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Validity and Reliability of the Artificial Intelligence Awareness Scale for Adolescents Aged 13–18: Implications for Public Policy and Governance

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Title

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Validity and Reliability Study of the Artificial Intelligence Awareness Scale for Ages 13-18: Public Policy and Governance Implications for Adolescent AI Literacy

Abstract

This research aimed to develop and validate a scale to measure AI awareness among adolescents aged 13–18. A descriptive survey model was employed, with data collected online from 122 voluntary participants (mean age 14.78).

Following a literature review and expert evaluation, an initial 26-item pool was developed. Item analysis resulted in the removal of three items, and exploratory factor analysis supported a two-factor structure comprising 23 items and explaining 37.4% of the total variance. The first factor, "Perceived Benefits of AI," consisted of 16 items (Cronbach's α = .888), while the second factor, "AI Threat Perception," consisted of 7 items (Cronbach's α = .793). Confirmatory factor analysis of the two-factor structure yielded acceptable fit indices.

Keywords: Artificial intelligence, public policy, adolescent, awareness, scale development,

Introduction

The Language Association defines artificial intelligence (AI) as "the ability of a computer, a robot controlled by a computer, or a programmable device to exhibit functions such as perception, learning, reasoning, decision-making, problem-solving, communication, etc., in a human-like manner" (Turkish Language Association, 2025). The foundations of AI were laid in 1955 based on an assertion, within a summer research project, that every aspect of learning or any other feature of intelligence could in principle be so precisely described that a machine could be made to simulate it (McCarthy et al., 2006). This assertion is considered a precursor to modern AI research. Considering the current state of AI, it is evident that it is actively and effectively used in almost every field, from education and healthcare to management, auditing, finance, and the entertainment industry. Given that our century is characterized by speed, instant gratification, and change, it can be argued that AI applications have become an integral part of daily life.

AI is an interdisciplinary field encompassing computer science, mathematics, statistics, philosophy, psychology, and law, among others (Karaoğlan Yılmaz & Yılmaz, 2023). Education can also be included among these fields. The rapid development in AI, coupled with the influence of implemented policies, is also seen as a significant emerging area of

research for determining the future of AI in learning within education (Holmes et al., 2021). The Ministry of National Education in Turkey carries out various projects related to training on AI applications and teaching AI. Based on this, it can be stated that many countries utilize AI technologies to improve their educational activities and achieve higher standards (Alan et al., 2024). From a public administration perspective, the integration of AI into education is not only a technical or pedagogical issue but also a matter of public policy, equitable resource allocation, and regulatory governance. The effectiveness of AI awareness programs depends on how public institutions design, implement, and monitor these initiatives across different school types (public vs. private) and socioeconomic backgrounds. Beyond its pedagogical dimension, artificial intelligence awareness can also be conceptualized as a component of public governance capacity. In contemporary governance approaches, the ability of individuals to understand and meaningfully engage with technological systems is closely linked to the concept of "policy capacity" and "state capacity." In this context, AI awareness among adolescents may be interpreted as an early indicator of a society's readiness to adopt, use, and regulate emerging technologies.

Moreover, the integration of AI into education systems reflects not only a service delivery issue but also a matter of public value creation. Governments are increasingly expected to design policies that ensure equitable access to digital competencies while simultaneously addressing risks such as privacy violations, algorithmic bias, and social inequality. Therefore, measuring AI awareness at an early age provides valuable input for evidence-based policymaking, particularly in the fields of education policy, digital governance, and youth-oriented public services.

It can be argued that the earlier the awareness of AI applications is acquired, the more its purposeful use will increase. Therefore, fostering this awareness during a period open to learning is critically important. This critical period falls within adolescence. The World Health Organization (WHO) defines adolescence as the period between ages 10-19 (WHO, 2022). UNICEF, on the other hand, defines adolescence in two stages: early adolescence (ages 10-14) and late adolescence (ages 15-19) (UNICEF, 2025). Although different age groupings exist, the 13-18 age group is considered part of adolescence, and this period is a process where abstract thinking skills develop. Consequently, the development of abstract thinking skills is crucial for acquiring awareness about AI applications. The skills gained during this period can influence knowledge and experiences in later years, enhancing the permanence of learning.

Based on the foregoing, the "Artificial Intelligence Awareness Scale for Children Aged 13-18" developed within this study aims to measure AI awareness among children aged 13-18. The pervasive presence of AI in nearly every field in the current era makes the development of awareness regarding these applications necessary. Stemming from this reality, it is believed that supporting the acquisition of this awareness as early as possible, along with its conscious and purposeful use, is crucial. This assumption makes the present study significant for the relevant age group.

