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Artificial intelligence self-efficacy: Scale development and validation

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Abstract
With the development of artificial intelligence (AI) applications, it has become critical for scholars, educators and practitioners to understand an individual's perceived self-efficacy regarding the use of AI technologies/products. Understanding users' subsequent behaviors toward the advancement of AI technology is also critical. Despite the growing focus on AI, a suitable scale for measuring AI self-efficacy (AISE) has yet to be developed. Current scales for measuring AISE (i.e., technology self-efficacy scales) are considered inapplicable because they neglect to evaluate perceptions of specific AI characteristics (e.g., AI-based configuration or anthropomorphic design). Given the limitations of existing self-evaluation and diagnostic instruments, the aim of this research is to investigate the construct of AISE, and develop and validate an AISE scale (AISES) for measuring an individual's perceived self-efficacy in regard to the use of AI technologies/products, in accordance with established exploratory and confirmatory scale development procedures. Specifically, a literature review is employed to generate initial items. An exploratory factor analysis is then performed for item purification purposes. At this stage, potential elements of AISE are extracted. Subsequently, factor extraction and confirmatory factor analysis are used to verify the construct structure of AISE. An analysis of 314 responses indicates that the AISE construct contains four factors: assistance, anthropomorphic interaction, comfort with AI, and technological skills. The scale is comprised of 22 items, and is found to have good fit, reliability, convergent validity, discriminant validity, content validity, and criterion-related validity. Moreover, nomological validity is built by the positive correlation between the AISE construct and motivated learning behaviors. This paper is the pioneer in developing and validating a scale to measure AISE. The findings extend existing knowledge of AISE and can help scholars further develop AISE theories. Our findings will also help educators and practitioners assess individuals' AISE and explore related behaviors.

Keywords Artificial intelligence · Scale development · Artificial intelligence self-efficacy · Motivated learning behavior · Adoption

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1 Introduction

While applications of artificial intelligence (AI) are increasing (Al Shamsi et al., 2022; Chou et al., 2022), some challenges remain. PwC's global artificial intelligence study showed that by 2030, AI could transform productivity (PwC Global, 2019). Nevertheless, there have been several significant barriers to AI adoption, such as skill acquisition and fear of the unknown (Goasduff, 2019). According to Gartner Research Circle and Gartner's, 2019 CIO Agenda survey, 56% of respondents said AI-related knowledge/skills are required for existing and newly created jobs, and 42% do not fully understand the benefits of implementing AI in the workplace and life (Gartner, 2019). Accordingly, it is vital for researchers to explore the initial phase where various factors may have a positive effect on the acceptance and adoption of AI technologies/products. In the literature, technology-centered perceptions, such as self-efficacy, have often been cited as crucial factors in the adoption of (new) information technology (IT) or information systems (IS) (Agarwal & Karahanna, 2000; Hsu & Chiu, 2004; Chen et al., 2011). Previous research on technology adoption has demonstrated that the higher a person's perceived self-efficacy regarding a particular application, the higher the perceived usefulness of that application (Igbaria & Iivari, 1995; Agarwal & Karahanna, 2000; John, 2013; Lee & Ryu, 2013). However, since perceived self-efficacy is a highly domain-specific construct, perceptions of general self-efficacy measures may not be sufficient to cover the scope of AI adoption (Bandura, 2006).

Computer self-efficacy has received much attention in prior studies (e.g., Compeau & Higgins, 1995; Teo & Koh, 2010; Thangarasu & De Paul, 2014), but few studies have assessed AI self-efficacy (AISE). To appraise how individuals perceive and adopt information technology (IT), previous studies have used various psychological scales that measure such things as computer self-efficacy (Compeau & Higgins, 1995), computer user self-efficacy (Cassidy & Eachus, 2002), teacher computer self-efficacy (Thangarasu & De Paul, 2014), ethical computer self-efficacy (Kuo & Hsu, 2001), mobile computing self-efficacy (Wang & Wang, 2008), Internet self-efficacy (Torkzadeh & van Dyke, 2001), information and communications technology (ICT) self-efficacy (Musharraf et al., 2018), online learning self-efficacy (Calaguas & Consunji, 2022), and robot use self-efficacy in healthcare work (Turja et al., 2017). Nevertheless, self-efficacy is domain-specific. One's sense of efficacy is not an overall belief but rather a complex belief system (Pütten & Bock, 2018). For example, Bandura (2006) showed that when performing as both corporate executives and parents, corporate executives may have a higher sense of organizational self-efficacy but a lower sense of parenting self-efficacy. Furthermore, even within a domain considered to be a single domain, such as technology use, self-efficacy expectations can vary, meaning that a person can demonstrate high self-efficacy in one subdomain (e.g., computer use) but not in other subdomains (e.g., robot use). Therefore, scales of perceived self-efficacy must be tailor-made to particular functional areas so that their measurement items meet the situational needs and circumstances under consideration

(Pütten & Bock, 2018). In this context, this research assumes that individuals' self-efficacy in the use of AI technologies/products may be significantly different from their self-efficacy regarding the use of information technologies such as computers. Previous research has found that experience and proficiency in computer programs lead to general computer self-efficacy (Hasan, 2003). Similarly, there is an expected relationship between perceived mastery of using specific AI technologies/products and AISE (Hong, 2022). However, the main difference between humans and machines is their mental or cognitive abilities, often referred to as "intelligence," and AI technologies/products attempt to reproduce this ability in computer systems (Wang, 2008). The ability to make decisions is what clearly differentiates AI technologies/products from computer programs. Individuals with low AISE may perceive using AI technologies/products, such as self-driving cars or smart assistants, as more complicated and stressful (Hong, 2022). Accordingly, we believe that it is paramount to establish a specialized instrument to assess AISE.

