International Journal of Human–Computer Interaction

ISSN: 1044-7318 (Print) 1532-7590 (Online) Journal homepage: www.tandfonline.com/journals/hihc20

Turkish Adaptation of the AI Self-Efficacy Scale: A Psychometric Evaluation

Zeynep Aca, Umut Solmaz & Orhan Koçak

INTERNATIONAL JOURNAL OF HUMAN–COMPUTER INTERACTION
https://doi.org/10.1080/10447318.2025.2558027

Taylor & Francis
Taylor & Francis Group

Check for updates

Turkish Adaptation of the AI Self-Efficacy Scale: A Psychometric Evaluation

Zeynep Aca[a], Umut Solmaz[b] and Orhan Koçak[c]

[a]Faculty of Health Sciences, Department of Social Work, Bandırma Onyedi Eylül University, Balıkesir, Turkey; [b]Seben İzzet Baysal Vocational School, Department of Social Work and Counseling, Bolu Abant İzzet Baysal University, Bolu, Turkey; [c]Faculty of Health Sciences, Department of Social Work, Istanbul University-Cerrahpaşa, Istanbul, Turkey

ABSTRACT
This study aimed to examine the validity and reliability of the Turkish version of the Artificial Intelligence Self-Efficacy Scale, which assesses individuals' self-efficacy in using AI technologies. The sample included 532 active AI users over the age of 18 in Turkey in 2024. Linguistic and content validity analyses were conducted, followed by exploratory and confirmatory factor analyses to determine construct validity. In the exploratory factor analysis, the reliability coefficient was found to be 0.925, and no items were removed. In the confirmatory factor analysis, three items were excluded to improve model fit. The resulting 19-item scale showed acceptable fit indices: RMSEA = 0.066, NFI = 0.927, SRMR = 0.041, RFI = 0.912, GFI = 0.903, TLI = 0.948, CFI = 0.958, and $\chi^2/df = 2.284$. The test-retest and internal consistency results supported the scale's reliability. The findings indicate that the Turkish version is a valid and reliable tool for measuring AI self-efficacy among adult users.

KEYWORDS
Artificial ıntelligence; self-efficacy; scale; validity; reliability

1. Introduction

The term "artificial intelligence" (AI) refers to systems that utilise technologies such as algorithms, machine learning, sensory feedback systems, and automation to perform only the functions for which they are programmed (Russell & Norvig, 2016; Thierer et al., 2017). As a subfield of computer science, AI aims to transform machines into entities capable of imitating human cognitive processes and acting intelligently (Brynjolfsson & McAfee, 2014). In this process, computers, robots, or software are designed to emulate human thought patterns by being endowed with the ability to think intelligently (Moore, 2019).

The advent AI has precipitated a paradigm shift, heralding a new era characterised by technological, industrial and social transformation. This transformative technology has exerted profound and far-reaching impacts on various domains, including educational transformation, economic development, social progress, and the international political and economic landscape (UNESCO, 2021). AI, which is becoming ubiquitous, has become an indispensable component of business models across various sectors, including healthcare, education, public administration, strategic planning, and the criminal justice system (Dwivedi et al., 2021; King & Grudin, 2016). The integration of AI into various industries has become imperative due to technological advancements, thereby necessitating adaptation and adoption (Wang et al., 2023; Morales-García et al., 2024).

In order to successfully implement new technologies, it is essential to identify the factors that influence users' decisions to accept or reject technology (Hasan, 2006; Latikka et al., 2019; Venkatesh, 2000). Individual factors such as perception and familiarity with technology have been demonstrated to play a crucial role in technology adoption (Agarwal & Karahanna, 2000; Chen et al., 2011; Hsu & Chiu, 2004; Pütten & Von Der Bock, 2018). A substantial body of research on technology adoption has demonstrated that individuals with a higher perceived self-efficacy regarding a specific application are more

CONTACT Umut Solmaz umut.solmaz@ibu.edu.tr Seben İzzet Baysal Vocational School, Department of Social Work and Counseling, Bolu Abant İzzet Baysal University, Bolu, Turkey

likely to accept that technology (Agarwal & Karahanna, 2000; Hsia et al., 2014; John, 2013; Lee & Ryu, 2013; Tsai et al., 2019; Yang, 2010). However, while much of this literature has concentrated on general technology self-efficacy, there is still a lack of focus on domain-specific measures for AI, which possesses unique features such as autonomy, adaptive learning, and anthropomorphic interaction. This gap underlines the need to develop and validate instruments that specifically assess self-efficacy in AI usage.

Self-efficacy is defined as an individual's belief in their ability to achieve desired goals. Individuals with high self-efficacy believe they can successfully complete tasks, whereas those with low self-efficacy perceive tasks as more complex (Bandura, 1997). In this context, technology self-efficacy refers to an individual's belief in their ability to effectively use technology to derive benefits (Holden & Rada, 2011), playing a crucial role in the adoption of innovative technologies (Hong, 2022). The notion of computer self-efficacy has been a focal point in numerous research studies (Compeau & Higgins, 1995; Teo & Koh, 2010; Thangarasu et al., 2014; Torkzadeh & Van Dyke, 2002). Research has explored various dimensions of self-efficacy in information technologies (IT), including computer self-efficacy (Compeau & Higgins, 1995), self-efficacy in robot use (Latikka et al., 2019), and teacher computer self-efficacy (Thangarasu et al., 2014), internet self-efficacy (Torkzadeh & Van Dyke, 2002), and software self-efficacy (Agarwal et al., 2000; Hasan, 2006). However, in terms of predictive capability, perceived self-efficacy is more accurately assessed through domain-specific measures rather than general evaluations (Bandura, 1986). For instance, Marakas et al. (1998) advocate for task-specific assessments of computer self-efficacy. Therefore, general self-efficacy perceptions may be inadequate in explaining AI adoption (Bandura, 2006). AI self-efficacy (AISE) is defined as an individual's self-assessment of their specific competencies in using AI technologies and products, and thus differs from general judgments regarding technological skills. Based on previous literature on technology self-efficacy, AISE can be defined as individuals' general beliefs about their ability to interact with and effectively utilise AI. Consequently, the development of a specialized instrument to assess AISE is imperative (Wang et al., 2023). This indicates a clear research gap: although several scales exist for technology self-efficacy, few tools explicitly capture the unique challenges and competencies associated with AI technologies.

Bandura's self-efficacy theory posits that individuals' beliefs in their capabilities to execute behaviors necessary to produce specific performance attainments play a critical role in determining their actions, motivations, and emotional reactions (Bandura, 1977, 1986). While general technology self-efficacy assesses confidence in the use of digital tools broadly, artificial intelligence self-efficacy (AISE) introduces unique challenges due to the complex, adaptive, and human-like features of AI technologies. Unlike traditional digital tools, AI systems often involve elements such as decision-making autonomy, predictive analytics, and interaction through natural language—features that may evoke uncertainty or perceived risk. This justifies the need for a domain-specific measure. In particular, the inclusion of dimensions like "anthropomorphic interaction" in the AISE scale captures users' comfort and efficacy in interacting with AI systems that simulate human characteristics, such as voice assistants or AI chatbots. This facet reflects not only technical proficiency but also psychological readiness, trust, and acceptance, which are essential for meaningful AI adoption. Therefore, AISE extends beyond the scope of conventional technology self-efficacy and addresses competencies that are central to the evolving nature of human-AI collaboration.

The Artificial Intelligence Self-Efficacy Scale (AISES) was developed by Wang and Chuang (2024) as a 22-item instrument specifically designed to measure self-efficacy perceptions in the context of AI technologies. The scale encompasses four key dimensions: assistance, anthropomorphic interaction, comfort with AI, and technological skills. Its cultural appropriateness was tested within the Taiwanese context. By assessing self-efficacy in the AI domain, the scale highlights the complexity of this technology and its impact on individuals across various educational and professional settings (Morales-García et al., 2024). However, despite the presence of this scale, its applicability outside of the original cultural context has yet to be sufficiently tested, which presents an important opportunity for adaptation studies.