Method

Research Design

This study, which was conducted to develop a scale aimed at measuring the artificial intelligence awareness levels of children aged 13-18, adopted a descriptive survey model among quantitative research methods. In this model, the process proceeds without any intervention on the group being studied (Karasar, 2018; Şata, 2020).

Study Group

This study was conducted with children in the 13-18 age group. Participation was based on voluntary basis. Data were collected online from children whose parents provided consent for participation and who themselves voluntarily agreed to participate. The inclusion criteria were being between 13-18 years old and attending a formal educational institution. The exclusion criterion was not attending formal education. In line with the specified criteria, the study was conducted with 122 volunteer participants. Following the data collection, the responses provided online were examined, and since there were no missing items and/or data loss, all responses were included in the evaluation. The demographic characteristics of the participants are presented in Table 1.

Table 1: Distribution of Students' Socio-Demographic Characteristics

Variables	$\bar{X}$**±SD**	**Min.-Max.**
Age	14.78 ± 1.62	13-18
Gender	**n**	**%**
Girl	83	68
Boy	39	32
Type of School Attended	n	%
Private School	98	80.3
Public School	24	19.7
AI-supported activities included in education	n	%
Yes	34	27.9
No	88	72.1
Mother's Education Level	n	%
Primary School	21	17.2
Middle School	10	8.2
High School	29	23.8
Associate Degree	11	9.0

Bachelor's Degree	32	26.2
Postgraduate Degree	19	15.6
Mother's Occupational Group	n	%
Private Sector	38	31.1
Public Sector	35	28.7
Homemaker	46	37.7
Retired/Not Working	3	2.5
Father's Education Level	n	%
Primary School	9	7.4
Middle School	13	10.7
High School	36	29.5
Associate Degree	9	7.4
Bachelor's Degree	33	27.0
Postgraduate Degree	22	18.0
Father's Occupational Group	n	%
Private Sector	74	60.7
Public Sector	41	33.6
Retired/Not Working	7	5.7
Total	**122**	**100.0**

A total of 122 students participated in the study, as shown in Table 1. The mean age of the students was 14.78 with a standard deviation of 1.62. The age distribution ranged from 13 to 18 years.

Regarding gender distribution, 68% of the students were girls (n=83) and 32% were boys (n=39). When examining the types of schools attended, 80.3% were enrolled in private schools (n=98), while 19.7% attended public schools (n=24).

When asked whether AI-supported activities or studies were included in the educational process, 27.9% of the students (n=34) reported that such activities were implemented, whereas 72.1% (n=88) stated that they had not participated in any AI-supported work.

Analysis of the mothers' educational levels showed that 17.2% had completed primary school (n=21), 8.2% middle school (n=10), 23.8% high school (n=29), 9% held an associate degree (n=11), 26.2% had a bachelor's degree (n=32), and 15.6% had a postgraduate degree (n=19). In terms of maternal occupational groups, 31.1% worked in the private sector (n=38), 28.7% in the public sector (n=35), 37.7% were homemakers (n=46), and 2.5% were retired or not working (n=3).

The distribution of fathers' educational levels was as follows: 7.4% had completed primary school (n=9), 10.7% middle school (n=13), 29.5% high school (n=36), 7.4% held an associate degree (n=9), 27% had a bachelor's degree (n=33), and 18% had a postgraduate degree

(n=22). Regarding paternal occupational groups, 60.7% worked in the private sector (n=74), 33.6% in the public sector (n=41), and 5.7% were retired or not working (n=7).

Development of the Data Collection Tool and Data Collection Process

In the initial phase of this study, which was planned as a scale development for children aged 13-18, a comprehensive literature review was conducted. The review revealed a scarcity of studies targeting this specific age group, thus aiming to contribute to this field. Accordingly, studies conducted with individuals under the age of 18 were examined, and an initial item pool was generated. This pool, consisting of 26 items, was presented for evaluation to three faculty members specializing in child development and two faculty members with research experience in artificial intelligence fields. Based on the feedback from these experts, the items were refined without removing any, and the final set was administered online to the target age group who had provided parental consent and voluntarily agreed to participate. Data were collected between May 28 and July 26, 2025.

