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Artificial Intelligence Literacy Scale

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SUMMARY

The aim of this study is to develop a reliable and valid scale to determine individuals' levels of artificial intelligence literacy. The study was conducted during the spring semester of the 2024–2025 academic year with the participation of pre-service teachers enrolled in the Faculty of Education at Muğla Sıtkı Koçman University in Turkey. A total of 412 pre-service teachers participated in the exploratory factor analysis, while 211 pre-service teachers participated in the confirmatory factor analysis. The results of the exploratory factor analysis indicated that the scale has a three-factor structure consisting of 16 items. Reliability analyses showed that the scale demonstrates adequate internal consistency at both the overall scale level and across its subdimensions. The confirmatory factor analysis results further revealed that the model fit indices were at acceptable to good levels. The scale consists of three subdimensions: Artificial Intelligence Knowledge and Usage Competence, Societal Impacts of Artificial Intelligence, and Ethical Awareness in the Context of Artificial Intelligence. The scale explains 56.92% of the total variance. Overall, the findings suggest that the Artificial Intelligence Literacy Scale is a valid and reliable measurement instrument that can be used to assess individuals' artificial intelligence literacy levels.

Keywords: Artificial intelligence literacy, artificial intelligence, scale development

INTRODUCTION

Alan M. Turing opened his groundbreaking 1950 paper with the following question: "I propose to consider the question, Can machines think?" (Turing, 1950). Shortly thereafter, the term artificial intelligence was first introduced at the Dartmouth Summer Research Project on Artificial Intelligence by John McCarthy and his colleagues—Marvin Minsky (MIT), Claude Shannon (Bell Labs), and Nathaniel Rochester (IBM) (Rajaraman, 2014). Nearly more than seventy years have passed since these pioneering developments. Defined as a new technological science aimed at simulating and extending human intelligence (Wang et al., 2023), artificial intelligence today influences humanity at both micro and macro levels (Soto-Sanfiel et al., 2024). Artificial intelligence has begun to significantly transform work, education, transportation, and healthcare services (Pekün, 2025; Shin & Shin, 2020; Sindermann et al., 2021; Vayena et al., 2018). In this context, artificial intelligence is fundamentally reshaping how people learn and work (Ng et al., 2024). AI is not limited to domains requiring high levels of expertise; it is also increasingly integrated into everyday applications (Laupichler et al., 2023). From smart home devices to language learning applications, and from social media platforms to conversational agents, artificial intelligence is used across a wide range of contexts. In short, artificial intelligence has transformed daily life and the ways in which humans interact with one another (Tenberga & Daniela, 2024). As interfaces evolve accordingly, the boundary between humans and machines is becoming increasingly blurred (Stolpe & Hallström, 2024). This ambiguity brings with it various concerns and anxieties, such as the hacking of personal data, the dissemination of harmful content, and the spread of misinformation (Hwang et al., 2023).

Artificial intelligence, which possesses human-like capabilities and differs from traditional technologies in its ability to perceive and interpret its environment (Höhener, 2024), offers a range of opportunities and challenges for all segments of society (Kim & Lee, 2022). In this regard, Pinski and Benlian (2023) argue that artificial intelligence comprises three core components: autonomy, learning, and opacity. Some scholars (Höhener, 2024; Soto-Sanfiel et al., 2024) have further suggested that these components pose significant challenges for non-experts in human–AI interaction. For instance, individuals' lack of competence in using AI-based tools effectively and responsibly may lead them to believe misinformation, fail to distinguish deepfakes and fabricated content (Chu-Ke & Dong, 2024), overlook biased perspectives embedded in AI-generated outputs (Kim & Ryoo, 2026), and misunderstand the legal consequences associated with the misuse of artificial intelligence (Erkan, 2025). Consequently, people may develop a natural distrust toward AI-generated recommendations, decisions, or predictions and may avoid using such technologies altogether (see "algorithm aversion," Dietvorst et al., 2015). To benefit from the opportunities offered by artificial intelligence while managing its associated risks, individuals need to possess a foundational understanding of AI. Moreover, individuals' competencies in effectively using, interpreting, and evaluating AI systems have become increasingly important in contemporary society (Hornberger et al., 2023). However, despite being extensively exposed to AI technologies in their daily lives, individuals cannot be assumed to possess the necessary digital skills in this domain (Wang et al., 2023). Accordingly, competencies in artificial intelligence are not only essential for future AI professionals but also critically important for individuals who are not computer scientists, mathematicians, or AI engineers (Laupichler et al., 2022). This is because individuals will inevitably be required to interact with and utilize this transformative technology, either directly or indirectly. To describe individuals' capacity to engage with and use this technology, the concept of artificial intelligence literacy has been introduced (Wang et al., 2023).