Given the limitations of existing self-reporting instruments, this research aims to cultivate and validate a new measure, the AISE scale (AISES), which captures the individual's perceived self-efficacy in using AI technologies/products. This study also explores perceptions of the psychological outcomes of AI advancement on individuals' subsequent motivations and behaviors. This instrument will provide a basis for assessing AISE. Most importantly, it may help improve the development of AI technologies/products. Several dimensions must be defined conceptually and operationally to assess the nature and scope of AISE. The sequence of scale development was as follows: (1) identify all dimensions of AISE contained in a single measuring instrument; (2) explore the interrelationships between dimensions in AISE; (3) develop a more accurate assessment instrument to measure AISE; and (4) contribute more important AISE related theories to the literature.

The rest of this research is arranged as follows. The next section reviews the related literature specific to the research domain of AISE, and proposes the constructs and hypotheses of AISE. The methods of item generation processes, data collective procedures, and scale purification processes are presented in detail. The theoretical and practical implications of this current research are then addressed, and we identify the limitations of this research and suggest avenues for future research.

2 The domain of AISE

2.1 General self-efficacy and task-specific self-efficacy

Self-efficacy is essential in shaping personal beliefs and behaviors (Compeau & Higgins, 1995). Based on social cognitive theory (SCT), general self-efficacy refers to people's general beliefs about their skills and capabilities to cope with challenging situations (Bandura, 1977, 1986). Beyond general self-efficacy, task-specific self-efficacy measures one's level of confidence in a specific task or situation; for example, technology-specific self-efficacy refers to an individual's confidence in his or her ability to master a particular form of technology (Ajzen, 2002). General and task-specific self-efficacy both refer to one's belief in one's ability to attain desired outcomes, but task-specific self-efficacy is more prone to context-specific or technology-specific beliefs than general self-efficacy (Chen et al., 2001). Wu et al. (2007) argued that general self-efficacy affects an individual's level of effort and performance on an identifiable task or specific situation. Previous studies have found that general self-efficacy positively affects individual follow-up task-specific self-efficacy (Gardner & Pierce, 1998; Agarwal et al., 2000; Hasan, 2006; Rahman et al., 2016).

In the literature, some constructs have involved task-specific self-efficacy, such as Internet self-efficacy, computer self-efficacy (Torkzadeh & van Dyke, 2001), ICT self-efficacy (Musharraf et al., 2018), and academic self-efficacy (Alt, 2015). Among them, computer self-efficacy is a widely studied task-specific self-efficacy that affects an individual's perception regarding technology adoption. It indicates the individual's perception of his or her ability to use a computer, as opposed to his/her level of knowledge and comprehension of the computer (Compeau & Higgins, 1995; Thatcher & Perrewe, 2002). Individuals with higher computer self-efficacy operate computers more frequently and have lower anxiety about computers (Compeau & Higgins, 1995). In addition to these task-specific perceptions of self-efficacy, this study assumes that individuals' AISE may vary widely. Therefore, this study argues for the requirement to establish a particularized mechanism to measure self-efficacy in using AI.

2.2 Conceptualization of AISE

Constructing conceptual definitions and theoretical implications is critical to establishing trustworthy instruments and acquiring proper and valid measurements (Gerbing & Anderson, 1988). Self-efficacy is considered a factor in completing a task (Cassidy & Eachus, 2002). Various scales have been created to assess self-efficacy in specific fields. Computers and robots, which require self-efficacy in technology, share similarities with AI. The AISE measure assesses self-efficacy concepts related to technology, such as computer self-efficacy, computer user self-efficacy, robot use self-efficacy, and attitude toward robots that have been utilized in some prior research (e.g., Compeau & Higgins, 1995; Cassidy & Eachus, 2002; Ninomiya et al., 2015; Turja et al., 2017; Musharraf et al., 2018). For example, Cassidy and Eachus (2002) established a 30-item computer user self-efficacy scale (CUSE) to evaluate general computer self-efficacy in an adult student population. Turja et al. (2017) used robot use self-efficacy in healthcare work (RUSH) to assess nursing workers' beliefs about their ability to use robots. The instrument involves three dimensions (technological skills, confidence in learning how to use robots, and confidence in guiding others in robot use). The self-efficacy subscale in the multidimensional robot attitude scale proposed by Ninomiya et al. (2015) is designed to measure people's attitudes toward domestic robots in general. The scale consisted of twelve dimensions (interest, appearance, familiarity, operation, utility, self-efficacy, negative attitude, cost, control, variety, social support, and environment fit).

Although computer self-efficacy and robot use self-efficacy have been studied in great detail in these areas, the impact on AISE remains largely unknown. Some studies, such as Hong (2022) and Kwak et al. (2022), adopted revised technology self-efficacy scales to measure AISE in using AI technologies/products. However, though the scales evaluated the influence of users' general technology perceptions on their AI technology usage, they neglected to evaluate these perceptions in terms of specific AI features (e.g., AI-based configuration or anthropomorphic design). AISE is more than one's judgment of one's own capability to apply technology skills; it is a self-assessment of specific individual skills involved in the use of AI technologies/products. Accordingly, based on previous technology-related self-efficacy research, AISE can be defined as individuals' general belief in their ability to use and interact with AI. AISE can be operatively viewed as a holistic perception or belief with multiple elements. Furthermore, in this research context, the AISE concentrates on the variable itself rather than the model evaluation procedure or response, which facilitates the processing of the AISE as a single variable, independent of various predecessors or consequences.

3 Hypothesis development for nomological validity test

Since the primary purpose of developing the AISES is to predict subsequent motivations and behaviors, the measurement of self-perceived skills and abilities regarding AI technologies/products must be closely linked to motivation and behavior theories. This study believes that self-efficacy (or self-confidence) derived from SCT is a psychological mechanism that motivates individuals' behaviors positively. Bandura (1991) provided an in-depth conceptual analysis and empirical support for how SCT's self-efficacy and social cognitive determinants determine motivated human behavior. In addition, several prior studies have examined individual beliefs in terms of the link between technology-associated self-efficacy (such as computer self-efficacy) and subsequent performance (e.g., John, 2013; Rahman et al., 2016).

