı artırma ve öğretmenlerin iş yükünü azaltma gibi açılardan önemli bir potansiyel taşıdığı vurgulanmaktadır (Chiu, 2021; Darayseh, 2023; Xia et al., 2023). Bununla birlikte, olağanüstü durumlarda (ör., pandemi ve deprem gibi) uzaktan eğitimin öne çıkması, öğretmenlerin dijital yeterlikleri ile YZ uygulamalarına ilişkin farkındalık ve kullanım kapasitelerinin önemini daha görünür hâle getirmiştir (Özutku & Başboğaoğlu, 2022; Williamson & Eynon, 2020). Bu çerçevede, YZ'nin eğitimde etkili biçimde kullanılabilmesi için öğretmenlerin yalnızca araçları tanımaları değil, aynı zamanda bu araçların pedagojik değerini anlamaları ve etik boyutlarını değerlendirebilmeleri gerekmektedir (Holmes et al., 2022).

Çalışmanın problem alanı, öğretmen adaylarının YZ farkındalığının çok boyutlu bir yapı olmasına karşın, bu yapıyı bütüncül biçimde ölçmeye yönelik psikometrik açıdan güçlü ölçme araçlarının sınırlı olmasıdır. Farkındalık; bilgi, algı ve dikkat bileşenlerini içeren bir kavram olarak ele alınmakta, eğitim bağlamında ise paydaşların bir konuya ilişkin tanışıklık düzeylerini ve pedagojik kullanım biçimlerini kapsayan bir çerçeve sunmaktadır (Çetindamar et al., 2022). Öğretmen adaylarının YZ farkındalığı; teknolojileri tanıma, bu teknolojilerin olanaklarını ve sınırlılıklarını değerlendirme ve pedagojik amaçlarla etik ilkeler doğrultusunda kullanabilme yeterliklerini kapsamaktadır (Kong et al., 2023). Yüksek düzeyde YZ farkındalığına sahip öğretmen adaylarının, öğrencilere kişiselleştirilmiş öğrenme fırsatları sunabildikleri ve öğretim süreçlerini daha etkili hâle getirebildikleri bildirilmektedir (Çetindamar et al., 2022; Wang et al., 2022). Ayrıca öğretmen adaylarının YZ farkındalığının artması, öğrencilerin YZ okuryazarlığının geliştirilmesine de katkı sağlayabilmektedir (Lee et al., 2021).

Bununla birlikte alanyazın, öğretmen adaylarının YZ'nın potansiyel yararlarının farkında olmalarına rağmen, uygulamaya dönük bilgi ve becerilerde yetersizlik yaşayabildiklerini göstermektedir (Çam et al., 2021; Tekin, 2023). Öğretmenlerin YZ'ya ilgi duymakla birlikte kullanım deneyimlerinin sınırlı kaldığına dair bulgular da mevcuttur (Ferikoğlu & Akgün, 2022). Bu durum, eğitimde YZ'nın etkili ve sorumlu biçimde kullanılmasının önünde bir engel oluşturabilmekte dolayısıyla öğretmen adaylarının YZ farkındalık düzeylerini güvenilir biçimde belirlemeye dönük ölçme araçlarına olan ihtiyacı güçlendirmektedir. Bu gerekçelerle çalışmanın amacı, öğretmen adaylarının YZ farkındalık düzeylerini belirlemeye yönelik geçerli ve güvenilir bir ölçek geliştirmektir. Araştırmada geliştirilen ölçeğin, öğretmen adaylarının dijital yeterliklerini destekleyerek eğitimde YZ uygulamalarının yaygınlaşmasına katkı sağlaması beklenmektedir.

Yöntem: Araştırma, nicel araştırma yaklaşımı kapsamında yer alan tarama modeliyle yürütülmüştür. Tarama modeli, belirli bir konuya ilişkin algı, tutum ve farkındalığın sistematik biçimde incelenmesini mümkün kılmaktadır (Creswell, 2014; Büyüköztürk, 2024). Bu bağlamda öğretmen adaylarının YZ farkındalıkları, katılımcıların öz-bildirimlerine dayalı olarak ölçülmüştür. Araştırmanın örneklemi uygun örnekleme yöntemiyle belirlenmiş; ölçek geliştirme çalışmalarında sıklıkla tercih edilen bu yöntemle erişilebilir katılımcılar üzerinden veri toplanmıştır (Patton, 2002).