The term artificial intelligence literacy is reported to have been first used by Konishi in a study conducted in 2015 (Laupichler et al., 2022). Artificial intelligence literacy has since been defined by numerous scholars. For example, Wang et al. (2023) describe AI literacy as the ability to correctly identify, use, and evaluate AI-related products within ethical standards. Similarly, Weber et al. (2023, p. 6) define artificial intelligence literacy as "*a set of socio-technical competencies of humans that shape relevant types of human–AI interaction.*" However, the literature most frequently refers to the definition proposed by Long and Magerko (2020). Long and Magerko (2020, p. 2) define artificial intelligence literacy as "*a set of competencies that enables individuals to critically evaluate AI technologies; communicate and collaborate effectively with AI; and use AI as a tool online, at home, and in the workplace*." In addition, these researchers conceptualized AI literacy as encompassing 17 competencies and 15 design considerations (Zhou et al., 2025). This framework is organized around five guiding questions: What is AI? What can AI do? How does AI work? How should AI be used? and How do people perceive AI? (Lintner, 2024; Long & Magerko, 2020; Stolpe & Hallström, 2024). In their study, Long and Magerko (2020) also included technical details related to AI competencies, which may be attributed to their strong backgrounds in engineering research (Zhou et al., 2025). By contrast, Ng et al. (2021), based on an extensive literature review, proposed that AI literacy encompasses the dimensions of knowing and understanding, using and applying, evaluating and creating, as well as AI ethics. Furthermore, drawing on Bloom's taxonomy, Ng et al. (2021) structured the concept in a hierarchical manner, progressing through knowing, understanding, applying, analyzing, evaluating, and creating. These theoretical frameworks may contribute to the blurring of boundaries between digital literacy and artificial intelligence literacy (Wang et al., 2023).

Digital literacy is sometimes regarded as an umbrella term that includes the ability to use artificial intelligence effectively (Baskara, 2025). However, it is important to emphasize that digital literacy does not substitute for artificial intelligence literacy (Hwang et al., 2023). These two forms of literacy differ in terms of their scope, components (dimensions), focus, and modes of interaction with humans. Although AI technology is technically grounded in digital technologies, at the conceptual level it constitutes an interdisciplinary field that integrates insights from neuroscience as well as other disciplines such as epistemology, mathematics, psychology, linguistics, and sociology (Wang et al., 2023). Moreover, differences between interaction with artificial intelligence and interaction with digital technologies further indicate a clear distinction between these two literacy concepts (Tenberga & Daniela, 2024). While digital literacy comprises technical, cognitive, and socio-emotional dimensions (Ng et al., 2012), artificial intelligence literacy— as discussed above— encompasses the dimensions of knowing and understanding AI, using and applying AI, evaluating and creating with AI, and AI ethics (Ng et al., 2021). In other words, digital literacy provides individuals with the foundational skills required to function in digital environments, whereas artificial intelligence literacy enables individuals to effectively use and critically evaluate AI technologies, thereby facilitating their responsible and efficient integration into various domains of daily and professional life (Tenberga & Daniela, 2024). Such integration requires a specific level of competence that allows for the critical assessment of the benefits and limitations of AI tools and applications (Laupichler et al., 2023). Therefore, in what is increasingly described as the age of AI (Hwang et al., 2023), artificial intelligence literacy has emerged as a necessary and essential skill.

