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## Development of Artificial Intelligence Awareness Scale (AIAS): Validity and Reliability Study

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### Abstract

This study presents the development, validation, and reliability assessment of the Artificial Intelligence Awareness Scale (AIAS), specifically designed to evaluate university students' awareness of artificial intelligence (AI). Despite significant advances in AI technologies and their increasing integration into daily life and educational environments, there is currently no existing measurement instrument that comprehensively evaluates AI awareness among students, incorporates the most recent AI developments, and takes non-technical users into consideration. To address this gap, the present study employed an exploratory sequential mixed-methods design. An initial literature review and expert consultations guided the formation of a preliminary item pool, which was refined through qualitative evaluations. The finalized 20-item draft scale was administered to 361 university students enrolled in social science departments. Exploratory factor analysis (EFA) resulted in an 11-item scale with two distinct factors: "Literacy" (7 items, factor loadings ranging from .48 to .72) and "Threats" (4 items, factor loadings ranging from .56 to .70). Confirmatory factor analysis (CFA) confirmed the two-factor structure, yielding acceptable fit indices (RMSEA = .084, SRMR = .074, GFI = .93). Internal consistency reliability was acceptable (Cronbach's alpha = .64 overall; .67 for Literacy and .59 for Threats; McDonald's Omega = .65 overall; .67 for Literacy and .61 for Threats), and test-retest stability over a four-week period was high ( $r = .80$ ). Results demonstrate that AIAS is a valid and reliable instrument for measuring university students' AI awareness. The scale is particularly valuable for identifying specific areas where educational interventions are needed and informing policy decisions.

**Keywords:** Artificial Intelligence, Artificial Intelligence Awareness, Artificial Intelligence literacy, Artificial Intelligence Threats.

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2026, 15 (1), 181-202 | Araştırma Makalesi

## Yapay Zekâ Farkındalığı Ölçeğinin (YZFÖ) Geliştirilmesi: Geçerlik ve Güvenirlik Çalışması

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### Öz

Yapay zekâ teknolojilerindeki gelişmeler, eğitim alanı başta olmak üzere birçok sektörde dönüştürücü bir potansiyel taşımaktadır. Bu teknolojilerin eğitimde gösterdiği ivme, üniversite öğrencilerinin farkındalık düzeylerinin incelenmesini öncelikli bir konu haline getirmektedir. Bu bağlamda çalışmada, üniversite öğrencilerinin yapay zekâ farkındalığını değerlendirmek üzere Yapay Zekâ Farkındalık Ölçeği geliştirilmiş ve geçerlik ile güvenirlik analizleri gerçekleştirilmiştir. Yapay zekâ teknolojilerinin hızla yaygınlaşmasına rağmen, öğrencilerin farkındalık düzeylerini güncel gelişmeler ışığında ve teknik bilgisi olmayan kullanıcıları da kapsayacak biçimde ölçen bütüncül bir araca rastlanmamaktadır. Bu eksikliği gidermek amacıyla çalışmada keşfedici ardışık karma yöntem deseni kullanılmıştır. Öncelikle, alanyazın taraması ve uzman görüşleriyle bir ön madde havuzu oluşturulmuş, bu havuz nitel değerlendirmelerle gözden geçirilerek sadeleştirilmiştir. Son hâliyle 20 maddeden oluşan taslak ölçek, sosyal bilimler alanında öğrenim gören 361 üniversite öğrencisine uygulanmıştır. Açımlayıcı faktör analizi (AFA) sonucunda ölçek 11 madde ve iki farklı faktörden oluşacak şekilde yapılandırılmıştır: "Okuryazarlık" (7 madde, faktör yükleri .48 ile .72 arasında) ve "Tehditler" (4 madde, faktör yükleri .56 ile .70 arasında). Doğrulamalı faktör analizi (DFA) iki faktörlü yapıyı doğrulamış ve kabul edilebilir uyum indeksleri elde edilmiştir (RMSEA = .084, SRMR = .074, GFI = .93). İç tutarlılık güvenirliliği, Cronbach alfa = genel ölçek için .64 Okuryazarlık alt boyutu için .67 ve Tehditler alt boyutu için .59; McDonald's Omega = genel ölçek için .65 Okuryazarlık alt boyutu için .67 ve Tehditler alt boyutu için .61 olarak bulunmuş, dört haftalık test-tekrar test uygulamasında yüksek derecede stabilite ( $r = .80$ ) gözlenmiştir. Sonuçlar ölçeğin geçerlik ve güvenirlik testlerinin güçlü olduğunu göstermekler birlikte, özellikle eğitim politikalarının geliştirilmesi ve bu politika kararlarının şekillendirilmesinde önemli bir kaynak olarak değerlendirilebilir.

**Keywords:** Yapay Zekâ, Yapay Zekâ Farkındalığı, Yapay Zekâ Okuryazarlığı, Yapay Zekâ Tehditleri

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## 1. Introduction

The conceptual foundations of artificial intelligence (AI) were established at the Dartmouth Conference in 1956. Since then, scholarly interest in AI has fluctuated, with notable periods of stagnation, commonly referred to as “AI winters.” Recent technological advances, however, have reignited interest in AI advancements (Haenlein & Kaplan, 2019, p. 5). Consumer-oriented applications such as Siri, Alexa, Google Assistant, and household robotics (e.g., the iRobot Roomba) marked the initial integration of AI into everyday life. In addition, as Ng (2016) pointed out a decade ago, AI was already transforming several sectors such as e-commerce, finance, web search and advertising. However, recent developments accelerated AI tools’ rapid dissemination. Dimitrieska (2024, p. 24) explains this by making a distinction between traditional AI and generative AI and posits that the transition from the former to the latter is a significant milestone. This evolution has been propelled by an unprecedented volume of data, enhanced computational infrastructure, and breakthroughs in machine-learning algorithms, collectively ushering in a new era of AI innovation (Casal-Otero et al., 2023, p. 1). Still, these advances had initially caught the attention of only a limited, technical audience. When these new advancements in AI were presented with interfaces that anyone could use, they began to spark rapidly growing interest. In particular, OpenAI’s image generation system DALL-E 2, unveiled in April 2022, and its text generation system ChatGPT, in November 2022, left the public in awe. ChatGPT became the fastest-growing consumer application in history, reaching 100 million monthly active users within two months (Hu, 2023). Subsequently, several companies introduced similar AI tools: Anthropic’s Claude, Google’s Bard and Gemini, and xAI’s Grok are among several text-generation “chat” systems. In addition, there are tools that create still images, video, audio, music, and many other kinds of content. As Korseberg & Elken (2025, p. 967) suggest, the rapid proliferation and adoption of these AI technologies are creating challenges for society at large, which is struggling to keep pace with these transformative developments.

