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Research Paper

Adaptation and Validation of the Turkish Version of the Artificial Intelligence Self-Efficacy Scale

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ABSTRACT

This study aimed to adapt the Artificial Intelligence Self-Efficacy Scale developed by Wang and Chuang (2024) into Turkish and evaluate its validity and reliability. The study was conducted with two independent samples: a group of 291 university students participated in the exploratory factor analysis (EFA), while a separate group of 374 participants was involved in the confirmatory factor analysis (CFA). The 22-item scale, along with demographic questions and one item on AI usage, was administered online. Cronbach's alpha was used to assess reliability, and correlations with AI usage were examined to evaluate criterion validity. EFA revealed a four-factor structure: assistance, anthropomorphic interaction, comfort with AI, and technological skill, with factor loadings ranging from 0.43 to 0.85. The total variance explained by the factors ranged from 41.23% to 67.47% across the sub-dimensions. A weak negative correlation was found between AI self-efficacy and AI usage levels. The Cronbach's alpha coefficient was 0.958 for the overall scale, indicating high internal consistency. CFA results confirmed that the Turkish version of the scale is a valid and reliable instrument for measuring AI self-efficacy.

INTRODUCTION

Artificial intelligence (AI) has become a transformative force across various sectors. According to Gartner's (2024) report, AI applications are increasingly integrating into both individual and corporate workflows. AI's capabilities in data analysis, generative content, and predictive modeling provide significant insights and operational efficiencies. However, this deep integration raises questions about how effectively individuals can utilize these complex tools. Specifically, an individual's perception of self-efficacy towards AI technologies may play a decisive role in their productivity and the overall success of technology integration.

Bandura's Social Learning Theory (1977) emphasizes how individuals' perceptions of self-efficacy shape their behaviors. According to this theory, individuals who believe in their abilities are more willing and determined to accomplish a particular task. In the context of AI, employees' perceptions of self-efficacy may directly affect their capacity to use advanced applications effectively. Individuals with high self-efficacy are more likely to succeed in AI-related tasks and efficiently integrate these technologies into business processes. Consequently, measuring and understanding AI self-efficacy is crucial for enhancing both individual performance and organizational success.

In recent years, studies on how individuals use and perceive AI technologies (An et al., 2023; Krieger et al., 2024; Neri & Cozman, 2020) have generally relied on general models such as computer or communication self-efficacy. However, as AI technologies become increasingly complex, a specific understanding of self-efficacy tailored to these unique tools is required. While Wang and Chuang (2024) developed a comprehensive scale to address this need, there is currently no Turkish adaptation available. Adapting this scale into Turkish will provide researchers and practitioners with a specialized tool to measure AI-related knowledge and beliefs in a local context, filling a significant gap in the national literature.

THEORETICAL FRAMEWORK

The rapid development of AI technologies has prompted increased scrutiny of individuals' self-efficacy perceptions. Based on Bandura's (1977) Social Cognitive Theory, AI self-efficacy is defined as an individual's judgment of their capacity to organize and perform actions required to effectively engage with AI technologies (Morales-García et al., 2024; Wang & Chuang, 2024). This perception significantly influences the adoption, use, and performance of AI tools across educational and professional contexts (Bittencourt et al., 2023).

In addition to self-efficacy, Rogers' Diffusion of Innovations theory explains how innovations are adopted within a social system through specific stages (Rogers et al., 2014). For educators, effective integration depends on their progress through these stages, which can be evaluated using the Level of Use (LoU) framework (Loucks et al., 1975). The LoU framework is a structured model that outlines how users transition from non-use to advanced, reflective implementation of new technologies. A detailed explanation of the LoU framework based on the study is given in Table 1:

Table 1. Definitions of LoU*

Level	Definitions
0. Non-use	I have very little or no knowledge about the use of artificial intelligence, I am not interested in it, and I am not making any effort to engage with it.
1. Orientation	I am in the process of accessing and researching information about using artificial intelligence.
2. Preparation	I am preparing to use artificial intelligence for the first time.
3. Mechanical use	I am focused on short-term or daily use, and I don't have much time for reflection. My efforts are primarily directed towards acquiring the skills needed to meet the requirements of online technologies.
4. Routine use	I feel comfortable using artificial intelligence. However, I am also researching how I can improve my usage.
5. Refinement	I am working to maximize the impact of artificial intelligence in my life.
6. Integration	I am combining my own work with the activities of my colleagues to increase the impact of artificial intelligence.
7. Renewal	I am evaluating the use of artificial intelligence, working on making necessary changes, finding alternatives, enhancing the effectiveness of current AI tools, and exploring new goals for myself and my profession.