Understanding and recognizing artificial intelligence, as well as developing a nuanced awareness of how AI affects humans and how humans, in turn, influence AI, constitute key aspects of artificial intelligence literacy (Stolpe & Hallström, 2024). Accordingly, both the introduction and the measurement of AI literacy represent crucial means of preparing society for an increasingly pervasive and progressively significant AI technology (Koch et al., 2024). For this reason, individuals' levels of artificial intelligence literacy need to be assessed in a valid and reliable manner (Laupichler et al., 2023). In this context, numerous measurement instruments have been developed to address the various dimensions and characteristics of artificial intelligence literacy (Hwang et al., 2023; Kong et al., 2021; Laupichler et al., 2023; Lee & Park, 2024; Ng et al., 2024; Pinski & Benlian, 2023; Weber et al., 2023). Notably, the Meta AI Literacy Scale (MAILS), developed by Carolus et al. (2023), consists of 34 items across multiple dimensions—use and apply AI, understand AI, detect AI, AI ethics, create AI, AI self-efficacy, and AI self-competency—along with a 10-item short version of the scale (Koch et al., 2024). Another prominent instrument is the 12-item Artificial Intelligence Literacy Scale (AILS), developed by Wang et al. (2023), which comprises four dimensions: awareness, usage, evaluation, and ethics. In addition, the 56-item SAIL4ALL scale developed by Soto-Sanfiel et al. (2024), consisting of four factors/dimensions—What is AI? What can AI do? How does AI work? and How should AI be used?—also merits attention. These diverse measurement structures reflect the multifaceted nature of artificial intelligence literacy, encompassing behavioral, ethical, and technical components (Jin et al., 2025). However, a closer examination of how authors conceptualize artificial intelligence literacy reveals that most existing scales are grounded in a shared set of core competencies. These competencies include an understanding of the technical aspects of AI, awareness of the societal impacts of AI, and AI ethics. Across different measurement instruments, these three components consistently emerge as the fundamental elements of artificial intelligence literacy (Lintner, 2024).

Although a number of artificial intelligence literacy scales adapted into the Turkish language have been identified in the literature (Akyürek, 2025; Çelebi et al., 2023; Eniş-Erdoğan & Ekşioğlu, 2024; Polatgil & Güler, 2023; Yılmaz & Yılmaz, 2023), no artificial intelligence literacy scale originally developed in the Turkish language has been found. Only one study (Tekin, 2025) was identified in which an artificial intelligence literacy scale was developed specifically for middle school students. Consequently, no scale developed in the Turkish language aimed at assessing the artificial intelligence literacy levels of adults has been identified. Based on this gap in the literature, the purpose of the present study is to develop a valid and reliable scale capable of assessing adults' levels of artificial intelligence literacy. The conceptual foundation of the scale developed in this study is grounded in the artificial intelligence literacy frameworks proposed by Long and Magerko (2020) and Ng et al. (2021).

Assessing individuals' levels of artificial intelligence literacy is important not only for identifying users' domain-specific competencies but also for revealing the knowledge and skills they need to develop in this area (Hornberger et al., 2023). Moreover, such assessments are expected to contribute to a better understanding of human–AI interaction and to provide a foundation for further theoretical exploration. In addition, determining individuals' levels of artificial intelligence literacy is considered to offer valuable guidance in the process of designing instructional programs in this field. At the same time, measurement instruments developed within this context can also be used to evaluate the development of individuals' artificial intelligence literacy over time.

METHOD

Participants for the Exploratory Factor Analysis

The study sample consisted of two independent groups for the exploratory factor analysis (EFA) and the confirmatory factor analysis (CFA). The EFA sample comprised 412 pre-service teachers enrolled in the Faculty of Education at Muğla Sıtkı Koçman University during the spring semester of the 2025 academic year. Participants were drawn from different grade levels and academic departments within the Faculty of Education to enhance the diversity of the pre-service teachers' personal and academic characteristics. The characteristics of the study sample are summarized in Table 1.

Table 1. Demographic Characteristics of the EFA Sample

Characteristics	**f**	**%**
Departments		
Primary School Teaching	28	6.8
Social Studies Education	21	5.1
Preschool Education	28	19.7
Science Education	27	6.6
Mathematics Education	55	13.3
Turkish Language Education	47	11.4
English Language Teaching	48	11.7
German Language Teaching	37	9.0
Guidance and Psychological Counseling	81	19.7
Special Education	40	9.7
Gender		
Female	298	72.3
Male	114	27.7

Year of Study		
First Year	82	19.9
Second Year	126	30.6
Third Year	154	37.4
Fourth Year	50	12.1
Total	**412**	**100.0**

As shown in Table 1, the study sample consisted of 412 pre-service teachers enrolled in the Faculty of Education. The largest proportions of participants were from the departments of Guidance and Psychological Counseling and Mathematics Education, while the remaining participants were distributed across other departments. In addition, the majority of the pre-service teachers in the sample were female. With respect to year of study, most participants were in their second and third years, whereas the smallest proportion consisted of fourth-year students.

