Journal of Psychological Perspective. 2025; 7(2): 151-160
ISSN 2502-4825 (print), ISSN 2502-9495 (online)
DOI: 10.47679/jopp.7210452025

RESEARCH ARTICLE

Ensuring Reliability: Adaptation and Validation of the AI Anxiety Scale (AIAS) in Indonesia

Shifa Ramadini[1], Ratri Pratiwi[2*)]

Published online: 9 June 2025

Abstract

This study aims to adapt Wang and Wang's Artificial Intelligence Anxiety Scale (2019) into the context of Indonesian culture and language. The research involved 222 respondents, consisting of 89 males and 133 females, aged between 15 and over 35 years old. The adaptation process followed six stages: (1) initial translations by translators with different backgrounds, (2) synthesis of the translations into a single version, (3) back-translation by native speakers of the source language, (4) content validation by an expert committee, (5) testing the pre-final version on relevant subjects, and (6) submission of documentation for evaluation. Reliability testing was conducted using Cronbach's alpha, while logical validity was assessed with Aiken's V and construct validity using confirmatory factor analysis (CFA). The results indicated that the adapted scale had high reliability, with a Cronbach's alpha value of 0.916, and adequate validity, with an Aiken's V value greater than 0.50. The confirmatory factor analysis demonstrated a good model fit, with an RMSEA value of 0.066, CFI of 0.938, and TLI of 0.927. The Indonesian version of the Artificial Intelligence Anxiety Scale is deemed valid and reliable, making it suitable for use in Indonesia

Keywords: AI anxiety, adaptation scale, job replacement, technology anxiety, confirmatory factor analysis

INTRODUCTION

In an era of rapid digital transformation, artificial intelligence (AI) has significantly changed the landscape of work. AI is the ability of a computer or robot to perform tasks normally associated with intelligent beings, as defined by Copeland (Encyclopedia Britannica, 1998). As technology develops, AI covers a wide range of tasks and applications and is used by companies to improve efficiency and performance (Kuzey, Uyar, & Delen, 2014; PwC, 2019).

Huang and Rust's (2018) research shows that artificial intelligence (AI) can replace human tasks by replicating various levels of intelligence. The application of AI spans various sectors, such as tourism (Ravi & Ravi, 2015; Davahli et al., 2020; Ivanov et al., 2019), finance (Robertson, 2014), health (Gleichgerrcht et al., 2021), retail (Kumar et al., 2019), and law (Gupta et al., 2019). Governments are also applying AI to support intelligent transportation systems (Singh et al., 2020), smart cities (Mishra & Chakraborty, 2020), aerospace design (Visintin et al., 2014), and 6G-based quantum communication infrastructure (Manzalini, 2020). Fernandez (2018) found that AI can assist with the analytical task of selecting qualified employees, a process usually performed by the human resources department.

However, there are economic risks, especially job losses due to automation, creating uncertainty and deep economic inequality (Frey & Osborne, 2017; Acemoglu & Restrepo, 2017). It also raises ethical and social issues, such as human rights violations and discriminatory bias (Gillespie, Lockey, & Curtis, 2021; Organisation for Economic Co-operation and Development, 2019). Research by Kim et al. (2023) suggests that AI may replace jobs, triggering anxiety about the future of work. This was highlighted by a language teacher in Turkey who expressed concern about her job being replaced by AI (Eyüp & Kayhan, 2023). According to the American Psychological Association (2023), four in ten workers (38%) are concerned about their jobs being replaced by artificial intelligence. Furthermore, workers who express concern about artificial intelligence tend to report poor mental health (American Psychological Association, 2023).

Advances in AI technology raise major concerns regarding job replacement by machines (Graham et al., 2019). Data from Cox (2023) shows that many workers are worried about the impact of AI on their jobs. While these concerns are legitimate, experts suggest that the focus

[1,2] Faculty of Psychology, University of Mercu Buana Yogyakarta

*) corresponding author

Ratri Pratiwi
Faculty of Psychology, University of Mercu Buana Yogyakarta

Email: ratri.pratiwi@mercubuana-yogya.ac.id

Submitted: 10 January 2025 Revised: 09 April 2025 Accepted: 16 May 2025

should not be on fear, but rather on investing in training and education to work alongside technology (Cox, 2023; PwC, 2019).

According to Johnson and Verdicchio (2017), artificial intelligence anxiety is a social phenomenon that reflects the fear of job replacement by technology. Graham et al. (2019) stated that this concern is not only economic but also impacts mental well-being. Nam (2019) added that the perception of robotic automation creates complexity in people's attitudes towards technology. Lemay, Basnet, and Doleck (2020) observed that although artificial intelligence brings progress, feelings of anxiety about the future of work pose psychological challenges.