Çalışmaya 2024–2025 akademik yılında bir devlet üniversitesinin eğitim fakültesinde ve pedagojik formasyon alan diğer fakültelerde öğrenim gören toplam 300 gönüllü öğretmen adayı katılmıştır, katılımcıların 229'u kadın (%76), 71'i erkektir (%24). Ölçek geliştirme bağlamında 300 kişilik örneklemin "iyi" düzeyde olduğu ve faktör analizi için yeterli kabul edildiği belirtilmektedir (Field, 2018).

Ölçek geliştirme sürecinde, önce kavramsal çerçeve oluşturulur daha sonra alanyazın taraması temelinde bir madde havuzu geliştirilmiştir. Bu kapsamda etik (veri gizliliği, önyargı), pedagojik (öğretim süreçlerine entegrasyon), teknolojik yeterlik ve sosyal farkındalık gibi boyutları dikkate alınarak 77 taslak madde hazırlanmıştır. Maddeler, katılımcıların orta noktaya yönelimini azaltmak ve görüşleri daha net ayrıştırmak amacıyla 6'lı Likert tipi derecelendirme biçiminde düzenlenmiştir (Preston & Colman, 2000).

Kapsam geçerliğinin sağlanması için YZ ve Eğitim Teknolojileri alanında uzman 5 öğretim elemanının görüşüne başvurulmuş, uzman değerlendirmeleri Lawshe tekniğiyle nicel olarak analiz edilmiştir (Lawshe, 1975). Bu süreç sonucunda taslak ölçek 71 madde üzerinden analize alınmış, madde eleme süreci sonunda nihai ölçek 39 maddeye indirgenmiştir.

Veri analizinde öncelikle veri temizleme ve betimsel istatistikler yapılmış, ardından yapı geçerliğini test etmek amacıyla Açımlayıcı Faktör Analizi (AFA) ve Doğrulayıcı Faktör Analizi (DFA) uygulanmıştır. AFA, ölçeğin temel faktör yapısını ortaya koymak için SPSS ile yürütülmüş, faktör yükü düşük (örn. < .40) ya da birden çok faktöre yüksek yüklenen maddeler ölçekten çıkarılmıştır. DFA ise AFA ile ortaya çıkan yapının doğrulanması amacıyla AMOS programı kullanılarak gerçekleştirilmiştir.

İç tutarlılık güvenirliği Cronbach alfa katsayısı ile incelenmiştir. Ayrıca çalışmada EFA ve CFA analizlerinin aynı veri setinde yapılması, örneklem büyüklüğü ve veri toplama kısıtları bağlamında yöntemsel bir sınırlılık olarak belirtilmiştir.

Bulgular: Ölçek verilerinin faktör analizine uygunluğunu değerlendirmek amacıyla Kaiser–Meyer–Olkin (KMO) örneklem yeterliği ve Bartlett Küresellik Testi kullanılmıştır. Bulgular, KMO değerinin .929 olduğunu ve örneklem yeterliğinin "mükemmel" düzeyde değerlendirilebileceğini göstermiştir (Field, 2018; Kalaycı, 2010; Karagöz, 2016). Bartlett testi sonucunun da anlamlı olduğu ($\chi^2(2485)=14904.950$, $p<.05$) belirlenmiştir. Bu iki gösterge, veri setinin faktör analizi için uygun olduğunu ortaya koymaktadır.

AFA sürecinde, faktör sayısının belirlenmesinde özdeğerler, yamaç-birikinti grafiği ve açıklanan varyans oranları birlikte değerlendirilmiştir. İlk aşamada özdeğeri 1'in üzerinde olan çok sayıda faktör görülmekle birlikte, faktörlerin açıklanan varyans katkıları ve grafik eğilimleri dikkate alındığında iki faktörlü yapının daha uygun olduğu sonucuna ulaşılmıştır. Bu süreç sonunda ölçeğin "Yapay Zekâ Kabulü" ve "Yapay Zekâdan Kaçınma" isimli iki faktörlü bir yapı sergilediği belirlenmiştir.

"Yapay Zekâ Kabulü" boyutu 26 maddeden oluşmakta ve açıklanan varyansın %32.99'unu temsil etmektedir, bu boyuttaki maddelerin faktör yükleri .605 ile .787 arasında değişmektedir. Kabul boyutu, YZ'nın eğitimsel işlevlerine (ör. motivasyonu artırma, katılımı destekleme, öğrenmeyi kolaylaştırma) ilişkin olumlu algılar ve YZ'a yönelik ilgi/benimseme eğilimleriyle ilişkilidir.