Participants for the Confirmatory Factor Analysis

The confirmatory factor analysis (CFA) was conducted with the participation of 211 pre-service teachers enrolled in the Faculty of Education at Muğla Sıtkı Koçman University during the spring semester of the 2024–2025 academic year. The demographic characteristics of the pre-service teachers who participated in the CFA are presented in the table below.

Table 2. Demographic Characteristics of the CFA Sample

Characteristics	**f**	**%**
Departments		
Primary School Teaching	20	9.5
Social Studies Education	13	6.2
Science Education	13	6.2
Turkish Language Education	34	16.1
English Language Teaching	72	34.1
Special Education	13	6.2
Preschool Education	36	17.1
Mathematics Education	10	4.7
Gender		
Female	139	65.9
Male	70	33.2
Year of Study		
First Year	83	39.3
Second Year	56	26.5
Third Year	23	10.9
Fourth Year	47	22.3
Total	**211**	**100,0**

As shown in the table above, pre-service teachers from eight different academic departments participated in the confirmatory factor analysis. The largest proportion of participants was from the Department of English Language Teaching, followed by Preschool Education and Turkish Language Education. Approximately 66% of the participants were female, and most were in their first and second years of study. The total sample consisted of 211 pre-service teachers, and this sample size meets the minimum thresholds recommended in the literature for confirmatory factor analysis.

Scale Development Process

The scale development process was conducted in several sequential stages. First, a comprehensive review of the relevant literature was carried out, focusing on studies related to artificial intelligence. Based on the information obtained from the literature, a general conceptual framework concerning attitudes toward artificial intelligence was established.

Second, drawing on the literature and consultations with subject-matter experts, an initial item pool consisting of 33 items was generated. To determine the level of agreement with each item, a five-point Likert-type response format was employed. The response options were arranged as follows: “strongly disagree,” “disagree,” “neutral,” “agree,” and “strongly agree.”

Third, the draft items were examined by experts in terms of language use, grammatical accuracy, and content validity. In line with the critiques and suggestions provided by the experts, necessary revisions were made to the items, and the number of items was reduced from 33 to 28.

Fourth, the revised draft scale was administered as a pilot study to 30 third-year pre-service teachers enrolled in the Faculty of Education at Muğla Sıtkı Koçman University. Following the pilot administration, items that were found to be unclear or difficult to understand were revised or removed.

Fifth, the refined draft scale consisting of 23 items was administered to a larger sample of 412 pre-service teachers studying at the Faculty of Education of Muğla Sıtkı Koçman University. The collected data were entered into the SPSS software and subjected to statistical analyses to examine the validity and reliability of the scale.

As a result of the exploratory factor analysis, the number of items was reduced to 16, and the scale was found to have a three-factor structure. Subsequently, confirmatory factor analysis was conducted to test the final structure of the scale. The analyses performed during the scale development process and the findings obtained from these analyses are presented in the following section.

FINDINGS

This section presents information regarding the scale development process and the statistical analyses conducted for the scale.

Construct Validity

To examine the construct validity of the scale, Kaiser–Meyer–Olkin (KMO) and Bartlett’s test of sphericity were first conducted. The results indicated a KMO value of .914 and a Bartlett’s test value of χ^2 = 3930.980 with 253 degrees of freedom (p = .000). According to Pallant (2003), a KMO value of .60 or higher and a statistically significant Bartlett’s test ($p \leq .05$) indicate that the data are suitable for factor analysis. Based on these criteria, it was determined that factor analysis could be performed on the 23-item draft scale. Factor analysis is a statistical technique used to determine whether the items of a scale can be grouped into a smaller number of underlying factors that represent distinct constructs (Balcı, 2009).

In the subsequent stage, the number of factors representing the items of the scale was determined. The primary aim of factor analysis is to identify the factors that best represent the scale items and to determine the appropriate number of factors. In this context, it is important to extract as few factors as possible while ensuring that the scale explains as much variance as feasible. Among the most important techniques used to determine the number of factors in factor analysis are principal component analysis, which is the most commonly used approach, along with the Kaiser criterion and the scree plot (Pallant, 2003).