The rapid progress made in the field of AI in recent years has created the need to examine AI from multiple perspectives. Due to the convenience AI tools offer in university students’ academic work, these students constitute a key target audience for such tools. Therefore, it is essential that university students use AI effectively and in compliance with ethical guidelines. A growing body of research has focused on the development of scales related to AI. Some of these are aimed at the educator, such as Zhang et al. (2025, p. 1)’s scale for teachers’ AI learning and Chiu et al. (2025, p. 6667)’s scale on teacher AI competence. Others are aimed at the student: Yilmaz et al. (2024, p. 8703) designed a scale for the measurement of students’ generative AI acceptance; Li & Wang (2025, p. 1) developed the Functional Attitudes toward AI scale to examine university students’ attitudes. In addition, several scholars worked on AI literacy scales (Pinski & Benlian, 2023, p. 165; Gokcearslan et al., 2024, p. 1; Ma & Chen, 2024, p. 146419; Carolus et al., 2023, p. 1). There are also a limited number of studies focusing on AI Awareness (Ferikoğlu & Akgün, 2022, p. 215; Scantamburlo et al., 2025, p. 477). However, a review of the existing literature reveals a notable gap: There is currently no scale that comprehensively addresses AI awareness among students, integrates the latest developments in AI, and is tailored for individuals without a technical background. The development of an AI Awareness Scale (AIAS) aims to address this gap. Systematic measurement of students’ AI awareness will enable universities, policymakers, and the students themselves to

identify knowledge gaps, reveal areas in need of support, and guide educational or policy interventions accordingly.

## 2. Artificial Intelligence Awareness

AI awareness is the understanding of what artificial intelligence can and cannot do (its limits), the opportunities it offers, the threats it poses, and its impact on society. AI is advancing fast, and as Chiu et al. (2024, p. 4) posit, students should stay up-to-date on AI advancements. Generative AI extends beyond text generation to include the creation of images, audio, video, and computer code, with output quality improving significantly as new models are released. These tools offer considerable potential for enhancing productivity, streamlining repetitive tasks; however, they also disrupt established workflows, challenge traditional roles, and introduce new risks that users must recognize and address. In addition, as Ogunleye et al. (2024, p. 16) state, students need to be aware of the limitations and shortcomings of AI. Thus, AI awareness is essential, as this technology is increasingly extending into all areas of life. A high level of awareness is necessary to make informed decisions about its appropriate use, the types of regulations that should be implemented, and the domains where clear boundaries must be established.

Students' AI awareness is crucial not only for their academic success at university but also for their post-university lives, that is, their careers. Within the university context, AI can be utilized ethically and effectively in a variety of ways. For example, AI-powered translation tools enable access to academic texts in multiple languages, facilitating deeper engagement with global scholarship. Generative tools such as ChatGPT can support brainstorming processes and foster creativity, while image-generation applications may enhance the visual quality of student presentations. More than a decade ago, Woolf et al. (2013, p. 67) predicted that "AI will be a game changer in education". Many studies published since the proliferation of generative AI tools suggest a change in education is happening. For instance, upon reviewing reports and policies published by UNESCO, OECD, and education ministries of the United States and China, Zhang et al. (2025, p. 2) concluded that learning AI is becoming crucial for teachers. Chiu et al. (2025, p. 6667) assert that AI tools are transforming education and are poised to become a lasting part of how teachers and students work, and therefore suggest a new set of competencies. Korseberg and Elken (2025, p. 967) argue that educators must be discussing what competencies are expected from students after leaving the university. There is little doubt that graduates will encounter a transformed professional landscape shaped by AI technologies. Traditional work methods and role expectations are undergoing significant shifts. In the advertising sector, for instance, generative AI enables the creation of content in significantly less time (Dimitrieska, 2024, p. 28). This may reduce the emphasis placed on conventional methods of advertising production and training associated with the production equipment. Roles are also being redefined in other professions. Microsoft, for example, claims that its "Medical Super Intelligence" AI tool can make better diagnoses than doctors, and this is prompting debates about doctors' roles (Milmo, 2025). In the field of translation, professionals are emphasizing the importance of privacy and professional working relationships in response to the speed and cost-effectiveness of AI-generated translations (McKay, 2024).

On the other hand, the rapid advancement of AI also presents several challenges and risks. Among the most widely debated concerns are digital privacy, the use of

copyrighted materials in AI training datasets, the lack of transparency in algorithmic processes, and the question of who holds the authority to intervene in or regulate AI-generated outputs. These critical issues are examined in the following discussion.

