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Development and validation of an artificial intelligence anxiety scale: an initial application in predicting motivated learning behavior

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ABSTRACT

While increasing productivity and economic growth, the application of artificial intelligence (AI) may ultimately require millions of people around the world to change careers or improve their skills. These disruptive effects contribute to the general public anxiety toward AI development. Despite the rising levels of AI anxiety (AIA) in recent decades, no AI anxiety scale (AIAS) has been developed. Given the limited utility of existing self-report instruments in measuring AIA, the aim of this paper is to develop a standardized tool to measure this phenomenon. Specifically, this paper introduces and defines the construct of AIA, develops a generic AIAS, and discusses the theoretical and practical applications of the instrument. The procedures used to conceptualize the survey, create the measurement items, collect data, and validate the multi-item scale are described. By analyzing data obtained from a sample of 301 respondents, the reliability, criterion-related validity, content validity, discriminant validity, convergent validity, and nomological validity of the constructs and relationships are fully examined. Overall, this empirically validated instrument advances scholarly knowledge regarding AIA and its associated behaviors.

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1. Introduction

Despite the potential of artificial intelligence (AI) to increase global economic productivity, the transformative effect that AI will have on the workforce fuels concerns about its ongoing development and application. Some scholars and practitioners have argued that automation technologies such as AI will have a particularly disruptive effect on the workforce (Brynjolfsson & McAfee, 2014). Others have expressed concern about the adoption of AI, pointing out that it may get out of control and disrupt society (Future of Life Institute, 2015). Automation and computerization will certainly transform how work is done, as AI changes or eliminates jobs and creates new ones. A 2017 report by McKinsey Global Institute (MGI) suggested that, depending on the speed of AI adoption, 75 million to 375 million workers (from 3–14% of the global workforce) may be required to change occupations and/or upgrade their skills by 2030 (Manyika et al., 2017). Moreover, all workers will be required to adapt to working with increasingly powerful machines, requiring that individuals are appropriately prepared to meet these and related future employment needs. Learning in-demand skills and resetting expectations about work will be important to help employees remain relevant and achieve their career goals.

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The study of AI anxiety (AIA) in the information system (IS) literature traces back to the first generation of computers, when researchers explored a widespread contemporary concern that computers threatened the meaning of being "human". While computer anxiety has received much attention among researchers (e.g. Barbeite & Weiss, 2004; Charlton & Birkett, 1995; Chu & Spires, 1991; Chuo, Tsai, Lan, & Tsai, 2011; Esterhuyse, Scholtz, & Venter, 2016; Hackbarth, Grover, & Yi, 2003; Heinssen, Glass, & Knight, 1987; Igbaria, Schiffman, & Wieckowski, 1994; Korobili, Togia, & Malliari, 2010; Marcoulides, 1989; Saadé & Kira, 2009), few studies have evaluated AIA among the general public. Several psychological scales such as the computer anxiety scale (Charlton & Birkett, 1995; Cohen & Waugh, 1989; Heinssen et al., 1987; Marcoulides, 1989), mobile computer anxiety scale (Wang, 2007), Internet anxiety scale (Chou, 2003), and robot anxiety scale (Nomura, Suzuki, Kanda, & Kato, 2006) have been used in prior studies to assess how individuals perceive and adopt information technology (IT). However, traditional measurements of computer anxiety, Internet anxiety, and robot anxiety are considered to be insufficient when applied to AI technologies/products: unlike its peer anxieties, AIA may result from inaccurate perceptions of technological development, confusion about autonomy, and sociotechnical blindness (Johnson & Verdicchio, 2017). Despite growing concerns about AI, a suitable scale for measuring AIA has yet to be developed. The literature has posited an expected relationship between AIA and personal behavior (e.g. motivated learning behavior). Therefore, there is a need to develop an instrument that measures AIA in individuals.

Given the limited utility of existing self-report instruments, the aim of this study is to explore perceptions of the psychological consequences of AI development in relation to subsequent behaviors in individuals. In order to evaluate the nature and scope of AIA, its several different dimensions must be defined in terms of concept and operation. The order of scale development is as follows: (1) identify all AIA aspects for inclusion in a single measurement instrument; (2) explore interrelationships among the AIA dimensions; (3) develop an assessment tool that evaluates AIA more accurately than currently available instruments; and (4) contribute additional important AIA-related theories to the IS literature.

This remainder of this paper is arranged as follows. Section two lays out the theoretical basis for developing an AIA construct; section three details the approach used in item generation and data collection; section four summarizes the results for the purification of the AI anxiety scale (AIAS) and the measurements and dimensionality of AIA in order to determine the basic, elemental structure of the scale and to assess its psychometric properties in terms of criterion-related, content, discriminant, convergent, and nomological validities; and sections five and six detail the norms of the instrument formation as well as discuss its theoretical and practical implications. The final section discusses the results of the AIAS.