According to the literature, factor loadings should be greater than .45; however, in cases where the number of items is limited, factor loadings as low as .30 may be considered acceptable (Büyüköztürk, 2010). In the present study, a minimum factor loading of .50 was preferred for the scale items. After the items that did not meet this criterion were removed, the remaining 16-item scale yielded a KMO value of .932 and a Bartlett’s test value of χ^2 = 2603.416 with 120 degrees of freedom (p = .000). The factor loadings of the 16 retained items ranged from .516 to .756. The scree plot for the scale is presented in Figure 1.

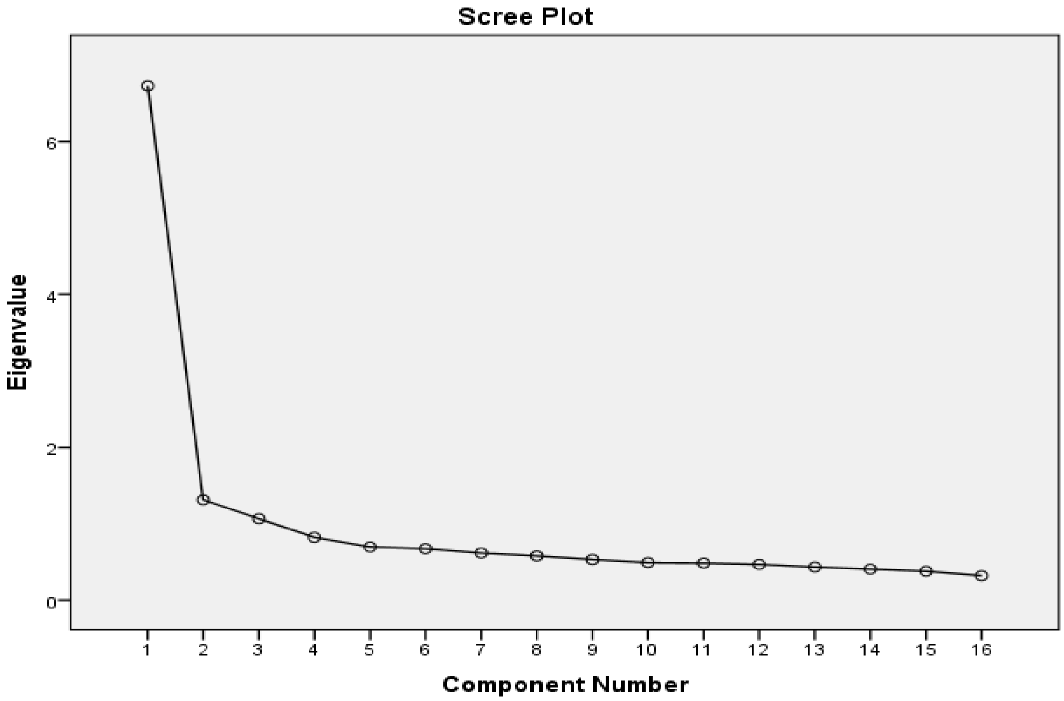

Figure 1. Scree Plot of the Factors

As shown in Figure 1, the slope of the curve decreases after the first three factors and then continues in a relatively horizontal manner. An examination of the scree plot indicates that the curve levels off after the third factor, suggesting that the subsequent factors make a limited contribution to explaining variance. In addition, the eigenvalues of the factors following the third factor are below 1. The eigenvalues, percentages of explained variance, and cumulative variance percentages for the remaining 16 items of the scale are presented in the table below.

Table 3. Eigenvalues and Explained Variance

Factor	Eigenvalue	Percentage of Variance (%)	Cumulative Variance (%)
1	6.729	42.059	42.059
2	1.312	8.203	50.262
3	1.065	6.658	56.920

As shown in the table above, the proportions of variance explained by the three factors range from 42% to approximately 6.7%. Overall, the scale accounts for 56.92% of the total variance. In the context of social sciences, this level of explained variance is generally considered adequate for factor analytic studies (Kline, 1994). The factors identified in the scale and the items associated with each factor are presented in the table below.

Table 4. Factor Loadings

Factor 1		Factor 2		Factor 3	
Item	Factor Loading	Item	Factor Loading	Item	Factor Loading
i16	.726	i17	.756	i6	.742
i10	.720	i18	.657	i7	.698
i12	.714	i15	.601	i9	.626
i1	.665	i14	.598	i21	.544
i8	.625	i20	.516	i19	.516
i4	.613				

As shown in the table above, the first factor comprises six items, while the second and third factors each include five items. An examination of the item content suggests that the first factor is primarily associated with artificial intelligence knowledge and usage competence. The second factor appears to relate to the societal implications of artificial intelligence, whereas the third factor seems to reflect ethical awareness in the context of artificial intelligence.

