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Adaptation of Artificial Intelligence Literacy Scale into Turkish: A Sample of Pre-Service Teachers

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Abstract

This study aims to adapt the Al-LS translated by Wang et al. (2022) into Turkish and create a scale suitable for assessing the AI-L of pre-service teachers. The study used the survey method within the scope of the quantitative method. The sample of the study consisted of 440 pre-service teachers (pre-school and primary pre-service teachers) from a state university in the Eastern Anatolia Region of Turkey. The original scale consists of 12 items, 4 factors, and a 5-point Likert-type structure. In the first stage, we conducted translation studies to assess the language validity of the adapted scale. Then, the data collected from the part of the sample determined for EFA (Exploratory Factor Analysis) were analyzed. The results show that the adapted scale preserves the original scale structure. The data collected from the part of the sample designated for CFA (Confirmatory Factor Analysis) was also analyzed. The results of the analysis show that the scale has acceptable and good-fit indices. In terms of reliability, Cronbach's Alpha reliability coefficients show that the scale has a reliable structure. The results of the analysis indicate that the scale adapted to Turkish has a valid and reliable structure.

Keywords: Artificial intelligence, artificial intelligence literacy (AI-L), Al literacy, scale adaptation

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Introduction

In this so-called "Age of Artificial Intelligence" (Davenport & Ronanki, 2018), the competencies required to survive and adapt to this era are becoming increasingly critical skills. With the advent of artificial intelligence (AI) technology, our lives have changed dramatically. The proliferation of smart devices and applications developed with AI integration has increased the knowledge level of ordinary users about AI, causing them to become more aware of AI (Wang et al., 2022). Many researchers have emphasized that there is an urgent need for individuals to develop the skills to use AI in the future (Kandlhofer et al., 2016; Su, 2018; Tarafdar et al., 2019) and that high AI competence can have a positive impact on human-AI interactions (Jarrahi, 2018; Stembert & Harbers, 2019). Despite summarizing the basic competencies required to use AI technology (Long & Magerko, 2020), a standard framework or practical tool to measure them is still lacking. To fill this gap, Wang et al. (2022) proposed the concept of "AI literacy" to describe individuals' competencies in using AI technology (Wang et al., 2022).

Artificial intelligence literacy

Due to the complexity of the concept of intelligence and its use in a wide variety of fields, the definition of AI remains unclear (Jiang et al., 2022). However, AI-L is defined as having the competence to understand basic knowledge and concepts. Burgsteiner et al. (2016) and Kandlhofer et al. first used this term (Burgsteiner et al., 2016; Kandlhofer et al., 2016). Long and Magerko (2020) characterize this literacy as the capacity of individuals to critically assess, articulate, and cooperate with AI (Long & Magerko, 2020). They also emphasize a set of skills necessary to ensure the effective use of AI in daily life.

AI literacy is necessary for the workforce to make the most of AI and develop a harmonious relationship with the technology (Kong et al., 2024). Wang et al. (2022) define AI-L as the ability to recognize, use, and evaluate AI products in accordance with ethical standards (Wang et al., 2022). Scholars generally recognize literacy as a fundamental skill that includes the ability to read, write, and communicate (Searle, 2020). The new generation's literacy skills are necessary for integration into the digital world. In this context, Chenqi and Guoqing (2020) emphasized the concept of “smart literacy” and expanded this term to include digital and AI-L (Chenqi et al., 2023). Information literacy is associated with the ability of individuals to search, evaluate, and use information effectively (Lanning & Gerrity, 2022; Nzomo et al., 2021; Seifi et al., 2020). 21st-century teachers are able to transfer new knowledge and skills to students by using smart technology with these technical skills (Almazroa & Alotaibi, 2023; González-Pérez & Ramírez-Montoya, 2022; Kennedy & Sundberg, 2020). The rapid proliferation of AI technologies makes it imperative for teachers to consider ethical issues in how to use and integrate these technologies into their teaching processes (Adams et al., 2023; Akgun & Greenhow, 2022; Lavidas et al., 2022; D. T. K. Ng et al., 2023). As a result, AI literacy includes critical skills necessary for individuals to effectively manage the processes of learning and living with AI-supported technologies (Kong et al., 2024; Long & Magerko, 2020; Markauskaite et al., 2022; Zhang, 2022).