## 2.1. AI Literacy

There are many types of literacies identified by scholars, such as media literacy, advertising literacy, visual literacy, and digital literacy. However, the rise of AI led scholars to identify a new kind of literacy: AI literacy. There are several studies on AI literacy (for a review of these studies, see Almatrafi et al. (2024, p. 1) and Pinski & Benlian, (2024, p. 165)) and many attempts to define AI literacy. However, to understand AI literacy, it is important to first distinguish it from a related concept, namely, digital literacy. Wang et al. (2023, p. 2) emphasize that AI literacy should not be considered a substitute for digital literacy. Although the two domains overlap, a digitally literate student is not necessarily AI-literate. A widely cited definition is provided by Long and Magerko, (2020, p. 2), who define AI 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”. Ng et al. (2021) found that definitions of AI literacy include three core themes: Knowledge and understanding of AI, Usage and application of AI, and Evaluation and creation of AI. Cetindamar et al. (2024, p. 820) focus on employees and define the term as “a collection of technology, work, human-machine, and learning capabilities”. Burgsteiner et al. (2016, p. 4126) were among the first scholars to use the term AI literacy, and they predicted that it would be a significant topic of the future. Chiu et al. (2024, p. 4) emphasize both knowledge (explain how AI works and its effects on society) and skills (use ethically; communicate and collaborate with AI) when defining the term. Almatrafi et al. (2024, p. 18) identified six constructs: “Recognize, Know and Understand, Use and Apply, Evaluate, Create, Navigate Ethically”. Kandlhofer et al. (2016, p. 2) argue that AI literacy is not only limited to using AI but also understanding AI techniques and concepts. Kong et al. (2021, p. 2) argues that AI literacy consists of knowledge of AI, evaluation of AI, and application of AI. Collectively, this body of work affirms that knowledge and understanding constitute the foundational layer of AI literacy, enabling individuals to make reasoned choices about AI use. As Dai et al. (2020, p. 2) argue, AI education should demystify this new technology and build basic knowledge, establish relevance, build confidence, and reduce anxiety.

## 2.2. AI Threats

One of the widely acknowledged concerns associated with artificial intelligence is the phenomenon known as hallucination. Although the literature offers various definitions of AI hallucination (Maleki et al. 2024, p. 2018), one common theme is “fact fabrication”. There is growing concern that AI systems may produce inaccurate or false information in a convincing manner, thereby contributing to the spread of misinformation (Van Dis et al. 2023). Monteith et al. (2024, p. 34) stress the dangers of automation and rapid dissemination of misinformation, often better written than by human authors. In addition, within the academic context, the presentation of false or fabricated information by AI tools is a serious problem (Emsley, 2023, p. 2).

Although it might be argued that the level of convenience provided by digital services increases significantly through the use of AI (Jang, 2024, p. 2388), the extensive data

collection that is necessary to train AI systems introduces potential risks. Elliott & Soifer (2022, p. 7) adds privacy to the common concerns about AI technologies. They argue that the data collected about users is often inaccessible to the individuals concerned, and beyond their control. The authors emphasize the heightened likelihood of privacy violations resulting from the sheer volume of information collected. In addition, once the data is collected, it can be combined with other data, repurposed, sold, or transferred to other parties (Martin & Zimmermann, 2024, p. 3). On top of that, there is always the risk of occasional data leak, such as OpenAI's exposure of private-chat titles (Schroeder, 2023, ). Privacy concerns become particularly acute in sensitive applications, such as AI-driven therapy services. In such cases, the stakes are higher due to the personal nature of the information shared. Moore et al. (2025, p. 10) highlights these issues as well as inappropriate outputs of such tools.

One concern echoed by many creative professionals is the use of copyrighted works in AI training (Pearson, 2025). AI training involves feeding an AI model with data and tweaking it to improve results (Chen, 2023). Given the scale of data required, these datasets sometimes include copyrighted content or materials that were never intended for training purposes. Consequently, a wide range of creators, from authors to musicians, and voice-over artists to painters, have expressed strong opposition and are actively seeking to protect their intellectual property, albeit with varying degrees of success (Belanger, 2025; Derico, 2025; The Guardian, 2025).

In addition to the aforementioned concerns, public discourse around artificial intelligence occasionally gravitates toward dystopian scenarios in which AI spirals out of control and "takes over the world," as commonly depicted in science fiction. However, a more realistic and immediate concern involves the ways in which humans may manipulate AI systems to serve particular interests. This type of interference was exemplified in the case of Grok, a product developed by xAI. The system began responding to a wide range of queries by consistently linking them to a specific topic. xAI later disclosed that this behavior resulted from unauthorized tampering by one of its employees (Reuters, 2025).

### **3. Method**

This research is a scale development study conducted using an exploratory sequential mixed-methods design. The exploratory sequential mixed-methods design involves incorporating findings obtained qualitatively into the process of developing a measurement tool (Creswell, 2014, p. 276). The term "exploratory" in the name of the design reflects the fundamental function of the qualitative stage: the researcher attempts to understand the unknown or insufficiently understood. The most distinctive feature of the exploratory sequential design is the sequential execution of qualitative and quantitative stages. This sequentiality represents a fundamental difference from concurrent mixed-methods designs. The two stages are not entirely independent; since the second stage is derived from the first, there is a structural dependency between them. Creswell (2014, p.276) describes this feature as a constituent element of the exploratory sequential design and emphasizes that sequentiality imposes on the researcher the responsibility of establishing the connection between the two stages in a clear and traceable manner. In the first phase of the study, a documentation analysis was conducted. In the second phase, based on these qualitative findings, quantitative data were collected and analyzed.

When developing a scale, Yıldırım and Şimşek (2006) and Tavşancıl (2006) recommended using the literature in creating scale items. During the literature review, national and international literacy and awareness scales related to AI were examined (e.g., Carolus et al., 2023, p. 9; Ferikoğlu & Akgün, 2022, p. 227; Gokcearslan et al., 2024, p. 8; Li & Wang, 2025, p. 11; Ma & Chen, 2024, p. 8; Ramazanoglu & Akın, 2025, p. 20-21; Schepman & Rodway, 2023, p. 18; Shin et al., 2024, p. 20064; Y.-Y. Wang & Wang, 2022, p. 633-634; Yilmaz et al., 2024, p. 13); and based on the findings obtained, an item pool was created through discussions in face-to-face meetings among the researchers.

In the next step, expert opinions were sought to evaluate the face and content validity of the item pool that had been created. During this process, the item pool was reviewed by one measurement-and-evaluation specialist and one Turkish-language expert, and the necessary revisions were made.