Item Discrimination

In this section, item–total correlations were examined to evaluate the extent to which each item is related to the overall scale score. The correlation between an item score and the total score of the scale provides an indication of how effectively the item represents the underlying construct. In the literature, item–total correlation coefficients greater than .30 are generally considered acceptable indicators of item discrimination (Büyüköztürk, 2010). The item–total correlation coefficients for the scale are presented in the table below.

Table 5. Item-Total Correlation

Factor 1		**Factor 2**		**Factor 3**	
Item	Item–Total Correlation	Item	Item–Total Correlation	Item	Item–Total Correlation
i1	.549	i14	.582	i21	.640
i4	.670	i15	.562	i19	.681
i8	.656	i17	.515	i6	.438
i10	.609	i18	.512	i7	.541
i12	.543	i20	.656	i9	.575
i16	.607				

As shown in the table above, the item–total correlation coefficients of the scale items range from .438 to .681. Accordingly, all items exceed the commonly accepted lower threshold of .30, suggesting that none of the items require revision based on item–total correlation criteria.

In addition, to examine criterion-related validity, item discrimination was further assessed by comparing the extreme groups based on the total scale scores. For this purpose, participants were divided into the upper 27% and lower 27% groups according to their mean scale scores, and independent-samples t-tests were conducted to examine whether there were significant differences between the mean item scores of these two groups for each item as well as for each factor. The results of the analysis indicated that the differences between the upper and lower groups were statistically significant for all items and for the overall factor at the $p < .001$ level.

Findings Related to the Reliability of the Scale

Reliability analyses were conducted for the scale consisting of a total of 16 items and three factors. In this context, the reliability of both the overall scale and its subdimensions was calculated using Cronbach's alpha coefficients. The results of the reliability analyses for the scale are presented in the table below.

Table 6. Reliability of The Scale

Reliability Test	**Overall Scale**	**Factor 1**	**Factor 2**	**Factor 3**
Cronbach Alpha	.905	.843	.777	.787

As shown in the table above, the Cronbach's alpha coefficient for the overall scale was .905. Furthermore, the Cronbach's alpha coefficients for the subdimensions were .843, .787, and .777, respectively. These findings indicate that the scale and its subdimensions demonstrate adequate internal consistency (Büyüköztürk, 2010).

Findings Related to the Confirmatory Factor Analysis

Following the exploratory factor analysis, a three-factor structure of the scale was identified. To evaluate the structural validity of this factor structure, confirmatory factor analysis (CFA) was conducted using the LISREL software. CFA is a theory-driven analytical technique employed to examine the extent to which the hypothesized measurement model fits the observed data, as assessed through various model fit indices.