In Turkey, a plethora of scales related to artificial intelligence (AI) have been developed or adapted, including the General Attitude Towards AI Scale (Kaya et al., 2022), the AI Addiction Scale (Savaş, 2024), the AI Scale (Süleymanoğulları et al., 2024), the AI Literacy Scale (Çelebi et al., 2023; Polatgil &

Güler, 2023; Karaoğlan Yılmaz & Yılmaz, 2023), the AI Anxiety Scale (Akkaya et al., 2021; Kolcu et al., 2021; Terzi, 2020), and the AI Perception Scale (Kurtboğan & Ak, 2024). A scale specifically addressing AI self-efficacy has also been proposed, such as the Generative AI and Competency Scale (Arslankara & Usta, 2024), which measures generative AI usage and competency as part of lifelong learning self-efficacy. In addition, recent studies have focused on generative AI by developing instruments such as the Generative Artificial Intelligence Attitude Scale for Students (Marengo et al., 2025) and the Generative Artificial Intelligence Acceptance Scale (Yılmaz et al., 2024), while other works have explored the role of cognitive flexibility, digital competencies, self-regulation, and metacognitive awareness in shaping generative AI anxiety and attitudes (Yılmaz et al., 2025; Karaoğlan Yılmaz & Yılmaz, 2025). Moreover, empirical studies have demonstrated the effects of generative AI-based tool use on computational thinking, programming self-efficacy, and motivation (Yılmaz & Yılmaz, 2023a), as well as students' perspectives on the use of ChatGPT for programming education (Yılmaz & Yılmaz, 2023b). While these studies contribute to the growing body of knowledge on AI, they primarily emphasize attitudes, anxiety, acceptance, or general competencies, and no validated Turkish version of the AI Self-Efficacy Scale exists. This underscores the necessity of adapting Wang and Chuang (2024) scale into Turkish to fill this critical gap in the literature.

In this context, the present study aims to address this gap by providing an instrument for the self-assessment of specific individual skills related to the use of AI technologies and products in Turkey. The adaptation of this scale will establish a valid and reliable instrument to assess Turkish-speaking individuals' perceptions of AI interaction and usage. Additionally, the scale will allow for an examination of the psychological implications of AI development on individuals' future motivations and behaviours. The scale's development did not target a specific demographic, thus allowing for its application across various domains, including education, healthcare, marketing, finance, and manufacturing. In this regard, the scale has the potential to contribute to the development of AI technologies and products across different sectors (Wang & Chuang, 2024). Consequently, it may aid in the formulation of policies and strategies aimed at the adoption and effective utilisation of AI technologies.

Accordingly, the present study seeks to answer the following research questions:

1. Does the Turkish version of the AI Self-Efficacy Scale demonstrate validity and reliability comparable to the original?
2. Is the factor structure of the adapted version consistent with the theoretical framework established by Wang and Chuang (2024)?

Based on the literature, the following hypotheses are also proposed:

- **H1:** The Turkish version of the AI Self-Efficacy Scale will demonstrate a factor structure consistent with the original (Wang & Chuang, 2024).
- **H2:** The Turkish version of the AISES will demonstrate high internal consistency and test–retest reliability, comparable to the original.
- **H3:** The adapted version will exhibit construct validity in line with related technology self-efficacy instruments (Compeau & Higgins, 1995; Morales-García et al., 2024).

2. Material and methods

This section of the study provides exhaustive information regarding the following aspects: the instruments utilised for data collection, the characteristics of the study group, the ethical procedures followed, the research methodology employed, and the study process.

2.1. Study design, sample and data collection

The present study was designed using a quantitative research methodology. Quantitative research involves the conducting of studies on a sample group that is representative of a population, thus allowing for generalisation (Creswell, 2009). Accordingly, data were collected through the implementation of a survey method, which is one of the data collection techniques employed.

In this study, the adaptation of the Artificial Intelligence Self-Efficacy Scale into Turkish was carried out through a quantitative methodology focusing on testing the validity and reliability of the adapted instrument. The independent variable, defined as participants' prior experience with AI products, guided the structuring of the research instruments. First, the Demographic Information Form was administered to determine participants' socio-demographic characteristics and AI usage history. Then, the Artificial Intelligence Self-Efficacy Scale (AISES), which consists of four sub-dimensions (assistance, anthropomorphic interaction, comfort with AI, and technological skills), was applied. During the linguistic and content validity stages, expert opinions were obtained to ensure cultural appropriateness, and a pilot study was conducted to assess comprehensibility. For validity, exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were performed, while reliability was tested through Cronbach's alpha and test–retest procedures. This systematic approach integrated both the theoretical justification (self-efficacy theory) and statistical verification, thereby strengthening the methodological rigor of the study.

In order to ensure the generalisability of the Turkish version of the measurement instrument for assessing artificial intelligence self-efficacy, inclusion criteria were established. Participants had to be residents of Turkey, aged 18 and above, and have responded "yes" to the question "Have you experienced AI products?". In quantitative research, it is recommended that the sample size be at least ten times the number of measurement items (Boateng et al., 2018). The data collection process was meticulously structured into three phases.

The data collection process in this study was conducted in three phases.In the first phase, a pilot study was carried out with 50 participants to assess the comprehensibility of the Turkish-translated survey questions.In the second phase, data were collected from 401 participants as the initial step in assessing the construct validity of the scale. Although the response rate was 401, the analysis was conducted on 267 participants, as only individuals who had used AI products were considered ($N = 401$). During this phase, construct validity and internal consistency were examined.In the third phase, data were collected from 400 participants. While the response rate was 400, the analysis was performed on 300 participants, focusing solely on individuals who had used AI products ($N = 400$).

The data collection process was conducted between May and December 2024. Informed consent was obtained from all participants, and the survey questions were administered via Google Forms. The generated link was distributed to participants by the researchers.

2.2. Ethical considerations

This study was conducted in accordance with the Declaration of Helsinki. Ethical approval was obtained from the Ethics Committee for Social and Human Sciences Research at Bandırma Onyedi Eylül University (Date: 30/04/2024; Decision No: 2024-4).

Informed consent was obtained from all participants by means of a consent option that was selected by the participants, thus indicating that they had been informed about the study and had agreed to participate. Following this, the survey was completed by the participants via Google Forms. Additionally, permission emails were obtained from the original authors who developed the scale.

2.3. Measures

This section provides information regarding the measurement instrument utilised in the study and the demographic information form.

2.3.1. Demographic information form

The form in question comprised a series of questions designed to elicit information regarding the demographic characteristics of the participants, including their age, gender, educational background, occupation, average monthly income, prior interaction with AI products, and previous experience in using AI products. The primary objective of the form was to provide a detailed description of the characteristics of the participants in the two sample groups, with a particular emphasis on distinguishing individuals who have used AI products.

2.3.2. Artificial Intelligence Self-Efficacy Scale

The Artificial Intelligence Self-Efficacy Scale (AISES) was developed by Wang and Chuang (2024) to measure individuals' self-efficacy levels in AI usage. The scale consists of 22 items and is structured into four dimensions: assistance (items 1–7), comfort with AI (items 13–18), technological skills (items 19–22), and anthropomorphic interaction (items 8–12). Each dimension comprises a minimum of four items, and the scale is designed using a 7-point Likert-type format, with no reverse-coded items.

The original reliability coefficients of the scale were reported as 0.95 for the overall scale, 0.94 for the assistance dimension, 0.97 for anthropomorphic interaction, 0.96 for comfort with AI, and 0.86 for technological skills. In the present study, the overall reliability was calculated as 0.925.

The analysis of the present study confirmed that the assistance, comfort with AI, technological skills, and anthropomorphic interaction dimensions remained consistent with the original scale. However, three items from the assistance dimension (items 5, 6, and 7) were deemed inappropriate and subsequently removed. Consequently, the final scale structure was established with 19 items.

2.4. Cultural adaptation procedure

This section of the study outlines the stages of the adaptation process for the scale intended for translation into Turkish culture.

2.4.1. Language validity

Initially, the original English version of the scale was translated into Turkish by five independent native Turkish speakers. Subsequently, these three translators collaborated with the researchers to evaluate the translations and reach a consensus on a single version of the text. The finalised Turkish version of the scale was then back-translated into English by a native English speaker.