2. Theoretical foundation

2.1. Technophobia and anxiety

Technophobia (or computerphobia) is defined as irrational fear or anxiety about the impact of advanced technology (Ha, Page, & Thorsteinsson, 2011). Technophobia is evidenced by the presence of one or more of the following: anxiety about current or future interactions with computer-related technologies; overall negative attitudes toward computer-related technologies, their behaviors, and/or social impacts; and specific negative cognitions of self-critical internal dialogues in actual computer-related technology interactions or when considering future interactions (Rosen & Weil, 1990). The concept of technophobia arises when the factors of *anxiety* and (negative) *attitude* are combined (Brosnan, 1998). Specifically, anxiety (e.g. computer anxiety) should not be confused with holding a negative attitude (e.g. negative attitude toward computers), which involves beliefs and feelings regarding computer-related technology rather than emotional responses toward using technology (Heinssen, Glass, & Knight, 1984, 1987). Moreover, negative attitudes may not significantly impact

actual advanced-technology-related behaviors (Nomura et al., 2006). Therefore, this study focuses on anxiety in order to discover the deeper, internal factors that are associated with AI. Epstein (1972) defined anxiety as a distracting state of awakening after perceived threats or as unresolved fear. The two types of anxiety that are commonly referenced are *trait* anxiety and *state* anxiety (Spielberger, 1966). The former is defined as a relatively stable, unitary, and long-lasting personality trait, while the latter is considered to be a transitory state that changes over time (Cambre & Cook, 1985). Typically, technological anxiety (e.g. computer anxiety, Internet anxiety, and online course anxiety) is a state of anxiety that may change in response to changing conditions (Bolliger & Halupa, 2012; Cambre & Cook, 1985; Heinssen et al., 1987; Oetting, 1983; Raub, 1981). Technophobia has been studied extensively in the context of information technology (Nomura et al., 2006). This study focuses on anxiety toward AI, which is assessed using a scale developed through the process described below.

2.2. Conceptualization of AIA

Establishing a conceptual definition and theoretical meaning for constructs is a critical part of developing reliable measures and obtaining useful and effective results (Gerbing & Anderson, 1988). The AIA measure assesses concepts related to AI-related anxiety such as computer anxiety and robot anxiety, and has been utilized in several investigations (e.g. Beckers & Schmidt, 2001; Bolliger & Halupa, 2012; Chu & Spires, 1991; Haring, Mougenot, Ono, & Watanabe, 2014; Heinssen et al., 1987; Hiroi & Ito, 2011; Johnson & Verdicchio, 2017; Nomura et al., 2006; Nomura, Kanda, Suzuki, & Kato, 2008; Ray, Mondada, & Siegwart, 2008; Rosen & Weil, 1995; Wang, 2007; Wu et al., 2014). Computer anxiety is considered to be an irrational fear, apprehension, or phobia that arises following personal interaction with a computer or thinking about using a computer (Herdman, 1983; Howard, 1986; Marcoulides, 1989). Based on its multidimensional and psychological nature, scholars have employed a diverse range of assessment methods to measure computer anxiety (e.g. Beckers & Schmidt, 2001; Brosnan & Lee, 1998; Dyck & Smither, 1994; Erickson, 1987; Heinssen et al., 1987; Loyd & Gressard, 1984; Marcoulides, 1989; Marcoulides & Wang, 1990; Maurer, 1983; Mclnerney, Mclnerney, & Sinclair, 1994; Nickell & Pinto, 1986; Raub, 1981; Rosen & Weil, 1995; Wang, 2007). The 19-item computer anxiety rating scale (CARS; Heinssen et al., 1987) is currently the most commonly used. The CARS includes 10 negative items (e.g. I feel apprehensive about using computers) and nine positive items (e.g. I look forward to using a computer in my job). The positive items are reverse scored, and all of the scores are summed to generate a score that reflects the degree of computer anxiety. Robot anxiety, another measure of AI-related anxiety, was defined by Nomura et al. (2006) as: ''the emotions of anxiety or fear preventing individuals from interaction with robots having functions of communication in daily life, in particular, communication in a human-robot dyad'' (p. 373). The robot anxiety scale (Nomura et al., 2006, 2008) is an 11-item, three-subscale (anxiety toward behavioral characteristics of robots, toward discourse with robots, and toward the communication capability of robots) instrument that was designed to measure AI-related anxiety. Other robot anxiety measures include negative images of an assistive robot, negative feelings toward humanoid robots, and root anxiety toward humanoid robots (Haring et al., 2014; Nomura, 2017; Ray et al., 2008; Wu et al., 2014).

Although the fields of computer anxiety and robot anxiety have been studied in great detail, the effects of AIA remain largely unknown. Based on prior anxiety studies conducted in the AI field (e.g. Johnson & Verdicchio, 2017), AIA may be defined as an overall, affective response of anxiety or fear that inhibits an individual from interacting with AI. Thus, AIA may be operationally considered as a general perception or belief with multiple dimensions. Moreover, AIA in the present research context focuses on the variable itself, rather than the process of response or model evaluation, which promotes the operation of AIA as a single variable, independent of numerous antecedents or consequences.