The role of self-efficacy in academic learning has also been discussed in the literature. At the beginning of a learning activity, learners have different perceptions of their ability to acquire knowledge, their performance skills, their mastery of materials, and so forth (Schunk, 1989). The initial perception of self-efficacy varies with personal factors, past experiences, aptitudes (e.g., attitudes, abilities), and situational factors (e.g., rewards, teacher feedback). Learners use these factors to drive their positive learning behaviors and to assess different learning outcomes. Schunk (1991) noted that when learners feel they are making progress in their learning, their motivation to learn increases, a finding which was also supported by Zimmerman (2000) and Piniel and Csizér (2013), who argued that self-efficacy is an antecedent (e.g., through anxiety or perceived usefulness) to motivated learning behaviors. This drives the hypothesis that AISE may positively impact the development of AI-related knowledge/skills. Individuals with higher AISE tend to have a higher motivation to perform learning behaviors.

In accordance with Piniel and Csizér (2013), this study uses five items to measure motivated learning behavior. The five items are often used in empirical research to measure individuals' intended behavior (Dörnyei & Ushioda, 2011). In this study, motivated learning behavior refers to the degree to which an individual is willing to work hard and persistently learn AI-related knowledge/skills. With the aim of evaluating the nomological validity of the proposed AISES (Churchill, 1995), this research poses the following hypothesis:

H1. A positive relationship exists between AISE and motivated learning behavior.

4 Generation of scale items

The aim of this research is to establish the AISES. Operationally, AISE may be viewed as a total rating of self-efficacy regarding miscellaneous dimensions. Various possible measurement items exist for the AISE construct. After surveying various studies connected to AISE (e.g., Compeau & Higgins, 1995; Cassidy & Eachus, 2002; Hsu & Chiu, 2004; Rahman et al., 2016; Turja et al., 2017; Latikka et al., 2019), this research adopted 72 items to report the numerous dimensions of the AISE construct in the initial item pool, which covered the dimensions of robot use self-efficacy, technology self-efficacy, and computer self-efficacy. To ensure that all critical items were included, this study conducted personal interviews regarding AISE with the assistance of two professors and two researchers majoring in information education. These experts were asked to review the initial item pool of the AISES and ensure that the conceptual domain and the definition of the AISES were appropriate. Based on the consensus of the experts, the review yielded the recommended deletion of 38 redundant items. The remaining 34 items were then revised to ensure the proper wording in order to assess the proposed scale comprehensively. In the end, we generated an exploratory 39-item instrument, including 34 scale items and five behavioral measurement items (i.e., motivated learning behavior). Seven-point Likert scales were adopted for replies to these measurement items.

5 Data collection and scale purification

5.1 Sample and procedure

This study was conducted using a convenience sampling method with non-probability sampling techniques. To improve the generalizability of the AISES, this research conducted an online survey to collect research data for scale development. The questionnaire was uploaded to a professional survey website in Taiwan (https://www.surveycake.com/tw/). Participants clicked the hyperlink to access the questionnaire, which was divided into three sections: questionnaire information page, demographic items, and initial item pool. Specifically, the questionnaire information page briefly described the applications of AI and asked participants to participate voluntarily. The demographic items collected participants' background data which were required for this study. The initial item pool comprised 72 items identified through a comprehensive literature review. At the same time, the survey link was posted on social networking sites (e.g., PPT bulletin board system, i.e., the largest social networking site in Taiwan, and Facebook groups related to the survey). There were no restrictions to the sample requirements, so all Internet users were invited to participate if they were interested in the research topic. A total of 679 Internet users clicked the link to the online survey, and 318 respondents completed the questionnaire successfully, yielding 314 usable replies. The valid replies were used as the data for analysis. The respondents' characteristics are listed in Table 1. The ratio of male to female respondents was nearly equal. In addition, 61.8% of the respondents had bachelor's degrees, and 28.9% had a master's degrees or above, meaning that most of the respondents were university graduates. Most respondents were students between the ages of 18 and 30, with a monthly income of less than NTD 60,000 (approximately $2000 USD). Up to 83.4% of the respondents had experience using or developing AI products, and about half had interacted with humanoid AI products.

5.2 Test for non-response bias

To examine non-response bias, this study adapted a time-trend extrapolation procedure (Armstrong & Overton, 1977). A multivariate analysis of variance (MANOVA) test (computed using alpha = 0.05) was conducted to determine mean vector differences for all the items between early respondents (first quartile) and later respondents (fourth quartile). The results showed no significant differences (Wilks' $\lambda = 0.732$, $F = 1.408$, $p > 0.05$), indicating that non-response bias is not an issue.

5.3 Reduction of the number of items

Since this research aimed to establish a generic measure instrument with psychometric characteristics to estimate AISE, the item analysis method was used to purify the scale. In order to purify, verify and identify the factor structure of the AISES, exploratory factor analysis (EFA) and reliability testing were iteratively performed on the initial AISES. The overall sample ($n = 314$) was randomly split into two halves, and the first random sample ($n_1 = 157$) was used for analysis.

The aim of purifying the scale includes examining Cronbach's alpha and estimating item-to-total correlations to exclude inappropriate items (Cronbach, 1951). To avoid false part-whole correlations (Cohen & Cohen, 1975), the corrected item-to-total correlation was used as the criterion for deciding whether to remove the item. An iterative algorithm was then employed to estimate Cronbach's alpha, and item-to-total correlations were made for each AISE item. If any corrected item-to-total correlation is lower than 0.4, its related items should be deleted (Hinkin, 1998). We found that the corrected item-to-total correlations of all 34 items were above 0.4, and Cronbach's alpha was 0.97. Therefore, the 34 measurement items were considered reliable and appropriate for further analysis with EFA.