Pre-service teachers' artificial intelligence literacy

AI literacy has rapidly gained importance as one of the critical skills of the 21st century (Muthmainnah et al., 2022). Long and Magerko (2019) define AI-L as the ability of individuals to critically analyze AI technologies, communicate with them, and collaborate effectively with them. This skill has an interdisciplinary nature that intersects with information and digital literacy (Ng, 2012). The increasing role of AI in education requires teachers to master these technologies (Ahmad et al., 2021; Aravantinos et al., 2024; Kim, 2024). The rapid development of educational technologies necessitates pre-service teachers' ability to integrate AI into pedagogical processes (Ahmad et al., 2021). Increasing pre-service teachers' professional competencies by using AI technologies also enables them to provide a more qualified education to students (Kirschner & Selinger, 2003).

The wide range of applications of these technologies and the demand for advanced programming skills have led to the spread of AI education to different levels, despite its initial limitation to computer science departments (Ayanwale et al., 2024). In this setting, pre-service teachers must develop the competencies necessary for the efficient utilization of AI in pedagogical practices (Lameras & Arnab, 2021). Advances in technological devices and age-appropriate software provide opportunities for pre-service teachers to improve the learning experiences of young learners (Aravantinos et al., 2024; Ayanwale et al., 2024). This further increases the necessity of pre-service teachers knowing and understanding AI literacy in their future classrooms. Teachers with AI-L will both equip their students to interact safely with these technologies and integrate AI seamlessly into their teaching processes (Ayanwale et al., 2024; Shah, 2023). AI-L requires teachers to learn not only how to use technology but also its ethical use (Ng et al., 2023). Since the use of AI in education brings about various ethical issues, pre-service teachers must gain awareness of these issues and increase their ability to develop solutions (Holmes & Porayska-Pomsta, 2023). Ethical and responsible technology use plays a critical role in the healthy integration of AI into educational processes. AI-L enables pre-service teachers to direct this technology in accordance with pedagogical purposes and contributes significantly to their professional development (Ayanwale et al., 2024). Teachers with AI literacy can respond more effectively to the educational needs of the future by gaining a competitive advantage in the digitalized education world (Aravantinos et al., 2024; Ng et al., 2023; Zhang, 2022).

Today, AI has profound effects in many areas, from education to health, economy to social life (Ahmad et al., 2021). For this reason, it is of great importance for individuals to gain artificial intelligence literacy in order to use technology consciously and effectively (Wang, 2022). Especially in education, the acquisition of AI literacy by pre-service teachers plays a critical role in terms of both learning how to use these technologies and preparing the students they will be educating for the digital world in the future (Ng et al., 2023).

In this study, the AI-LS adapted for pre-service teachers is considered a tool that will contribute to the effective use of technology in education. The scale aims to determine the extent to which pre-service teachers can use AI technologies effectively and serves to increase their awareness and skills in this field. In addition, taking into account the linguistic and cultural differences specific to Turkish in the scale adaptation will increase the validity and reliability of the scale and provide more robust data on the integration of AI technologies in education.

Although some scales for AI literacy have been translated into Turkish, there are not enough studies on whether they fully meet the needs of pre-service teachers (Çelebi et al., 2023). Preservice teachers have different requirements in terms of technology integration and digital pedagogical competencies compared to other professional groups. This situation reveals the necessity of adapting AI-LS specifically for pre-service teachers. Existing scales usually target the general population or different professional groups but do not fully reflect the pedagogical needs of pre-service teachers in their educational processes (Çelebi et al., 2023).

Çelebi et al. (2023) adapted the AI-LS developed by Wang et al. into Turkish (Çelebi et al., 2023). However, this study focused on adults under the age of 20 and over 40 and did not include an application for pre-service teachers. Similarly, Eniş-Erdoğan and Ekşioğlu's (2024) adaptation study was conducted with a sample of 226 teachers, and data were collected through both face-to-face and online surveys (Google Form) (Erdoğan & Ekşioğlu, 2024). In contrast, this study was conducted with a sample of pre-service teachers (440 participants), and the validity and reliability of the scale were tested by taking into account the specific pedagogical needs of this group. This difference emphasizes the critical importance of providing pre-service teachers with AI-L in their professional development process. Since AI-L supports pedagogical practices associated with the effective use of educational technologies, this adaptation study conducted on pre-service teachers is thought to make a unique and meaningful contribution to the literature. In addition, the fact that our study had a large sample size and the data were collected entirely by face-to-face method increased the reliability and general validity of the results obtained. This provided a more robust statistical basis for the Turkish adaptation of the scale. In conclusion, our study provides original and important findings on language validity and scale adaptation processes in a sample of pre-service teachers and differs significantly from previous studies in this field.