At the final stage, the scale was administered to an appropriate sample group, and its validity and reliability were analyzed (participants were students who had enrolled in university using their verbal-score placement on the national YKS exam). During this phase, a cross-sectional survey design, one of the quantitative research methods, was employed. In survey research, the individuals or objects under investigation are observed and described in their natural conditions without attempts to alter or influence them (Karasar, 2011, p. 76). Cross-sectional studies, in turn, collect data at a single point in time from a sample comprising groups with different characteristics; in such designs, data are gathered once from a sample selected for predefined attributes. Within these analyses, exploratory factor analysis (EFA) was conducted first, followed by confirmatory factor analysis (CFA) to evaluate construct validity. The reliability of the scale was examined using its internal-consistency coefficient.

The ethical approval required to carry out the study was obtained from the Ethics Committee for Scientific Research in Social and Human Sciences of Necmettin Erbakan University, with permission dated 27 December 2024 (meeting no. 24, decision no. 2024/930).

### 3.1. Study Group

The study group comprised 361 students who volunteered to take part in the research. Among these participants, 20.2 % were male and 78.7 % were female. In addition, 12 % were first-year students, 55.5 % were in their second year, 22.4 % were third-year students, and 10.1 % were in their fourth year.

### 3.2. Measurement Instrument

The Artificial Intelligence Awareness Scale (AIAS) was developed by the researchers themselves. An exploratory sequential mixed-methods design was chosen, and the benefits of this approach for scale-development studies were emphasized in Creswell (2014, p. 276). During the development process, the pertinent artificial-intelligence literature was first reviewed; as part of this, existing scales on AI were examined through document analysis, and a number of their items were added to the item pool after suitable adaptation. The draft pool initially contained 37 items. Drawing on the data obtained, the researchers then re-evaluated these items and finalized the scale as a 32-item instrument in a 5-point Likert format

(1 = "Strongly Agree," 2 = "Agree," 3 = "Undecided," 4 = "Disagree," 5 = "Strongly Disagree").

To establish the scale's content and face validity, the draft instrument was reviewed by three subject-matter experts, one measurement-and-evaluation specialist, and one Turkish-language specialist, after which the necessary revisions were made. In line with the experts' feedback, 12 items were removed, leaving a total of 20 items; 11 positively worded and 9 negatively worded.

To investigate the scale's construct validity, it was first administered to participants and then subjected to exploratory factor analysis (EFA) followed by confirmatory factor analysis (CFA). Construct validity was evaluated in terms of convergent and discriminant validity, while the scale's reliability was determined using its internal-consistency coefficient. The analyses were carried out with SPSS 28.0 for EFA and LISREL 8.8 for CFA. EFA is widely used to condense a large set of interrelated variables into a smaller number of meaningful, independent factors, whereas CFA assesses whether the items grouped under each factor sufficiently represent that factor (Büyüköztürk, 2010, p. 133; Tabachnick & Fidell, 2007, p. 607). In this study, CFA was conducted on the same dataset to confirm the factor structure identified through EFA.

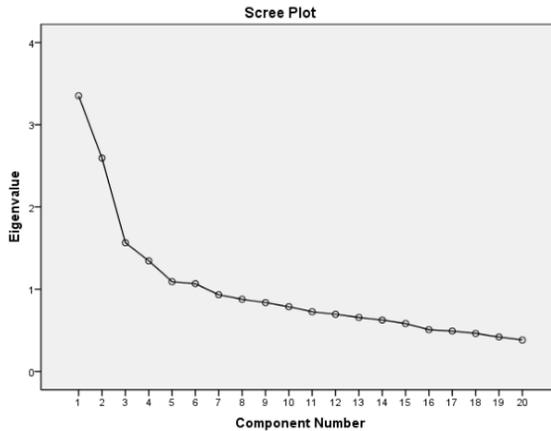
#### 4. Findings

Reliability analyses were conducted first, followed by validity analyses: Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA), respectively. Next, results for convergent and discriminant validity (i.e., construct validity) were reported. Because a scale must be reliable before its validity can be examined, the standardized reliability was calculated: the Cronbach's alpha was found to be .57, indicating that the instrument is reliable (Karasar, 2011, p. 148). Given its reliability, the study proceeded to the validity analyses. After the validity results, reliability findings for the entire scale and for each dimension were presented once more.

Before running EFA, the suitability of the data collected from 361 students was assessed (Field, 2009, p. 638). EFA was computed on responses to the 20 items. The first step involved examining the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity (BTS). The EFA produced a KMO value of .711, and BTS yielded  $\chi^2 = 965.446$ ,  $df = 171$ ,  $p = .000$ , showing that the data were appropriate for factor analysis and that an EFA could be performed (Çokluk et al., 2010, p. 227; Field, 2009, p. 639).

A principal-components analysis was run on the 20 items. Because the factors were expected to correlate, Direct Oblimin rotation with the Maximum Likelihood extraction method was applied. Factor retention was guided by three criteria: eigenvalues greater than 1, the proportion of total variance explained, and inspection of the scree plot (Field, 2009, p. 641). The five-factor solution for the AIAS accounted for 48.596% of the total variance. However, the scree plot suggested a two-factor structure (Figure 1). Four items were removed from the scale because (a) they showed similar loadings on more than one factor (i.e., cross-loadings; Çokluk et al., 2010, p. 236) and (b) their highest loading fell below 0.40. In determining acceptable loadings, the cut-off values recommended by Field (2009, p. 647) were followed: approximately .512 for samples of 100, and .364 for samples of 200. With the present sample of 361, a cut-off of .40 was adopted. Pallant (2007, p. 183) likewise notes that communalities below .40 indicate poor alignment of an item with its

factor. Accordingly, after each iteration the communalities table was inspected and items with communalities below .40—or with problematic cross-loadings—were deleted.