Artificial intelligence anxiety includes various dimensions that influence individuals in dealing with technological developments. Wang and Wang (2019) identified the main dimensions as learning, job replacement, sociotechnical blindness, and artificial intelligence configuration. Learning reflects individuals' anxiety about their ability to understand complex AI technologies. Job replacement includes the fear of being replaced by AI. Sociotechnical blindness describes the lack of social and ethical understanding related to AI. Artificial intelligence configuration includes concerns about regulating and supervising AI. Each of these dimensions contributes to different levels of anxiety, depending on the characteristics of the individual and their situation.

The development of automation and artificial intelligence (AI) technology has sparked mixed views on its impact on the workforce. According to the Pew Research Center (2019), only 22% of adults in the United States feel that these advancements benefit workers, while 48% think otherwise. Differences exist based on age, with 55% of people aged 50 and above perceiving a negative impact. The majority of respondents believe that in the next 30 years, robots and computers will take over many human jobs, and most consider these changes detrimental to the country. Additionally, research by McKinsey & Company (2019) estimates that automation could replace up to 23 million jobs in Indonesia by 2030. These findings suggest that while technology offers efficiency, concerns over its negative impact remain significant.

This research focuses on workers' anxieties regarding the potential replacement of jobs by artificial intelligence technology. In Indonesia, the utilization of artificial intelligence has expanded to sectors such as education, healthcare, manufacturing, services, and products (Chaudhuri, Krishnan, & Poorani, 2022; Tuomi, 2018). The government is also adopting artificial intelligence to improve the effectiveness and productivity of government agencies, accelerate decision-making, and create greater efficiency and innovative public services (Direktorat Jenderal Kekayaan Negara, Kementerian Keuangan RI, 2023).

Key challenges include labor reduction and high investment in technology (Fallis, Nasution, in Ririh, Laili, Wicaksono, & Tsurayya, 2020). Recent research suggests that the psychological impact of job replacement by AI is more complex than expected (Kim et al., 2023; Makmur & Alijoyo, 2023). AI anxiety can reduce job satisfaction, create instability in the work environment, and damage social relationships in the workplace (Rhee & Jin, 2021).

Based on the previous explanation, research on the adaptation of artificial intelligence anxiety scales is very important in the field of psychology, especially industrial and organizational psychology, given the increasing anxiety among workers related to job replacement by AI technology. The adaptation of this scale is crucial because it provides a valid and reliable tool to measure the level of anxiety experienced by workers, enabling more targeted interventions. Industrial and organizational psychology theories, such as job stress theory and motivation theory, are relevant in this context. Job stress theory explains that uncertainty and concern about job loss due to AI can cause significant stress, affect workers' mental well-being, and reduce job satisfaction and commitment (Lazarus & Folkman, 1984). Meanwhile, motivation theories, such as expectancy theory, suggest that workers' beliefs about their ability to adapt to new technologies affect their motivation to learn and develop (Vroom, 1964).

This research focuses on the adaptation of the Artificial Intelligence Anxiety Scale (AIAS) developed by Wang and Wang (2019) in Taiwan and later adapted by Terzi (2020) in Turkey. The AIAS consists of 21 items covering dimensions of AI anxiety, such as learning, job replacement, socio-technical blindness, and AI configuration. The choice to adapt the AIAS for Indonesia is motivated by the growing interest in understanding the impact of AI on workers in Indonesia, particularly in light of the increasing integration of AI into various sectors. While much of the existing data on AI anxiety pertains to Western populations, such as those in the United States, there is a lack of research specifically addressing AI-related anxieties within the Indonesian workforce. This research aims to fill this gap by producing a valid and reliable measurement tool that captures AI anxiety within the cultural and linguistic context of Indonesia. In doing so, it will contribute to a better understanding of how Indonesian workers perceive AI and how these perceptions may affect their engagement with AI technologies in the workplace.

MATERIALS AND METHODS

Research Instrument

The instrument used in this study is the Artificial Intelligence Anxiety Scale (AIAS) developed by Wang and Wang (2019), consisting of 21 items, as shown in the Appendix. AIAS comprises four dimensions: learning, which reflects individuals' anxiety about their ability to understand and use AI applications at work; job replacement, which measures concerns about job loss due to AI automation that can replace human roles; sociotechnical blindness, which reflects anxiety related to a lack of understanding that AI functions through collaboration between technology, human interaction, and social institutions; and AI configuration, which pertains to concerns about AI having a human-like appearance, evoking a fear of uncanny technology due to its visual resemblance to humans. The scale uses a seven-point Likert scale with response options ranging from "1 = Strongly Disagree" to "7 = Strongly Agree," allowing respondents to indicate their level of agreement with each item.

Research Subjects

This study involved 222 respondents with specific characteristics, including individuals of male or female gender; ages ranging from 15 to 61 years (late adolescence to late adulthood); educational backgrounds of Junior High School, Senior High School, bachelor's degree, master's degree. Doctorate or higher; fields of work such as manufacturing, services, science and technology, education/research, medicine, and students; as well as experiences such as using or developing AI products or interacting with humanoid AI products (AI-based robots resembling humans).