This study aims to adapt the translated AI-LS into Turkish by Wang et al. (2022) for pre-service teachers in Turkey, and to develop a valid and reliable scale for measuring their AI-L. In this context, the validity and reliability of the scale were tested in terms of both linguistic adaptation and psychometric properties. The aim is to provide the Turkish education system with a tool that can reliably measure the AI-L levels of pre-service preschool and primary school teachers. This evaluation of pre-service teachers' AI knowledge and skills allows for the improvement of educational programs. In this context, the following question was sought to be answered. *"What are the validity and reliability evidences of the AI-LS adapted to Turkish culture?"*

Method

Research Model

This study aims to create a scale that can be used to determine the AI-L levels of pre-service teachers by adapting a measurement tool developed to examine the AI-L levels of adults in Turkish culture. In this direction, scale adaptation, validity, and reliability studies were conducted. The scale adaptation process includes language validity, content validity, construct validity, and reliability analysis (Yasir, 2016). The two-way translation method translated the scale items into Turkish during the language validity stage, and expert opinions ensured cultural adaptation. Experts evaluated the adequacy of the scale items in terms of scope for content validity. Construct validity was tested with confirmatory factor analysis (CFA), and Cronbach's alpha coefficient was calculated for reliability. These validity and reliability studies were designed to answer the research problem and aim to reveal whether the scale is a valid and reliable measurement tool suitable for Turkish culture. The research was conducted within the framework of the survey method, which is a descriptive model. This method collected and analyzed the participants' current AI-L levels over a specific period. The survey model aims to describe certain characteristics of a group and to reveal the current situation (Büyüköztürk, 2018). The data collected were examined in alignment with the aim of the research, demonstrating the validity and reliability of the AI-LS adapted to Turkish culture.

Process

For the adaptation, validity, and reliability studies of the AI-LS', the necessary information about the scale and permission for use were obtained by contacting the responsible author, one of the researchers who developed the scale, via e-mail. After the scale permission, the adaptation studies of the scale were started by obtaining the permission of the ethics committee of Fırat University. The adaptation of the scale went through a two-stage linguistic translation process. First, two academics with a PhD in the English language and literature translated the scale from English into Turkish. Next, they examined the translation and made linguistic corrections. Afterward, four academics who adapted the scale came together to form the final version of it. In the pilot application phase, the scale was first applied with a small group of 36 pre-service teachers, and missing or incomprehensible items were corrected during this application. The revised scale was compared to the original scale, revealing no significant differences across the items. A total of 440 pre-service teachers received the final 12-item scale.

Study Groups

The study employed convenience sampling, a non-random sample method, to establish the study groups among pre-service instructors at Elazığ Fırat University. Convenience sampling consists of individuals that the researcher can easily reach and collect data from (Robinson, 2014). Therefore, the research scope entailed the formation of three distinct study groups.

Table 1.
Demographic data of the participants

Variable	Category	EFA Group		CFA Group	
		N	%	N	%
Gender	Female	169	80.48	204	92,3
	Male	52	19.52	15	7.7
Department	Pre-School Education	116	52.49	101	46.12
	Primary Classroom Education	105	47.51	118	53.88

We conducted the language translation study on the first group, which consisted of 36 people. The second group consisted of 221 participants, and exploratory factor analysis (EFA) was conducted with the data collected from this group. The third group consisted of 219 participants, and this group was used for confirmatory factor analysis (CFA). These candidates were volunteer students studying in the departments of preschool and classroom education at Fırat University, Faculty of Basic Education. Since participation in the study was completely voluntary, no coercive reminder was made. Table 1 displays the demographic information of the pre-service teachers who participated in the study.

Data Collection Tool

Wang et al., (2022) developed the AI-LS to aid individuals in deepening their understanding of AI (Wang et al., 2022). This scale was based on theoretical frameworks for measuring AI literacy and literature considered important in this field by the researchers. Wang et al. (2022) emphasized that digital literacy and AI literacy are not the same concepts and stated that digital literacy contents are not suitable for directly defining AI literacy. Therefore, Wang et al. (2022) assert that while digital literacy tools may not be sufficient to directly measure AI literacy, they can contribute to the development of AI literacy through their theoretical framework. Given the challenges in defining AI literacy, Wang et al. (2022) identified the technological-cognitive-ethical model and the KSAVE model. These models, comprising knowledge (Knowledge-K), skills (Skills-S), attitudes (Attitudes-A), values (Values-V), and ethics (Ethics-E) components, are deemed suitable for this field. Since the KSAVE model offers a more general framework beyond digital skills, it can inclusively assess AI literacy skills (Wang et al., 2022). According to this framework, AI literacy is defined as the ability to be aware of, apply, and use AI technologies, perform tasks competently, analyze data critically, and evaluate this data considering ethical responsibilities (Wang et al., 2022).