Finally, the original scale and its back-translated version were compared and harmonized by the researchers to ensure consistency. Throughout the translation process, terminology selection and sentence structures were refined to preserve the semantic accuracy of the source language. After these necessary revisions, the adaptation process was finalized.

2.4.2. Content validity

In order to evaluate the content validity and comprehensibility of the Turkish version of the scale, it was sent to five academic experts, and their expert opinions were obtained. The Davis method was employed for content validity evaluation (Davis, 1992). According to this method, experts were invited to rate each item on a four-point scale: 1 = not relevant, 2 = somewhat relevant, 3 = quite relevant, and 4 = highly relevant. The Content Validity Index (CVI) was determined by dividing the number of experts who assigned a rating of 3 or 4 to an item by the total number of experts. The CVI was evaluated for each item and for the overall scale.

2.4.3. Pilot study

In order to evaluate the comprehensibility of the items in the final Turkish version of the scale, an evaluation was conducted with 50 participants. The survey form was administered to these 50 individuals, and their opinions on the items were collected. Based on the feedback received from the participants, necessary revisions were made to the items. These participants were subsequently excluded from the sample group.

2.5. Statistical analysis

The statistical analyses were conducted using IBM SPSS Statistics 25.0, while factor analysis was conducted using AMOS 26.0. The content validity of the scale was assessed using the Content Validity Index (CVI).

In order to evaluate the construct validity of the research, exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were conducted. Reliability was assessed by calculating the item-total correlation and the reliability coefficient. The test-retest reliability was evaluated by computing the item correlation coefficient. Descriptive statistics were presented as frequency and percentage, mean, and standard deviation. The results were considered statistically significant at a 95% confidence interval, with a significance level set at $p < 0.05$.

3. Results

This section presents the socio-demographic characteristics of the participants, as well as the validity and reliability analyses of the study, including values related to construct and content analyses, which are provided in tabular format.

3.1. Participant socio-odemographic characteristics

In this section, the socio-demographic characteristics of the participants are presented for two analysis groups (Table 1).

An analysis of the demographic characteristics of the participants revealed that, in the exploratory factor analysis (EFA) group, 70.6% were female, 50.1% held a bachelor's degree, and 66.1% had used an AI product. The mean age of participants in this group was 26.33 years.

In the confirmatory factor analysis (CFA) group, 70.8% were female, 44.0% held a bachelor's degree, and 75.0% had used an AI product. The mean age of participants in this group was 25.61 years (Table 1).

3.2. Validity

In this section of the study, the construct validity of the scale was investigated, with the results of the analyses presented in tabular format. As part of the construct validity assessment, exploratory factor analysis (EFA), reliability analysis, and item-total correlation were evaluated. Subsequently, to confirm the structure, confirmatory factor analysis (CFA) was conducted.

3.2.1. Construct validity

In the assessment of construct validity, exploratory factor analysis (EFA) was conducted as the primary step. In EFA, a Kaiser-Meyer-Olkin (KMO) value above 0.60 and a significance level below 0.05 are indicative of construct validity (IBM, 2025). Within this framework, exploratory factor analysis was performed on the existing items of the Artificial Intelligence Self-Efficacy Scale. The analysis yielded a KMO value of 0.89 and a significance level of 0.000, as illustrated in Table 2.

As a result of the factor analysis conducted, a reliability analysis was performed to measure the item-total correlations and internal consistency of the existing items. The values related to the reliability analysis are presented below.

3.3. Reliability

To assess the reliability of the scale in both data groups, reliability coefficients were calculated following both exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). The analysis results indicated that the reliability coefficients for both the dimensions and the overall scale were high (Table 3).

3.3.1. Reliability analysis

Following the reliability analysis, the item-total correlation analysis of the scale was conducted, revealing that the correlation coefficients for all items were above 0.30 (Section 3.3.2).

3.3.2. Item-Total correlation analysis

An evaluation of the item-total correlations of the existing items in the scale revealed that the correlation coefficients ranged between 0.533 and 0.728 (Table 4).

Table 1. Participant socia-demographic characteristics.

	EFA ($N = 401$)		CFA ($N = 400$)	
	n(%)	Ort.±Ss	*n*(%)	Ort.±Ss
Gender				
Male	118(29.4)		117(29.3)	
Female	283(70.6)		283(70.8)	
Educational Status				
Elemantary/Middle School	8(2.0)		3(0.8)	
High School	124(30.9)		160(40.0)	
University	201(50.1)		176(44.0)	
Master/PhD	68(17.0)		61(15.3)	
Use of Artificial Intelligence Product				
Yes	265(66.1)		300(75.0)	
No	136(33.9)		100(25.0)	
Age		26.33 ± 8.46		25.61 ± 9.14

*CFA: Confirmatory factor analysis; EFA: Exploratory factor analysis; *N*: Sample Size; *n*: Number of Respondents; *SD*: Standard Deviation; %=Percentage.

Table 2. Exploratory factor analysis.

Factors	Items	Factor loading				Factor explained variance	Alfa
Comfort with Artificial Intelligence	AI17	0.860				39.970	0.925
	AI15	0.851					
	AI16	0.804					
	AI14	0.724					
	AI13	0.708					
	AI7	0.589					
	AI6	0.562					
	AI18	0.470					
Anthropomorphic Interaction	AI10		0.913			12.106	
	AI11		0.862				
	AI12		0.848				
	AI9		0.790				
	AI8		0.692				
Assistance	AI2			0.899		8.399	
	AI1			0.873			
	AI3			0.854			
	AI4			0.734			
	AI5			0.652			
Artificial Intelligence Self-Efficacy	AI19				0.750	6.418	
	AI20				0.723		
	AI21				0.722		
	AI22				0.701		
	Total Explained Variance					66.892	
	KMO						0.896
	Barlett's Sphericity Test					Chi-Square	3840.64
						df	231
						p	0.000

Note. AI: Artifical Intelligence; *p*: Degree of Freedom; *p*: Significance Value.

Table 3. Reliability analysis.

	Exploratory factor analysis		Doğrulayıcı faktör analizi	
Scale name	Number of questions	Cronbach's alpha value	Number of questions	Cronbach's alpha value
Comfort with Artificial Intelligence	8	0.911	6	0.928
Anthropomorphic Interaction	5	0.912	5	0.915
Assistance	5	0.896	4	0.928
Technological Skills	4	0.834	4	0.848
Artificial Intelligence Self-Efficacy	22	0.925	19	0.938

3.4. Confirmatory factor analysis

A confirmatory factor analysis is a process that is conducted for the purpose of verifying a given structure. This analysis involves the examination of compatibility values and the validation of the structure (Tabachnick & Fidell, 2015). In this context, the compatibility values that are present in the structure of the scale are as follows (see Table 5):

Table 4. Item-total correlation.

Questions	Item-Total correlation
AI1	0.603
AI2	0.636
AI3	0.639
AI4	0.589
AI5	0.533
AI6	0.627
AI7	0.577
AI8	0.565
AI9	0.612
AI10	0.554
AI11	0.578
AI12	0.577
AI13	0.705
AI14	0.699
AI15	0.728
AI16	0.714
AI17	0.683
AI18	0.703
AI19	0.569
AI20	0.598
AI21	0.621
AI22	0.591

AI: Artifical Intelligence.

In confirmatory factor analysis (CFA), an RMSEA value below 0.05 or 0.06 indicates a perfect fit, while a value between 0.05 and 0.08 is considered acceptable (Gunzler et al., 2021; Whittaker & Schumacker, 2022). In this study, the RMSEA value was found to be 0.066, indicating that it falls within the acceptable range.For the SRMR value, it is required to be below 0.08 (Sureshchandar, 2023). In this study, the SRMR value was 0.041. The acceptable threshold for CFI, NFI, and TLI values has been identified as 0.90 and above (Zyphur et al., 2023). According to the literature, the acceptable range for the CMIN/DF value is between 1 and 3 (Boateng et al., 2018). In this study, CMIN/DF was found to be 2.284, which falls within the acceptable range. Upon consideration of the indices under review, it is evident that the model fit indices demonstrate an acceptable level of fit (see Table 5). The path diagram of the examined structure is presented below (see Figure 1).