2.3. A theoretical framework for assessing AIA

The phrase "AI anxiety" refers to feelings of fear or agitation about out-of-control AI (Johnson & Verdicchio, 2017). As the main purpose of developing an AIA measure is to predict behavior, measuring self-perceived fear and unease about AI technologies/products is necessarily closely linked to behavior theory. Based on the theory of reasoned action (TRA; Fishbein & Ajzen, 1975), current study recommends that personal beliefs lead to behavioral intentions. Personal belief is an essential precondition to forming a behavioral intention to act in the preliminary motivation stage. Given this theoretical basis, AIA can be seen as a belief that serves as a precursor or intermediary of behavioral intention that links causal factors and attitudes to subsequent behaviors. Many scholars have studied personal beliefs in the context of the connection between computer-related anxiety and subsequent performance (e.g. Brosnan & Lee, 1998; Igbaria et al., 1994; Russon, Josefowitz, & Edmonds, 1994; Wang, 2007). Based on their findings, anxiety perceptions associated with an AI technology/product clearly restrict or increase future behavioral intention.

The effects of anxiety may be either facilitating or debilitating. Facilitating anxiety enhances performance, whereas debilitating anxiety inhibits performance (Alpert & Haber, 1960). Surprisingly, the facilitating aspect of anxiety has rarely been studied in the context of IT. This situation may reflect the hypothesis that facilitating anxiety is usually associated with cognitively less-demanding tasks, while IT adoption is often considered as a complex task where anxiety is more likely to inhibit adoption. Nonetheless, the existing findings of studies on AIA and the positive relationship between AIA and learning behavior must be noted. Researchers and educators believe that facilitating anxiety affects approach behavior, which is initiated by the presentation of a stimulus that is perceived as rewarding and positively influences motivated learning behavior (Piniel & Csizér, 2013). In this study, motivated learning behavior refers to the effort and persistence that individuals commit to learning another professional skill. Bernazzani (2017) pointed out that AI technologies/products are likely to replace some jobs, including: retail salespeople, advertising salespeople, market research analysts, computer support specialists, couriers, proofreaders, receptionists, compensation and benefits managers, bookkeeping clerks, and telemarketers. Increasing dependence on AI technologies/products may ultimately lead to loss of meaning, as human work is replaced by automation and computerization (Nauman, 2017). Moreover, people may be required to change careers and improve their skills. This leads to the assumption that AIA may affect professional skill development positively, as individuals with a high degree of AIA tend to have a higher degree of motivated learning behavior. To validate the proposed *nomological* validity of the AIAS (Churchill, 1995), the following hypothesis is proposed:

H1. A positive correlation exists between AIA scores and motivated learning behavior.

3. Research method

3.1. Generation of scale items

In terms of operations, AIA may be seen as a total rating of anxiety about different attributes. Several possible measurement items exist for the AIA construct. After reviewing numerous studies connected to AIA, robot anxiety, and computer anxiety (e.g. Haring et al., 2014; Johnson & Verdicchio, 2017; Nomura, 2017; Nomura et al., 2006, 2008; Ray et al., 2008; Wang, 2007; Wu et al., 2014), this study adopted 59 items to represent the various dimensions of the AIA construct in order to generate a preliminary item pool for the AIAS. In order to ensure the inclusion of all key attributes and items, this item pool was reviewed by two IS professors, two AI experts, and four AI technology/product users. This review resulted in the recommended deletion of nine items due to redundancy. The remaining 50 items were subsequently revised to ensure proper wording in order to conduct a comprehensive assessment of the proposed scale.

An exploratory 57-item AIAS, including 50 dimension items, two total measures (which considered AIA as a whole), and five behavioral intention measures (e.g. motivated learning behavior), was generated. Instrument items were scored using a 7-point Likert-type response scale (Appendix A). A demographic datasheet was included as part of the developed questionnaire.

3.2. The sample and procedures

To improve the generalizability of the results, the data used to develop the AIAS were collected through an online survey in Taiwan. The questionnaire was uploaded to a survey portal (https://www.surveycake.com) for online users to complete. Participants were instructed to respond to each questionnaire item by choosing the response that accurately described their level of agreement. The online survey yielded 301 usable responses from participants of different demographic backgrounds. Table 1 summarizes the respondents' demographic information.

4. Scale development

4.1. Item analysis and reliability estimates

The 50-item scale was obtained by analyzing the data provided by the abovementioned respondents. This approach was justified since the aim of this study was to develop a standard measurement tool with ideal psychometric characteristics to evaluate AIA.

The objectives of purifying the scale included removing the coefficient alpha (or Cronbach's alpha) and estimating item-to-total correlations to eliminate inappropriate items (Cronbach, 1951). In order to avoid false part-whole correlations (Cohen & Cohen, 1975), the corrected item-to-total correlation was the criterion used to decide whether to eliminate an item. Next, an iterative algorithm was used to calculate the coefficient alpha, and item-to-total correlations were performed for each AIA item. Any corrected item-to-total correlation below 0.40 resulted in the deletion of its associated item.

Table 1. Respondent characteristics ($n = 301$).