Wang et al. (2022) developed the AI-LS to improve the understanding of artificial intelligence (Wang et al., 2022). In this study, the ‘AI-LS' developed by Wang et al. (2022) was used to determine pre-service teachers' AI-L. This scale consists of seven Likert scale items (1: strongly disagree-7: strongly agree). The scale consists of 4 factors with 3 items each. The authors define AI literacy as the ability to be aware of and comprehend AI technology in practical applications; to be able to apply and use AI technology to perform tasks competently; and to be able to analyze, select, and critically evaluate data and information provided by AI while promoting awareness of one's own personal responsibilities and respect for mutual rights and obligations (Wang et al., 2022). From this point of view, an item pool of 65 items ranging from 10 to 24 under each dimension was created in the first stage. For this part of the study, five subject-matter experts classified the 65 items under the four specified factors. The items that did not fit into these factors were asked to be added to the uncategorized category. An item that at least four of the five experts categorized similarly was considered to address a construct. A total of 42 items met this criterion, while 15 items were either unclassified or misclassified by one domain expert. Furthermore, more than one domain expert categorized or misclassified 23 items, resulting in their exclusion from further steps. Experts reviewed the items selected in the first step and rated the extent to which each item corresponded to the construct on a three-point Likert scale (1 = no fit, 2 = moderate fit, and 3 = good fit). Experts accepted an item if at least three of them rated it as a 'good fit' and none rated it as a 'poor fit'. Based on this criterion, the researchers eliminated 10 items and selected 31 items for the remaining steps. Finally, three experts participated in a focus group to complete the items, improve their wording, and enhance their format. The authors interviewed the other two experts separately who could not participate in the focus group. The authors eliminated two items and rephrased 14 items after completing the focus group discussion and interviews. All experts suggested and approved the addition of one more item. Thus, the researchers obtained a 31-item scale consisting of nine items related to AI awareness, nine items related to AI use, six items related to AI evaluation, and seven items related to AI ethics. Data from two different samples were collected in the final version of the form: Sample 1, consisting of 601 data points, was used for item reduction, and Sample 2, consisting of 325 data points, was used for model validation. After finalizing the items in the scale, we conducted CFA using the data from Sample 2, and determined the scale to have a structure consisting of 14 items and 4 factors. The CFA analysis conducted using the data from Sample 2 confirmed that the theoretical model used for AI literacy is acceptable, with good fit indices (CFI = 0.99, TLI = 0.99, GFI = 0.98, RMSEA = 0.01, SRMR = 0.03). Cronbach's alpha for the final version of the scale was 0.83, while the alpha values for the four constructs were 0.73, 0.75, 0.78, and 0.73, respectively. Although all four constructs exhibited reliability above 0.70, the instrument itself scored above 0.80, indicating that the instrument as a whole is more reliable than the individual constructs.

Data Analysis

In order to determine the psychometric properties of the 'Artificial Intelligence Literacy Scale' (AILS-TR) adapted to Turkish, validity and reliability analyses were conducted with the data obtained from a total of 440 pre-service teachers. In the analyses conducted with this data set, exploratory factor analysis (EFA) was first applied, and the factor structure of the scale was examined using this method. EFA is an appropriate analysis method for exploring the structure of the scale and determining the factors (Yang, 2005). The goal was to confirm the factor structure unique to the pre-service teacher sample. Confirmatory Factor Analysis (CFA) was conducted with the data obtained from a different sample of 219 pre-service teachers to determine whether the obtained structure was valid or not. CFA is an appropriate analysis to ensure the validation of the identified factor structure in another sample (Brown & Moore, 2012). The data were analyzed with SPSS 22 and AMOS 23 packages. In CFA, model fit indices (RMSEA, NFI, CFI, IFI) were analyzed to determine whether the factor structure of the scale was valid and reliable in the general sample. These fit indices are necessary for verifying the structure of the scale because they show how well the model fits the data (Marsh et al., 2004). The validity studies analyzed factor eigenvalues, the slope-accumulation graph of these values, and the variance ratios of the factors. According to the results obtained from EFA, model fit indices were tested with CFA to confirm the factor structures (Asparouhov & Muthén, 2009). The model was tested with accepted criteria in RMSEA (Root Mean Square Error Approximation), NFI (Normed Fit Index), CFI (Comparative Fit Index), and IFI (Incremental Fit Index) fit indices. Within the scope of reliability studies, the internal consistency coefficient (α) was calculated for the total scale and each factor. According to Tavakol and Dennick (2011), the internal consistency coefficient, also known as Cronbach's alpha, serves as an appropriate reliability analysis to evaluate if the scale consistently measures the intended construct (Tavakol & Dennick, 2011). Cronbach's alpha values calculated for each factor in the scale were used to assess whether the sub-dimensions of the scale were reliable.