4. Discussion

In this study, the Turkish version of the Artificial Intelligence Self-Efficacy Scale, which was originally developed in English, was analysed with Turkish-speaking individuals over the age of 18 who had experience with AI products. The linguistic equivalence and content validity of the Turkish version were ensured.

In order to undertake a content validity analysis, item-level content validity indices (I-CVI) and scale-level content validity indices (S-CVI) were calculated. This analysis, which was conducted with the assistance of five experts, resulted in an I-CVI value of 0.94, which can be categorised as excellent. Additionally, the study found that the inter-rater agreement (S-CVI = 0.93) indicated a high level of content validity (Davis, 1992; Polit & Beck, 2003; Polit et al., 2007).

The basis of scale adaptation studies is strong theoretical foundations, with the factor structure of the measured variable known in advance. Accordingly, it is recommended that the factor structure of the measurement instrument be tested and confirmed using Confirmatory Factor Analysis (CFA) (Carpenter, 2018; Kline, 2013).

In the context of scale adaptation studies, the factor loadings of items should be subjected to meticulous scrutiny. In the event that an item manifests comparable loadings to multiple other items, it may be imperative to consider its removal from the scale (Stanton et al., 2002). Consequently, three items that exhibited a disruptive influence on the model fit indices were eliminated, and the fit indices were subsequently recalculated based on a remaining 19 items. This finding may also reflect cultural and contextual differences in how Turkish participants perceive their own competence in explaining or generalising AI-related tasks, suggesting that AI self-efficacy is not only a technical construct but is also shaped by socio-cultural experiences and expectations.

Table 5. Confirmatory factor analysis fit indices ($N = 400$).

Index	Scale value
SRMR	0.041
CFI	0.958
NFI	0.927
TLI	0.948
CMIN/DF	2.284
RMSEA	0.066

Note: RMSEA: Root Mean Square Error of Approximation; NFI: Normed Fit Index; CFI: Comparative Fit Index; SRMR: Standardized Root Mean Square Residual; TLI: Tucker-Lewis Index; CMIN/DF: Chi-square fit index.

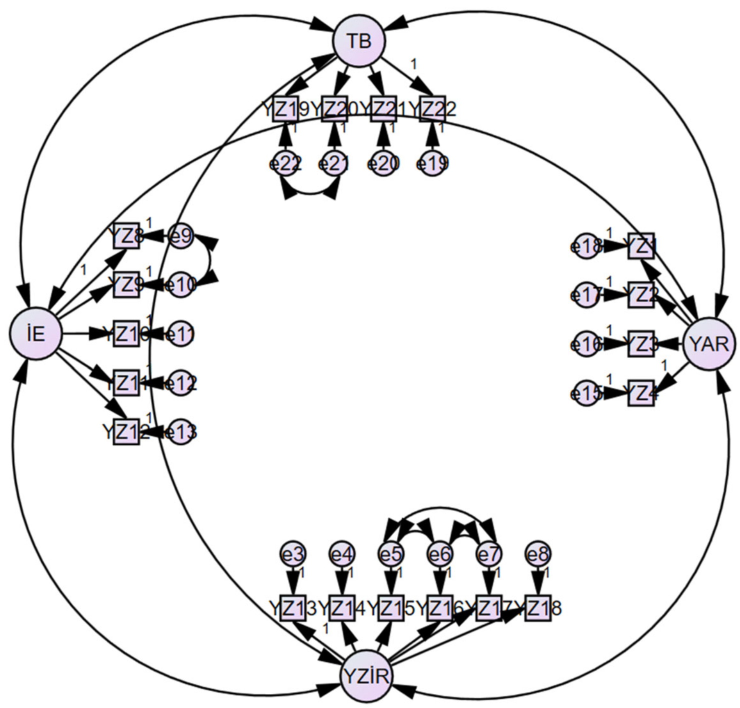

Figure 1. Path diagrams.

The goodness-of-fit indices assessed for CFA indicated that the RMSEA value (0.066) was within the acceptable range for model fit (Kline, 2023). Since 0.066 falls between 0.05 and 0.08, it is considered an adequate fit (Hu & Bentler, 1999; Gunzler et al., 2021). A similar conclusion was reached by Sureshchandar (2023) who found that the SRMR value (0.041) indicated excellent model fit. According to the extant literature, SRMR values less than 0.08 are considered to indicate a good fit (Hu & Bentler, 1999; Kline, 2023), while values less than 0.05 are classified as excellent (Gunzler et al., 2021; Kline, 2023). The study results showed NFI = 0.927, RFI = 0.912, GFI = 0.903, TLI = 0.948, and CFI = 0.958. Given that TLI approaches 0.95 and CFI exceeds 0.95, it can be concluded that the model demonstrates excellent fit to the data (Hu & Bentler, 1999; Sureshchandar, 2023). Furthermore, the model is deemed to demonstrate a satisfactory fit and an adequate structure, as evidenced by the NFI, RFI, and GFI all measuring 0.90 or higher (Hu & Bentler, 1999; Lomax, 2013). Finally, the χ^2/df ratio was found to be 2.284, which falls within the acceptable range of 2 to 3, indicating that the model provides an acceptable fit (Kline, 2023).

The factor loadings, which indicate the relationship or weight of each variable with each factor (Kline, 2023), were found to be above 0.50. According to Hair et al. (2013), factor loadings should be at least between 0.30 and 0.40 for the structure to be interpretable. Loadings above 0.50 are considered practically significant, while those exceeding 0.70 are regarded as indicators of a well-defined structure. Tavakol and Wetzel (2020) state that a factor loading greater than 0.30 signifies a moderate relationship between the item and the factor. In this context, all 22 items exceeded the minimum threshold. However, due to inconsistencies between the factor loadings and fit indices, three items from the first dimension (assistance) were removed following confirmatory factor analysis (CFA) (Brown, 2015; Kline, 2013). This adjustment aligns with Bandura's (1977, 1986) self-efficacy theory, which emphasises the domain-specific nature of self-efficacy beliefs. The retention of four sub-dimensions in the Turkish version demonstrates that AI self-efficacy captures not only technical skills but also the psychological readiness to interact with autonomous and anthropomorphic AI systems.

Beyond psychometric validation, these results have important implications for practice. The Turkish AISES can be employed in educational and training contexts to assess learners' confidence in AI usage, to evaluate the effectiveness of AI-related curricula, and to inform interventions aimed at increasing technology acceptance. The scale also provides opportunities to explore demographic differences—for example, between younger and older users or across gender—which may further enrich theoretical understanding of AI self-efficacy in diverse populations.

The reliability of the scale was assessed using the test-retest method and the reliability coefficient. The reliability coefficients for the subdimensions of the scale were found to be 0.94 for assistance, 0.97 for anthropomorphic interaction, 0.96 for comfort with AI, and 0.86 for technological skills. However, as three items from the assistance dimension (items 5, 6, and 7) were deemed unsuitable, they were removed from the scale. Consequently, the revised 19-item scale was recalculated, resulting in a reliability of 0.925. As posited by Tavakol and Dennick (2011), the acceptable range of reliability coefficients is reported to vary between 0.70 and 0.95. In accordance with this, coefficients of 0.90 or above are classified as "excellent", those of 0.80 as "very good", and those of 0.70 as "adequate" (Kline, 2023). Utilising these criteria, the Cronbach's alpha values for the overall scale and its subdimensions can be classified as adequate to very good. Moreover, an analysis of the reliability coefficients of the original scale (Wang & Chuang, 2024) and its adapted version revealed that the subdimension reliability coefficients remained constant. While the overall reliability coefficient of the original scale was 0.95, the current scale's reliability coefficient was 0.925.

The findings indicate that the statistical reliability levels of the original and adapted scales are similar, demonstrating that both versions exhibit high reliability. The minimal difference between the reliability coefficients suggests that the original and adapted versions are closely aligned in terms of reliability, with both scales demonstrating high internal consistency. Taken together, these outcomes not only confirm the methodological robustness of the adaptation but also provide a theoretically grounded instrument for future studies on AI adoption, learning, and professional practice in Turkey.