**(Loucks et. al., 1975)*

The LoU framework illustrates that adopting an innovation is a non-linear process; instead, it involves navigating various stages that reflect different levels of engagement and understanding. Each level signifies a unique interaction with the innovation, emphasizing the importance of support and professional development in facilitating effective use in educational contexts.

LITERATURE REVIEW

Studies on AI self-efficacy have been conducted across various contexts. Asio and Gadia (2024) explored student attitudes, confirming that AI literacy and self-efficacy are significant determinants of positive attitudes toward AI. Similarly, Wang et al. (2023) found that AI competence positively affects students' creativity and learning performance in higher education, aligning with European Union priorities in the Digital Education Action Plan. Regarding measurement tools, Morales-García et al. (2024) adapted a Spanish version of a general self-efficacy scale for AI among medical students with high reliability (alpha = 0.91). Pütten and Bock (2018) developed a unidimensional scale for human-robot interaction, while Wu et al. (2024) confirmed a valid and reliable scale for AI-supported learning among Chinese university students.

Recent research has also linked AI use to socio-psychological factors. Rodríguez-Ruiz and Marín-López (2024) found that students with lower self-control may depend more heavily on AI, while Qin et al. (2025) introduced the "Artificial Intelligence Quotient" to frame AI capability as a distinct type of intelligence related to personality traits. These findings underscore the need to consider AI self-efficacy within the broader construct of digital competence (Werner, 2025; Vuorikari et al., 2022).

In the Turkish context, Çelebi et al. (2023) observed lower variance in the anthropomorphic interaction and assistance sub-dimensions during their AI literacy scale adaptation. Similarly, Yıldırım and Karaman (2025) addressed technical and attitudinal dimensions, revealing differences in confidence levels based on professional experience. Despite these advances, Lintner (2024) highlights persistent methodological gaps in scale reporting, such as inadequate transparency regarding missing data, which hinders cross-cultural comparisons supported by initiatives like Erasmus+ and Jean Monnet Modules.

While AI self-efficacy research has expanded, there is limited work linking it to ethical use and international policy frameworks like DigCompEdu (European Commission, 2025). Future research designs are needed to analyze how teacher competencies develop through collaboration (Kaya et al., 2025). After adapting the Artificial Intelligence Self-Efficacy Scale, research to be conducted will contribute to the field in this regard.

METHOD

Participants

The participants consisted of university students selected through purposive sampling from the faculty of education at a university. This sampling method was preferred because pre-service teachers and education faculty students are the primary stakeholders who will integrate AI technologies into future K-12 classrooms; thus, their self-efficacy is critical for digital transformation in education.

The study was conducted with two independent samples. A total of 291 different participants took part in the EFA, and a separate group of 374 participants took part in the CFA phase of the study. The scale, translated into Turkish, along with demographic questions and questions about AI usage levels, was administered to participants online. The study was based on voluntary participation. Initially, data were collected from Sample 1 (n=291) to explore the factor structure. Subsequently, data were collected from Sample 2 (n=374) to confirm the established structure. This dual-sample approach was employed to ensure the cross-validity and robustness of the Turkish adaptation.

The participants were university students from various departments. Specifically, 68 were from Child Development, 59 from Primary School Teaching, 39 from Preschool Education, 33 from Mathematics, 31 from Accounting and Finance, 22 from Social Studies, 16 from English, 13 from Visual Arts Education, 10 from Business Administration, and 10 from Computer and Instructional Technology Education. The remaining 83 participants were enrolled in other academic programs. The participants' ages ranged from 18 to 54, with a mean age of 29.9 (Table 2).