Findings

Exploratory Factor Analysis (EFA) Findings

For the construct validity analysis of the scale, the suitability of the data set was first examined. Various criteria specified in the literature were considered to evaluate the suitability of the data set. These criteria include checking the normal distribution of the data set, the suitability of the sample size, and the adequacy of the sample (KMO and Barlett's Sphericity Test) (Field, 2013; Pallant, 2020). Field (2013), examined the normality assumptions of the data of 221 pre-service teachers for EFA. The skewness and kurtosis values of the data were calculated. Skewness and kurtosis values should be between +1.96 and -1.96 (Can, 2017). The analysis revealed that the skewness value of the items in the data set ranged between -.260 and .701, and the kurtosis value ranged between -1.005 and .577. The obtained values showed that the data met the normal distribution criteria. Therefore, it was concluded that the data set followed a normal distribution. Then, Bartlett's test of sphericity and KMO statistics were used to test the suitability of the data set for EFA. The analysis determined that the data set was suitable for factor analysis (Barlett's Test of Sphericity: $\chi 2$=1361.313; df=66; p=.000<.05; KMO=.806). Here, a KMO value greater than.70 indicates that the data set is large enough to allow factorization (Bryman & Cramer, 2002), and according to the Bartlett Sphericity Test, the data set is sufficient for multivariate normal distribution criteria. Principal component analysis was used in EFA. Additionally, factor analysis involved the application of rotation techniques (Tabachnick et al., 2013). The researchers commonly used the varimax vertical rotation technique to examine scale structures with two or more factors by rotating the items (Büyüköztürk, 2018). Heckler (1996) determined the lower cut-off points of the calculated factor loadings as.40, while Costello & Osborne (2019)set the common factor variance at .40. In addition, it was ensured that the load differences of the item loadings between different subscales were at least .10 (Menard, 2002). The exploratory factor analysis revealed a 4-factor structure for the scale, with eigenvalues greater than 1.00. Table 2 displays the results of the exploratory factor analysis.

Table 2
Exploratory Factor Analysis Findings

	Factors and Item Factor Loadings				Co-Variance
Item No	*Factor1*	*Factor2*	*Factor3*	*Factor4*	
1	.917				.890
2**	.719				.737
3	.904				.865
4		.717			.705
5**		.793			.760
6		.757			.801
7			.838		.805
8			.794		.748
9			.852		.803
10				.738	.722
11**				.710	.740
12				.783	.776
Explained Variance	21.213	19.124	16.799	15.793	
Total Variance %	21.213	40.337	57.136	72.928	

p*<.001 ** *Items are reverse-coded.

As seen in Table 2, the factor loadings of the scale ranged between .719 and .917 in Factor 1, .717 and .793 in Factor 2, .794 and .852 in Factor 3, and .710 and .783 in Factor 4. The common variances of the scale varied between .737 and .890 in Factor 1, .705 and .801 in Factor 2, .748 and .805 in Factor 3, and .722 and .776 in Factor 4. As a result of EFA, a 12-item scale with factor loadings ranging between .710 and .850 and common variances ranging between .705 and .890 was obtained. Figure 1 shows the slope accumulation graph for the scale.