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's sphericity test were performed with EFA to verify the feasibility of factor analysis (Hair et al., 2006). The KMO and Bartlett's sphericity test produced significant results (MSA = 0.954; $\chi^2 = 6117.459$; $p < 0.001$), indicating that the intercorrelation matrix

Table 1 Sample characteristics

Variable	Level	Count	Percentage (%)
Gender	Male	135	43.0
	Female	179	57.0
Age	18 or below	14	4.5
	18-22	85	27.1
	23-30	126	40.1
	31-35	44	14.0
	36-40	27	8.6
	41-45	14	4.5
	46-50	2	0.6
	51 or above	2	0.6
Education	High school or below	21	6.7
	Junior college	6	1.9
	Bachelor's degree	194	61.8
	Master's degree	89	28.3
	Ph.D.	2	0.6
Occupation	Student	131	41.7
	IT industry	34	10.8
	Finance and insurance	19	6.1
	Service	51	16.2
	Mass communication	6	1.9
	Homebuilding	11	3.5
	Military	23	7.3
	Medical	7	2.2
	Housekeeping	2	0.6
	Free job	8	2.5
	Job-waiting	6	1.9
	Other	16	5.1
Income (NTD)	20,000 or below	131	41.7
	20,001-40,000	90	28.7
	40,001-60,000	71	22.6
	60,001-80,000	11	3.5
	80,001-100,000	3	1.0
	100,000 or above	8	2.5
Have previously used or developed AI products	Yes	262	83.4
	No	52	16.6
Have previously interacted with humanoid AI products	Yes	154	49.0
	No	160	51.0

$n = 314$

contained sufficient common variance to make factor analysis worthwhile. Next, to verify the discriminant validity of the AISES, we performed principal-components analysis (PCA) with the varimax orthogonal rotation method. The PCA results suggest that the four factors with eigenvalues greater than 1.0 accounted for 75.71% of the extracted total variance in the AISES. Lastly, we extracted the factor structure of the AISES and used the following criteria to determine whether to keep or remove items: (1) eigenvalue of a factor greater than 1; (2) important factor loadings on multiple factors; (3) unimportant factor loadings (lower than 0.50); (4) at least three indicators or items in a single factor, and (5) single item factors (Straub, 1989; Hair et al., 2010).

On the basis of these five rules and the EFA results, this research study preserved four dimensions, with the final set of 22 items used for subsequent analysis and Cronbach's alpha results. These four dimensions were interpreted as assistance, anthropomorphic interaction, comfort with AI, and technological skills. The factor loadings for the 22 items are shown in Table 2. All items loading onto the single factor revealed unidimensionality. In addition, no cross-loading items were noted on the 22-item scale, supporting the discriminant validity of the AISES.

Table 2 Rotated factor loadings for the 22-item instrument (Sample 1)

Item code	Assistance	Anthropomorphic interaction	Comfort with AI	Technological skills
Q14	0.880			
Q13	0.876			
Q12	0.804			
Q15	0.779			
Q10	0.764			
Q16	0.727			
Q17	0.723			
Q33		0.915		
Q32		0.913		
Q34		0.910		
Q31		0.907		
Q30		0.835		
Q25			0.790	
Q26			0.766	
Q24			0.756	
Q23			0.748	
Q22			0.653	
Q29			0.605	
Q4				0.853
Q5				0.833
Q6				0.661
Q3				0.619

$n_1 = 157$. Absolute values less than 0.60 were suppressed

5.4 Internal consistency assessment

Assessments of the reliability of the developed scale were generally measured using Cronbach's alpha to assess the internal consistency of items depicting each factor. The 22-item scale had a Cronbach's alpha score of 0.958, surpassing the minimum acceptable alpha score of 0.7 (Nunnally, 1978). The alpha scores for the factors of assistance, anthropomorphic interaction, comfort with AI, and technological skills were 0.942, 0.970, 0.963, and 0.869, respectively. All surpassed the minimum acceptable alpha score of 0.7, and the internal consistency was acceptable. The corrected item-to-total correlation scores for each item, as shown in Table 3, were above 0.4 (Wang, 2003). As reported by the reliability analysis results, the AISES showed good psychometric properties, as demonstrated by its theoretical structure.

5.5 Convergent and discriminant validity

This research used a correlation matrix to assess the convergent and discriminant validity of the 22-item scale (Wang, 2003). Convergent validity determines whether the correlations between measures of the same theoretical structure are significantly different from zero and of sufficient size (Wang et al., 2020). The smallest within-factor correlations are assistance (0.594), anthropomorphic interaction (0.811), comfort with AI (0.764), and technological skills (0.534), as shown in Table 4. All the within-factor correlations are importantly different from zero ($p < 0.001$). Accordingly, the result achieved convergent validity.

Discriminant validity was evaluated by examining how often each item had a higher correlation with items from other factors than with items from its own factor (Wang et al., 2020). Table 4 shows the correlations between the 22-item scale and identifies only one violation of discriminant validity (the correlation between AS7 and EM5). Wang et al. (2020) considered this to be acceptable. Thus, the results suggest that the scale has achieved discriminant validity.

5.6 Content validity

As mentioned, the AISES meets the requirements of factor structure and internal consistency. Nevertheless, internal consistency is a basic standard for proving the construct validity of an instrument, while content validity (or face validity) is a qualitative criterion that expresses the extent to which a particular specialty of the content of the theoretical notion is being evaluated (Carmines & Zeller, 1979; Nunnally, 1978; Hair et al., 2006). Content validity comprises subjective judgments about the meaning of a measurement by a group of experts or by assessing the instrument's items as a measurement characteristic (Churchill Jr, 1979; Houser, 2012). In this research, the content validity of the AISES was developed through a strict process, including conceptual construct, item design, and purification of the AISES.