Table 1. Subject Demographic Data (N=222)

	Number	Percentage
Gender		
Male	89	40,9%
Female	133	59,91%
Age		
15-18 years	25	11,26%
19-22 years	81	36,49%
23-26 years	95	42,79%
27-30 years	19	8,56%
31-34 years	1	0,45%
35> years	1	0,45%
Last Education		
JHS/Equivalent	3	1,35%
SHS/Equivalent	83	37,39%
Associate's degree/Bachelor's Degree	115	51,80%
Master's Degree	18	8,11%
Doctorate Degree	3	1,35%
Field of Work/Activity		
Services	64	28,83%
Student/College Student	91	41,0%
Manufacturing	3	1,35%
Medical	2	0,9%
Education/Research	13	5,86%
Science and Technology	43	19,37%
Art	4	1,80%
Retail	2	0,9%
Work Content/Material that Can Be Replaced by AI		
Yes	112	50,45%
No	110	49,55%
Ever Used AI Products		
Yes	175	78,83%
No	47	21,17%
Ever Developed AI Products		
Yes	50	22,52%
No	172	77,48%
Ever Interacted with Humanoid AI Products		
Yes	15	6,76%
No	207	93,24%

Research Procedures

The adaptation process of the measurement instrument followed the six systematic stages proposed by Beaton, Bombardier, Guillemin, and Ferraz (2000). The first stage involved translation by two experts: one with content expertise and the other a psychological scientist. The second stage, synthesis, entailed reviewing both translations to identify similarities and discrepancies, leading to a consensus version. In the back-translation stage, the synthesized version was translated back into the original language (English) by a native speaker unfamiliar with the questionnaire's concepts. Subsequently, content validity was assessed by an expert committee consisting of eight professionals with a master's degree in psychology or professional psychology. The evaluation results were analyzed using Aiken's V technique (Azwar, 2018), which yielded coefficients ranging from 0.81 to 0.97. Based on Aiken (1985), a coefficient of ≥0.71 is acceptable for eight raters at a significance level of p 0.05. These results indicate that all items on the Artificial Intelligence Anxiety adaptation scale were valid. Azwar (2018) further asserts that an Aiken's V greater than 0.50 reflects a high coefficient. Following expert feedback, adjustments were made to the structure and wording of several items, resulting in a pre-final version.

To assess clarity and comprehensibility, a pre-final version test was conducted with participants who met the criteria of the instrument. Qualitative evaluation involving six participants indicated that the items were generally well understood. Minor revisions were made to wording based on participant feedback without altering item meanings. Finally, all documentation and outcomes were submitted to the instrument's original adapters for further evaluation.

Psychometric evaluation involved reliability testing using Cronbach's Alpha to assess internal consistency. According to Azwar (2020), a Cronbach's Alpha above 0.70 indicates satisfactory reliability. Construct validity was tested using Confirmatory Factor Analysis (CFA) to assess model fit with empirical data. Model evaluation employed several fit indices. RMSEA values below 0.05 indicate a very good fit, and values between 0.05 and 0.08 are considered acceptable (Browne & Cudeck, 1993). CFI values above 0.90 indicate good fit, with values exceeding 0.95 considered excellent (Bentler, 1990). TLI values should exceed 0.90 (Tucker & Lewis, 1973), SRMR should be less than 0.08 (Hu & Bentler, 1999), and a X^2/df ratio below 3 indicates a good fit (Wheaton et al., 1977). Additionally, a p-value greater than 0.05 suggests no significant discrepancy between the model and the observed data (Bollen, 1989). All reliability and CFA analyses were conducted using Jamovi version 2.4.8.

RESULTS OF STUDY

CFA Reliability and Validity Test

As shown in Table 2, the AI-related anxiety scale demonstrated a high level of reliability (Cronbach's α = 0.916), indicating excellent internal consistency in measuring AI-related anxiety. The item-total correlation coefficients, ranging from 0.294 to 0.700, suggest good variability in item contributions to the overall scale, although item S15 in the sociotechnical blindness dimension has a slightly lower correlation coefficient, falling just below 0.30. The reliability coefficients for each dimension are also presented in Table 2. The dimensions of the AI-related anxiety scale exhibited adequate to good reliability: learning (α = 0.894), job replacement (α = 0.874), AI configuration (α = 0.856), and sociotechnical blindness (α = 0.761).

The results of the CFA analysis produced an initial model (before adjustment), as listed in Table 3. Based on the results, several indicators of model fit were not met, namely RMSEA of 0.090, CFI of 0.880, TLI of 0.862, SRMR of 0.063, and X^2/df of 2.825 ($p < 0.001$). As listed in Table 4, some factor loadings were also low, with values below 0.5, indicating indicators that did not strongly measure the hypothesized latent constructs.

To improve the model fit, the researcher identified pairs of items with high modification indices to correct the correlation error terms. The error term correlations added were between items J9 and J10, L6 and L7, J11 and J12, and L1 and C20, as these pairs had high modification indices. Modification indices are used in Confirmatory Factor Analysis (CFA) to identify potential areas where the model might not fully represent the relationships between observed variables. High modification indices suggest that adding correlations between error terms could improve the model′s fit. This adjustment is based on statistical evidence derived from the existing data and does not involve collecting new data. This is a common procedure in CFA to improve model fit without altering the underlying theoretical structure (Brown, 2015).