Characteristic	Items	Frequency	Percentage
Gender	Male	196	65.1
	Female	105	34.9
Age	15 or below	1	0.3
	16–20	45	15.0
	21–30	147	48.8
	31–40	78	25.9
	41–50	4	1.3
	51–60	2	0.7
	61 or above	24	8.0
Education	High school or below	32	10.6
	Junior college	4	1.3
	Bachelor's degree	181	60.2
	Master's degree or above	84	27.9
Occupation	Manufacturing	20	6.6
	Service	60	19.9
	Science and technology	29	9.6
	Student	117	39.0
	Government	23	7.6
	Education/Research	2	0.7
	Medical	7	2.3
	Other	43	14.3
Work content may be replaced by AI	Yes	118	39.2
	No	183	60.8
Have previously used or developed AI products	Yes	202	67.1
	No	99	32.9
Have previously interacted with humanoid AI products	Yes	115	38.2
	No	186	61.8

The corrected item-to-total correlations of two items, Q31 and Q50, fell below 0.40 and were therefore deleted. The remaining 48-item instrument had high reliability (coefficient alpha = 0.986).

4.2. Identifying the factor structure of the AIAS

Through exploratory factor analysis (EFA), the basic structure of the 48-item instrument was further verified. Before using EFA to identify the elemental structure of the AIA construct, Bartlett's sphericity test was performed with significant results ($\chi^2 = 19774.6$; $p < 0.001$), showing that the intercorrelation matrix contained enough common variance to make the factor analysis valuable. The 301 responses were analyzed using principal-components analysis (PCA) and an orthogonal rotation method (varimax rotation). The PCA findings show that the four factors with eigenvalues greater than 1.00 accounted for 79.638% of the extracted total variance in the AIAS. In testing for unidimensionality/convergence and for the discriminant validities of the AIAS using EFA, this study followed the five rules that are often used as the criteria for deciding whether to retain or eliminate items (Hair, Anderson, Tatham, & Black, 1998; Hair, Black, Babin, & Anderson, 2010; Straub, 1989): (1) values larger than the basic root criterion (eigenvalue >1.00); (2) insignificant factor loadings (<0.50); (3) significant factor loadings on multiple factors; (4) at least three indicators or items in a single factor; and (5) single item factors.

Based on these five rules and the EFA results, the present research study retained four dimensions (factors), with the final set of 21 items used for the subsequent analysis and coefficient alpha results. These four dimensions were interpreted as learning, job replacement, sociotechnical blindness, and AI configuration. Table 2 summarizes the factor loadings for the 21-item instrument. All items loading onto the same factor demonstrated convergent validity and unidimensionality. No cross-loading items were found among the four factors, in support of the discriminant validity of the AIAS.

4.3. Reliability

Reliability is typically estimated using the coefficient alpha to measure the internal consistency of an instrument. A coefficient alpha of 0.964 was obtained for this study, exceeding the minimum 0.70

Table 2. Rotated factor loadings for the 21-item AI anxiety scale.

Item code	Learning	Job replacement	Sociotechnical blindness	AI configuration
Q3	0.906			
Q2	0.896			
Q5	0.894			
Q4	0.890			
Q6	0.872			
Q1	0.848			
Q8	0.810			
Q7	0.589			
Q16		0.792		
Q17		0.752		
Q18		0.701		
Q15		0.700		
Q11		0.656		
Q9		0.599		
Q45			0.822	
Q46			0.692	
Q44			0.662	
Q47			0.642	
Q29				0.818
Q30				0.794
Q32				0.695

Note: Absolute values less than 0.50 were suppressed.

Table 3. Item-to-total correlations of AIA measures.

Item code	Original item code	Item description	Corrected item-to-total correlation
L1	Q3	Learning to understand all of the special functions associated with an AI technique/product makes me anxious.	0.832
L2	Q2	Learning to use AI techniques/products makes me anxious.	0.816
L3	Q5	Learning to use specific functions of an AI technique/product makes me anxious.	0.816
L4	Q4	Learning how an AI technique/product works makes me anxious.	0.816
L5	Q6	Learning to interact with an AI technique/product makes me anxious.	0.830
L6	Q1	Taking a class about the development of AI techniques/products makes me anxious.	0.798
L7	Q8	Reading an AI technique/product manual makes me anxious.	0.781
L8	Q7	Being unable to keep up with the advances associated with AI techniques/products makes me anxious.	0.721
J1	Q16	I am afraid that an AI technique/product may make us dependent.	0.612
J2	Q17	I am afraid that an AI technique/product may make us even lazier.	0.570
J3	Q18	I am afraid that an AI technique/product may replace humans.	0.703
J4	Q15	I am afraid that widespread use of humanoid robots will take jobs away from people.	0.739
J5	Q11	I am afraid that if I begin to use AI techniques/products I will become dependent upon them and lose some of my reasoning skills.	0.738
J6	Q9	I am afraid that AI techniques/products will replace someone's job.	0.695
S1	Q45	I am afraid that an AI technique/product may be misused.	0.575
S2	Q46	I am afraid of various problems potentially associated with an AI technique/product.	0.674
S3	Q44	I am afraid that an AI technique/product may get out of control and malfunction.	0.710
S4	Q47	I am afraid that an AI technique/product may lead to robot autonomy.	0.691
C1	Q29	I find humanoid AI techniques/products (e.g. humanoid robots) scary.	0.750
C2	Q30	I find humanoid AI techniques/products (e.g. humanoid robots) intimidating.	0.788
C3	Q32	I don't know why, but humanoid AI techniques/products (e.g. humanoid robots) scare me.	0.779