4.1. Limitations and future research directions

A key limitation of this study is the overrepresentation of female participants and the relatively low average age of the sample, which may restrict the generalisability of the findings and limit the detection of potential variations in adaptation to AI products based on age. Another limitation is the cross-sectional design, which does not allow for the observation of changes in AI self-efficacy and usage over time. Furthermore, since the survey was administered online via Google Forms, the identities and characteristics of the participants could not be independently verified, raising the possibility of non-genuine responses or duplicate participation, which may affect data validity.

In addition to these considerations, further limitations should be acknowledged. The study relied solely on self-report instruments, which may be subject to biases such as social desirability and self-selection. Participants who were already interested in AI technologies might have been more inclined to take part, potentially inflating self-efficacy levels. Moreover, the adaptation was restricted to a single scale, preventing cross-validation with other measures of AI attitudes, anxiety, or literacy that have been developed in recent years. While exploratory and confirmatory factor analyses strengthened the psychometric evidence, the absence of mixed-methods or longitudinal approaches limited the scope of interpretation. Finally, the reliance on an online distribution method may have unintentionally excluded individuals with limited internet access or low digital literacy, which restricts the inclusivity of the sample.

It is recommended that future research explore the potential for AI adaptation and self-efficacy to vary across different gender groups, facilitating comparative analyses between these groups. Similarly, studies could investigate how socio-economic conditions influence perspectives on AI products and their frequency of use. Additionally, it would be beneficial to examine AI adaptation among older individuals in greater depth, with longitudinal studies enabling the observation of changes in AI self-efficacy and usage over time. Finally, the incorporation of diverse testing and measurement tools in future research endeavours has the potential to yield more reliable and comprehensive results, thereby minimising individual biases.

5. Conclusions

The findings of this study demonstrate that the Turkish version of the Artificial Intelligence Self-Efficacy Scale, comprising three subscales and 19 items, is a valid and reliable measurement instrument for a sample of individuals aged 18 and above. As the scale was not developed for a specific group, sector, or profession, its Turkish version is valid and applicable across various fields where AI products are utilised.

In response to the first research question, the Turkish version of the AI Self-Efficacy Scale demonstrated validity and reliability comparable to the original instrument developed by Wang and Chuang (2024). Both exploratory and confirmatory factor analyses confirmed the four-factor structure, with only minor modifications in the "assistance" dimension. This indicates that the adapted version successfully captures the theoretical dimensions of AI self-efficacy in the Turkish context. Regarding the second research question, the factor structure of the Turkish version was largely consistent with the theoretical framework of the original scale, with acceptable fit indices and high reliability values across all subscales.

When compared with other instruments developed in Turkey, such as the General Attitude Towards AI Scale (Kaya et al., 2022), the AI Addiction Scale (Savaş, 2024), the AI Literacy Scale (Çelebi et al., 2023; Polatgil & Güler, 2023; Yılmaz & Yılmaz, 2023b), the AI Anxiety Scale (Akkaya et al., 2021; Kolcu et al., 2021; Terzi, 2020), and the AI Perception Scale (Kurtboğan & Ak, 2024), the current study highlights a different but complementary dimension. While these scales focus on attitudes, knowledge, or emotional responses to AI, the AISES specifically captures individuals' beliefs about their ability to effectively use AI technologies, thereby addressing a more behavioral and competency-oriented construct. Similarly, the Generative AI and Competency Scale (Arslankara & Usta, 2024) approaches self-efficacy indirectly through competency assessment, whereas the AISES directly measures perceived efficacy across multiple domains of AI interaction.

Recent international research further reinforces the significance of this focus. Yılmaz et al. (2025) and Karaoğlan Yılmaz & Yılmaz (2025) emphasized that cognitive flexibility, self-regulation, and meta-cognitive awareness shape students' generative AI anxiety and attitudes. Marengo et al. (2025) and Yılmaz et al. (2024) validated attitude and acceptance scales for generative AI, highlighting the growing need for reliable tools in this field. Additionally, Yılmaz and Yılmaz (2023a) and Yılmaz and Yılmaz (2023b) showed that AI-based tools can enhance computational thinking, programming self-efficacy, and motivation, while also shaping student perspectives on ChatGPT for programming education. Taken together, these studies demonstrate that AI self-efficacy is a foundational construct that influences attitudes, acceptance, learning outcomes, and user trust.

Compared to these instruments, the Turkish version of AISES complements the literature by focusing explicitly on self-efficacy, as defined by Bandura (1977, 1986), rather than on attitudes, anxieties, or knowledge. This distinction strengthens its utility as both a research and practical tool, enabling the assessment of individual readiness to engage with AI in diverse cultural and educational contexts.

What we learned from this study is that AI self-efficacy, beyond being a technical skill, encompasses socio-cultural and psychological readiness to engage with AI. The Turkish version of the AISES provides researchers and practitioners with a tool to examine these dynamics in education, healthcare, and professional development. In practice, the scale may support the evaluation of AI training programs, measure the effectiveness of AI-based curricula, and identify demographic variations in AI adoption. Thus, this study contributes not only to the psychometric literature but also to the growing body of research on AI literacy, generative AI acceptance, and user readiness in diverse cultural contexts. Although the present study was carried out with Turkish-speaking participants, the implications of the findings extend beyond this immediate context. The adapted AISES can be utilised in different educational and professional settings, including higher education, vocational training, and workplace development, to assess learners' and employees' confidence in engaging with AI. As AI technologies are increasingly integrated into global curricula and organizational practices, the scale offers a valuable tool for cross-cultural comparisons and for identifying how socio-economic and institutional contexts shape AI self-efficacy. This broader application underlines the potential of the AISES not only as a psychometric instrument for Turkey but also as a contribution to international discussions on digital competencies and AI adoption

5.1. Implication for artifical intelligence

In this study, the AI Self-Efficacy (AISE) Scale was adapted into Turkish. The scale was originally developed, validated, and introduced by Wang and Chuang (2024) as a comprehensive psychometric instrument for assessing general AI self-efficacy. It underwent a validity and reliability assessment in Turkish to establish a framework that enables comparative evaluation of AI technologies and products. The scale can be utilised to compare the four factors of personal AI self-efficacy across different AI technologies and products.

Recent years have seen rapid advancements in the field of AI, with significant impact on various industries and wider society. These developments have included substantial progress in machine learning, deep learning and natural language processing, enabling AI models to be employed in a variety of applications, including image recognition, language translation and gaming (Padmaja et al., 2024). In line with these developments, the AI Self-Efficacy Scale (AISE) has been developed as an assessment tool that measures individuals' perceptions of AI products and the frequency of their interactions with these technologies. This facilitates a comparative analysis of different AI products.The applicability of AISE across various fields, including education, healthcare, and technology, is essential for understanding both the effectiveness of AI products and users' trust in these technologies.

The advent of AI has precipitated a profound metamorphosis in the domain of education, heralding a new era of advancement in teaching and learning methodologies (Guilherme, 2019). The imminent integration of AI products is poised to impart long-term benefits in the educational sector (Wang et al., 2023). These technologies are already being leveraged in educational services and curriculum design, and their utilisation is projected to escalate in the near future. These technologies are poised to support instructors by facilitating feedback on student work and enhancing virtual teaching assistant applications. Furthermore, AI products have the potential to improve language translation and enhance accessibility for students with disabilities (Brown et al., 2020). Notable examples include Amazon's Alexa Education Skills API and the use of Microsoft Translator to expand language options in a public school in North Carolina.Additionally, Osetskyi et al. (2020) examined the use of AI in education across various countries and found that modern technologies significantly impact teaching quality and individual competitiveness. In this context, the AI Self-Efficacy Scale (AISE) has the potential to enhance the quality of educational processes and promote the widespread adoption of AI products (Luckin et al., 2016). Furthermore, such assessments can facilitate the development of personalised learning experiences (Osetskyi et al., 2020).