"Yapay Zekâdan Kaçınma" boyutu ise 13 maddeden oluşmakta, açıklanan varyansın %14.69'unu karşılamakta ve faktör yükleri .550 ile .859 aralığında yer almaktadır. Kaçınma boyutu, kişisel verilerin toplanması endişeleri, geleceğe yönelik rahatsızlık, iş güvencesi tehdidi algısı ve YZ'yı tehlikeli bulma gibi risk algılarına dayalı tepkileri içermektedir.

Güvenilirlik analizi sonuçları, ölçeğin iç tutarlılığının yüksek olduğunu ortaya koymuştur. Ölçeğin tamamı için Cronbach alfa .892; "Yapay Zekâ Kabulü" için .954 ve "Yapay Zekâdan Kaçınma" için .903 olarak hesaplanmıştır.

Ölçeğin doğrulayıcı faktör analizi sonuçları, iki faktörlü modelin kabul edilebilir uyum indekslerine sahip olduğunu göstermiştir ($\chi^2/df=3.217$; GFI=.909; NFI=.907; CFI=.907; TLI=.904; RMSEA=.086). Bu bulgu, AFA ile elde edilen yapının doğrulandığını ve ölçeğin yapısal geçerliliğinin desteklendiğini göstermektedir.

Ayrıca ölçeğin ayırt ediciliğini değerlendirmek amacıyla üst %27 ve alt %27 gruplar arasındaki fark incelenmiş, hem ölçek toplam puanında hem de alt boyutlarda üst grup lehine anlamlı farklılıklar bulunmuştur ($p<.05$). Bu sonuçlar, ölçeğin farklı farkındalık düzeylerindeki bireyleri ayırt edebilme gücünü ve iç tutarlılığını desteklemektedir.

Genel olarak bulgular, öğretmen adaylarının YZ farkındalığının tek boyutlu bir yapı olmadığını, hem fırsatlara yönelik kabul edici eğilimleri hem de risk ve etik kaygılarla ilişkili kaçınmacı eğilimleri birlikte içeren iki boyutlu bir özellik sergilediğini göstermektedir. Bu iki boyutun birlikte ölçülmesi, öğretmen adaylarının YZ'yı pedagojik ve toplumsal sonuçlarıyla birlikte değerlendirebilme kapasitelerinin anlaşılması açısından önem taşımaktadır.

Öneriler: Bu araştırmada geliştirilen Yapay Zekâ Farkındalık Ölçeği, öğretmen adaylarının YZ'ya ilişkin kabul ve kaçınma boyutlarını bütüncül biçimde ölçebilen, geçerli ve güvenilir bir araç olarak değerlendirilebilir. Bu bulgu doğrultusunda, öğretmen yetiştirme programlarında YZ'ya yönelik içeriklerin planlanması ve izlenmesi için ölçekten yararlanılması önerilmektedir. Özellikle "kabul" boyutundaki yüksek motivasyonun pedagojik uygulamaya dönüştürülebilmesi için, öğretmen adaylarına YZ'nın öğretim tasarımında ve sınıf içi uygulamalarda nasıl kullanılabileceğini hedefleyen uygulamalı etkinlikler ve ders içerikleri sunulabilir.

Öte yandan "kaçınma" boyutunda belirlenen kaygılar (ör. veri gizliliği, iş güvencesi, YZ'nın tehlikeli algılanması) dikkate alınarak öğretmen eğitimi programlarında etik, veri koruma ve sorumlu kullanım temalı modüllerin güçlendirilmesi önerilmektedir. Böylelikle kaçınma eğiliminin yalnızca belirsizlik ve endişeye dayalı değil, bilgiye ve eleştirel değerlendirmeye dayalı bilinçli bir farkındalığa evrilmesi desteklenebilir.

Araştırmanın yöntemsel sınırlılığı olarak EFA ve CFA'nın aynı örneklem üzerinde yürütülmesi vurgulanmıştır, bu nedenle gelecekte yapılacak çalışmalarda ölçeğin farklı üniversitelerde, farklı branşlarda ve bağımsız örneklemlerde yeniden test edilmesi, ölçeğin genellenebilirliğini artıracaktır.