Table 3 Corrected item-to-total correlations of AISE measures (Sample 1)

Item code	Original item code	Item description	Corrected item-to-total correlation
AS1	Q14	Some AI technologies/products make learning easier.	0.673
AS2	Q13	I find that AI technologies/products are helpful for learning.	0.638
AS3	Q12	AI technologies/products are good aids to learning.	0.660
AS4	Q15	Using AI technologies/products makes learning more interesting.	0.634
AS5	Q10	I'm confident in my ability to learn simple programming of AI technologies/products if I were provided the necessary training.	0.642
AS6	Q16	AI technologies/products help me to save a lot of time.	0.702
AS7	Q17	I find it easy to get AI technologies/products to do what I want it to do.	0.728
AI1	Q33	I think the interactive process of AI technologies/products is very vivid, just like chatting with a real person.	0.705
AI2	Q32	I think the way that AI technologies/products express content when interacting is unique, just like a real person.	0.683
AI3	Q34	I think there is no difference between the dialogue method of AI technologies/products compared with the dialogue with real people.	0.663
AI4	Q31	I think the tone of AI technologies/products when interacting is the same as that of real people.	0.712
AI5	Q30	I feel that the way of expression of AI technologies/products in the interactive text is the same as that of real people.	0.760
CF1	Q25	When interacting with AI technologies/products, I feel very calm.	0.805
CF2	Q26	When interacting with AI technologies/products, I find it easy.	0.811
CF3	Q24	When interacting with AI technologies/products, I feel comfortable in my heart.	0.825
CF4	Q23	When interacting with AI technologies/products, I feel very peaceful.	0.805
CF5	Q22	When interacting with AI technologies/products, I feel very relaxed.	0.852
CF6	Q29	I can happily interact with AI technologies/products smoothly.	0.859
TS1	Q4	When using AI technologies/products, I am not worried that I might press the wrong button and cause risks.	0.580
TS2	Q5	When using AI technologies/products I am not worried that I might press the wrong button and damage it.	0.524
TS3	Q6	When using an AI technology/product, there is nothing that I do not know why.	0.630
TS4	Q3	AI technologies/products jargon does not baffle me.	0.743

$n_1 = 157$. *AS* assistance, *AI* anthropomorphic interaction, *CF* comfort with AI, *TS* technological skills

Table 4 Correlation matrix of AISE measures (Sample 1)

	AS1	AS2	AS3	AS4	AS5	AS6	AS7	AI1	AI2	AI3	AI4	AI5	CF1	CF2	CF3	CF4	CF5	CF6	TS1	TS2	TS3	TS4
AS1	1																					
AS2	*0.851*	1																				
AS3	*0.780*	*0.762*	1																			
AS4	*0.755*	*0.706*	*0.673*	1																		
AS5	*0.741*	*0.679*	*0.691*	*0.614*	1																	
AS6	*0.668*	*0.660*	*0.712*	*0.640*	*0.657*	1																
AS7	*0.715*	*0.654*	*0.716*	*0.594*	*0.684*	*0.791*	1															
AI1	0.298	0.277	0.242	0.301	0.275	0.371	0.411	1														
AI2	0.268	0.292	0.210	0.371	0.258	0.362	0.333	*0.886*	1													
AI3	0.214	0.252	0.208	0.272	0.210	0.348	0.296	*0.895*	*0.881*	1												
AI4	0.276	0.285	0.209	0.302	0.275	0.384	0.382	*0.902*	*0.882*	*0.878*	1											
AI5	0.357	0.341	0.317	0.367	0.330	0.418	0.461	*0.855*	*0.829*	*0.811*	*0.874*	1										
CF1	0.597	0.503	0.559	0.570	0.571	0.619	0.613	0.495	0.492	0.441	0.527	0.564	1									
CF2	0.589	0.500	0.617	0.519	0.569	0.617	0.655	0.496	0.489	0.470	0.496	0.586	*0.848*	1								
CF3	0.579	0.536	0.600	0.589	0.507	0.662	0.650	0.513	0.512	0.504	0.555	0.589	*0.846*	*0.849*	1							
CF4	0.538	0.501	0.593	0.534	0.555	0.592	0.561	0.542	0.503	0.514	0.549	0.573	*0.850*	*0.792*	*0.805*	1						
CF5	0.637	0.612	0.615	0.602	0.585	0.643	0.607	0.521	0.549	0.543	0.585	0.599	*0.804*	*0.790*	*0.829*	*0.830*	1					
CF6	0.642	0.585	0.620	0.571	0.639	0.634	0.696	0.564	0.539	0.506	0.574	0.654	*0.801*	*0.817*	*0.786*	*0.764*	*0.805*	1				
TS1	0.403	0.376	0.444	0.348	0.452	0.297	0.477	0.329	0.282	0.295	0.316	0.389	0.441	0.459	0.436	0.432	0.495	0.537	1			
TS2	0.285	0.313	0.339	0.257	0.355	0.310	0.347	0.280	0.303	0.333	0.315	0.340	0.442	0.404	0.378	0.472	0.471	0.452	*0.720*	1		
TS3	0.306	0.257	0.384	0.268	0.303	0.331	0.419	0.534	0.467	0.533	0.516	0.563	0.458	0.498	0.527	0.477	0.517	0.515	*0.606*	*0.534*	1	
TS4	0.546	0.514	0.603	0.478	0.571	0.591	0.653	0.400	0.328	0.364	0.388	0.478	0.634	0.688	0.674	0.621	0.672	0.696	*0.667*	*0.620*	*0.600*	1

$n_1 = 157$. Within-factor correlations are in italic. All correlation coefficients are significant at $p < 0.01$

5.7 Criterion-related validity

Criterion-related validity was used to examine whether the 22-item scale is highly correlated with the assessment of the valid criterion (DeVellis, 2003). We examined the correlations between the sum scores of the 22-item scale and the assessment of the valid criterion (four global items of AISE), and the correlations between the assessment of the valid criterion and the sum scores of the four dimensions of the AISES. The results reveal that the four criteria earned a Cronbach's alpha of 0.852. We expected a positive correlation between the sum score on the 22-item scale, and the score of the global items of the 22-item scale was adequate for estimating AISE. We found that the correlation coefficient is positive and significant ($r=0.802$; $p<0.001$). Moreover, a valid criterion was expected to correlate with the mean scores of the four dimensions of AISE. The results indicate that the criterion had positive and significant correlations with assistance ($r=0.719$; $p<0.001$), anthropomorphic interaction ($r=0.521$; $p<0.001$), comfort with AI ($r=0.764$; $p<0.001$), and technological skills ($r=0.664$; $p<0.001$). These findings suggest that the 22-item scale has acceptable criterion-related validity (Cohen, 1988).