The rapid advancement of AI technology represents a significant opportunity for its integration into clinical applications, with the potential to transform healthcare services (Alowais et al., 2023). AI products have the capacity to enhance diagnostic accuracy, prediction, and classification of diseases, leading to reduced costs and time savings (Ahsani et al., 2022). The utilisation of AI in clinical laboratory testing has the potential to enhance the accuracy, speed, and efficiency of laboratory processes (Undru et al., 2022). In emergency departments, AI products can optimise patient flow, prioritise high-risk cases, and reduce unnecessary visits (Gandhi & Sabik, 2014). Furthermore, the employment of AI-driven predictive analytics has the potential to forecast hospital readmissions and identify patients at risk of developing chronic diseases, such as endocrine or cardiovascular conditions (Nelson et al., 2019; Donzé et al., 2013). This, in turn, can contribute to reducing healthcare costs and improving patient outcomes (Alowais et al., 2023). The AI Self-Efficacy Scale (AISE) can thus be used to assess healthcare professionals' confidence in AI products and their self-efficacy in utilising these technologies. Such evaluations can provide valuable data for overcoming barriers to the adoption of AI-based healthcare technologies and identifying the training needs of healthcare professionals regarding AI integration.

AI products have become a staple in numerous sectors, particularly the technology sector, where they have the potential for extensive application. These products have been shown to facilitate the efficient collection and processing of market data, thereby reducing information asymmetry and optimising the production process and governance structure of businesses (Ballestar et al., 2021; Venables, 2001). The integration of AI products into data analysis processes has been demonstrated to enhance accuracy and reliability. Technologies such as automation, blockchain, and the Internet of Things (IoT) further improve efficiency in data collection, processing, and analysis, leading to a more effective analytical process (Liu et al., 2020). These technologies enable precise data processing while minimising human intervention, ultimately enhancing the accuracy of outcomes. Similarly, AI products can provide robust data support for technological innovations (Li et al., 2024). In this context, the AI Self-Efficacy Scale (AISE) can serve as a valuable tool for assessing technology professionals' confidence and competencies in AI products, thereby identifying training and development needs within the sector (Li et al., 2024).

Acknowledgements

The authors gratefully acknowledge the collaborative efforts and contributions of all co-authors in the design, execution, and reporting of this study.

Author contributions

CRediT: **Zeynep Aca**: Conceptualization, Resources, Writing – original draft, Writing – review & editing; **Umut Solmaz**: Conceptualization, Formal analysis, Methodology, Validation; **Orhan Koçak**: Methodology, Supervision, Validation.

Disclosure statement

The authors declare that there are no conflicts of interest regarding the publication of this article.

ORCID

Zeynep Aca http://orcid.org/0000-0002-3399-5310
Umut Solmaz http://orcid.org/0000-0003-1112-3041
Orhan Koçak http://orcid.org/0000-0002-0281-8805

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

References

Agarwal, R., & Karahanna, E. (2000). Time flies when you're having fun: Cognitive absorption and beliefs about information technology usage. *MIS Quarterly*, *24*(4), 665–694. https://doi.org/10.2307/3250951

Agarwal, R., Sambamurthy, V., & Stair, R. M. (2000). Research report: The evolving re lationship between general and specific computer self-efficacy an empirical assessment. *Information Systems Research*, *11*(4), 418–430. https://doi.org/10.1287/isre.11.4.418.11876

Ahsan, M. M., Luna, S. A., & Siddique, Z. (2022). Machine-learning-based disease diagnosis: A comprehensive review. *Healthcare (Basel, Switzerland)*, *10*(3), 541. https://doi.org/10.3390/healthcare10030541

Akkaya, B., Özkan, A., & Özkan, H. (2021). Yapay Zeka Kaygı (YZK) Ölçeği: Türkçeye uyarlama, geçerlik ve güvenirlik çalışması. *Alanya Akademik Bakış*, *5*(2), 1125–1146. https://doi.org/10.29023/alanyaakademik.833668

Alowais, S. A., Alghamdi, S. S., Alsuhebany, N., Alqahtani, T., Alshaya, A. I., Almohareb, S. N., Aldairem, A., Alrashed, M., Bin Saleh, K., Badreldin, H. A., Al Yami, M. S., Al Harbi, S., & Albekairy, A. M. (2023). Revolutionizing healthcare: The role of artificial intelligence in clinical practice. *BMC Medical Education*, *23*(1), 689. https://doi.org/10.1186/s12909-023-04698-z

Arslankara, V. B., & Usta, E. (2024). Generative artificial intelligence as a lifelong learning self efficacy: Usage and Competence Scale. *Journal of Teacher Education and Lifelong Learning*, *6*(2), 288–302. https://doi.org/10.51535/tell.1489304

Ballestar, M. T., Camiña, E., Díaz-Chao, Á., & Torrent-Sellens, J. (2021). Productivity and employment effects of digital complementarities. *Journal of Innovation & Knowledge*, *6*(3), 177–190. https://doi.org/10.1016/j.jik.2020.10.006

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review*, *84*(2), 191–215. https://doi.org/10.1037/0033-295x.84.2.191

Bandura, A. (1997). *Self-efficacy: The exercise of control*. W H Freeman/Times Books/Henry Holt & Co.

Bandura, A. (2006). *Guide for constructing self-efficacy scales*. In F. Pajares & T. Urdan (Eds.), *Adolescence and education (Self-efficacy and adolescence)*. (Vol. 5, pp. 307–337). Information Age.

Bandura, A. (1986). *Social Foundations of Thought and Action: A Social Cognitive Theory*. Prentice Hall.

Boateng, G. O., Neilands, T. B., Frongillo, E. A., Melgar-Quiñonez, H. R., & Young, S. L. (2018). Best Practices for Developing and Validating Scales For Health, Social and Behavioral Research: A Primer. *Frontiers in Public Health*, *6*(149), 1–18. https://doi.org/10.3389/fpubh.2018.00149

Brown, T. A. (2015). *Confirmatory factor analysis for applied research*. Te Guilford Press.

Brown, M., McCormack, M., Reeves, J., Brook, D. C., Grajek, S., Alexander, B., Bali, M., Bulger, S., Dark, S., Engelbert, N., Gannon, K., Gauthier, A., Gibson, D., Gibson, R., Lundin, B., Veletsianos, G., Weber, N. (2020). 2020 Educause Horizon Report Teaching and Learning Edition. Louisville, CO: EDUCAUSE. Retrieved January 21, 2025 from https://www.learntechlib.org/p/215670/

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant Technologies*. WW Norton & Company.

Carpenter, S. (2018). Ten steps in scale development and reporting: A guide for researchers. *Communication Methods and Measures*, *12*(1), 25–44. https://doi.org/10.1080/19312458.2017.1396583

Chen, K., Chen, J. V., & Yen, D. C. (2011). Dimensions of self-efficacy in the study of smart phoneacceptance. *Computer Standards & Interfaces*, *33*(4), 422–431. https://doi.org/10.1016/j.csi.2011.01.003

Creswell, W. J. (2009). *Research Design: Qualitative, Quantitative and Mixed Methods Approaches*. SAGE Publications.

Compeau, D. R., & Higgins, C. A. (1995). Computer self-efficacy: Development of a measure and initial test. *MIS Quarterly*, *19*(2), 189–211. https://doi.org/10.2307/249688

Çelebi, C., Yılmaz, F., Demir, U., & Karakuş, F. (2023). Artificial Intelligence Literacy: An Adaptation Study. *Instructional Technology and Lifelong Learning*, *4*(2), 291–306. https://doi.org/10.52911/itall.1401740

Davis, L. L. (1992). Instrument review: Getting the most from a panel of experts. *Applied Nursing Research*, *5*(4), 194–197. https://doi.org/10.1016/S0897-1897(05)80008-4

Donzé, J., Aujesky, D., Williams, D., & Schnipper, J. L. (2013). Potentially avoidable 30-day hospital readmissions in medical patients: Derivation and validation of a prediction model. *JAMA İnternal Medicine*, *173*(8), 632–638. https://doi.org/10.1001/jamainternmed.2013.3023

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., … Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, *57*(2021), 1–47. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Gandhi, S. O., & Sabik, L. (2014). Emergency department visit classification using the NYU algorithm. *The American Journal of Managed Care*, *20*(4), 315–320.