Table 2. Descriptive Statistics of Participants

		n	%
Gender	Female	314	84.0
	Male	60	16.0
Level of Use	0.Non-use	29	7.8
	1.Orientation	91	24.3
	2.Preparation	25	6.7
	3. Mechanical Use	123	32.9
	4. Routine Use	78	20.9
	5. Refinement	17	4.5
	6. Integration	5	1.3
	7. Renewal	6	1.6

Table 2 presents the demographic and usage-level characteristics of the participants involved in adapting the Artificial Intelligence Self-Efficacy Scale (AISES). The sample was predominantly female (84.0%), which aligns with the study's focus on university students from various departments, many of which have higher female enrollment. While the high percentage of female participants represents the typical demographic profile of the Faculty of Education at the university where the study was conducted, it is acknowledged as a limitation for generalizing the findings across gender groups.

Regarding AI usage, participants' levels were distributed across all stages of the LoU framework. The most significant proportion of participants reported being at the Mechanical Use stage (32.9%), followed by Orientation (24.3%) and Routine Use (20.9%). These stages indicate initial or habitual engagement with AI technologies, often characterized by task-based interaction without extensive reflection or innovation. Notably, fewer participants were situated at advanced levels such as Refinement (4.5%), Integration (1.3%), and Renewal (1.6%), which emphasize reflective practice, collaboration, and innovation in AI use. This distribution suggests that while participants are generally familiar with and utilize AI tools, they have not yet progressed to transformative or integrative use. These findings underscore the importance of educational interventions that enhance AI self-efficacy and promote progression through the LoU stages toward more sophisticated and meaningful engagement with AI technologies.

Data Collection Tool

The AISES, developed by Wang and Chuang (2024), consists of 22 items and four sub-dimensions. The scale was designed in a 7-point Likert format, where higher scores indicate stronger levels of artificial intelligence self-efficacy. The scale was adapted into Turkish and administered to participants via an online survey, along with demographic questions including gender and a single item measuring AI usage level. The final version of the usage-level item was adapted from Loucks et. al., (1975) and refined based on expert feedback from a specialist in instructional technologies. EFA conducted by Wang and Chuang revealed that the scale had four distinct factors with eigenvalues exceeding the acceptable threshold, and factor loadings ranging from [insert actual range if available]. These results supported the multidimensional structure of the scale. CFA results also supported the model's structure (χ^2 = 388.828, df = 196, $p < 0.001$; χ^2/df = 1.984; RMSEA = 0.079; SRMR = 0.071; CFI = 0.941; TLI = 0.930), indicating acceptable model fit. The scale's reliability was high, with a Cronbach's alpha of 0.958 for the overall scale. The Cronbach's alpha scores for the four sub-dimensions were as follows: assistance (α = 0.942), anthropomorphic interaction (α = 0.970), comfort with AI (α = 0.963), and technological skills (α = 0.869).

Translation of the Scale

A forward translation method was used to adapt the Artificial Intelligence Self-Efficacy Scale into Turkish, involving bilingual translators. Subsequently, an expert panel, including language experts and domain specialists, reviewed and refined the translation to ensure conceptual and cultural equivalence. These steps are consistent with best practice guidelines for cross-cultural adaptation of measurement instruments (Beaton et al., 2000; Rademakers et al., 2020). First, a literature review on artificial intelligence and self-efficacy was conducted using the Scopus and Web of Science databases to ensure content validity. Two faculty members from the English Language Education Department provided expert opinions on the translated items. Necessary adjustments were made based on their feedback to enhance clarity and cultural appropriateness. For example, rigid phrases like "it is the same" were softened to "I think it is the same." In addition, an expert in the Instructional Technologies field reviewed the translations of items related to artificial intelligence, and the sub-dimensions were named accordingly. The original, translated, and modified items are presented in Table 3.