Table 2. Scale Reliability Test

Scale	Scale Reliability Statistics
	Cronbach's α 0.916
Learning	0.894
Job Replacement	0.874
Sociotechnical Blindness	0.761
AI Configuration	0.856

Table 3. Model Fit Before & After Modification

Model Fit	Before		After	
	Result	Note	Result	Note
RMSEA	0,090	Not fit	0,066	Fit
CFI	0,880	Not fit	0,938	Fit
TLI	0,862	Not fit	0,927	Fit
SRMR	0,063	Fit	0,057	Fit
$X^2//df$	2,825	Fit	1,966	Fit
p	<,001	Not fit	<,001	Not fit

Description of expert requirements for model fit:

1. RMSEA < 0.05: very good; 0.05–0.08: good (Browne & Cudeck).
2. CFI > 0.90: good; > 0.95: better (Bentler, 1990).
3. TLI > 0.90 (Tucker & Lewis, 1973).
4. SRMR < 0.08 (Hu & Bentler, 1999).
5. $X^2/df < 3$ (Wheaton et al., 1977).
6. p > 0.05 (Bollen, 1989).

After the adjustments were made, the fit indices in Table 3 showed significant improvement. RMSEA decreased to 0.066, CFI increased to 0.938, TLI increased to 0.927, SRMR decreased to 0.057, and X^2/df improved to 1.966 ($p < 0.001$). According to the recommendations of several researchers, such as Wheaton et al. (1977), an X^2/df below 3 indicates a good fit. In addition, Bentler (1990) and Hu & Bentler (1999) recommend a CFI above 0.90 as an indication of good fit, with higher values above 0.95 indicating an excellent fit. Tucker & Lewis (1973) and Hu & Bentler (1999) suggest a TLI above 0.90 as a sign of good fit, and Hu & Bentler (1999) recommend an SRMR below 0.08 for good fit. In terms of RMSEA, Steiger (1990) and Browne & Cudeck (1993) suggest values below 0.05 for an excellent fit and between 0.05 and 0.08 for a good fit.

Based on Table 3, adjusting the model by adding the correlation between the error terms successfully improved the significance of the model fit. Although the Chi-square test showed a p-value < 0.001, other fit indices confirmed that the adjusted model had a good fit with the data. This indicates that the adjustments made successfully improved the accuracy and validity of the hypothesized latent construct measurements.

Correlating error terms in CFA is typically performed to account for residual variances that are shared between measurement items, which might be due to conceptual overlap, similar content, or wording. This does not imply that the items themselves are erroneous but rather that they share unmodeled variance not captured by the initial model. Such modifications are based on modification indices, which are indicators that suggest how to improve the model fit. These adjustments are made to better represent the underlying construct and enhance the overall model accuracy (Brown, 2015).

Table 4. Factor Loadings before and after Adjustment

Factor	Indicator	Std Est	
		Before	**After**
Learning	L1	0.809	0.820
	L2	0.918	0.919
	L3	0.894	0.893
	L4	0.800	0.803
	L5	0.748	0.746
	L6	0.548	0.528
	L7	0.665	0.652
	L8	0.413	0.422
Job Replacement	J9	0.628	0.613
	J10	0.599	0.587
	J11	0.821	0.761
	J12	0.869	0.829
	J13	0.697	0.694
	J14	0.782	0.807
Sociotechnical Blindness	S15	0.454	0.456
	S16	0.713	0.712
	S17	0.763	0.765
	S18	0.765	0.764
AI Configuration	C19	0.783	0.781
	C20	0.826	0.827
	C21	0.840	0.840

According to the information in Table 4, the CFA analysis also showed factor loading values ranging from 0.422 to 0.919 with statistical significance ($p < 0.001$), confirming that all loading values were significantly connected to the measured latent factors. Most of the items showed factor loading values above 0.50, indicating moderate to strong correlations with the latent factors, which strengthens the overall construct validity (Hair et al., 2019). There were two items with lower factor loadings, namely items L8 (0.422) and S15 (0.456), which fell within the range of 0.40 to 0.50. Although these values are considered marginal, they were retained as they covered important aspects of the construct that were not addressed by the other items.

As for the covariance results between factors in this analysis, Table 5 shows significant relationships across all factor pairs, with p-values < 0.001 for all covariances involved. This indicates that all the factors are significantly related to each other. The strength of these relationships can be categorized as weak (below 0.30), moderate (0.30–0.50), and strong (above 0.50), based on the guidelines by Hair et al. (2019).

Looking specifically at the covariance values: The covariance between the learning factor and job replacement is 0.441, which is in the moderate range, indicating a moderate relationship between perceptions of learning and job replacement. Similarly, the covariance between learning and sociotechnical blindness is 0.500, suggesting a moderate to strong relationship, and the covariance between learning and AI configuration is 0.480, also indicating a moderate correlation.