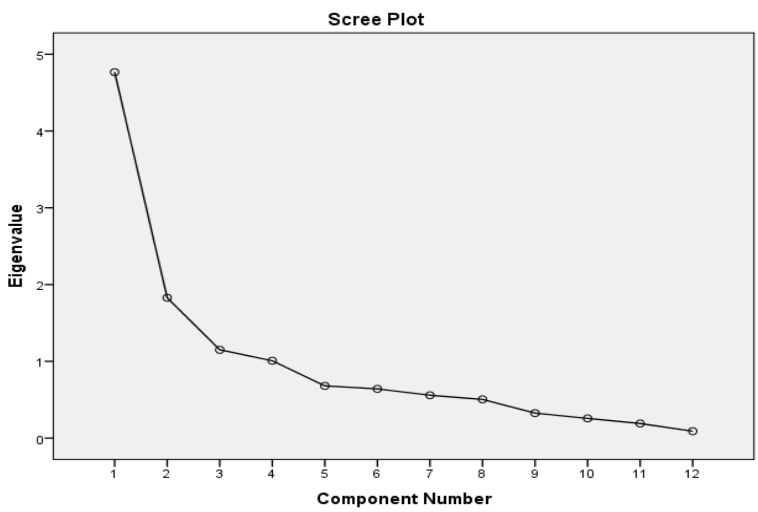

Figure 1. Slope Accumulation Graph of the Scale

The agglomeration points in the slope accumulation graph shown in Figure 1 confirmed the 4-factor structure. Thus, the 12-item, 4-factor, 7-point Likert-type scale was found to meet the prescribed conditions without removing any item from the original scale (Cattell, 1966). Confirmatory Factor Analysis (CFA) Findings To confirm the 4-factor scale structure determined by EFA, we conducted CFA using a separate data set. For this reason, the accuracy of the structure was examined with CFA using data obtained from 219 more pre-service teachers. CFA was developed as an analysis technique to measure the construct validity of the scale (Büyüköztürk, 2018). First, skewness and kurtosis values were calculated to examine the normality of the data set. The skewness and kurtosis values of the data were calculated. Skewness and kurtosis values should be between +1.96 and -1.96 (Can, 2017). Skewness values vary between -1.268 and .580, and kurtosis values vary between -.926 and 1.375. These values show that the data meet the normal distribution criteria. Accordingly, the data set was accepted as normally distributed, and CFA analysis was conducted. The analysis examined the fit indices of the four-factor structure. Table 3 displays the fit indices of the scale, including $\chi2/df$, root mean square error of approximation (RMSEA), adjusted goodness of fit index (AGFI), goodness of fit index (GFI), comparative fit index (CFI), tucker-lewis index (TLI), normalized fit index (NFI), and root mean square of standardized residuals (SRMR) (Schermelleh-Engel et al., 2003).

Table 3.
Fit Indices and Value Ranges

Index	Good Fit	Acceptable Fit	The fit indices in this study
$\chi2/df$	$0 \leq \chi2/df \leq 2$	$2 \leq \chi2/df \leq 3$	.943
RMSEA	$0 \leq$ RMSEA $\leq 0,05$	$0.05 \leq$ RMSEA ≤ 0.10	.018
AGFI	$0.90 \leq$ AGFI ≤ 1.00	$0.85 \leq$ AGFI ≤ 0.90	.947
GFI	$0.95 \leq$ GFI ≤ 1.00	$0.90 \leq$ GFI ≤ 0.95	.997
CFI	$0.97 \leq$ CFI ≤ 1.00	$0.95 \leq$ CFI ≤ 0.97	.997
TLI	$0.95 \leq$ TLI ≤ 1.00	$0.90 \leq$ TLI ≤ 0.95	.996
NFI	$0.95 \leq$ NFI ≤ 1.00	$0.90 \leq$ NFI ≤ 0.95	.967
SRMR	$0 \leq$ SRMR ≤ 0.05	$0.05 \leq$ SRMR ≤ 0.10	.0317

(Brown & Moore, 2012; Tabachnick et al., 2013)

As seen in Table 3, the fit indices revealed that the model was compatible. Figure 2 shows the path diagram based on the asymptotic covariance matrix calculated from the results of the confirmatory factor analysis.