Notes: L: learning; J: job replacement; S: sociotechnical blindness; C: AI configuration.

recommended by Hair et al. (2010). The reliability of each of the four factors was: learning = 0.974; job replacement = 0.917; sociotechnical blindness = 0.917; and AI configuration = 0.961. All values supported acceptable internal consistency. In addition, considering a minimum value of 0.30 (Nurosis, 1994), in order to improve the coefficient alpha levels, a corrected item-to-total correlation was performed. As shown in Table 3, each item had a corrected item-to-total correlation exceeding 0.40. According to the reliability analysis results, the theoretical structures of the AIAS all exhibited desirable psychometric properties.

4.4. Content validity

In this study, the AIAS met the requirements for internal consistency and consistent factor structure. High internal consistency, however, is an elementary criterion for demonstrating the construct validity of an instrument, while content validity, a qualitative criterion, reflects the extent of a specific domain of the theoretical concept content being measured (Carmines & Zeller, 1979; Nunnally, 1978). Content validity includes a subjective judgment on the meaningfulness of a measurement that is made either by evaluating the instrument's items as a measured attribute (face validity) or by a panel of experts (Churchill, 1979; Houser, 2012). Also, content validity can be examined through a comprehensive review of the literature on the concept or representatives of relevant populations who provide data on their lived experiences based on the results of qualitative research (Salmond, 2008). In this study, the content validity of the AIAS was established via the rigorous procedure of conceptualizing the AIA construct, creation of the AIA items, and purification of the AIA scale.

4.5. Criterion-related validity

Criterion-related validity relates to the correlation between the external performance and the features of an instrument (Houser, 2012). In the current study, criterion-related validity means concurrent validity, while the total scores of the AIAS (the sum of the 21 items) and those for the valid criterion (the sum of the two global items) were assessed at the same time. These two criterion items earned a coefficient alpha of 0.933. Moreover, the correlation between the total score and the valid criterion should be positive if the scale is able to measure the AIA construct. The results show a criterion-related validity of 0.864 for the 21-item instrument and a significance level of 0.001, indicating acceptable criterion-related validity (Cohen, 1988).

4.6. Discriminant and convergent validity

While the EFA was used as an initial examination for discriminant and convergent validity, a correlation matrix method was then used to estimate the validities of the AIAS. Convergent validity tests whether a correlation analysis of the same theoretical structure measures differs from zero, and is large enough to ensure the further study of discriminant validity. The minimum within-item correlations were learning = 0.624; job replacement = 0.480; sociotechnical blindness = 0.703; and AI configuration = 0.860. These correlations were significantly different from zero at the level of $p < 0.001$ and sufficient to justify further examination of discriminant validity.

Discriminant validity was evaluated using the confidence interval approach (Anderson & Gerbing, 1988). The correlations between the four dimensions are outlined in Table 4. These four dimensions were significantly correlated, indicating a common AIA construct across them. Nevertheless, the confidence intervals for the pairwise correlation between these four variables do not include the value of 1.00. Thus, the discriminant validity of the multiple-item scales was supported.

4.7. Nomological validity

Nomological validity is a form of constructive validity. In the current study, nomological validity was evaluated by testing H1. The AIA construct and the total score of the behavioral intention construct (i.e. motivated learning behavior) should be positively correlated if the 21-item instrument has nomological validity. A subsequent correlation analysis found that the AIA construct had a significantly positive effect on the behavioral intention construct ($r = 0.190$, $p < 0.01$). As a result, H1 was supported, confirming the nomological validity of the proposed AIA measures.

5. Theoretical implications

This study conceptualized an AIA construct, developed a generic AIA scale (AIAS), and evaluated this scale using complete and satisfactory psychometric attributes. The validated 21-item AIAS includes four factors: learning, job replacement, sociotechnical blindness, and AI configuration. The analyses described in section four demonstrated acceptable reliability, criterion-related validity, content validity, discriminant validity, convergent validity, and nomological validity for the 21-item instrument. Figure 1 shows the measurement model of the AIA construct.

Table 4. Correlations among the dimensions of AI anxiety.

	Factor 1: Learning	Factor 2: Job replacement	Factor 3: Sociotechnical blindness	Factor 4: AI configuration
Factor 1	1.000			
Factor 2	0.593**	1.000		
Factor 3	0.494**	0.725**	1.000	
Factor 4	0.701**	0.590**	0.598**	1.000

Note: **$p < 0.01$.