Data Analysis

The statistical software SPSS 30.0 was used in the study. Descriptive statistics such as frequency, percentage, arithmetic mean, standard deviation, minimum, and maximum were utilized for data analysis. Parametric tests were employed in the analysis of the data. An independent samples t-test was used to compare the means of two independent groups, while a one-way analysis of variance (ANOVA) was used to compare the means of more than two independent groups. For the ANOVA test, if homogeneity of variances was met for group differences, the Tukey HSD test was used; if not, the Tamhane's T2 post-hoc test was applied. Exploratory factor analysis was used to test the construct validity of the scales, Cronbach's alpha coefficient was used for reliability analysis, and the Pearson correlation test was used for correlation analysis.

Abbreviations

$\bar{X}$: Mean

S.D.: Standard Deviation

Findings

This section presents the findings obtained from the data within the scope of the study.

Exploratory Factor Analysis (Validity and Reliability)

Exploratory Factor Analysis of the 26-Item Artificial Intelligence Awareness Scale

Table 2: Item Analysis Results for the 26-Item Artificial Intelligence Awareness Scale

Items	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
1. Artificial intelligence is a useful tool for simplifying daily life.	4.15	0.90	0.518	0.800
2. The development of AI means it could replace human activities.	3.39	1.03	0.121	0.808
3. AI helps make us more engaged in areas like entertainment and games.	3.74	1.09	0.502	0.800
4. Services provided by AI (e.g., voice assistants) are useful.	4.21	0.50	0.509	0.803
5. It bothers me that AI appears to make better decisions than we do.	3.09	1.59	0.336	0.818
6. Receiving training on AI usage contributes to my personal development.	3.80	1.01	0.532	0.799
7. AI could increase or cause unemployment in society.	3.68	1.18	0.206	0.813
8. I am worried that the misuse of AI could pose a danger to people.	4.11	0.81	0.293	0.809
9. Services offered by AI can make people's work more efficient.	4.05	0.66	0.514	0.802
10. I believe AI is an innovation that will transform human life, alongside technological change.	3.88	0.79	0.525	0.801
11. AI might violate our privacy while collecting personal data.	3.78	1.12	0.274	0.810
12. AI can make my learning process more effective and efficient.	3.96	0.93	0.535	0.800
13. The conveniences offered by AI may cause a decline in people's thinking and problem-solving abilities, leading to laziness.	3.87	1.29	0.438	0.812
14. AI can enhance people's creativity.	3.32	1.39	0.457	0.802
15. AI taking over routine tasks gives individuals more free time, offering opportunities to focus on creative and strategic activities.	3.39	1.48	0.361	0.806
16. AI can diagnose diseases more quickly in the healthcare field.	3.84	1.31	0.364	0.811
17. AI replacing human interactions could increase social loneliness.	4.02	1.29	0.306	0.809
18. The advancement of AI can create new job opportunities for people.	3.32	1.38	0.578	0.810
19. I support the use of AI in education and have a positive attitude towards this process.	3.93	1.22	0.457	0.802
20. AI can make people's decision-making processes fairer.	3.30	1.06	0.368	0.806
21. AI helps me learn more about the world around me.	4.03	0.81	0.516	0.801
22. Overdevelopment of AI could lead to people losing their own skills.	3.80	1.48	0.375	0.815
23. AI works only for the benefit of technology companies.	2.43	1.60	0.059	0.822
24. AI could create a revolution that simplifies people's lives.	3.92	0.74	0.521	0.801
25. I think the use of AI should be limited.	3.53	1.47	0.379	0.820
26. Students' opinions should be considered when deciding on AI use in schools.	4.33	0.98	0.416	0.804

As shown in Table 2, As shown in Table 2, three items (Items 2, 7, and 23) had corrected item-total correlation coefficients below .30. These items were excluded from subsequent factor analyses. The remaining 23 items were retained for exploratory factor analysis.

Table 3: Reliability Analysis of the Scale

Cronbach's α	Number of Items
0.813	26

The Cronbach's alpha method, one of the reliability analysis techniques, was applied to all items used in the scale and also on a factor basis. This method investigates whether the questions in the scale represent a whole with a homogeneous structure. It is calculated by the ratio of the variances of the questions in the scale to the total variance. It takes a value between 0 and 1. A value between 0.60 and 0.80 is considered quite reliable, and a value between 0.80 and 1.00 indicates high reliability. Additionally, care is taken to ensure that the correlations of the items in the scale are not below 0.20 (Büyüköztürk, 2012). Items falling below this value are not included in the reliability analysis. In this way, the reliability level of the scale is seen to be high.

When the reliability analysis was applied to the artificial intelligence awareness scale in this manner, the minimum Cronbach's alpha coefficient was found to be 0.813. The internal consistency of the initial 26-item version was examined using Cronbach's alpha, which yielded a coefficient of .813. Following item analysis, three items were excluded because their corrected item-total correlations were below .30. The internal consistency coefficients of the two factors in the resulting 23-item structure were .888 and .793, respectively.