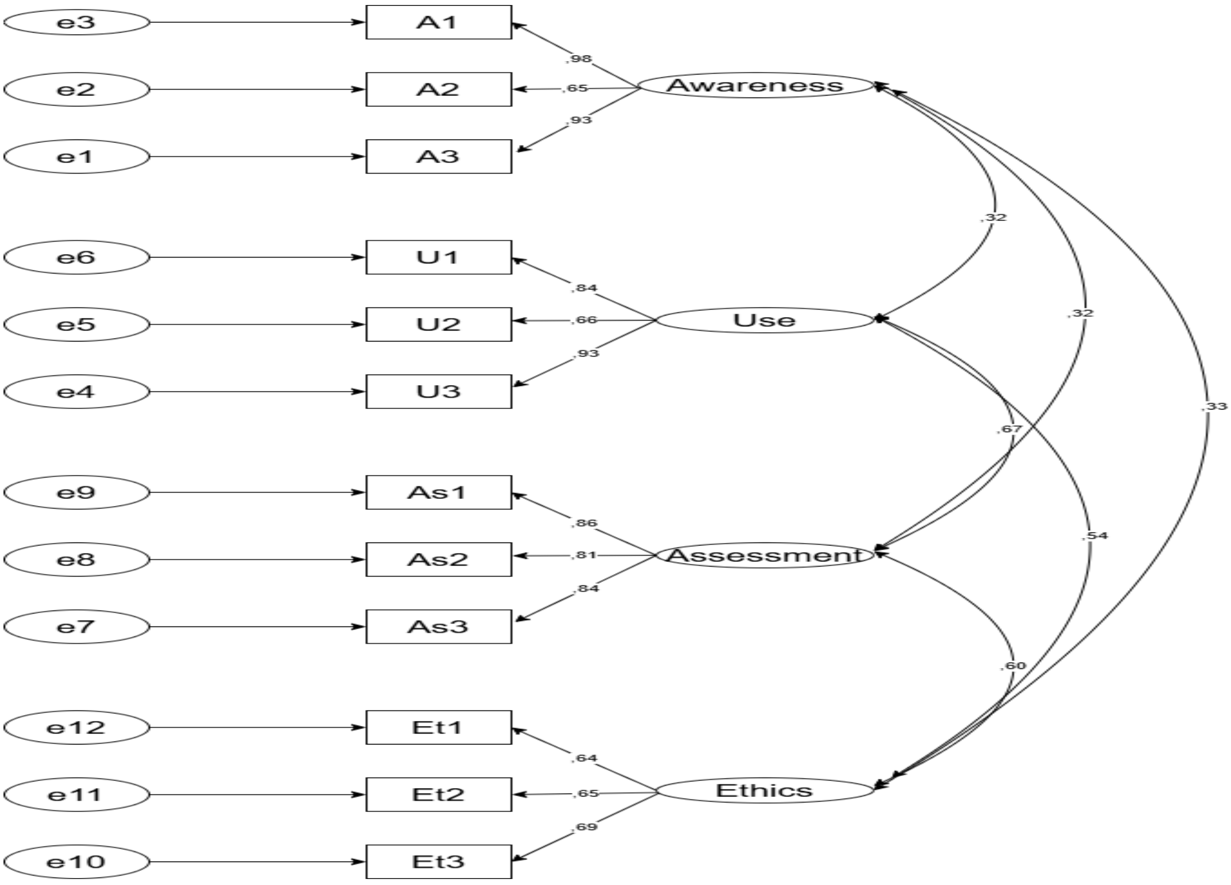

Figure 2. Confirmatory Factor Analysis Results

When the measurement model presented in Figure 2 is examined, the theoretical structure of the four-factor scale consisting of 12 items (awareness, use, evaluation, and utilization) proposed as a result of EFA is confirmed as a result of CFA. The CFA confirmed that the scale met the construct validity criteria. Factor loadings ranged between .65 and .98 for the awareness sub-dimension, between .66 and .93 for the 'use' sub-dimension, between .81 and .86 for the 'evaluation' sub-dimension, and between .64 and .69 for the 'ethics' sub-dimension.

Findings on Item Analysis and Reliability

Table 4.
Findings Related to Item Analysis

Item	Item Total Correlation	Mean		t	*p*
		upper %27	lower %27		
1	.759	6.6667	5.4444	9.099	.000
2	.551	6.0741	5.5185	4.523	.000
3	.773	6.6667	5.3704	9.084	.000
4	.919	6.8519	4.4815	18.019	.000
5	.741	6.4815	4.8519	8.444	.000
6	.919	6.8889	4.5556	18.364	.000
7	.887	6.8889	4.7407	14.295	.000
8	.892	6.9630	4.9630	15.344	.000
9	.853	6.4815	4.6296	11.245	.000
10	.755	6.5185	4.7407	8.087	.000
11	.816	6.9259	5.2963	11.759	.000
12	.801	6.6296	4.2222	11.110	.000

According to the independent t-test results in Table 4, the relationship levels of all items belonging to the AI literacy scale were found to be significant between the upper 27% and lower 27% groups. In addition, the item-total correlation values of the scale items ranged between .551 and .919. It is stated that item-total correlations above .30 measure the expected property of the item (Pallant, 2020). All of the scale items intend to measure the same behavior.

Findings related to reliability

Cronbach's alpha internal consistency coefficient was calculated for the reliability study of the AI literacy scale. Cronbach's alpha for the total scale was calculated as .85, while Cronbach's alpha values for the subscales were calculated as .82, .79, .87, and .69, respectively. When Cronbach's alpha value is .70 or higher, it is known that the items consistently measure the same feature and there is item homogeneity (Johnson & Christensen, 2019), but it has been stated that. 60 or higher can be accepted in newly developed factors or factors with fewer questions (Alemdar & Köker, 2013). Therefore, these calculated internal consistency coefficients indicate a high level of reliability in three factors and a good level in one factor for the scores obtained from the scale.