Table 5. Factor Covariances

		Est	Std Est
Learning	L	1.000[a]	
	JR	0.441	0.441
	SB	0.500	0.500
	AI Conf	0.480	0.480
Job Replacement	JR	1.000[a]	
	SB	0.832	0.832
	AI Conf	0.508	0.508
Sociotechnical Blindness	SB	1.000[a]	
	AI Conf	0.633	0.633
AI Configuration	AI Conf	1.000[a]	

In contrast, the covariance between job replacement and sociotechnical blindness is 0.832, which falls into the strong category, signifying a very strong relationship between the perception of job replacement and sociotechnical blindness. Additionally, the covariance between job replacement and AI configuration is 0.508, showing a strong relationship, while the covariance between sociotechnical blindness and AI configuration is 0.633, also a strong correlation. These varying levels of correlation do not imply that the relationships between dimensions are poor, but rather suggest that some dimensions (e.g., job replacement and sociotechnical blindness) are more closely related than others, reflecting their specific conceptual linkages.

Based on Figure 1, it can be explained that Factor 1 (learning) is a latent construct measured by items L1, L2, L3, L4, L5, L6, L7, and L8. The unidirectional arrows from Factor 1 (learning) to items L1, L2, L3, L4, L5, L6, L7, and L8 represent factor loadings. Factor 2 (job replacement) is a latent construct measured by items J9, J10, J11, J12, and J14. The unidirectional arrows from Factor 2 (job replacement) to items J9, J10, J11, J12, and J14 represent factor loadings. Factor 3 (sociotechnical blindness) is a latent construct measured by items S15, S16, S17, and S18. The unidirectional arrows from Factor 3 (sociotechnical blindness) to items S15, S16, S17, and S18 represent factor loadings. Factor 4 (AI configuration) is a latent construct measured by items C19, C20, and C21. The unidirectional arrows from Factor 4 (AI configuration) to items C19, C20, and C21 represent factor loadings.

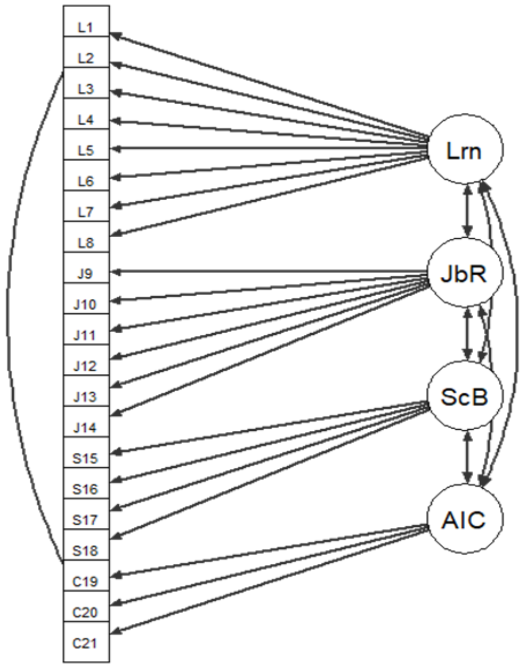

Figure 1. AIAS Model Diagram

Notes:
1. Circles represent latent variables/factors.
2. Squares represent observation variables.
3. One-way arrow lines connect latent variables to observation variables, indicating factor loadings.
4. Two-way arrow lines between two latent variables show covariance or correlation between factors.

The bidirectional arrows between: Factor 1 (learning) and Factor 2 (job replacement), Factor 2 (job replacement) and Factor 3 (sociotechnical blindness), Factor 3 (sociotechnical blindness) and Factor 4 (AI configuration), Factor 1 (learning) and Factor 3 (sociotechnical blindness), and Factor 2 (job replacement) and Factor 4 (AI configuration), indicate covariance or relationships between the factors.

Moreover, the adaptation of the Artificial Intelligence Anxiety Scale (AIAS) in this study showed strong reliability, with a Cronbach's alpha value of 0.916, slightly lower than the results reported by Wang & Wang (2019) and Terzi (2020). In addition to reliability, this scale is also considered effective for use in various cultural contexts, not only in Indonesia. Adequate content validity and CFA test results showing model fit demonstrate the flexibility of this scale in measuring AI anxiety in different populations. The scale is also relevant for application in cross-cultural research without requiring significant modifications, making it a measurement tool with the potential for use in various countries.

In addition, this scale can be related to various other variables that contribute to the main variable itself, including learning, AI configuration, job replacement, and sociotechnical blindness (Johnson & Verdicchio, 2017). In future research, this scale can also be used to study the influence of AI anxiety based on factors such as gender, job sector, age, and geographical location, thus providing a more comprehensive understanding of the factors that influence AI anxiety.

However, this study has some weaknesses that need to be considered. The generalization of the results is limited as the sample did not cover a wider population across different parts of Indonesia. In addition, data collected through respondents' self-assessments is prone to subjective bias. For future research, it is recommended to use a more representative sample and conduct further development to explore potential cultural biases that may not have been fully addressed in this study.