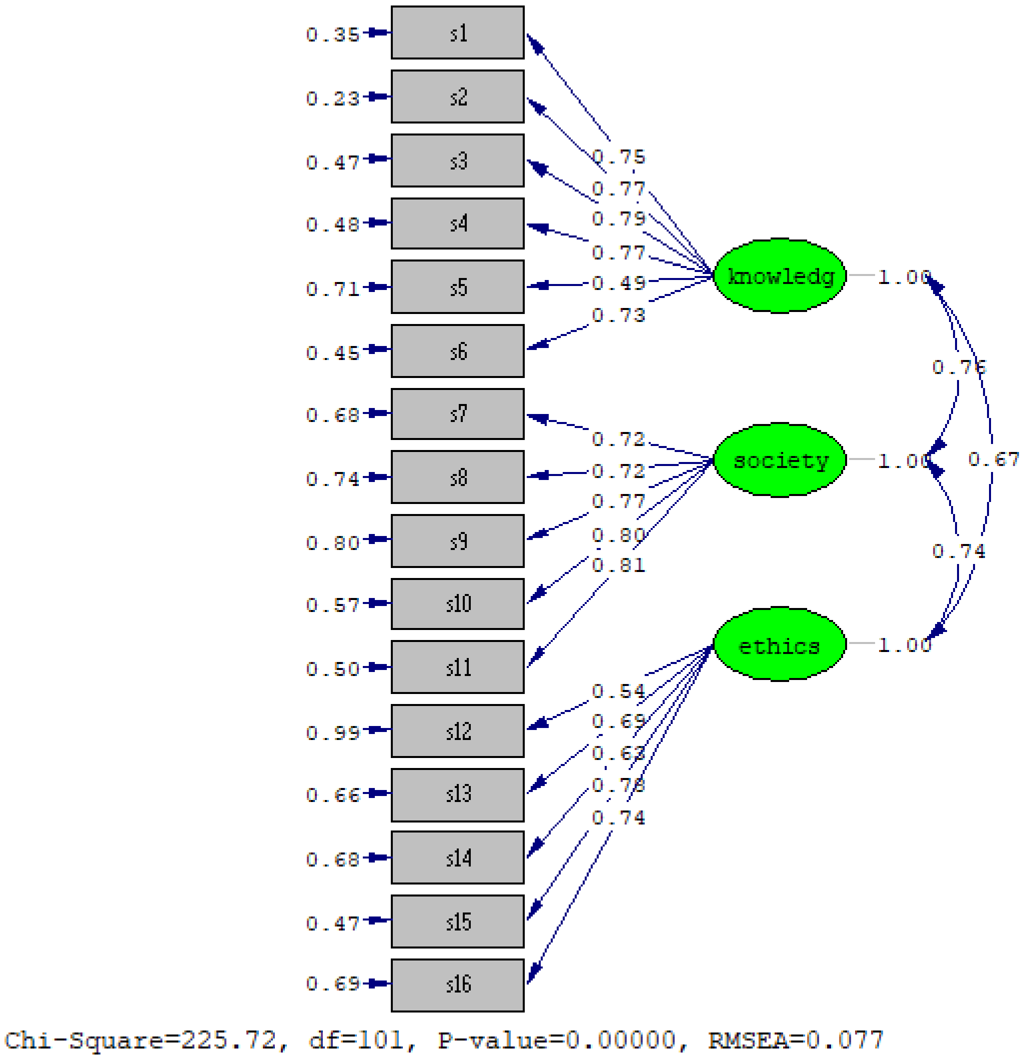

Figure 2. Confirmatory Factor Analysis Results

Within the scope of the confirmatory factor analysis (CFA) conducted for the 16-item model, various model fit indices were examined. The CFA results yielded the following fit indices: SRMR = 0.059, RMSEA = 0.077, RMR = 0.066, AGFI = 0.84, GFI = 0.88, NFI = 0.94, NNFI = 0.96, CFI = 0.97, and IFI = 0.97. Although the chi-square test was statistically significant, this result alone does not necessarily indicate poor model fit, as the chi-square statistic is known to be sensitive to large sample sizes. The χ^2/df ratio was found to be 2.23, which falls within the commonly accepted range of 2 to 3, suggesting an acceptable level of model fit.

The SRMR value being below 0.08 indicates a good fit between the model and the observed data. Similarly, the RMR value of 0.066 suggests that the residuals are within an acceptable range, indicating an adequate model–data fit. The GFI (0.88) and AGFI (0.84) values point to an acceptable level of model fit. Furthermore, the NFI, NNFI, CFI, and IFI values indicate a very good level of fit. The RMSEA value of 0.077 also suggests that the model demonstrates an acceptable fit to the data (Blunch, 2008; Hooper et al., 2008; Kenny, 2015; Kline, 2005). Overall, based on both absolute and incremental fit indices, the scale demonstrates an acceptable and robust model fit (Schermelleh-Engel et. al., 2003; Schumacker & Lomax, 2004; Tabachnick & Fidell, 2001).

CONCLUSION AND DISCUSSION

Based on the exploratory factor analysis conducted on the collected data, the scale was found to exhibit a three-factor structure consisting of 16 items. The scale comprises the subdimensions of artificial intelligence knowledge and usage competence, the societal impacts of artificial intelligence, and ethical awareness regarding artificial intelligence. The scale explains 56.92% of the total variance. The Cronbach's alpha reliability coefficients indicated adequate internal consistency for both the overall scale and its subdimensions. Based on the results of the validity and reliability analyses, the Artificial Intelligence Literacy Scale can be considered a valid and reliable measurement instrument.

The minimum score that can be obtained from the scale is 16, while the maximum score is 80. Higher scores on the scale may be interpreted as indicating higher levels of artificial intelligence literacy. In this respect, the scale developed in the present study is expected to offer methodological and practical contributions to research in the field of artificial intelligence literacy.