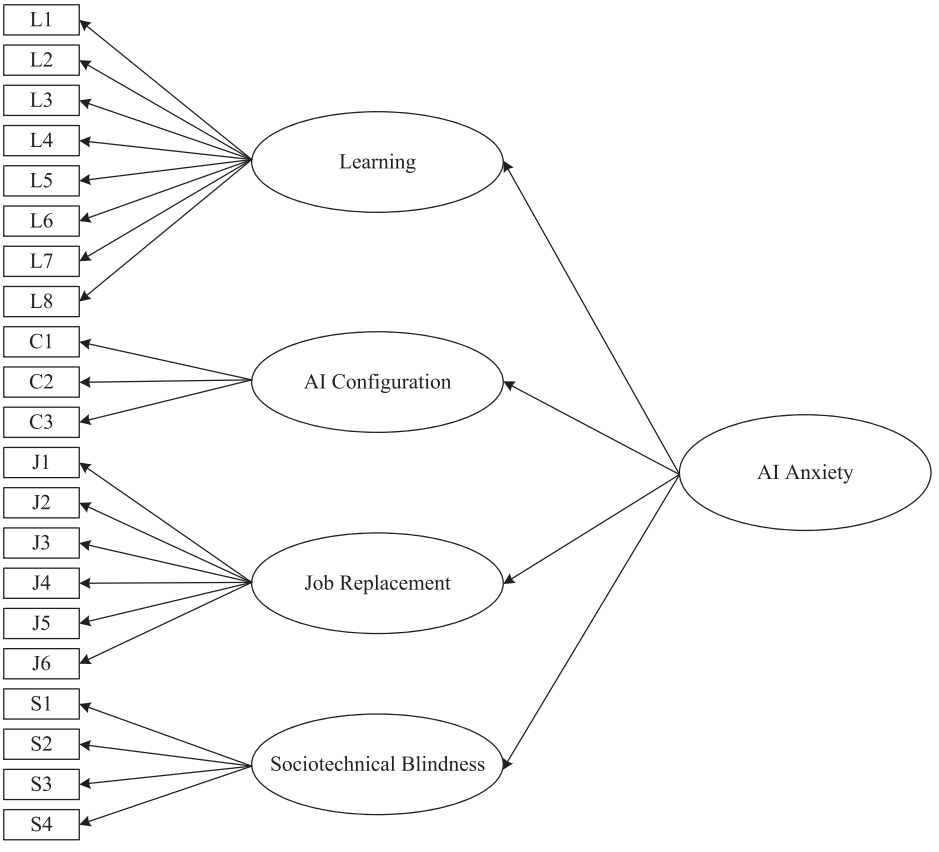


Figure 1. A model for measuring AI anxiety.

The AIA construct in the AI area differs somewhat from both the computer-anxiety and robot-anxiety constructs. It is worth reiterating here that the developed AIAS incorporates three dissimilar components: (1) learning (similar to the computer-anxiety construct); (2) AI configuration (similar to the robot-anxiety construct), and (3) job placement and sociotechnical blindness (unique to the AIA construct).

Moreover, the AIAS may be utilized to compare individual perceptions of anxiety toward using specific AI technologies/products in terms of its four factors. The AIAS was designed to accommodate a wide range of AI technologies/products and to provide an evaluation framework for conducting comparative analyses. Furthermore, when needed, the instrument may be adapted or adopted for use in specific contexts. Based on the literature (e.g. Brosnan & Lee, 1998; Conrad & Munro, 2008; Farina, Arce, Sobral, & Carames, 1991; Igbaria et al., 1994; Russon et al., 1994; Wang, 2007), researchers may use the AIAS to extend scholarly investigations into causal relations in issues such as AIA, motivated learning behavior, user attitude, neuroticism of personality traits, self-efficacy, perceived fun, perceived usefulness, and subsequent performance. The results provide new insights and understanding regarding ways to implement AI development more successfully. Future studies in this area may use the AIAS to develop and examine hypotheses and theories on individual behaviors related to AI technologies/products, especially in terms of evaluating self-perceived anxiety related to instances of AI technology/product adoption.

According to the initial research findings, AIA, as a facilitating anxiety, influences motivated learning behavior to some extent. This is consistent with the findings of Kleinmann (1977) and Piniel and Csizér (2013), in that individuals with higher degrees of facilitating anxiety were found to invest more

effort and persistence into learning professional knowledge and skills. Similarly, Macher, Paechter, Papousek, and Ruggeri (2012) supported the relationships between subject-specific anxieties (e.g. statistics anxiety) and learning strategies. While many companies have used AI techniques to automate processes, the greater impact of the technology may be to complement and augment human capabilities rather than replace them (Wilson & Daugherty, 2018). Using bank counter service personnel as an example, if transfer, deposit, and financial product purchase services can be completed using AI technologies and products, counter service personnel can be transformed into customer relationship managers who provide services that machines cannot perform. Such counter service personnel with higher levels of AIA are likely to actively learn the essential knowledge and skills required of customer relationship managers, including computer skills, product/service knowledge, communication skills, customer service skills, team collaboration skills, time management skills, presentation skills, and negotiation skills to improve their career development (JobHero, 2019). Currently, however, empirical evidence on the link between AIA and learning behaviors is very limited. Accordingly, the AIAS has the potential to provide IS researchers with an evidence-based basis to interpret, justify, and compare the differences between different outcomes.