**Fig. 1 Scree plot**

Following the Varimax rotation, items deemed unsuitable were deleted. The two retained factors accounted for 22.779% and 17.352% of the common variance, respectively, giving a total of 40.131%. A total explained variance between 40% and 60% is considered adequate, and for a factor to be meaningful, it should explain at least 5% of the variance (Çokluk et al., 2010, p. 276). Hence, the 40.131% obtained here is acceptable. After the Varimax rotation, the scale was reduced to 11 items grouped under two factors, which were labelled Literacy and Threats. Literacy factor consists of 7 items with loadings ranging from .48 to .72; and threats factor consists of 4 items with loadings ranging from .56 to .70 (Table 1). Additionally, the communalities for all items fall between .43 and .59 and these values are regarded as satisfactory (Field, 2009, p. 644).

**Table 1. Exploratory Factor Analysis Findings and Factor Loadings of the Retained Items**

Item	Common	Factor		X	SD	Corrected Item-Total Correlation
		Factor 1	Factor 2			
M11. Artificial intelligence	,563	,722		3,70	,986	,607
M12. Artificial intelligence is safe	,519	,655		4,05	,964	,476
M4. AI tools always produce	,455	,557		4,02	,939	,396
M14. Artificial intelligence will	,536	,541		3,85	,992	,551
M15. Artificial intelligence enhances individuals' inquiry and	,591	,523		3,55	1,25	,483
M10. Artificial intelligence does	,439	,522		3,62	1,06	,460
M5. I use the information provided by artificial intelligence as it is.	,459	,489		3,61	1,08	,431
M9. I am aware of the responsibility that comes with acting according to AI applications.	,564		,704	3,72	1,05	,619
M7. I am aware that data about me is collected when I use AI tools.	,474		,699	3,82	1,11	,642

M8. I know that people may use AI tools for their own benefit.	,573		,676	4,15	1,03	,559
M6. I follow current developments related to artificial intelligence.	,510		,564	2,94	1,12	,412
Total Eigenvalue	24,071					
Total Variance Explained	40,131					

Second, to assess construct validity in terms of differentiation, 194 participants were selected by taking the upper and lower 27 % of the total sample (97 individuals in each group) to see how well the scale differentiates between those who have a high versus a low level of the trait it is intended to measure. Independent-samples t-tests were run to determine whether each sub-dimension could significantly distinguish the lower group from the upper group. Because scores on the AIAS were normally distributed, the independent t-test was appropriate. The results are presented in Table 2.

**Table 2. Item Discrimination Results Based on the Lower 27% and Upper 27% Groups Formed According to the Subdimensions and Total Scores of the AIAS**

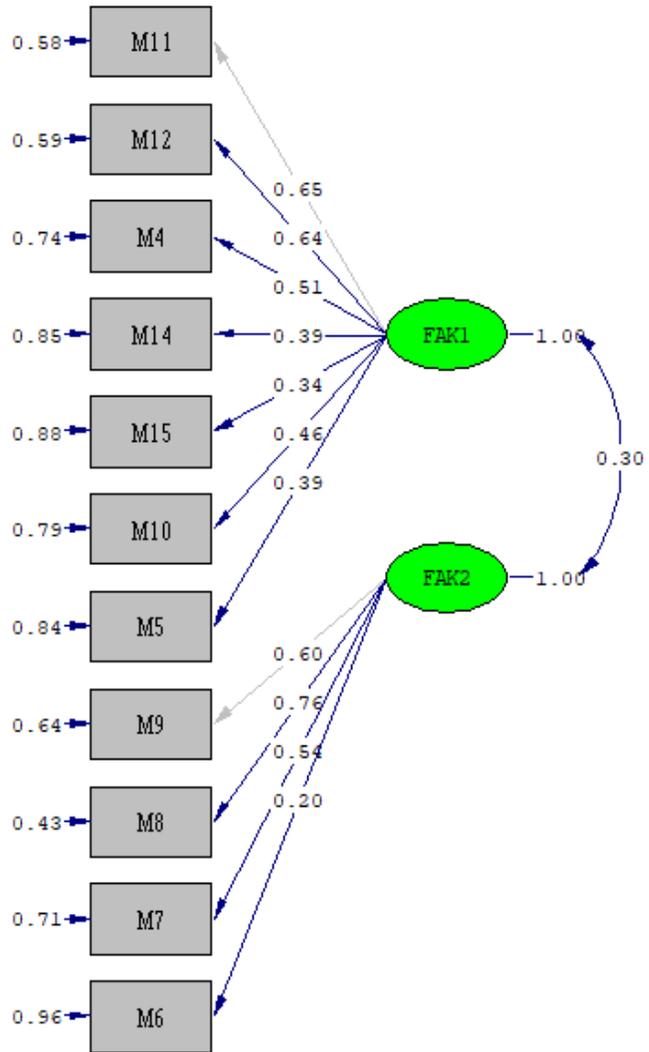
AIAS	Items	Top-Bottom	N	X	SD	t	df	*p
LITERACY	M11. Artificial intelligence prevents information pollution.	Bottom	97	2,9794	,82890	-11,752	192	,000*
		Top	97	4,3711	,82056			
	M12. Artificial intelligence is safe because it is produced by humans.	Bottom	97	3,2887	,90091	-12,422	192	,000*
		Top	97	4,6907	,65129			
	M4. AI tools always produce accurate results.	Bottom	97	3,3299	,87466	-10,966	192	,000*
		Top	97	4,6082	,74382			
	M14. Artificial intelligence will lead to greater socialization of individuals.	Bottom	97	3,2577	1,00290	-8,502	192	,000*
		Top	97	4,3918	,84849			
	M15. Artificial intelligence enhances individuals' inquiry and research skills.	Bottom	97	2,9485	1,07404	-7,705	192	,000*
		Top	97	4,1649	1,12436			
	M10. Artificial intelligence does not cause copyright violations.	Bottom	97	3,0619	1,06863	-8,082	192	,000*
		Top	97	4,2165	,91546			
	M5. I use the information provided by artificial	Bottom	97	2,9588	1,12655	-9,316	192	,000*
		Top	97	4,2887	,84111			