Table 3. Adaptation of Original, Translated and Modified Items

Item number	Sub dimension	Turkish translation	Item	Turkish translation
1	Assistance	Fayda	Some AI technologies/products make learning easier.	Bazı yapay zekâ teknolojileri/ürünleri, öğrenmeyi kolaylaştırır.
2	Assistance	Fayda	I find that AI technologies/products are helpful for learning.	Yapay zekâ teknolojileri/ürünlerini öğrenmeye katkı açısından faydalı bulurum.
3	Assistance	Fayda	AI technologies/products are good aids to learning.	Yapay zekâ teknolojileri/ürünleri, öğrenme sürecinde iyi yardımcılardır.
4	Assistance	Fayda	Using AI technologies/products makes learning more interesting.	Yapay zekâ teknolojileri/ürünlerini kullanmak, öğrenmeyi daha ilginç hale getirir.
5	Assistance	Fayda	I'm confident in my ability to learn simple programming of AI technologies/products if I were provided the necessary training.	Gerekli eğitim verilirse, yapay zekâ teknolojileri/ürünlerinin basit programlamasını öğrenme konusunda kendime güveniyorum.
6	Assistance	Fayda	AI technologies/products help me to save a lot of time.	Yapay zekâ teknolojileri, ürünleri bana çok zaman kazandırıyor.
7	Assistance	Fayda	I find it easy to get AI technologies/products to do what I want it to do.	Yapay zekâ teknolojileri/ürünlerine istediğim şeyi yaptırmanın kolay olduğunu düşünüyorum.
8	Anthropomorphic interaction	Algılanan antropomorfizm	I think the interactive process of AI technologies/products is very vivid, just like chatting with a real person.	Yapay zekâ teknolojileri/ürünleri ile olan etkileşim sürecinin, gerçek bir kişiyle sohbet ediyormuş gibi etkili olduğunu düşünüyorum.
9	Anthropomorphic interaction	Algılanan antropomorfizm	I think the way that AI technologies/products express content when interacting is unique, just like a real person.	Yapay zekâ teknolojileri/ürünlerinin etkileşim şeklinin, tıpkı gerçek bir insanla olduğu gibi, mükemmel olduğunu düşünüyorum.
10	Anthropomorphic interaction	Algılanan antropomorfizm	I think there is no difference between the dialogue method of AI technologies/products compared with the dialogue with real people.	Yapay zekâ teknolojileri/ürünleri ile gerçekleştirilen sohbet ile gerçek insanlarla yapılan sohbet arasında fark olmadığını düşünüyorum.
11	Anthropomorphic interaction	Algılanan antropomorfizm	I think the tone of AI technologies/products when interacting is the same as that of real people.	Yapay zekâ teknolojileri/ürünlerinin etkileşim sırasında kullandığı vurgu/ hız/ses yüksekliği vs., gerçek insanlarınkiyle aynı olduğunu düşünüyorum.
12	Anthropomorphic interaction	Algılanan antropomorfizm	I feel that the way of expression of AI technologies/products in the interactive text is the same as that of real people.	Yapay zekâ teknolojileri/ürünlerinin, etkileşimli metinlerdeki ifade şeklinin gerçek insanlarınkiyle aynı olduğunu düşünüyorum.

13	Comfort with AI	Yapay zekâ ile rahatlık	When interacting with AI technologies/products, I feel very calm.	Yapay zekâ teknolojileri/ürünleri ile etkileşim halindeyken, kendimi çok rahat hissediyorum.
14	Comfort with AI	Yapay zekâ ile rahatlık	When interacting with AI technologies/products, I find it easy.	Yapay zekâ teknolojileri/ürünleri ile etkileşim kurmak benim için kolaydır.
15	Comfort with AI	Yapay zekâ ile rahatlık	When interacting with AI technologies/products, I feel comfortable in my heart.	Yapay zekâ teknolojileri/ürünleri ile etkileşim halindeyken duygusal açıdan rahat hissediyorum.
16	Comfort with AI	Yapay zekâ ile rahatlık	When interacting with AI technologies/products, I feel very peaceful.	Yapay zekâ teknolojileri/ürünleri ile etkileşim halindeyken, kendimi çok huzurlu hissediyorum.
17	Comfort with AI	Yapay zekâ ile rahatlık	When interacting with AI technologies/products, I feel very relaxed.	Yapay zekâ teknolojileri/ürünleri ile etkileşim halindeyken, kendimi rahatlamış hissediyorum.
18	Comfort with AI	Yapay zekâ ile rahatlık	I can happily interact with AI technologies/products smoothly.	Yapay zekâ teknolojileri/ürünleri ile mutlu bir şekilde sorunsuz etkileşim kurabiliyorum.
19	Technological skills	Teknolojik Beceri	When using AI technologies/products, I am not worried that I might press the wrong button and cause risks.	Yapay zekâ teknolojileri/ürünlerini kullanırken, yanlış bir şey yapıp risk oluşturacağımdan endişelenmiyorum.
20	Technological skills	Teknolojik Beceri	When using AI technologies/products I am not worried that I might press the wrong button and damage it.	Yapay zekâ teknolojileri/ürünlerini kullanırken, yanlış bir şey yapıp onu bozacağımdan endişelenmiyorum.
21	Technological skills	Teknolojik Beceri	When using an AI technology/product, there is nothing that I do not know why.	Bir yapay zekâ teknolojisi/ürünü kullanırken, nasıl yapıldığını bilmediğim bir şey yok.
22	Technological skills	Teknolojik Beceri	AI technologies/products jargon does not baffle me.	Yapay zekâ teknolojileri/ürünlerinin terminolojisi bende kafa karışıklığına sebep olmaz.