Ethical Approval

Ethical approval for this study was granted by the Mugla Sitki Kocman University Social and Human Sciences Scientific Research Ethics Committee prior to data collection (Protocol No. 250012, Decision No. 37; 18 March 2025).

Conflict of Interest

The authors declare that there is no conflict of interest.

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YAPAY ZEKA OKURYAZARLIĞI ÖLÇEĞİ

	Kesinlikle katılmıyorum	Katılmıyorum	Kararsızım	Katılıyorum	Kesinlikle katılıyorum
1. Yapay zekanın ne olduğunu açıklayabilirim.					
2. Yapay zekanın insanlığa sunduğu fırsatları açıklayabilirim.					
3. Günlük yaşamda çeşitli yapay zeka araçlarını (sohbet robotu, çeviri uygulaması gibi) kullanabiliyorum.					
4. Yapay zekanın oluşturduğu çıktıları ihtiyaçlarıma göre düzenleyebilirim.					
5. İhtiyacıma yönelik en uygun yapay zeka aracını seçebilirim.					
6. İstediğim sonucu elde edebilmek için yapay zeka araçlarına nasıl komut vereceğimi bilirim.					
7. Yapay zeka sistemlerinin siber saldırı ya da veri çalma gibi kötü amaçlarla kullanılabileceğinin farkındayım.					
8. Yapay zeka sistemlerine toplumun her kesiminin eşit bir biçimde ulaşamadığını biliyorum.					
9. Yapay zeka sistemlerinin toplumdaki birçok mesleği yok edebileceğinin farkındayım.					
10. Yapay zeka sistemlerinin yeni meslekler ortaya çıkarabileceğini biliyorum.					
11. Yapay zekanın gelecekte eğitim, sağlık ve adalet gibi farklı alanlara entegre olabileceğinin farkındayım.					
12. Yapay zeka sistemlerinin bazı konularda önyargılı olabileceğini biliyorum.					
13. Yapay zeka ile oluşturulan ürünlerde telif hakkı sorunu olabileceğinin farkındayım.					
14. Yapay zekanın sınırlı olduğu durumları açıklayabilirim.					
15. Yapay zeka sistemlerinin verdiği kararları sorgulayabilirim.					
16. Yapay zeka ile üretilen bilgilerin doğruluğunu başka kaynaklarla kontrol etmem gerekebileceğini biliyorum.					

Not. Bu ölçekte yer alan tüm maddeler olumlu ifadelerden oluşmaktadır. Ters (negatif) madde bulunmamaktadır.

Alt Boyutlar

1-6 : Yapay Zeka Bilgisi ve Kullanım Yetkinliği

7-11 : Yapay Zekanın Toplumsal Etkileri

12-16 : Yapay Zeka Bağlamında Etik

ARTIFICIAL INTELLIGENCE LITERACY SCALE

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1. I can explain what artificial intelligence is.					
2. I can explain the opportunities that artificial intelligence offers to humanity.					
3. I can use various artificial intelligence tools (e.g., chatbots, translation applications) in daily life.					
4. I can modify outputs generated by artificial intelligence according to my needs.					
5. I can select the most appropriate artificial intelligence tool for my needs.					
6. I know how to provide effective prompts to artificial intelligence tools in order to obtain the desired outcomes.					
7. I am aware that artificial intelligence systems can be used for malicious purposes such as cyberattacks or data theft.					
8. I am aware that not all segments of society have equal access to artificial intelligence systems.					
9. I am aware that artificial intelligence systems may eliminate many occupations in society.					
10. I know that artificial intelligence systems may lead to the emergence of new professions.					
11. I am aware that artificial intelligence may be integrated into various fields such as education, healthcare, and justice in the future.					
12. I am aware that artificial intelligence systems may exhibit bias in certain contexts.					
13. I am aware that copyright issues may arise in products created using artificial intelligence.					
14. I can explain situations in which artificial intelligence has limitations.					
15. I can question the decisions made by artificial intelligence systems.					
16. I am aware that information generated by artificial intelligence may need to be verified using other sources.					

Note. All items in this scale are positively worded. No reverse-coded items are included.

Subdimensions

Items 1–6 : Artificial Intelligence Knowledge and Usage Competence

Items 7–11 : Societal Impacts of Artificial Intelligence

Items 12–16 : Ethical Awareness in the Context of Artificial Intelligence