5.8 Nomological validity

Nomological validity is one type of constructive validity, demonstrating whether the AISES was very predictable in theoretically relevant variables from extant theories (Hinkin, 1998). To examine H1, we adapted five items for measuring motivated learning behavior from Piniel and Csizér (2013), as shown in Table 5. These items were employed for assessing nomological validity and the corresponding Cronbach's alpha value. For the 22-item scale to have nomological validity, there must be a positive correlation between the mean score on the 22-item scale and the score of the theoretically-related variable (i.e., motivated learning behavior). The correlation analysis results demonstrate that the AISE score has a positive, significant correlation with motivated learning behavior ($r=0.738$, $p<0.001$). Specifically, the correlation coefficients between the four AISES dimensions (i.e., assistance, anthropomorphic interaction, comfort with AI, and technological skills) were all positive (i.e., 0.652, 0.609, 0.659, and 0.462) and significant ($p<0.001$). Thus, H1 is supported, and the nomological validity of the AISES is confirmed.

5.9 Confirmatory factor analysis

Confirmatory factor analysis (CFA) was conducted to provide evidence supporting the validity of an inner structure of the measurement instrument by validating the number of fundamental dimensions and patterns of item-to-factor relationships (i.e., factor loadings) (Rios & Wells, 2014). The other half of the random sample ($n_2=157$) was employed for this analysis. The literature has suggested the following lower-limit values: comparative fit index (CFI) ≥ 0.9, Tucker-Lewis index (TLI) ≥ 0.9, root mean square error of approximation (RMSEA) ≤ 0.08, and

Table 5 Items for examining nomological validity and construct reliability

Item	Cronbach's α value	Item source
Motivated learning behavior	0.920	Adapted from Piniel and Csizér (2013)
1. I am willing to work hard at learning AI-related knowledge/skills.		
2. Learning AI-related knowledge/skills is one of the most important aspects in my life.		
3. I am determined to push myself to learn AI-related knowledge/skills.		
4. I can honestly say that I am really doing my best to learn AI-related knowledge/skills.		
5. It is very important for me to learn AI-related knowledge/skills.		

standardized root mean square residual (SRMR) ≤ 0.10 (Hair et al., 2010; Bentler & Bonett, 1980). These criteria provide the most fundamental indication of how well a proposed theory fits the data. They were thus used to assess the factor structure of AISES. The evaluation of the average variance extracted (AVE), each item's loadings, and composite reliability (CR) were employed to measure construct reliability and convergent validity. Each item's loadings should be at least 0.5, and the composite reliability should be at least 0.7 (Hair et al., 2010). Convergent validity is established when all item loadings are significant (Anderson & Gerbing, 1988) and the average variance extracted (AVE) evaluation for all factors exceeds 0.5 (Fornell & Larcker, 1981). If the AVE estimates for a given pair of factors exceed the square of the factor correlation (Fornell & Larcker, 1981), and if the 95% confidence interval for the correlation between the two factors does not incorporate the value of one, then discriminant validity is ensured (Anderson & Gerbing, 1988).

As demonstrated in Tables 6 and 7, the results show that the model fit of the four-factor model acquired from EFA is adequate in terms of CFA ($\chi^2 = 388.828$; $df = 196$; $p < 0.001$; χ^2 $/df = 1.984$; CFI = 0.941; TLI = 0.930; RMSEA = 0.079; SRMR = 0.071). All CR values exceed 0.8, showing satisfactory construct reliability. The standardized item loadings are all greater than 0.6 and significant ($p < 0.001$). Furthermore, all AVE values are greater than 0.5, supporting convergent validity. The discriminant validity is supported, resulting from none of the 95% confidence intervals for the factor correlation assesses contained 1, and the square of the factor correlation evaluation was lower than the corresponding AVE evaluation for all pairs of factors.

In terms of nomological validity, the analysis results of the second half sample are in accordance with those of the first half sample. The mean AISE score is positively correlated with the motivated learning behavior ($r = 0.597$, $p < 0.001$). In detail, the motivated learning behavior positively correlates with the AISES dimensions, i.e., assistance ($r = 0.557$, $p < 0.001$), anthropomorphic interaction ($r = 0.459$, $p < 0.001$), comfort with AI ($r = 0.562$, $p < 0.001$), and technological skills ($r = 0.272$, $p < 0.001$).

6 Discussion

In accordance with the scale development process recommended by Wang (2003), Hinkin (1998), and Churchill (1979) (including steps such as item generation, questionnaire administration, initial item reduction, CFA, convergent/discriminant validity, and replication), this study conceived a conceptual definition of the AISE construct, generated an operative plan of an initial AISE item pool, and empirically verified the generic AISES. Item purification and factor extraction were conducted in the EFA stage, and the factor structure of the AISES was confirmed in the CFA stage. The analysis results indicate that the AISE consists of four factors: assistance, anthropomorphic interaction, comfort with AI, and technological skills. The assistance dimension means the degree to which individuals perceive AI technologies/products as helpful or valuable for their tasks. The anthropomorphic interaction dimension refers to the degree of anthropomorphism individuals

Table 6 Confirmatory factor analysis (Sample 2)