Table 4: Results of the Kaiser-Meyer-Olkin (KMO) and Bartlett's Test for the Scale

Kaiser-Meyer-Olkin Test (KMO)		0,835
Bartlett's Test of Sphericity	Chi-Square (χ^2)	1040,065
	Degrees of freedom (df)	253
	p-value	0,001

As seen in Table 4, the prerequisites for factor analysis of the 26-item artificial intelligence scale are the presence of a certain degree of correlation among the variables and a KMO value above the acceptable threshold of 0.60. The KMO value measures the sampling adequacy for factor analysis. The KMO coefficient was determined to be 0.835, and Bartlett's test result was significant at the $p < .05$ level (Tatlıdil, 2022). This indicates that the sample size is adequate for conducting factor analysis. Based on these findings, principal component analysis as a form of exploratory factor analysis with varimax rotation was applied to the 26-item scale. The exploratory factor analysis of the 26-item scale resulted in a two-factor structure with eigenvalues greater than 1, explaining 37.4% of the total variance (Table 5).

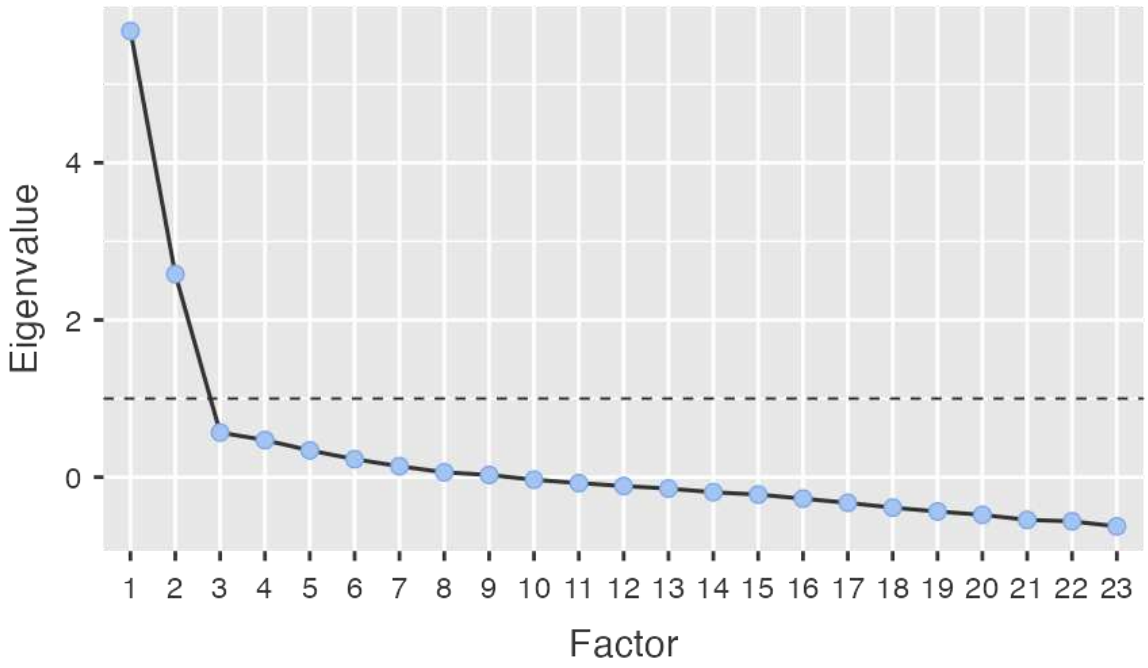


Figure 1: Scree Plot Test for the 26-item Artificial Intelligence Scale

Upon examination of the scree plot, it is observed that limiting the number of factors to two is adequate. As shown in Figure 1, the scree plot indicates a clear break after the second factor, supporting the retention of a two-factor structure. Following varimax rotation, the distribution of items across factors was examined, and all items demonstrated logical consistency within their respective factor structures.

Table 5: Total Variance Explained for the Artificial Intelligence Awareness Scale

Factors	**Initial Eigenvalues**			**Extraction Sums of Squared Loadings**			**Rotation Sums of Squared Loadings**		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5,662	24,813	24,813	32,5670	24,813	24,813	32,058	24,617	24,617
2	2,947	12,614	37,427	8,416	12,614	37,427	8,679	12,810	37,428

As can be seen in Table 5, The exploratory factor analysis of the remaining 23 items resulted in a two-factor structure explaining 37.4% of the total variance. The first factor explained 24.8% and the second factor explained 12.6% of the variance.