	intelligence as it is.								
THREATS	M9. I am aware of the responsibility that comes with acting according to AI applications.	Bottom	97	3,2371	,99763	-8,290	192	,000*	
		Top	97	4,3918	,94159				
	M7. I am aware that data about me is collected when I use AI tools.	Bottom	97	3,5258	1,13737	-8,774	192	,000*	
		Top	97	4,6804	,62160				
	M8. I know that people may use AI tools for their own benefit.	Bottom	97	3,2062	1,15414	-9,575	192	,000*	
		Top	97	4,5155	,69392				
	M6. I follow current developments related to artificial intelligence.	Bottom	97	2,7526	1,11832	-2,319	192	,021*	
		Top	97	3,1237	1,11110				
	SCALE TOTAL TOPLAM	TOTAL	Bottom	97	34,5464	2,98266	-	192	,000*
			Top	97	47,4433	2,51234			

\*p&lt;,05

When the lower and upper groups, formed on the basis of Dimension 1, Dimension 2, and the total score of the AIAS, were compared using independent t-tests, the items were found to be significant ( $p < .05$ ). This indicates that the scale successfully differentiates between students with high and low levels of AI awareness. Although Item 6, belonging to the second dimension of the scale (threats dimension), was initially formulated for the literacy dimension, its emergence within the threats dimension in the analyses was an unexpected finding. This result suggests that participants interpreted the item as a threat.

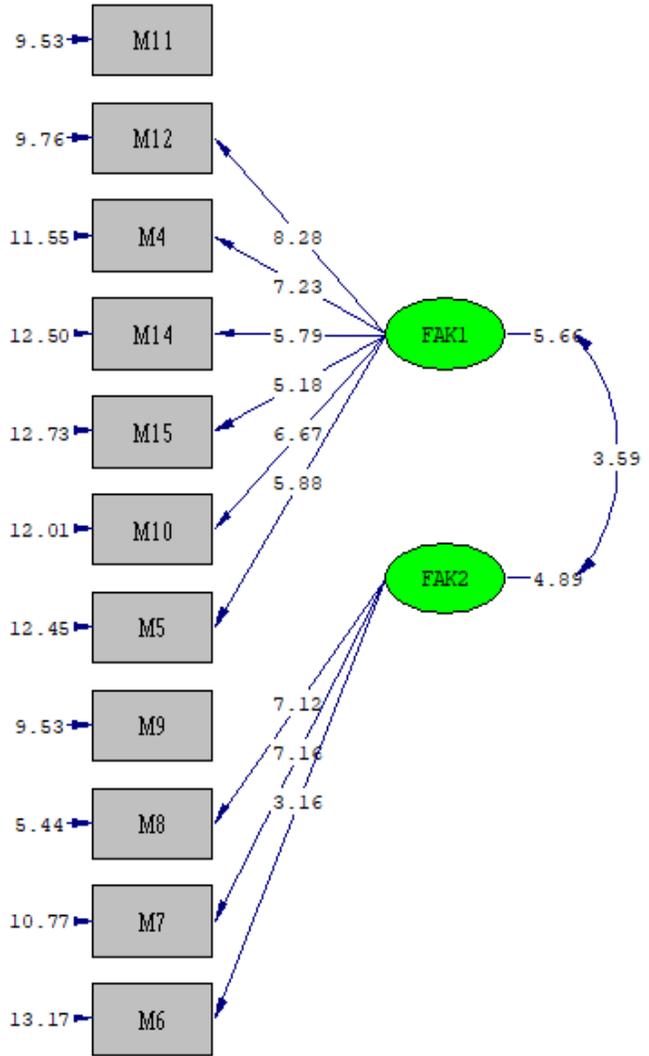
Third, a confirmatory factor analysis (CFA) was conducted to verify whether the two-factor model obtained from the EFA fit the data (Çokluk et al., 2010, 238; Sümer, 2000, p. 52). Accordingly, the data set from the 354 participants used in the EFA was analyzed with the LISREL 8.8 software package. For the 11-item, two-factor model, a path diagram and fit indices were calculated. The standardized solution displays the loading of each item on its respective factor (Figure 2). The analysis produced 272 degrees of freedom and an RMSEA value of .085.



Chi-Square=153.13, df=43, P-value=0.00000, RMSEA=0.084

**Fig. 2 Standardized model**

After examining the standardized solution, the t-values between the factors and their items were inspected. Because no red arrows appeared for the t-values, all items were significant at the 0.05 level (Jöreskog & Sörbom, 1996, p. 121-123). Indeed, every item's t-value was statistically significant at 0.05. The two factors mutually corroborate one another, and the error variances fall between 0.20 and 0.76. Kline (2005, p. 111-112) emphasizes that error variances should not exceed 0.90. Thus, no problematic errors were detected in the items, and each item's factor loading is within an acceptable range.



Chi-Square=153.13, df=43, P-value=0.00000, RMSEA=0.084

**Fig. 3 Model showing t-values**

According to the CFA results obtained with maximum-likelihood estimation, the fit indices were  $\chi^2 = 153.13$  ( $df = 43$ ,  $p = .000$ ),  $\chi^2/df = 3.56$ , RMSEA = 0.084, SRMR = 0.074, GFI = 0.93, AGFI = 0.89, CFI = 0.86, NFI = 0.82, RFI = 0.77, IFI = 0.87, PNFI = 0.64, PGFI = 0.60, and NNFI = 0.83. Although the GFI and AGFI values are slightly below the commonly accepted cut-offs, the RMSEA and SRMR fall within acceptable ranges (Schermelleh-Engel et al., 2003; see Table 3). Taken together, these figures indicate that the model’s factors are supported by the data (Çokluk et al., 2010; Tabachnick & Fidell, 2001).