Item	Factor loading
Assistance ($\alpha = 0.923$, $CR = 0.919$)	
AS1	0.734***
AS2	0.780***
AS3	0.859***
AS4	0.835***
AS5	0.758***
AS6	0.751***
AS7	0.788***
Anthropomorphic interaction ($\alpha = 0.954$, $CR = 0.950$)	
AI1	0.850***
AI2	0.908***
AI3	0.828***
AI4	0.937***
AI5	0.920***
Comfort with AI ($\alpha = 0.946$, $CR = 0.947$)	
CF1	0.867***
CF2	0.837***
CF3	0.939***
CF4	0.942***
CF5	0.913***
CF6	0.675***
Technological skills ($\alpha = 0.839$, $CR = 0.865$)	
TS1	0.810***
TS2	0.946***
TS3	0.636***
TS4	0.724***

$n_2 = 157$. Standardized loadings are reported. ***$p < 0.001$

Table 7 Correlation matrix and descriptive statistics of the constructs (Sample 2)

Construct	Assistance	Anthropomorphic interaction	Comfort with AI	Technological skills
1. Assistance	*0.620*			
2. Anthropomorphic Interaction	0.402 (0.111)	*0.791*		
3. Comfort with AI	0.667 (0.106)	0.621 (0.140)	*0.752*	
4. Technological skills	0.437 (0.123)	0.321 (0.150)	0.440 (0.128)	*0.620*
Mean	5.379	4.191	5.072	4.772
SD	0.945	1.323	1.111	1.125

$n_2 = 157$. Standard errors are in parentheses. The values on the diagonal (in italic) are average variance extracted (AVE) estimates perceive when interacting with AI technologies/products. The comfort with AI dimension represents an individual's emotional awareness when interacting with AI technologies/products. The technological skills dimension shows an individual's background knowledge and level of confidence in using AI technologies/products. The 22-item scale has sufficient reliability and content validity. Moreover, the AISES's criterion-related validity, discriminant validity, convergent validity, and nomological validity were verified. Consequently, the findings suggest that the AISES has well-established psychometric properties and provides several important theoretical and practical implications for AI contexts.

6.1 Theoretical implications

This study proposes a generic concept of AISE, develops an AISES, and evaluates the scale utilizing comprehensive and adequate psychometric properties. The validated AISES is conceived to be tailored to a large variety of AI technologies/products and to offer an assessment framework for comparative evaluation. The scale can be used to compare four factors of personal AISE using a specific AI technology/product. The measurement model of the AISE construct is shown in Fig. 1.

A central tenet of perceived self-efficacy is that it is domain-specific (Mozahem et al., 2021). The AISE construct can be adapted to be used in specific AI-related situations. Specifically, the AISE construct in the context of AI is distinct from computer self-efficacy scale (Teo & Koh, 2010) and robot use self-efficacy scale (Turja et al., 2017). The established AISE consists of three distinct components: (1) the assistance factor similar to the dimensions of robot use self-efficacy scale (i.e., technological assistive tool use); (2) the technological skills factor similar to the dimensions of computer self-efficacy scale (i.e., basic computer skills), and (3) factors that are unique to the AISE construct (i.e., anthropomorphic interaction, and comfort with AI). The AISES can help researchers develop and test AI-related theories and models, and extends academic research to causal issues, such as individuals' AISE, motivated learning behavior, anxiety, outcome expectations, affect, cognitive engagement, perceived usefulness of the AI technology, perceived enjoyment of the AI, perceived ease of use of the system, and subsequent behavioral performance (Aktağ, 2015; Chao, 2019; Chen, 2017; Hsia et al., 2014; John, 2013; Lee & Ryu, 2013; Piniel & Csizér, 2013; Wang & Wang, 2022). The findings provide new insights and understandings for more successful AI-related theory and model development and implementation. According to SCT, self-efficacy can be influenced by personal, behavioral and social/environmental factors. Regarding future research, this study suggests using the AISE to establish and test hypotheses and theories about individual behaviors in AI contexts, particularly in assessing perceived self-efficacy with AI technology/product adaptation and use.

Current preliminary findings confirm the impact of AISE on motivated learning behavior. This research result is in accordance with the view of SCT that self-efficacy is a crucial motivational process. The motivational outcome of self-efficacy is the option of effort, activity, accomplishment, and persistence. In comparison to individuals with low self-efficacy, people with high self-efficacy are