6. Practical implications

In conclusion, the 21-item AIAS was demonstrated to provide satisfactory reliability, criterion-related validity, content validity, discriminant validity, convergent validity, and nomological validity. While the AIAS can be utilized to evaluate an individual's AIA, a better way of measuring this is to compare an individual's AIA levels with norms – the overall distribution of the levels of an individual's AIA levels as rated by other people. The diversity of the sample used in this study makes the developed AIAS suitable for developing tentative, related standards. The percentile scores for the 21-item instrument are shown in Table 5. These include minimum = 21; maximum = 136; mean = 91.409; standard deviation = 26.570; mode = 130; median = 88; skewness = −0.016; and kurtosis = −0.583, indicating that the AIAS is able to assess AI anxiety in individuals more precisely than other currently popular measures. AIAS assessments offer quick feedback for end users as well as for AI technology/product developers and practitioners.

Automation technologies such as AI are expected to expand significantly in the near future. Perceptions of AIA among users of these technologies may significantly affect the pace and success of AI development. Therefore, reducing the perceived anxiety of users by promoting the expanded use of AI technologies/products and by expanding learning channels is crucial to successfully promoting user acceptance. The acceptable reliability and validity of the AIAS supports the use of this measure to provide AI technology/product developers and practitioners with a better understanding of the context and composition of end-user anxiety, and to help them take necessary and appropriate corrective measures. Providing AI technology/product-related education and learning channels will enable end users to increase their related knowledge and reduce their AIA, which should subsequently influence learning behaviors.

It is critical to have a multidimensional method of analyzing AIA. For AI practitioners, it is important to emphasize the different dimensions of anxiety, including learning, job replacement, sociotechnical

Table 5. Percentile scores for the 21-item AI anxiety scale.

Percentile	Value
10	58.0
20	70.0
30	77.0
40	84.0
50	88.0
60	95.0
70	105.4
80	117.8
90	130.0

blindness, and AI configuration. Apart from taking an overall measurement, the AIAS may be used to compare individual differences across various anxiety dimensions. When AI practitioners identify individuals who are insufficient in one or more of the dimensions, they may conduct further analyses and take appropriate corrective measures. Also, for instructors, understanding the interaction between students' AIA and learning behaviors is vital because the interventions can be adjusted as required. Scholars have suggested that students' intrinsic learning motivation is a significant component to be considered when gaining exposure to professional knowledge and skills due to the fact that interest in a topic leads to both reduced anxiety, as well as enhanced subsequent learning behaviors and learning outcomes (Macher et al., 2012). Based on the different dimensions of AIA (i.e. learning, job replacement, sociotechnical blindness, and AI configuration), instructors are advised to use the proposed AIAS to understand how to apply more effective teaching strategies to stimulate students' interest in learning AI-related knowledge and skills, perhaps by emphasizing the importance of relevant knowledge and practical skills for the students' later vocations. Through such measures, students will be better prepared for the development of AI and experience less AIA.

7. Limitations

Although the generic AIAS was developed through a rigorous validation procedure, some limitations may affect its validity. First, confirmatory factor analysis (CFA) must be applied in future studies on the AIAS in order to examine the hypotheses and generate path analysis diagrams that explain factors and variables (Child, 2006). Compared with common factor analysis and multitrait-multimethod analysis, the advantages of applying CFA to examine discriminant and convergent validity are generally accepted (Anderson & Gerbing, 1988).

Further, nonrandom sampling may limit the generalizability of research results due to lack of representativeness in populations beyond those sampled. In order to reduce sampling bias risk, future scholars are encouraged to use a randomized sample that involves different territories and countries. Moreover, subsequent research must identify or refine the basic structure of the 21-item instrument to measure the reliability and validity of the AIA instrument.

Lastly, to establish the short-term and long-term stability of this instrument, assessment of the test-retest reliability of the AIAS should be performed. Methods for estimating reliability include internal consistency reliability, which is usually evaluated by stability, reliability, and the coefficient alpha, while test-retest reliability is conducted to test the stability of an instrument over time. The test-retest method is more suitable for building a reliable instrument (Galletta & Lederer, 1989). Therefore, the reliability of this type of AIAS in terms of both short-term and long-term stability must be further studied using the test-retest method.