Procedure and Ethical Standards

The study was conducted following ethical procedures and was approved by the Publication and Ethics Committee of the Social and Human Sciences at Bursa Uludag University (Session Date: 2024/08, Decision No: 2). Data were collected online, using Google Forms over a two-month period during the spring semester. Participants were informed that participation was voluntary, and each survey took approximately 3–5 minutes to complete. Informed consent was obtained from all participants prior to the survey. To ensure privacy and confidentiality, no identifying information was collected. Data were stored in a password-protected digital environment accessible only to the researchers. These measures ensured the protection of participants' data and the ethical handling of all responses throughout the research process.

Data Analysis

The data, organized in Excel, was transferred to SPSS 29.0. Skewness and kurtosis values were examined to determine whether the data were normally distributed, and values between -1.5 and +1.5 were considered acceptable (Tabachnick & Fidell, 2014). EFA and CFA were conducted to examine the factor structure of the scale. To satisfy the requirement of independent validation, EFA and CFA were performed on two different datasets. EFA was performed using SPSS 29.0. Principal Component Analysis (PCA) with Direct Oblimin rotation was preferred for the initial extraction to determine the factor structure and explain the maximum variance, as is common in cross-cultural scale adaptations (Tabachnick & Fidell, 2014). Given the theoretical expectation that the factors would be correlated, an oblique rotation method (Direct Oblimin) was employed instead of an orthogonal rotation method, which assumes factor independence. This approach aligns with common practices in the social sciences, where constructs are often interrelated. The number of factors was determined based on the results of the EFA, taking into account eigenvalues greater than 1.0 and the scree plot.

The preconditions for EFA were checked, and the Kaiser-Meyer-Olkin measure of sampling adequacy was 0.905, while Bartlett's test of sphericity was significant ($\chi2=4390.655$; $p<0.001$), indicating that the data were suitable for factor analysis. CFA was conducted using Amos 29.0 on the second independent sample ($n=374$). Prior to CFA, item intercorrelation values were examined to ensure that the assumption of multicollinearity was met (Hair et al., 2010). The Maximum Likelihood estimation method was used in CFA because it provides robust parameter estimates when the data distribution is approximately normal (Hair et al., 2010). For model improvement, covariances were created between items under the same factor with high modification indices. The results of the CFA were evaluated using the following goodness-of-fit indices: Chi-square ($\chi 2$), Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), Standardized Root Mean Square Residual (SRMR), and Tucker-Lewis Index (TLI) (Bentler & Bonett, 1980; Hair et al., 2010; Kline, 2005). Fit criteria considered acceptable were RMSEA ≤ 0.08, CFI and TLI ≥ 0.90, and SRMR ≤ 0.08. Spearman's rank-order correlation analysis assessed the relationship between participants' self-efficacy and artificial intelligence usage levels for criterion-related validity.

FINDINGS

Construct Validity

The EFA results (Table 4) confirm that the scale has a four-factor structure consistent with the original instrument. To identify the underlying factor structure of the Turkish version, an EFA was conducted using Sample 1 (n=291).