Guilherme, A. (2019). AI and education: The importance of teacher and student relations. *Aı & SOCIETY*, *34*(1), 47–54. https://doi.org/10.1007/s00146-017-0693-8

Gunzler, D. D., Perzynski, A. T., & Carle, A. C. (2021). *Structural Equation Modeling For Health And Medicine*. Chapman and Hall/CRC Press.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2013). *Multivariate Data Analysis*. Pearson.

Hasan, B. (2006). Delineating the effects of general and system-specific computer selfefficacy beliefs on IS acceptance. *Information & Management*, *43*(5), 565–571. https://doi.org/10.1016/j.im.2005.11.005

Hong, J. W. (2022). I was born to love AI: The influence of social status on AI self-efficacy and intentions to use AI. *International Journal of Communication*, *16*(2022), 172–191. https://ijoc.org/index.php/ijoc/article/view/17728

Holden, H., & Rada, R. (2011). Understanding the influence of perceived usability and technology selfefficacy on teachers' technology acceptance. *Journal of Research on Technology in Education*, *43*(4), 343–367. https://doi.org/10.1080/15391523.2011.10782576

Hsu, M. H., & Chiu, C. M. (2004). Internet self-efficacy and electronic service acceptance. *Decision Support Systems*, *38*(3), 369–381. https://doi.org/10.1016/j.dss.2003.08.001

Hsia, J. W., Chang, C. C., & Tseng, A. H. (2014). Effects of individuals' locus of control and computer selfefficacy on their e-learning acceptance in high-tech companies. *Behaviour & Information Technology*, *33*(1), 51–64. https://doi.org/10.1080/0144929X.2012.702284

Hu, L., & Bentler, P. M. (1999). Cut off criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 1–55. https://doi.org/10.1080/10705519909540118

IBM (2025). KMO and Barlett's Test. *Erişim Adresi*. https://www.ibm.com/docs/en/spss-statistics/25.0.0?topic=detection-kmo-bartletts-test&utm_source=chatgpt.com

John, S. P. (2013). *Antecedents and effects of computer self-efficacy on social networking adoptionamong Asian online users* [Paper presentation]. Proceedings of the Nineteenth Americas Conference on Information Systems, Chicago, IL.

Karaoğlan Yılmaz, F. G., & Yılmaz, R. (2023). Yapay zekâ okuryazarlığı ölçeğinin Türkçeye uyarlanması. *Bilgi Ve İletişim Teknolojileri Dergisi*, *5*(2), 172–190. https://doi.org/10.53694/bited.1376831

Karaoğlan Yilmaz, F. G., & Yilmaz, R. (2025). Exploring the role of self-regulated learnings skills, cognitive flexibility, and metacognitive awareness on generative artificial intelligence attitude. *Innovations in Education and Teaching International*, *2025*(3), 1–14. https://doi.org/10.1080/14703297.2025.2484613

Kaya, F., Aydin, F., Schepman, A., Rodway, P., Yetişensoy, O., & Demir-Kaya, M. (2022). The roles of personality traits, AI anxiety, and demographic factors in attitudes toward artificial intelligence. *International Journal of Human-Computer Interaction*, *40*(2), 497–514. https://doi.org/10.1080/10447318.2022.2151730

King, J. L., & Grudin, J. (2016). Will Computers Put Us Out of Work? *Computer Magazine*, *49*(5), 82–85. https://doi.org/10.1109/MC.2016.126

Kline, R. B. (2013). Exploratory and confirmatory factor analysis. In Y. Petscher, C. Schatschneider, & D. L. Compton (Eds.), *Applied quantitative analysis education and the social sciences* (pp. 169–207). Routledge.

Kline, R. B. (2023). *Principles and practice of structural equation modeling*. The Guilford Press.

Kolcu, G., Özceylan, G., Başer, A., & Baktır Altuntaş, S. (2021). Yapay Zekâ Kaygısı Ölçeği'nin aile hekimlerinde geçerlik ve güvenirliğinin değerlendirilmesi. *Research Journal of Biomedical and Biotechnology*, *2*(1), 20–28.

Kurtboğan, H., & Ak, M. (2024). *İnsanlığın pi noktası: Yapay zekâ*. Nobel Bilimsel Eserler.

Latikka, R., Turja, T., & Oksanen, A. (2019). Self-efficacy and acceptance of robots. *Computers in Human Behavior*, *93*(2019), 157–163. https://doi.org/10.1016/j.chb.2018.12.017

Lee, D. Y., & Ryu, H. (2013). Learner acceptance of a multimedia-based learning system. *International Journal of Human–Computer Interaction*, *29*(6), 419–437. https://doi.org/10.1080/10447318.2012.715278

Liu, J., Chang, H., Forrest, J. Y.-L., & Yang, B. (2020). Influence of artificial intelligence on technological innovation: Evidence from the panel data of china's manufacturing sectors. *Technological Forecasting and Social Change*, *158*(2), 120–142. https://doi.org/10.1016/j.techfore.2020.120142

Li, D., Wang, H., & Wang, J. (2024). Artificial ıntelligence and technological ınnovation: evidence from China's strategic emerging ındustries. *Sustainability*, *16*(16), 7226. https://doi.org/10.3390/su16167226

Lomax, R. (2013). Introduction to Structural Equation Modeling. In Y. Petscher, C. Schatschneider, & D. L. Compton (Eds.), *Applied quantitative analysis education and the social sciences*. (pp. 245–264). Routledge.

Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). *Intelligence unleashed. An argument for AI in education*. Pearson.

Marakas, G. M., Mun, Y. Y., & Johnson, R. D. (1998). The multilevel and multifaceted character of computer self-eficacy: Toward clarification of the construct and an integrative framework for research. *Information Systems Research*, *9*(2), 126–163. https://doi.org/10.1287/isre.9.2.126

Marengo, A., Karaoglan-Yilmaz, F. G., Yılmaz, R., & Ceylan, M. (2025). Development and validation of generative artificial intelligence attitude scale for students. *Frontiers in Computer Science*, *7*(2025), 1–15. https://doi.org/10.3389/fcomp.2025.1528455

Moore, H. (2019). Application and benefits of artificial ıntelligence to mankind: Review. *IDOSR Journal of Computer and Applied Sciences (IDOSR-JCAS,)*, *4*(1), 35–39.

Morales-García, W. C., Sairitupa-Sanchez, L. Z., Morales-García, S. B., & Morales-García, M. (2024). Adaptation and psychometric properties of a brief version of the general self-efficacy scale for use with artificial intelligence (GSE-6AI) among university students. *Frontiers in Education*, *9*(2024), 1293437. https://doi.org/10.3389/feduc.2024.1293437

Nelson, K. M., Chang, E. T., Zulman, D. M., Rubenstein, L. V., Kirkland, F. D., & Fihn, S. D. (2019). Using predictive analytics to guide patient care and research in a national health system. *Journal of General İnternal Medicine*, *34*(8), 1379–1380. https://doi.org/10.1007/s11606-019-04961-4

Osetskyi, V., Vitrenko, A., Tatomyr, I., Bilan, S., & Hirnyk, Y. (2020). Artificial intelligence application in education: *Financial implications and prospects. Financial and Credit Activity: Problems of Theory and Practice, 2*(33), 574–584. https://doi.org/10.18371/fcaptp.v2i33.207246

Padmaja, C. V. R., Narayana, S. L., Anga, G. L., & Bhansali, P. K. (2024). The rise of AI: A comprehensive research review. *IAES International Journal of Artificial Intelligence (IJ-AI)*, *13*(2), 2226–2235. https://doi.org/10.11591/ijai.v13.i2.pp2226-2235

Polatgil, M., & Güler, A. (2023). Yapay Zekâ Okuryazarlığı Ölçeğinin Türkçe'ye Uyarlanması. *Sosyal Bilimlerde Nicel Araştırmalar Dergisi*, *3*(2), 99–114. https://doi.org/10.53694/bited.1376831

Polit, D. F., Beck, C. T., & Owen, S. V. (2007). Is the CVI an acceptable indicator of content validity? Appraisal and recommendations. *Research in Nursing & Health*, *30*(4), 459–467. https://doi.org/10.1002/nur.20199

Polit, D. F., & Beck, C. T. (2003). *Nursing research: Principles and methods*. Lippincott Williams & Wilkins.