DISCUSSION

In this study, the researcher successfully adapted the Artificial Intelligence Anxiety Scale, developed by Wang & Wang (2019), into the Indonesian cultural and linguistic context. This adaptation process involved a careful series of steps, including evaluating the construct validity, translation, and testing the psychometric characteristics of the adapted scale. The results of this study show that the adapted scale has a high level of reliability, with a Cronbach's alpha value of 0.916, which is well above the threshold set by Azwar (2020) at 0.70. This value indicates excellent internal consistency of the adapted scale in measuring anxiety related to artificial intelligence in Indonesia.

Specifically, the reliability of the dimensions of learning, job replacement, and AI configuration in the adapted scale showed adequate Cronbach's alpha values of 0.894, 0.874, and 0.856, respectively. Although the sociotechnical blindness dimension had a slightly lower Cronbach's alpha value of 0.761, this value is still acceptable for research purposes, given the theoretical relevance of the construct being measured. Compared to the original scale developed by Wang & Wang (2019), which showed a high reliability coefficient with a Cronbach's alpha of 0.986 for the entire scale, this adaptation did show a slight decrease in reliability. However, the obtained Cronbach's alpha value still falls within the very good and reliable category, reflecting strong internal consistency. In comparison, the AIAS adaptation by Terzi (2020) in Turkey also demonstrated strong reliability results with a Cronbach's alpha of 0.96 for the entire scale, indicating that this measure remains consistent across various cultural contexts.

The differences in reliability values may be influenced by cultural factors and the context in which the scale is adapted. The AIAS adaptation in Indonesia shows good alignment with the local context, although not as high as the reliability reported by Terzi (2020) in Turkey or by Wang & Wang (2019) in Taiwan. Cultural factors, such as differences in perception and responses to technological anxiety, may affect this reliability value. The adaptation of the scale from Taiwan to Indonesia is considered more appropriate compared to an adaptation from Turkey, given the regional proximity and cultural similarities between Indonesia and Taiwan, which can minimize significant changes in the social context affecting the validity of the scale. Therefore, despite the slight decrease in reliability, this adaptation remains effective in measuring anxiety related to artificial intelligence in Indonesia.

Content validity was also tested using the Aiken V coefficient, and the results showed that all items in the adapted scale were considered valid. Aiken V values higher than 0.50 indicate good content validity, in line with the guidelines provided by Aiken (1985). Confirmatory Factor Analysis (CFA) was also conducted to test the model fit and construct validity. In the initial model, some fit indices indicated that the model did not fit the data well. However, after adjustments were made by adding correlations between error terms for some items, the fit indices showed significant improvement. RMSEA decreased to 0.066, CFI increased to 0.938, and TLI rose to 0.927, indicating that the adjusted model has a good fit with the data.

The factor loadings for the 21 items ranged from 0.422 to 0.919, with most items showing values above 0.50, indicating moderate to strong correlations with the latent factors. Although two items, L8 and S15, had lower factor loadings, these items were retained for theoretical reasons. This suggests that although the contribution of these items to construct validity is weaker, they remain important in covering aspects of the construct not addressed by other items. The covariances between factors showed significant relationships, with p-values less than 0.001 for all factor pairs, and covariance values ranging from moderate to strong. This indicates that perceptions of learning, job replacement, sociotechnical blindness, and AI configuration are closely related in the context of AI use and its impact.

Overall, the results of this study indicate that the adapted artificial intelligence anxiety scale has strong reliability and validity, making it effective for measuring anxiety related to artificial intelligence in Indonesia. These findings address the research question by demonstrating that the adaptation process can effectively influence the understanding and measurement of anxiety towards the use of artificial intelligence in Indonesia. The theoretical implications of this study enrich the theoretical understanding of individual responses to the development of artificial intelligence technology in the Indonesian cultural context. Practically, the findings provide a valid and reliable tool that can be used by researchers and practitioners in Indonesia to measure and manage the psychological and social impacts of artificial intelligence technology development in the country.

CONCLUSIONS AND RECOMMENDATIONS

The findings of this study indicate that the adaptation of the Artificial Intelligence Anxiety Scale to the Indonesian cultural and linguistic context was conducted successfully. The scale has proven to be consistent and valid in measuring anxiety towards artificial intelligence technology in Indonesia. Despite some variations in the reliability of certain dimensions, the overall scale provides an effective measurement tool to analyze the psychological and social impact of artificial intelligence in the local context.

DECLARATION

Ethics approval (Not applicable)
Consent for publication (Not applicable)
Availability of Data and Material (ADM) (Not applicable)
Competing interests/Conflict of interest (No conflict of interest)
Funding (Not applicable)
Authors' contributions (Not applicable)

About the Authors

Shifa Ramadini has completed an undergraduate degree in psychology.
Ratri Pratiwi is a lecturer at the Faculty of Psychology at Mercu Buana University Yogyakarta. Her teaching duties include psychometry and the construction of psychological measuring instruments. Her research interests include the field of psychological measurement and cyber psychology.