Table 4. Rotated Factor Loadings for the 22-Item Instrument

Item code	Anthropomorphic interaction	Assistance	Comfort with AI	Technological skills
11. I think the tone of AI technologies/products when interacting is the same as that of real people.	.907			
12. I feel that the way of expression of AI technologies/products in the interactive text is the same as that of real people.	.878			
10. I think there is no difference between the dialogue method of AI technologies/products compared with the dialogue with real people.	.864			
9. I think the way that AI technologies/products express content when interacting is unique, just like a real person.	.785			
8. I think the interactive process of AI technologies/products is very vivid, just like chatting with a real person.	.766			
3. AI technologies/products are good aids to learning		.860		
1. Some AI technologies/products make learning easier.		.857		
2. I find that AI technologies/products are helpful for learning..		.811		
4. Using AI technologies/products makes learning more interesting.		.736		
7. I find it easy to get AI technologies/products to do what I want it to do.		.539		
5. I'm confident in my ability to learn simple programming of AI technologies/products if I were provided the necessary training.		.478	.405	
6. AI technologies/products help me to save a lot of time.		.462		
20. When using AI technologies/products I am not worried that I might press the wrong button and damage it.			.752	
22. AI technologies/products jargon does not baffle me.			.726	
19. When using AI technologies/products, I am not worried that I might press the wrong button and cause risks			.712	-.336
21. When using an AI technology/product, there is nothing that I do not know why.			.682	
14. When interacting with AI technologies/products, I find it easy.		.363	.383	
16. When interacting with AI technologies/products, I feel very peaceful.				-.847
17. When interacting with AI technologies/products, I feel very relaxed.				-.824
15. When interacting with AI technologies/products, I feel comfortable in my heart.				-.778
13. When interacting with AI technologies/products, I feel very calm.				-.508
18. I can happily interact with AI technologies/products smoothly.			.366	-.482

n_1=291. Absolute values less than 0.49 were suppressed. Rotation converged in 11 iterations. Extraction Method: Principal Component Analysis. Rotation Method: Oblimin with Kaiser Normalization

The results of the EFA supported a four-factor structure consistent with the original scale (Table 4). The analysis was conducted with Sample 1 (n = 291), utilizing Principal Component Analysis (PCA) with Direct Oblimin rotation. PCA was specifically chosen for the initial stage of this Turkish adaptation to identify the maximum explained variance and determine how well the original constructs translate into a different cultural context (Tabachnick & Fidell, 2014). The rotation converged in eleven iterations, and absolute factor loadings below .49 were suppressed for clarity. In addition to retaining factors with eigenvalues greater than 1.0, the scree plot and cumulative variance were examined to ensure a robust structure (Fabrigar et al., 1999). The four-factor solution explained 67.47% of the total variance, with the sub-dimensions contributing as follows: Assistance (41.23%), Anthropomorphic Interaction (53.28%), Comfort with AI (61.29%), and Technological Skills (67.47% cumulative). These results confirmed that the items clustered meaningfully under the related constructs, aligning perfectly with the theoretical framework of the original scale. Subsequently, CFA conducted on the second independent sample further supported the construct validity by showing acceptable fit indices.

Confirmatory Factor Analysis

CFA was performed on Sample 2, a new independent sample of 374 participants. This separate validation process was conducted to test the four-factor structure identified in the EFA: Anthropomorphic Interaction, Assistance, Comfort with Artificial Intelligence, and Technological Skills. CFA was conducted using the Maximum Likelihood method in AMOS. The results indicated that the four-factor model demonstrated an acceptable to good fit: $\chi^2(183) = 499.61$, $p < .001$; $\chi^2/df = 2.73$; CFI = .94; TLI = .923; RMSEA = .063; SRMR = .076. These values fall within the recommended cut-off criteria (Bentler & Bonett, 1980; Hair et al., 2010; Kline, 2005).

Table 5. Confirmatory Factor Analysis

	$\chi2$	df	$\chi2/df$	TLI	RMSEA	SRMR	CFI
Acceptable model fit values	$2df \leq \chi2 \leq 3df$	-	$3 \leq x^2/df \leq 5$	0.90≤	≤0.08	≤0.10	0.90≤
Original scale model fit values*	388.828	196	1.984	0.930	0,079	0.071	0.941
Model fit values	499.605	183	2.73	0.923	0.068	0.076	0.94

** (Wang & Chuang, 2024)*

Overall, the findings support that the four-factor structure of the Turkish version of the AISES provides a satisfactory representation of the data and aligns with the original theoretical model (Wang & Chuang, 2024).

Internal Consistency

Cronbach's alpha coefficient was calculated to determine the internal consistency. The reliability coefficient for the overall scale was 0.958, while the sub-dimensions yielded the following values: 0.821 for Assistance, 0.912 for Anthropomorphic Interaction, 0.905 for Comfort with AI, and 0.823 for Technological Skills. These values exceed the threshold of 0.70 (Nunnally, 1978), indicating high internal consistency. While Cronbach’s alpha is the primary measure reported, future studies may consider McDonald’s Omega to further validate internal consistency without the assumption of tau-equivalence (Hayes & Coutts, 2020).