Pütten, A. R., & Von Der Bock, N. (2018). Development and validation of the self-efficacy in human-robot-interaction scale (SE-HRI). *ACM Transactions on Human-Robot Interaction*, *7*(3), 1–30. https://doi.org/10.1145/3139352

Russell, S. J., & Norvig, P. (2016). *Artificial intelligence: A modern approach* (3rd ed.). Pearson Education Limited.

Savaş, B. Ç. (2024). Yapay Zekâya Bağımlılık Ölçeğinin Türkçe'ye uyarlanması: Geçerlik ve güvenirlik çalışması. *Herkes İçin Spor Ve Rekreasyon Dergisi*, *6*(3), 306–315. https://doi.org/10.56639/jsar.1509301

Stanton, J. M., Sinar, E. F., Balzer, W. K., & Smith, P. C. (2002). Issues and strategies for reducing the length of selfreport scales. *Personnel Psychology*, *55*(1), 167–194. https://doi.org/10.1111/j.1744-6570.2002.tb00108.x

Sureshchandar, G. S. (2023). Quality 4.0 measurement model using the Confirmatory Factor Analysis (Cfa) approach. *International Journal of Quality & Reliability Management*, *40*(1), 280–303. https://doi.org/10.1108/IJQRM-06-2021-0172

Süleymanoğulları, M., Özdemir, A., & Tekin, A. (2024). Yapay Zekâ Ölc¸eği: Gec¸erlik ve güvenirlik c¸alıs¸ması. *Education*, *Science and Sport*, *6*(1), 13–27.

Tabachnick, B. G., & Fidell, L. S. (2015). *Çok Değişkenli İstatistiklerin Kullanımı*. Nobel Akademik.

Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. *International Journal of Medical Education*, *2*, 53–55. https://doi.org/10.5116/ijme.4dfb.8dfd

Tavakol, M., & Wetzel, A. (2020). Factor Analysis: A means for theory and instrument development in support of construct validity. *International Journal of Medical Education*, *11*, 245–247. https://doi.org/10.5116/ijme.5f96.0f4a

Teo, T., & Koh, J. H. L. (2010). Assessing the dimensionality of computer self-efficacy among pre-service teachers in Singapore: A structural equation modeling approach. *International Journal of Education and Development Using Information and Communication Technology*, *6*(3), 7–18.

Terzi, R. (2020). An adaptation of artificial intelligence anxiety scale into Turkish: Reliability and validity study. *International Online Journal of Education and Teaching*, *7*(4), 1501–1515.

Thangarasu, S., & De Paul, S. V. (2014). Development and validation of teacher computer self efficacyscale. *IOSR Journal of Humanities and Social Science*, *19*(1), 33–39. https://doi.org/10.9790/0837-19143339

Thierer, A., O'Sullivan, A. C., & Russell, R. (2017). *Artificial ıntelligence and public policy*. Mercatus Research, Mercatus Center at George Mason University, https://www.mercatus.org/publications/artificial-intelligence-public-policy

Torkzadeh, G., & Van Dyke, T. P. (2002). Effects of training on Internet self-efficacy and computer user attitudes. *Computers in Human Behavior*, *18*(5), 479–494. https://doi.org/10.1016/S0747-5632(02)00010-9

Tsai, M. F., Hung, S. Y., Yu, W. J., Chen, C. C., & Yen, D. C. (2019). Understanding physicians' adoption of electronic medical records: Healthcare technology self-efficacy, service level and risk perspectives. *Computer Standards & Interfaces*, *66*(2019), 103342. https://doi.org/10.1016/j.csi.2019.04.001

Undru, T. R., Uday, U., Lakshmi, J. T., Kaliappan, A., Mallamgunta, S., Nikhat, S. S., Sakthivadivel, V., & Gaur, A. (2022). Integrating Artificial Intelligence for Clinical and Laboratory diagnosis - a review. *Maedica*, *17*(2), 420–426. https://doi.org/10.26574/maedica.2022.17.2.420

UNESCO (2021). *Intergovernmental Meeting of Experts (Category ll) related to a Draft Recommendation on the Ethics of Artificial Intelligence*. https://unesdoc.unesco.org/ark:/48223/pf000 0376712/PDF/376712eng.pdf.multi

Venables, A. J. (2001). Geography and international inequalities: The impact of new technologies. *J. Ind. Compet. Trade*, *1*(2), 135–159. https://doi.org/10.1023/A:1012830529827

Venkatesh, V. (2000). Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model. *Information Systems Research*, *11*(4), 342–365. https://doi.org/10.1287/isre.11.4.342.11872

Wang, S., Sun, Z., & Chen, Y. (2023). Efects of higher education institutes' artifcial intelligence capability on students' self efcacy, creativity and learning performance. *Education and Information Technologies*, *28*(5), 4919–4939. https://doi.org/10.1007/s10639-022-11338-4

Wang, Y. Y., & Chuang, W. Y. (2024). Artificial ıntelligence self-efficacy: Scale development and validation. *Education and Information Technologies*, *29*(4), 4785–4808. https://doi.org/10.1007/s10639-023-12015-w

Whittaker, T. A., & Schumacker, R. E. (2022). *A beginners guide to structural equation modeling*. Routledge.

Yang, K. (2010). The effects of technology self-efficacy and innovativeness on consumer mobile data service adoption between American and Korean consumers. *Journal of International Consumer Marketing*, *22*(2), 117–127. https://doi.org/10.1080/08961530903476147

Yılmaz, R., & Yılmaz, K. G. F. (2023a). Augmented ıntelligence in programming learning: Examining student views on the use of ChatGPT for programming learning. *Computers in Human Behaviour: Artificial Humans*, *1*(2), 1–7. https://doi.org/10.1016/j.chbah.2023.100005

Yilmaz, F. G. K., Yilmaz, R., & Ceylan, M. (2024). Generative artificial ıntelligence acceptance scale: A validity and reliability study. *International Journal of Human–Computer Interaction*, *40*(24), 8703–8715. https://doi.org/10.1080/10447318.2023.2288730

Yılmaz, R., & Yılmaz, K. G. F. (2023b). The effect of generative Artificial Intelligence (AI)-based tool use on students' computational thinking skills, programming self-efficacy, and motivation. *Computers and Education: Artificial Intelligence*, *4*(2023), 1–14. https://doi.org/10.1016/j.caeai.2023.100147

Yılmaz, K. G. F., Yılmaz, R., Ustun, B. A., & Uzun, H. (2025). Exploring the role of cognitive flexibility, digital competencies, and self-regulation skills on students' generative artificial intelligence anxiety. *Computers in Human Behaviour: Artificial Humans*, *5*(2025), 1–8. https://doi.org/10.1016/j.chbah.2025.100187

Zyphur, J. M., Bonner, V. C., & Tay, L. (2023). Structural equation modeling in organizational research: The state of our science and some proposals for ıts future. *Annual Review of Organizational Psychology and Organizational Behavior*, *10*(1), 495–517. https://doi.org/10.1146/annurev-orgpsych-041621-031401

About the authors

Zeynep Aca is graduate of Ankara University, School of Political Sciences, Deparment of Labor Economics and Industrial Relations. She started her academic life in 2009 as research assistant at Uludağ University. She is associate professor at Bandırma Onyedi Eylül University, Department of Social Work, since 2019.

Umut Solmaz is a faculty member at Bolu Abant İzzet Baysal University, Department of Social Work and Counseling. He earned his B.A. in Social Work from Sakarya University and his M.A. and Ph.D. from Istanbul University-Cerrahpaşa. His research focuses on industrial social work, workplace issues, aging, and addiction.

Orhan Koçak is a Professor of Social Work at Istanbul University-Cerrahpaşa, Faculty of Health Sciences. He earned his M.A. in Social Policy and PhD in Labor Economics at Istanbul University. His research focuses on social policy, aging, and family issues, contributing significantly to the social work profession and discipline.