REFERENCES

Acemoglu, D. & Restrepo, P. (2017). Robots and jobs: Evidence from US labor markets. *Voxeu*. Accessed on November 4, 2023 from https://voxeu.org/article/robots-and-jobs-evidence-us.

Aiken, L. R. (1985). Three coefficients for analyzing the reliability and validity of ratings. *Educational and Psychological Measurement*, 45(1), 131–142. https://doi.org/10.1177/0013164485451012.

American Psychological Association. (2023, September 7). *Worried about AI in the workplace? You' re not alone*. https://www.apa.org/topics/healthy-workplaces/artificial-intelligence-workplace-worry

Azwar, S. (2018). *Penyusunan skala psikologi*. Yogyakarta, Indonesia: Pustaka Pelajar.

Azwar, S. (2020). *Dasar-dasar psikometrika*. Yogyakarta, Indonesia: Pustaka Pelajar.

Beaton, D. E., Bombardier, C., Guillemin, F., & Ferraz, M. B. (2000). Guidelines for the process of cross-cultural adaptation of self-report measures. *Spine*, *25*(24), 3186-3191. https://doi.org/10.1097/00007632-200012150-00014.

Bentler P. M. (1990). Comparative fit indexes in structural models. *Psychological bulletin*, 107(2), 238–246. https://doi.org/10.1037/0033-2909.107.2.238

Bollen, K.A. (1989). *Structural equations with latent variables*. John Wiley and Sons, Inc., New York. https://doi.org/10.1002/9781118619179

Brooks, A. (2019). The benefits of AI: 6 societal advantages of automation. Rasmussen University. Accessed on November 4, 2023 from https://www.rasmussen.edu/degrees/technology/blog/benefits-of-ai/.

Brown, T. A. (2015). *Confirmatory Factor Analysis for Applied Research* (2nd ed.). Guilford Press.

Browne, M. W., & Cudeck, R. (1993). *Alternative ways of assessing model fit*. In K. A. Bollen, & J. S. Long (Eds.), Testing Structural Equation Models (Vol. 154, pp. 136-162). Newbury Park, CA: Sage Focus Editions.

Chaudhuri, S., Krishnan, L. R. K., & Poorani, S. (2022). Impact of using ai in manufacturing industries. *Journal of the International Academy for Case Studies*, 28(S4), 1-10.

Copeland, B. J. (1998). Artificial intelligence (AI) | Definition, examples, types, applications, companies, & facts. Encyclopedia Britannica. Accessed on November 4, 2023 from https://www.britannica.com/technology/artificial-intelligence.

Cox, J. (2023, 30 April). Perkembangan AI: Para pekerja yang takut kehilangan pekerjaan karena kecerdasan buatan. *BBC News Indonesia*. Accessed from https://www.bbc.com/indonesia/articles/c51ley190njo.

Davahli, M. R., Karwowski, W., Sonmez, S., & Apostolopoulos, Y. (2020). The hospitality industry in the face of the COVID-19 pandemic: Current topics and research methods. *International Journal of Environmental Research and Public Health,* 17(20), 7366. https://doi.org/10.3390/ijerph17207366.

Direktorat Jenderal Kekayaan Negara, Kementerian Keuangan RI. (2023). Pemanfaatan kecerdasan buatan dalam lembaga pemerintah: meningkatkan efisiensi dan pelayanan publik yang lebih baik.. Accessed on November 4, 2023 from https://www.djkn.kemenkeu.go.id/kpknl-manado/baca-artikel/16383/Pemanfaatan-Kecerdasan-Buatan-dalam-Lembaga-Pemerintah-Meningkatkan-Efisiensi-dan-Pelayanan-Publik-Yang-Lebih-Baik.html.

Eyüp, B., & Kayhan, S. (2023). Pre-service Turkish language teachers' anxiety and attitudes toward artificial intelligence. *International Journal of Education and Literacy Studies*, *11*(4), 43-56. https://doi.org/10.7575/aiac.ijels.v.11n.4p.43.

Fernandez, J. (2018). The ball of wax we call HR analytics. *Strategic HR Review,* https://doi.org/10.1108/SHR-09-2018-0077.

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019.

Gillespie, N., Lockey, S., & Curtis, C. (2021). Trust in artificial intelligence: A five country study. The University of Queensland and KPMG Australia. https://doi.org/10.14264/e34bfA3

Gleichgerrcht, E., Munsell, B. C., Alhusaini, S., Alvim, M. K. M., Bargalló, N., Bender, B., … ENIGMA-Epilepsy Working Group. (2021). Artificial intelligence for classification of temporal lobe epilepsy with ROI-level MRI data: A worldwide ENIGMA-Epilepsy study. *NeuroImage. Clinical*, 31, 102765. https://doi.org/10.1016/j.nicl.2021.102765.