Discussion, Conclusion, and Recommendations

In this study, it was aimed at adapting the "AI-LS" developed by Wang et al. (2022) to Turkish to create a scale suitable for testing the AI-L of pre-service teachers. To ensure linguistic validity, we first translated the scale into Turkish and then back-translated it. The scale was finalized by taking expert opinions, and the analysis phase started.

EFA and CFA were conducted on the data obtained from different study groups to determine the construct validity of the scale. EFA revealed that the scale structure consisted of four factors similar to the original scale. The four-factor structure and fit indices were analyzed using CFA. The analysis determined that the scale had good fit indices. These findings support the conclusion that the Turkish AI-LS has a strong foundation in terms of validity and reliability. The researchers used Cronbach Alpha values to evaluate the reliability of the scale within the scope of the study. The Cronbach's alpha value obtained for the overall scale (α = .856) showed that the reliability was at a good level. Similarly, the Cronbach's alpha values obtained for the subscales of the scale are as follows: awareness (α= .820), use (α= .793), evaluation (α= .876), and ethics (α= .688). These values indicate that the subscales are also at a good level in terms of reliability. The results of the analysis clearly showed that the scale has a valid and reliable structure. In summary, we concluded that the 4-factor structure consisting of 12 items met the necessary conditions of the scale without removing any item. These findings indicate that the Turkish AI-LS has a solid foundation in terms of reliability. As a result of the factor analysis, each of the four factors of the scale was divided into sub-dimensions measuring specific skill areas. The first factor, "awareness," contains three items measuring the ability to understand and identify technology during AI applications. The second factor, "Use," contains three items measuring the ability to effectively apply and utilize AI technology. The third factor, "evaluation," includes three items measuring the ability to analyze, select, and critically evaluate AI applications. The fourth factor, "Ethics," includes three items measuring responsibility and risk awareness in the use of AI technology. These sub-dimensions represent different abilities within the structure of the scale.

A small number of studies include explanations for the conceptualization of literacy related to AI (Ng, 2012). AI, which has become increasingly important in daily life and business life, and AI literacy have been associated with literacy definitions in different disciplines (Long & Magerko, 2020; İpek et al., 2023). By assessing the AI literacy of pre-service teachers, who are highly focused on technology learning, it is possible to develop more advanced technology teaching programs and implement effective applications. These findings offer crucial insights into the integration of pre-service teachers' AI literacy levels into education curricula. In curriculum development processes, it is necessary to set goals for pre-service teachers to gain AI literacy and to include AI literacy skills in education programs. In this direction, the analysis of findings based on curriculum development models can significantly contribute to the development of educational policies. In the Turkish adaptation, the scale demonstrated successful results in terms of validity and reliability compared to the original research (Wang et al., 2022) where the scale was developed. In the original study, the scale proved suitable for adults, and in the Turkish adaptation, it was used to determine the AI literacy levels of pre-service teachers who continue their university education. The adapted AI literacy scale emerged as an important tool in determining the literacy levels of pre-service teachers in the field of AI. The contribution of this scale to the literature stands out by providing the opportunity to evaluate the knowledge, skills, and awareness levels of AI. In this context, future comprehensive studies can further strengthen the validity and reliability of the scale. These studies can also aid in the development of new models for curriculum development that incorporate AI literacy into teacher education programs. Research, especially with larger study groups, can increase the general validity of the scale and evaluate the AI literacy levels of individuals in different populations more comprehensively. Lubin (2021) states that digital literacy should be linked to data literacy, while Faruqe et al. (2021) argue that AI literacy should be linked to other types of literacy. Different types of literacy and AI literacy can be considered together. Furthermore, qualitative studies support the use of this scale to gain a deeper understanding of individuals' mindsets and experiences regarding AI. In terms of curriculum development models, these findings provide an opportunity to examine more deeply the necessity of incorporating AI literacy into teacher training programs and the impact of studies in this area on curricula. In light of the recommendations of this study, determining pre-service teachers' AI literacy can be an important step in terms of continuing research on AI literacy, adapting the scale to a wider user base, and contributing to the knowledge in this field. Thus, creating a foundation for more comprehensive studies to evaluate and enhance individuals' interaction with AI technologies can be achieved in today's world where these technologies are becoming increasingly prevalent.

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Ethics statement: In this study, we declare that the rules stated in the "Higher Education Institutions Scientific Research and Publication Ethics Directive" are complied with and that we do not take any of the actions based on "Actions Against Scientific Research and Publication Ethics". At the same time, we declare that there is no conflict of interest between the authors, which all authors contribute to the study, and that all the responsibility belongs to the article authors in case of all ethical violations.

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