Table 6: Factor Loadings and Structure of the Artificial Intelligence Awareness Scale

Factor 1: Perceived Benefits of AI (% Variance = 24.62, Cronbach's α = 0.888)

Item No.	Item Statement	Factor Loading
12	AI can make my learning process more effective and efficient.	0.729
9	Services offered by AI can make people's work more efficient.	0.686
19	I support the use of AI in education and have a positive attitude towards this process.	0.681
14	AI can enhance people's creativity.	0.659
21	AI helps me learn more about the world around me.	0.644
24	AI could create a revolution that simplifies people's lives.	0.628
1	AI is a useful tool for simplifying daily life.	0.606
3	AI helps make us more engaged in areas like entertainment and games.	0.598
4	Services provided by AI (e.g., voice assistants) are useful.	0.585
20	AI can make people's decision-making processes fairer.	0.562
6	Receiving training on AI usage contributes to my personal development.	0.559
18	The advancement of AI can create new job opportunities for people.	0.516
10	I believe AI is an innovation that will transform human life, alongside technological change.	0.514
15	AI taking over routine tasks gives individuals more free time, offering opportunities to focus on creative and strategic activities.	0.511
26	Students' opinions should be considered when deciding on AI use in schools.	0.482
16	AI can diagnose diseases more quickly in the healthcare field.	0.408

Factor 2: AI Threat Perception (% Variance = 12.61, Cronbach's α = 0.793)

Item No.	Item Statement	Factor Loading
13	The conveniences offered by AI may cause a decline in people's thinking and problem-solving abilities, leading to laziness.	0.740
22	Overdevelopment of AI could lead to people losing their own skills.	0.628
11	AI might violate our privacy while collecting personal data.	0.591
25	I think the use of AI should be limited.	0.588
17	AI replacing human interactions could increase social loneliness.	0.581
8	I am worried that the misuse of AI could pose a danger to people.	0.527
5	It bothers me that AI appears to make better decisions than we do.	0.520

Based on the factor loadings, items were retained in their respective factors if their loadings were above 0.40 and the difference between loadings on different factors was at least 0.10. Since no items violated these criteria, no items were removed based on the results of the exploratory factor analysis (Hair et al., 2010). Cronbach's alpha coefficient was used to calculate the internal consistency of the factors, and values above 0.70 indicate high reliability Tavşancıl, 2022).

An examination of the items belonging to each factor reveals the following:

- Under the first factor, Perceived Benefits of AI, 16 items were grouped, with loadings ranging between 0.408 and 0.729. The factor's Cronbach's alpha value was 0.888.
- Under the second factor, AI Threat Perception, 6 items were grouped, with loadings ranging between 0.520 and 0.740, and a Cronbach's alpha value of 0.793.