8. Conclusions

The main contributions of this study include the development of a generic instrument for measuring anxiety toward AI development and the findings pertaining to the relationships between AIA and motivated learning behavior in individuals. The development of the AIAS represents a significant step in the theoretical development process related to AIA and AI adoption. Based on prior research, this paper develops a conceptual definition of an AIA construct, operational designs of the preliminary AIA item list, and empirical validations of the generic AIAS. The research results show that the proposed AIAS has well-established psychometric properties, which facilitate the work of both AI developers and practitioners, who are responsible for applying and implementing AI technologies and products, and scholars and educators involved in developing and testing IS theories that explain and predict AI adoption behavior. The findings of this study provide a preliminary insight into the relationship between AIA and motivated learning behavior. However, more research in this area is required. In order to determine how these concepts are related to each other, other methods including cross-sectional studies will be useful in terms of analyzing a representative

subset including AIA, learning behaviors and other potential factors on relevant learning processes at a particular time. The AIAS demonstrates satisfactory reliability and validity across various AI technologies/products. Educators, scholars, and practitioners are encouraged to employ the AIAS in AI and learning environments. The generality of the proposed AIAS offers a general framework that may be used to conduct comparative analyses of the results of various studies.

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Appendix A. Measurement items of AI anxiety used in this study

50 items used in the exploratory factor analysis.

Q1. Taking a class about the development of AI techniques/products makes me anxious.
Q2. Learning to use AI techniques/products makes me anxious.
Q3. Learning to understand all of the special functions associated with an AI technique/product makes me anxious.
Q4. Learning how an AI technique/product works makes me anxious.
Q5. Learning to use specific functions of an AI technique/product makes me anxious.
Q6. Learning to interact with an AI technique/product makes me anxious.
Q7. Being unable to keep up with the advances associated with AI techniques/products makes me anxious.
Q8. Reading an AI technique/product manual makes me anxious.
Q9. I am afraid that AI techniques/products will replace someone's job.
Q10. Working with AI techniques/products makes me anxious.
Q11. I am afraid that if I begin to use AI techniques/products I will become dependent upon them and lose some of my reasoning skills.
Q12. I am afraid that AI techniques/products will increase their role in society.
Q13. Talking to friends/colleagues about AI techniques/products makes me anxious.
Q14. I am afraid that it is necessary to use an AI technique/product in my job.
Q15. I am afraid that widespread use of humanoid robots will take jobs away from people.
Q16. I am afraid that an AI technique/product may make us dependent.
Q17. I am afraid that an AI technique/product may make us even lazier.
Q18. I am afraid that an AI technique/product may replace humans.
Q19. I am afraid that an AI technique/product may replace pets.
Q20. Interpreting an AI technique/product output makes me anxious.
Q21. Getting error messages when operating an AI technique/product makes me anxious.
Q22. Causing a large amount of data to be destroyed while using an AI technique/product makes me anxious.
Q23. Using a specific AI technique/product that I have never used before makes me anxious.
Q24. If I were to use an AI technique/product, I would be afraid of making mistakes.
Q25. Disassembling AI technique/product components makes me anxious.
Q26. Looking at disassembled AI technique/product components makes me anxious.
Q27. Configuring an AI technique/product to utilize specific functions makes me anxious.
Q28. Configuring AI techniques/products makes me anxious.
Q29. I find humanoid AI techniques/products (e.g. humanoid robots) scary.
Q30. I find humanoid AI techniques/products (e.g. humanoid robots) intimidating.
Q31. The development of humanoid AI techniques/products (e.g. humanoid robots) is blasphemous.
Q32. I don't know why, but humanoid AI techniques/products (e.g. humanoid robots) scare me.
Q33. I am afraid that AI techniques/products (e.g. robots) may talk about irrelevant things in the middle of a conversation.
Q34. I am afraid that AI techniques/products (e.g. robots) may not be flexible in following the direction of our conversation.
Q35. I am afraid that AI techniques/products (e.g. robots) may not understand difficult conversation topics.
Q36. I am afraid of what kind of movements an AI technique/product will make.
Q37. I am afraid of what an AI technique/product is going to do.
Q38. I am afraid of how strong an AI technique/product is.
Q39. I am afraid of how fast an AI technique/product will move.
Q40. I am afraid of how I should talk to an AI technique/product.
Q41. I am afraid of how I should respond when AI techniques/products (e.g. robots) talk to me.
Q42. I am afraid that an AI technique/product will understand what I am talking about.
Q43. I am afraid that I will understand what an AI technique/product is talking about.
Q44. I am afraid that an AI technique/product may get out of control and malfunction.
Q45. I am afraid that an AI technique/product may be misused.
Q46. I am afraid of various problems potentially associated with an AI technique/product.
Q47. I am afraid that an AI technique/product may lead to robot autonomy.
Q48. I am afraid that an AI technique/product may lead us to lose our autonomy.
Q49. I am afraid that an AI technique/product may lead us to lose our human contacts.
Q50. I think that only people who are no longer independent would use an assistive AI product.
Q51. As a whole, I am anxious about the development of AI techniques/products.
Q52. As a whole, I am afraid to use AI techniques/products.

Q53. I am willing to work hard to learn another professional skill.
Q54. Learning another professional skill is one of the most important aspects in my life.
Q55. I am determined to push myself to learn another professional skill.
Q56. I can honestly say that I am really doing my best to learn another professional skill.
Q57. It is very important for me to learn another professional skill.