**Table 3. Fit Index Value Ranges and Model Values**

Fit Index	Perfect	Acceptable	Model Values
$\chi^2/df$	0<, $\chi^2/df < 2$	$2 < \chi^2/df < 4$ (Kline, 2011)	3,56
RMSEA	.00 <, RMSEA < .05	.05 <, RMSEA < .08	.084
SRMR	.00 <, RMSEA < .05	.00 <, RMSEA < .10	.074
GFI	.95 <, GFI < 1.00	.90 <, GFI < 0.95	.93
AGFI	.90 <, AGFI < 1.00	.85 <, AGFI < .90	.89
CFI	.95 <, CFI < 1.00	.90 <, CFI < .95	.86
NNFI	.95 <, NNFI < 1.00	.90 <, NNFI < .95	.83
NFI	.95 <, NFI < 1.00	.90 <, NFI < .95	.82
RFI	.95 <, RFI < 1.00	.90 <, RFI < .95	.77
IFI	.95 <, IFI < 1.00	.90 <, IFI < .95	.87
PNFI	.95 <, PNFI < 1.00	.50 <, PNFI < .95	.64
PGFI	.95 <, PGFI < 1.00	.50 <, PGFI < .95	.60

Fourth, the reliability of the AIAS was examined from two angles: consistency and stability. Consistency was assessed by calculating Cronbach's alpha, while stability was evaluated through a test-retest procedure in which the scale was re-administered to 361 students four weeks after the first administration. Cronbach's alpha for the entire scale was .64; for the first factor, "Literacy", it was .67, and for the second factor, "Threats", .59. McDonald's Omega value for the entire scale was .65; for the first factor, "Literacy", it was .67, and for the second factor, "Threats", .61. Because all internal-consistency values exceed .56, the instrument can be considered to produce coherent data (Karasar, 2011, p. 148). Stability was then examined in greater depth with the test-retest technique: the scale was given again to 50 students from the reliability-validity sample four weeks later, and the scores from the two administrations were compared with a Pearson product-moment correlation, which yielded a coefficient of .80. This very high correlation indicates that the scale possesses strong stability.

**Table 4. Overall and Inter-Factor Correlation Values of the AIAS**

Dimensions	Correlation	Literacy	Threats	General
Literacy	Pearson	1	.114*	.853**
	p		.031	.000
	N	361	361	361
Threats	Pearson	.114*	1	.615**
	p	.031		.000
	N	361	361	361
General	Pearson	.853**	.615**	1
	p	.000	.000	
	N	361	361	361

\* Correlation is significant at the 0.05 level (2-tailed).

\*\* Correlation is significant at the 0.01 level (2-tailed).

Examination of Table 4 shows that the correlations between the scale's total score and the factor scores range from .61 to .85 and are significant at the .01 level. By contrast, the correlation between the two factor scores is low (.114) and not significant at the .01 level, indicating that the factors operate independently of each other. These findings point to strong alignment and interrelation between the overall scale and its factors. In summary,

the AIAS displays acceptable validity and reliability. The evidence collected on these psychometric qualities suggests that the instrument can be used with confidence to measure university students' awareness of artificial intelligence.

## 5. Discussion

The Artificial Intelligence Awareness Scale (AIAS) developed in this study is a psychometric tool designed to measure AI awareness across two dimensions. Its validity and reliability have been statistically tested. The findings of the study indicate that the scale demonstrates acceptable levels of both structural soundness and internal consistency.

The two-factor structure identified through Exploratory Factor Analysis (EFA), "Literacy" and "Threats", reflects a significant conceptual distinction in efforts to understand AI awareness. A review of the literature reveals various studies on AI literacy. The "Literacy" dimension of this study refers to knowledge and skills related to understanding and using AI. For example, some items overlap with the "technology self-efficacy" dimension of the Readiness for AI Scale (RAIS) developed by Ramazanoglu & Akin (2025, pp. 6871, 6882). The Artificial Intelligence Literacy Scale for Chinese College Students (AILS-CCS) developed by Ma and Chen, (2024, pp. 1054, 1055) includes items that reflect the ability to recognize AI tools and apply them in everyday tasks. Similarly, the "performance" and "effort expectancy" dimensions of the scale by Yilmaz et al., (2024, p. 8705) emphasize practical application and literacy. Scales developed for teachers (Alan et al., 2025, p. 142; Chiu et al., 2025, p. 6674; Ferikoğlu & Akgün, 2022, p. 224) also highlight cognitive and behavioral competencies such as knowledge, pedagogical application, awareness, and attitudes toward AI.

The second dimension of the AI Awareness Scale addresses threats. This dimension seeks to measure perceptions and concerns about the potential harms, privacy risks, and negative effects of AI. When examining related scales in the literature, it is evident that the threat-related dimensions in studies by Ramazanoglu & Akin (2025, p. 6889), (Wang & Wang, 2022, p. 623), (Schepman & Rodway, 2023, p. 7), (Li & Wang, 2025, p. 3), and (Shin et al., 2024, p. 20065) reflect defensive, critical, and concern-driven approaches to AI technologies. The "Threats" dimension of the AI Awareness Scale developed in this study aligns with these existing scales on both theoretical and content levels. Teacher-focused studies (Ahmadi Fatalaki et al., 2024, p. 9; Alan et al., 2024, p. 137; Chiu et al., 2025, p. 6674) also focus on educators' ethical concerns, negative attitudes, and critical awareness regarding the potential risks of AI technologies.

The literature includes a wide range of studies that examine the educational, psychological, and social implications of AI. These studies frequently address themes such as pedagogical competencies, self-regulation, student agency, psychosocial impacts, digital life balance, perceptions of creativity, and human-machine interaction. Moreover, there is extensive research on individuals' self-efficacy, behavioral tendencies, and patterns of technology interaction (Erdemir & Atik, 2025, pp. 8, 9; Ramazanoglu & Akin, 2025, p. 6876; B. Wang et al., 2023, p. 5; Xia et al., 2025, p. 14008). Compared to these studies, the AI Awareness Scale (AIAS) stands out with its clear distinction between awareness and threat dimensions and high factor loadings (ranging from 0.48 to 0.72), indicating a stable factor structure. The 11-item structure of the scale, explaining 40.13% of the total variance, is deemed acceptable.