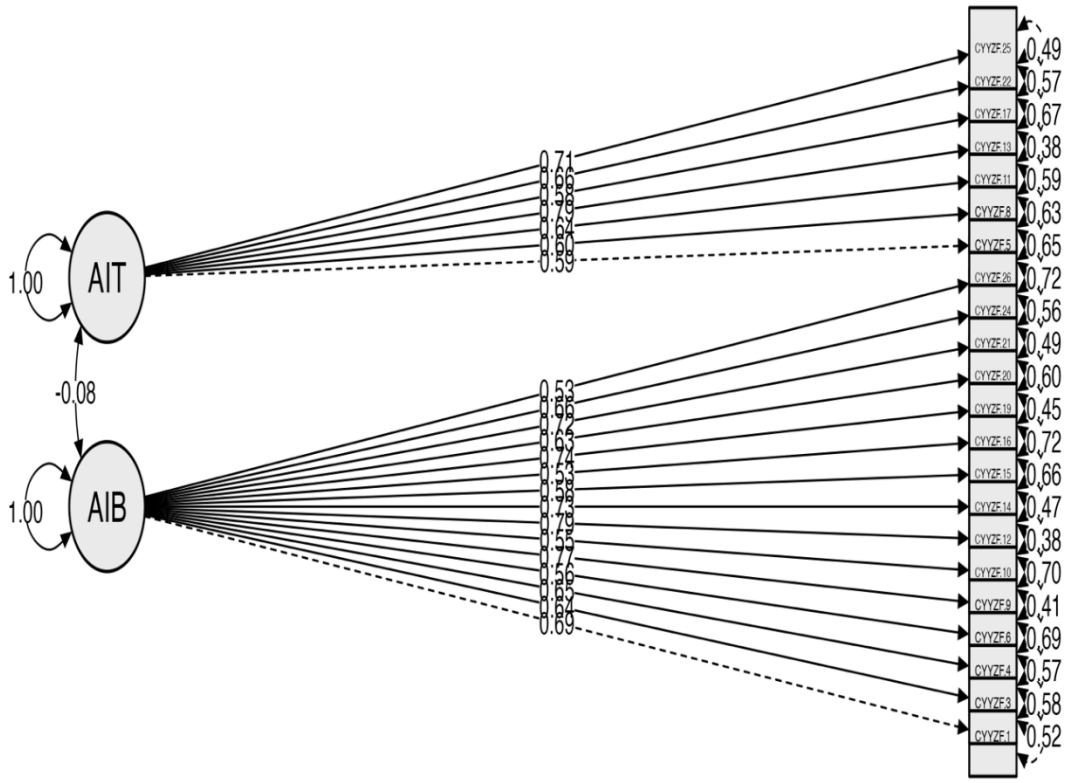


Figure 2: Confirmatory Factor Analysis Model of the Artificial Intelligence Awareness Scale for Children

The confirmatory factor analysis (CFA) was conducted to test the proposed two-factor structure obtained from the exploratory factor analysis. As shown in Figure 2, the hypothesized two-factor measurement model demonstrated an acceptable fit to the data. The fit indices indicate that the model adequately represents the observed data structure.

Table 7: Goodness-of-Fit Statistics for the Confirmatory Factor Analysis of the Artificial Intelligence Awareness Scale for Children

Fit Indices	Model Value	Reference Value
χ^2 (Chi-Square)	405.541	-
df (Degrees of freedom)	208	-
p-value	< .001	< .05
χ^2/df	1.950	< 5

RMSEA (Root Mean Square Error of Approximation)	0.089	< 0.10
GFI (Goodness-of-Fit Index)	0.950	> 0.90
AGFI (Adjusted Goodness-of-Fit Index)	0.925	> 0.90
NFI (Normed Fit Index)	0.911	> 0.90
CFI (Comparative Fit Index)	0.954	> 0.90
IFI (Incremental Fit Index)	0.954	> 0.90

The Confirmatory Factor Analysis (CFA) results presented in Table 7 indicate that the goodness-of-fit statistics for the initial model of the Artificial Intelligence Awareness Scale for Children are generally at an acceptable level. The model's chi-square value ($\chi^2 = 405.541$; $df = 208$; $p < .001$) was significant, indicating that the model is statistically related to the data (Kline, 2016).

The chi-square/degrees of freedom ratio ($\chi^2/df = 1.950$) remains below the recommended threshold (<5), demonstrating a good model fit (Shermelleh-Engel et al., 2003). The RMSEA value was 0.089; since it falls within the 0.08–0.10 range, it was evaluated as indicating a "reasonable fit" (Browne & Cudeck, 1993).

The model's other fit indices are quite strong. The GFI (0.950) and AGFI (0.925) values indicate a good fit of the model to the observed data [17]. Comparative fit indices such as the Normed Fit Index (NFI = 0.911), Comparative Fit Index (CFI = 0.954), and Incremental Fit Index (IFI = 0.954) reveal that the model exhibits an excellent, near-perfect fit (Bentler & Bonett, 1980; Hu & Bentler, 1999).

In conclusion, the 26-item artificial intelligence awareness scale was reduced to two main factors as a result of the exploratory factor analysis. The factors, derived from items meeting both item analysis and exploratory factor analysis criteria based on their loading values, were identified as *Perceived Benefits of AI* and *AI Threat Perception*. The fit statistics obtained from the CFA support the construct validity of the Artificial Intelligence Awareness Scale for Children and demonstrate that the model's measurement structure functions in a manner consistent with theoretical foundations.

Discussion, Conclusion, and Recommendations

This study was conducted to develop an artificial intelligence awareness scale for children aged 13-18. By adhering to scale development protocols and analyzing the resulting data, it was concluded that the developed scale—comprising 26 items and two sub-dimensions, *Perceived Benefits of AI* and *AI Threat Perception*—is a valid and reliable instrument.

A review of the literature indicates a recent increase in studies related to artificial intelligence. However, it is presumed that the scarcity of research focusing on the 13-18 age group, known as adolescence, makes this topic particularly significant. Therefore, this study is expected to make valuable contributions to the existing body of literature.