Criterion-Related Validity

A correlation analysis assessed criterion-related validity and examined the relationship between artificial intelligence self-efficacy and participants’ intelligence usage levels. The analysis revealed a significant, weak negative relationship ($r = -0.286$; $p < 0.05$). While this negative correlation appears counterintuitive, it provides critical evidence for criterion-related validity by showing that self-efficacy scores significantly relate to actual usage patterns, albeit in an inverse direction for this specific sample.

DISCUSSION, CONCLUSION AND SUGGESTIONS

This study validated the Turkish adaptation of the AISES, confirming it as a robust and reliable instrument for measuring individuals’ confidence in engaging with AI technologies. More than a psychometric tool, it serves as a practical lens for understanding where learners, educators, and professionals stand in their AI journey and how they can be supported to progress toward confident, responsible, and innovative use.

The findings of this study confirmed the validity and reliability of the Turkish adaptation of the AISES, showing that the four-factor structure—Assistance, Anthropomorphic Interaction, Comfort with AI, and Technological Skills—aligns with the original scale. These results are consistent with Wang and Chuang (2024), supporting the construct of AI self-efficacy within the framework of social cognitive theory. The high reliability and clear factor structure obtained in this study contrast with earlier Turkish studies, such as Çelebi et al. (2023) and Yıldırım and Karaman (2025), which reported lower explained variance in certain

dimensions. These differences likely arise from our study's specific focus on education faculty students, whose pedagogical background may lead to a more structured perception of AI tools as "assistive" compared to more diverse or general samples.
A notable and counterintuitive finding of this study was the weak negative correlation between AI self-efficacy and AI usage levels ($r = -0.286$). This inverse relationship suggests that as participants' frequency or complexity of AI use increases, their self-evaluated efficacy tends to decrease. This phenomenon can be interpreted through the lens of the Dunning-Kruger effect (Kruger & Dunning, 1999); individuals at the early "Mechanical Use" or "Orientation" stages may overestimate their competence due to a lack of awareness regarding AI's full complexity. Conversely, as users progress to more frequent or advanced usage, they may develop a more realistic—and thus more cautious—appreciation of the vast skills required to master AI, leading to lower self-efficacy scores. This highlights the need for training that not only increases usage but also builds deep, reflective competence.
Regarding the sample characteristics, the study was conducted with a predominantly female population (84.0%). While this reflects the typical demographic distribution in Turkey's faculties of education, it remains a limitation for the broader generalization of the findings across genders. Future studies should aim for more balanced samples to examine whether gender-based differences in digital self-efficacy, as noted in some STEM literature, persist in the specific domain of AI.

The findings showing that most participants remain at early or mechanical stages of AI engagement highlight a gap between basic familiarity and advanced, reflective application. This resonates with the literature, which points to a lack of empirical work linking AI self-efficacy to broader educational priorities such as ethical AI use and international frameworks like DigCompEdu (Chiu et al., 2025; European Commission, 2025; Ng et al., 2023). In alignment with the European Skills Agenda, the following recommendations are proposed:

Strategic Educational Design: The scale can be used to identify self-efficacy gaps and guide personalized learning pathways in teacher education and higher education.

Lifelong Learning: The AISES should be employed to assess learners' AI readiness and tailor civic education programs that promote democratic participation through AI literacy.

Sustainability and Ethics: Future research should explore how self-efficacy relates to sustainable AI practices, such as bias-aware decision making and transparent data governance.

Cross-Cultural Validation: Given the global nature of AI, the scale should be further validated in multilingual contexts within Erasmus+, Horizon Europe, or Jean Monnet Modules to enable comparative analyses.

Institutional Assessment: The scale can be embedded within frameworks like DigCompEdu or the SELFIE tool to assess the professional development needs of staff and students.

In conclusion, the adapted AISES provides a robust foundation for research, policy, and practice that aligns with key European and global education and innovation priorities. Its use can foster more inclusive, sustainable, and human-centered AI adoption, especially when embedded within broader efforts to empower educators, learners, and institutions in the digital age.

Ethics and Consent: Ethical approval for this study was obtained from Publication and Ethics Committee of the Social and Human Sciences at Bursa Uludag University (Session Date: 2024/08, Decision No: 2).

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