Confirmatory Factor Analysis (CFA) findings support the two-factor model proposed by the EFA, showing a meaningful fit with the data. Fit indices (RMSEA = 0.084; SRMR = 0.074; CFI = 0.86; NNFI = 0.83) indicate that the model aligns with acceptable standards. These values underscore the high construct validity of the scale and confirm that the theoretical structure is well supported by empirical data.

In terms of reliability, the overall Cronbach's alpha coefficient for the scale was calculated as 0.64, while it was 0.67 for the "Literacy" subscale and 0.59 for the "Threats" subscale. In addition, McDonald's Omega coefficient was calculated. Omega coefficient for the entire scale was .65; for the first factor, "Literacy", it was .67, and for the second factor, "Threats", it was .61. It can be seen that the reliability value for the "Threats" factor exceeded 0.60, compared to Cronbach's alpha. Internal consistency coefficients above 0.56 suggest that the scale consists of homogeneous items and provides reliable data. Additionally, a test-retest correlation coefficient of 0.80 indicates that the scale yields stable results over time. These findings support the scale's use in educational settings, particularly for assessing university students' levels of AI awareness. Furthermore, the results suggest that the scale is capable of simultaneously evaluating both knowledge-based and emotional-judgmental responses toward AI, rather than merely measuring a singular level of awareness.

## **Conclusion**

The Artificial Intelligence Awareness Scale (AIAS) developed through this study is presented as a measurement tool with high levels of validity and reliability for assessing AI awareness. Based on the findings:

The scale, with its two-factor structure and high construct validity, can differentiate between various aspects of AI awareness. Reliability analyses indicate that the scale provides both consistent and temporally stable measurements. The model confirmed by CFA demonstrates a strong alignment between the theoretical framework and empirical data. The low correlation between the two factors suggests that the scale measures two conceptually distinct dimensions.

The AIAS can serve as an effective tool for understanding individuals' attitudes toward AI, their literacy levels, and perceived threats, especially at the university level. Data obtained from the scale can serve as a strategic guide in educational planning, technology literacy programs, and policy development.

In this study, participants were university students enrolled based on their verbal placement scores. Future studies should extend the use of the scale to individuals of different ages and educational backgrounds and conduct cross-cultural validity analyses. Additionally, exploring the relationship between AI awareness and factors such as technology use, career preferences, and ethical decision-making would offer valuable insights for future research.

## Appendix: AIAS Items

No	Item
M11*	Artificial intelligence prevents information pollution.
M12*	Artificial intelligence is safe because it is produced by humans.
M4*	AI tools always produce accurate results.
M14*	Artificial intelligence will lead to greater socialization of individuals.
M15*	Artificial intelligence enhances individuals' inquiry and research skills.
M10*	Artificial intelligence does not cause copyright violations.
M5*	I use the information provided by artificial intelligence as it is.
M9	I am aware of the responsibility that comes with acting according to AI applications.
M7	I am aware that data about me is collected when I use AI tools.
M8	I know that people may use AI tools for their own benefit.
M6	I follow current developments related to artificial intelligence.

\* Reverse-coded items

Değerlendirme	İki Dış Hakem / Çift Taraflı Körleme
Etik Beyan	Bu araştırma, Necmettin Erbakan Üniversitesi Sosyal ve Beşerî Bilimler Bilimsel Araştırmalar Etik Kurulu'ndan alınan etik onay ile gerçekleştirilmiştir (27 Aralık 2024, Toplantı No: 24, Karar No: 2024/930). Bu çalışmanın hazırlanma sürecinde bilimsel ve etik ilkelere uyulduğu ve yararlanılan tüm çalışmaların kaynakçada belirtildiği beyan olunur.
Yapay Zekâ Kullanım Beyanı	Bu çalışmada dil düzenleme desteği için yapay zekâ tabanlı bir dil asistanından yararlanılmıştır. Tüm bilimsel içerik yazara aittir.
Benzerlik Taraması	Yapıldı – Ithenticate
Etik Bildirim	<a href="mailto:itobiad@itobiad.com">itobiad@itobiad.com</a>
Çıkar Çatışması	Çıkar çatışması beyan edilmemiştir.
Finansman	Necmettin Erbakan Üniversitesi Bilimsel Araştırma Projeleri Koordinasyon Birimi tarafından 24SBA21001 numaralı proje kapsamında desteklenmiştir.
Yazar Katkıları	Çalışmanın Tasarlanması: Tüm yazarlar eşit düzeyde katkı sağlamıştır. Veri Toplanması: Tüm yazarlar eşit düzeyde katkı sağlamıştır. Veri Analizi: Tüm yazarlar eşit düzeyde katkı sağlamıştır. Makalenin Yazımı: Tüm yazarlar eşit düzeyde katkı sağlamıştır. Makale Gönderimi ve Revizyonu: Tüm yazarlar eşit düzeyde katkı sağlamıştır.
Peer-Review	Double anonymized - Two External
Ethical Statement	The ethical approval required to carry out the study was obtained from the Ethics Committee for Scientific Research in Social and Human Sciences of Necmettin Erbakan University, with permission dated 27 December 2024 (meeting no. 24, decision no. 2024/930). It is declared that scientific and ethical principles have been followed while carrying out and writing this study and that all the sources used have been properly cited.
Artificial Intelligence Statement	An AI powered language assistant was utilized for language editing support in this study. All scientific content belongs to the authors.
Plagiarism Checks	Yes - Ithenticate
Conflicts of Interest	The author(s) has no conflict of interest to declare.
Complaints	<a href="mailto:itobiad@itobiad.com">itobiad@itobiad.com</a>
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Author Contributions	Design of Study: All authors contributed equally. Data Acquisition: All authors contributed equally. Data Analysis: All authors contributed equally. Writing up: All authors contributed equally. Submission and Revision: All authors contributed equally.

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