An examination of previous research reveals that the majority of studies have been conducted with individuals over the age of 18. Akkaya, Özkan, and Özkan (Akkaya et al., 2021), in their study "Adaptation of the Artificial Intelligence Anxiety Scale into Turkish" with university students, identified a 16-item scale with four sub-dimensions: "learning, job replacement, sociotechnical blindness, and AI configuration." Polatgil and Güler (2023) adapted the Artificial Intelligence Literacy Scale into Turkish with participants aged 18-60, resulting in a 12-item scale with four sub-dimensions. Similarly, Karaoğlan Yılmaz and Yılmaz (2023), in their adaptation of the Artificial Intelligence Literacy Scale into Turkish, worked with young adults and adults with high school or higher education levels, ultimately contributing a 31-item scale with "technical understanding, critical evaluation, and practical application" sub-dimensions to the literature. Furthermore, Süleymanoğulları et al. (2024) worked with undergraduate and graduate university students in their study, resulting in a valid and reliable 25-item scale with "interaction, pervasive impact, and anxiety" sub-dimensions added to the literature. Grassini (2023) developed a valid and reliable 4-item, unidimensional (attitude) artificial intelligence attitude scale for adult public samples. Carolus et al. (2023) collected data online from approximately 300 German-speaking adults and developed a modular artificial intelligence literacy scale encompassing the sub-dimensions of "Using and Applying AI, Understanding AI, AI Ethics, AI Creation, AI Self-Efficacy, and AI Self-Regulation." Laupichler et al. (2023) developed a valid and reliable 31-item artificial intelligence literacy scale for adult individuals, consisting of "Technical Understanding, Critical Evaluation, and Practical Application" sub-dimensions. Liu and Liu (2025) developed a 21-item artificial intelligence anxiety scale with five dimensions through qualitative interviews and quantitative surveys with English as a Foreign Language (EFL) teachers at the university level in China. The dimensions include technical competence, job loss, technological support, student experience, and research development. Confirmatory factor analysis demonstrated that the scale possesses high reliability and validity.

In addition to studies involving adults, research involving students also exists. However, these studies are relatively fewer compared to those conducted with individuals aged 18 and over. Alan et al. (2024) developed a 29-item scale with four components in their study to determine the attitudes of middle school students towards artificial intelligence, for which they conducted validity and reliability studies. Similarly, Öner et al. (2025) developed a 20-item artificial intelligence awareness scale with four sub-dimensions for adolescents aged 15-16. Ng et al. (2023) constructed a 25-item artificial intelligence literacy questionnaire for middle/high school students using expert reviews, pilot testing, and confirmatory factor analyses. The analyses revealed six factors: intrinsic motivation, self-efficacy, behavioral intention, behavioral engagement, knowing and understanding, and using and applying. The pilot study utilized a sample of 363 secondary school students; the scale was found to be suitable in terms of construct validity and internal consistency. Su (2024) developed and

validated a new assessment tool to measure AI literacy among kindergarten-aged children. The study utilized expert opinions, child implementations, and statistical analyses (item analysis/factor analyses, etc.); it was reported that a valid and reliable measurement tool was obtained following sample and expert reviews. This tool is suitable for measuring young children's basic AI concepts and attitudes. Chiu et al. (2025) developed and validated the "Student Artificial Intelligence Competency Self-Efficacy" (SAICS) scale for K-12 students. In the first stage, an eight-dimensional framework (e.g., interdisciplinary AI learning, assessment with AI, decision-making, data/ethics, etc.) was established via a three-round Delphi study; a 32-item scale was designed with four items per dimension. In the second stage, confirmatory factor analysis with 448 students demonstrated that the scale is reliable and valid and provides consistent measurement across genders. The instrument is recommended for assessing student AI competency in K-12 settings.

Literature reviews show an increase in studies on artificial intelligence in recent years. The fact that the majority of research has been conducted with individuals over 18, while studies with those under 18 are relatively limited, makes the present study, with its completed validity and reliability analysis, particularly important. Consequently, it is assumed that this scale developed for children aged 13-18 will make significant contributions to the literature and provide a foundation for future studies.

In addition to its contribution to the measurement literature, this study also offers implications for public administration and governance. AI awareness can be considered a foundational component of digital-era governance, as individuals' understanding of AI systems directly influences their interaction with public services, trust in institutions, and acceptance of policy interventions. Low levels of awareness may lead to resistance, misinformation, or ineffective policy implementation, whereas higher levels of awareness can enhance policy compliance and citizen engagement.

Therefore, the findings of this study suggest that AI awareness should not be treated solely as an educational outcome but as a strategic public policy objective. Governments need to incorporate AI literacy into broader policy frameworks related to digital transformation, education reform, and social inclusion.