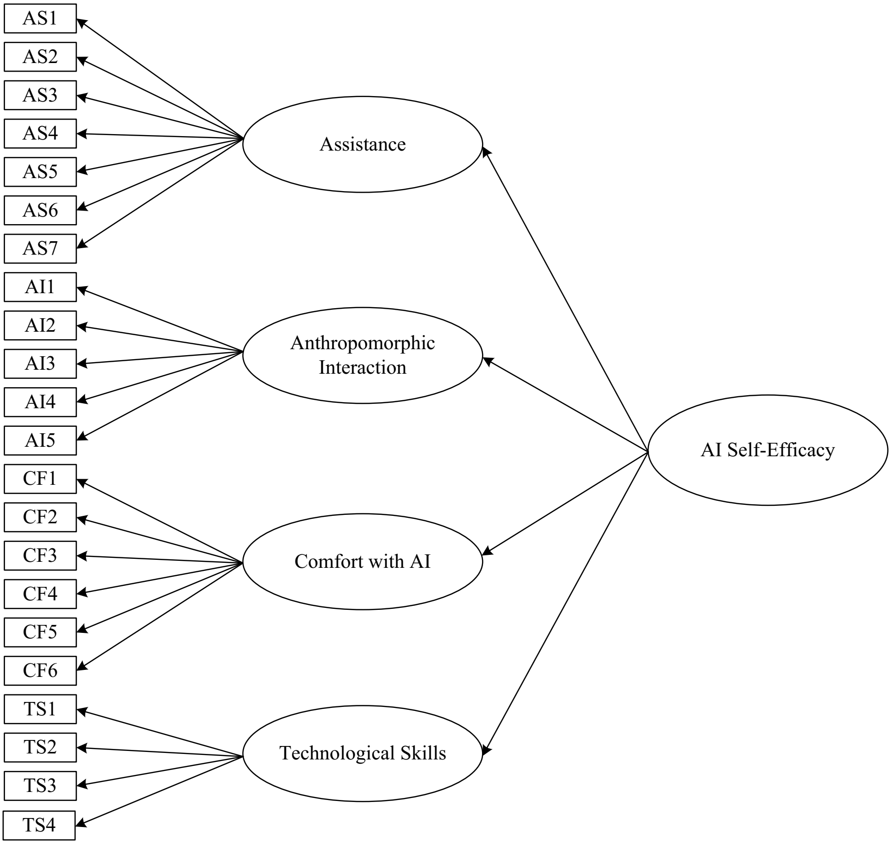

Fig. 1 A measurement model of AI self-efficacy

more likely to choose to participate in activities, engage in greater effort, persist longer—particularly in difficult moments—and achieve greater accomplishments (Schunk & DiBenedetto, 2020). Similarly, the result is in line with Zimmerman (2000) that an individual's motivation (clearly set proximal goals) to participate in and undertake a task or course of activity is based on a subjective judgment of capacities. The results subscribe to the notion that motivated learning behaviors (e.g., acquiring AI-related skills and expertise) are directly driven by the belief component (namely, AISE) responsible for a particular situation (e.g., AI technology/product adoption). Individuals who have a high level of AISE should engage in self-regulatory actions to enhance their AI-related knowledge and skills learning behaviors. Individuals who are less anxious about AI technology/product adoption and use may interpret this as their greater ability to adapt to the AI-enabled future. While many pedagogical and social elements at work in educational backgrounds may influence AISE, research on this topic has been insufficient. Also, current empirical evidence on the linkage between AISE and learning behavior is sparse. Therefore, the AISES has the potential to furnish scholars with an empirical basis by which to explain, demonstrate and compare discrepancies between different consequences.

6.2 Practical implications

The AISES has satisfactory reliability and validity, and can be used to assess individuals' AISE regarding AI technologies/products. Despite this, a better assessment is to collate the individual's AISE level compared to a norm (the overall distribution of the individual's AISE degrees as assessed by others). The diversity of the samples used in the study makes the AISES suitable for developing tentative relevant criteria. Table 8 reveals the percentile scores for the 22-item instrument. Other relevant sample statistical data are the minimum = 45; maximum = 154; mean = 110.108; standard deviation = 19.038; mode = 102; median = 109; skewness = –0.103; and kurtosis = –0.205. These statistics show that the AISES enables a more precise assessment of the individual's AISE for a specific AI technology/product. The 22-item instrument provides instant feedback to end users, AI technology/product developers, and practitioners, thereby advancing the development of AI technologies/products.

Several practical implications can be derived from this study. For practitioners, in addition to conducting an overall assessment, the AISES can also be used to compare individuals' self-efficacy across different dimensions. The 22-item instrument is designed to comply with a wide range of asynchronous AI technologies/products and provides a general framework for comparative analysis. When needed, this instrument can be adopted or adapted to meet the needs of a specific research or environment.

Moreover, the 22-item multi-dimensional AISES can be used as a self-evaluation tool for assessing AISE, and the AISE construct is an antecedent for subsequent motivational behaviors. Results indicate that AISE is positively correlated with motivated learning behaviors. AISE is critical in a motivational process that leads to subsequent behavioral outcomes (Schunk & DiBenedetto, 2020). The development of the AISES enables educators at universities to understand students' AISE, motivation, and the behaviors that result from it (e.g., motivation to learn AI-related knowledge and skills, AI learning acceptance, learning engagement, academic performance, etc.). AI-related curriculum design can focus on the four facets of AISE. Understanding these

Table 8 Percentile scores for the 22-item AI self-efficacy scale

Percentile	Value
10	87.0
20	93.0
30	99.0
40	103.0
50	109.0
60	115.0
70	122.0
80	129.0
90	136.0

four distinct aspects from a practical perspective will help universities segment students' AI abilities. Thus, educators can use more effective teaching strategies to assess individual differences in these aspects. With these measures, students will be better equipped and confident in their pursuit of AI development.

The AISES can also be considered a self-assessment tool for AI knowledge/skills learning and performance. Understanding employees' AISE can assist companies in promoting AI schemes, as self-efficacy is one of the antecedents of technology adoption (Aktağ, 2015). Given the positive correlation between self-efficacy and user adaptability (Yang & Pu, 2022), companies can increase their competitive advantage by promoting the improvement of their employees' AISE. In order to motivate employees to learn more, companies can hold lectures for employees to share their experiences and can design learning checklists based on the dimensions of AISE to help employees evaluate their learning effectiveness and job performance. Furthermore, companies adopting AI applications or services can use the AISES to understand the AI technology readiness of their employees, thereby providing an opportunity to confirm and improve their positioning.

7 Limitations and suggestions

This research developed a generic instrument to evaluate individuals' AISE and analyzed the relationship between AISE and motivated learning behaviors. The development of this instrument is an important step in advancing the understanding of AISE and acceptance of AI technologies/products. Although the development of this generic AISES has undergone a rigorous validation and verification process, our study has some limitations. First, since we adopted a nonrandom sample to establish the AISES, the results of this research may not be generalizable to people in other countries. There may be significant differences in nationality and individual behavioral characteristics. Accordingly, this study proposes that future researchers conduct cross-cultural or cross-nation studies to further verify the appropriateness of the AISES. Future research could use a cross-sectional study design to examine the impact of intrinsic motivation on AI-related knowledge and skills learning. Additionally, future research could examine the antecedents and outcomes of AISE in various AI contexts and across time. Future research should also explore the relationship between AISE, behavioral engagement in learning, satisfaction, associated behaviors, and motivation.

Data availability The data that support the findings of this study are not openly available due to human data and are available from the corresponding author upon reasonable request.

Declarations

Conflict of interest None.

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