Based on the findings of this study, the following recommendations are offered for researchers working in this field:

- While there is a relative abundance of studies targeting age groups of 18 and over, research focusing on the relevant age group (13-18) and younger remains limited. Prioritizing studies for this age group is recommended.
- Awareness-raising activities can be conducted to increase consciousness about the informed and purposeful use of AI. In this context, school-based programs could be developed.
- Awareness can be fostered by ensuring the more effective and active integration of AI within the education system.

- Studies could be conducted on the influence of family demographic characteristics, as well as the surrounding environment and culture, on AI usage.
- Longitudinal studies could be planned to examine the attitudes and habits of the under-18 group regarding AI use during their adulthood. This would allow for the observation of the long-term effects/contributions of AI use on individuals.

In addition to the recommendations above, the following public administration and policy-oriented suggestions are derived from the study's findings:

Equity in AI awareness: Given the overrepresentation of private school students in this sample, the Ministry of National Education should conduct a nation-wide, stratified study using this scale to assess whether AI awareness significantly differs between public and private schools. If disparities exist, targeted public programs and resource allocation should be implemented to close the gap.

Regulatory framework for AI in schools: The presence of a distinct 'AI Threat Perception' factor (including privacy, skill loss, and limitation requests) indicates that adolescents expect protective regulations. Public institutions such as the BTK (Information and Communication Technologies Authority) and KVKK (Personal Data Protection Authority) should collaborate with the Ministry of Education to develop age-appropriate, enforceable rules for AI use in K-12 settings.

3. Participatory school governance: Item 26 ('Students' opinions should be considered when deciding on AI use in schools') suggests that school administrations should adopt participatory and transparent decision-making mechanisms regarding AI tools. Public school principals should be encouraged to form student advisory groups on AI-related policies.

4. Public service design for youth: The high factor loadings on 'Perceived Benefits of AI' indicate that adolescents are open to AI-supported public services. Public institutions (e.g., İŞKUR for career guidance, MEB for exam preparation, Ministry of Health for adolescent mental health) can design AI chatbots or recommendation systems tailored for the 13–18 age group, provided that threat perceptions are mitigated through transparency and data protection measures.

In this regard, the developed scale can also serve as a diagnostic policy instrument for public institutions, enabling policymakers to assess AI awareness levels among adolescents and design targeted, evidence-based interventions. By providing measurable data on youth AI awareness, the scale contributes not only to academic research but also to the development of more responsive and inclusive public policies.

Limitations

This study has some limitations that should be considered when interpreting the findings. The relatively small sample size and the overrepresentation of private school students limit the generalizability of the results and may reflect underlying inequalities in access to AI-related

resources. In addition, the use of self-report data may introduce response bias. Finally, the cross-sectional design restricts the ability to capture changes in AI awareness over time. From a public policy perspective, these limitations suggest that the findings should be interpreted cautiously in terms of representing the broader adolescent population. Future research with more diverse and representative samples is needed to support inclusive and evidence-based policymaking in the field of AI and education.

Author Contributions

Author 1,2 and Author 3 contributed to the conceptualization and design of the study. Author 1 and 2 conducted data collection and formal analysis and drafted the manuscript. Author 2 supervised the research process and critically revised the manuscript for important intellectual content. Both authors contributed to validation of the results, approved the final version of the manuscript, and agree to be accountable for all aspects of the work.

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Data Availability

The data and materials supporting the findings of this study are available from the corresponding author upon reasonable request. Anonymized datasets, survey instruments, and relevant supplementary materials can be provided for the purposes of verification and replication, subject to applicable ethical and data protection requirements. The datasets generated and/or analyzed during the current study are available at: https://zenodo.org/records/18617769

Ethical Approval

Ethical approval for the study entitled “Validity and Reliability Study of the Artificial Intelligence Awareness Scale for Ages 13–18” was obtained from the Scientific Research and Publication Ethics Committee of Social Sciences and Humanities at Karamanoğlu Mehmetbey University on 24 April 2025 (Meeting No. 05, Decision No. 158; Decision No. 05-2025/158). The committee determined that the study was ethically appropriate, subject to obtaining the necessary permissions for its implementation. All necessary permissions for conducting the study were obtained prior to data collection. The study was conducted in accordance with the ethical principles of the Declaration of Helsinki and relevant national regulations. Participation was voluntary, and informed consent was obtained from the participants and their legal guardians prior to data collection.

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Supplementary Files

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- ArtificialIntelligenceAwarenessScaleforChildrenAged1318Responses.xlsx
- Scale.docx