Gupta, R., Tanwar, S., Tyagi, S., & Kumar, N. (2019). Tactile internet and its applications in 5G era: A comprehensive review. *International Journal of Communication Systems,* 32(14), e3981. https://doi.org/10.1002/dac.3981

Graham, S., Depp, C., Lee, E. E., Nebeker, C., Tu, X., Kim, H., & Jeste, D. V. (2019). Artificial intelligence for mental health and mental illnesses: An overview. *Current Psychiatry Reports*, 21(11). https://doi.org/10.1007/s11920-019-1094-0

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis (8th ed.).* Cengage Learning.

Huang, M. H., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of Service Research*, 21(2), 155-172.

Hu, L.T. and Bentler, P.M. (1999) Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, 6, 1-55. http://dx.doi.org/10.1080/10705519909540118

Ivanov, S., Gretzel, U., Berezina, K., Sigala, M., & Webster, C. (2019). Progress on robotics in hospitality and tourism:

A review of the literature. *Journal of Hospitality and Tourism Technology*. https://doi.org/10.1108/JHTT-08-2018-0087.

Johnson, D. G., & Verdicchio, M. (2017). AI anxiety. *Journal of the Association for Information Science and Technology*, 68(9), 2267-2270. https://doi.org/10.1002/asi.23867.

Kim, J., Kadkol, S., Solomon, I., Yeh, H., Soh, J. Y., Nguyen, T. M., Choi, J. Y., Lee, S., Srivatsa, A. V., Nahass, G. R., & Ajilore, O. (2023). AI anxiety: A comprehensive analysis of psychological factors and interventions. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4573394.

Kumar, V., Rajan, B., Venkatesan, R., & Lecinski, J. (2019). Understanding the role of artificial intelligence in personalized engagement marketing. *California Management Review*, 61(4), 135-155, https://doi.org/10.1177/0008125619859317.

Kuzey, C., Uyar, A., & Delen, D. (2014). The impact of multinationality on firm value: A comparative analysis of machine learning techniques. *Decision Support Systems*, 59, 127-142. https://doi.org/10.1016/j.dss.2013.11.001.

Lazarus, R., & Folkman, S. (1984). *Stress, Appraisal, and Coping*. New York: Springer.

Lemay, D. J., Basnet, R. B., & Doleck, T. (2020). Fearing the robot apocalypse: Correlates of AI anxiety. *International Journal of Learning Analytics and Artificial Intelligence for Education* (iJAI), 2(2), 24. https://doi.org/10.3991/ijai.v2i2.16759

Makmur, M. F., & Alijoyo, F. A. (2023). Dampak kecerdasan buatan terhadap creator, brand, dan agensi. *SEIKO: Journal of Management & Business*, 6(2), 128-140. ISSN: 2598-831X.

Manzalini, A. (2020). Quantum communications in future networks and services. *Quantum Reports*, 2(1), 221-232. https://doi.org/10.3390/quantum2010014.

McKinsey & Company. (2019). Automation and the future of work in Indonesia. *McKinsey*. Accessed on November 4, 2023 from https://www.mckinsey.com/featured-insights/asia-pacific/automation-and-the-future-of-work-in-indonesia.

Mishra, K. N., & Chakraborty, C. (2020). A novel approach toward enhancing the quality of life in smart cities using clouds and IoT-based technologies. In Digital Twin Technologies and Smart Cities (pp. 19-35). *Springer, Cham*. https://doi.org/10.1007/978-3-030-18732-32.

Nam, T. (2019). Citizen attitudes about job replacement by robotic automation. *Futures*, 109, 39-49. https://doi.org/10.1016/j.futures.2019.04.005.

Organisation for Economic Co-operation and Development (2019). *Artificial intelligence in society*. OECD Publishing

Pew Research Center. (2019, December 31). 5. The future of work in the automated workplace. *Pew Research Center's Social & Demographic Trends Project*. Accessed on November 4, 2023 from https://www.pewresearch.org/social-trends/2019/03/21/the-future-of-work-in-the-automated-workplace/

Pwc. (2019). Sizing the prize: Exploiting the AI revolution, what's the real value of AI for your business and how can you capitalise? *PwC's Global Artificial Intelligence Study*. Accessed on November 4, 2023 from https://www.pwc.com/gx/en/issues/data-and-analytics/publications/artificial-intelligence-study.html.

Ravi, K., & Ravi, V. (2015). A survey on opinion mining and sentiment analysis: tasks, approaches and applications. *Knowledge-based systems*, 89, 14-46. https://doi.org/10.1016/j.knosys.2015.06.015.

Rhee, T., & Jin, X. (2021). The effect of job anxiety of replacement by artificial intelligence on organizational members' job satisfaction in the 4th industrial revolution era: The moderating effect of job uncertainty. *Journal of Digital Convergence*, 19(7), 1-9. https://doi.org/10.14400/JDC.2021.19.7.001.

Ririh, K. R., Laili, N., Wicaksono, A., & Tsurayya, S. (2020). Studi komparasi dan analisis SWOT pada implementasi kecerdasan buatan (*Artificial Intelligence*) di Indonesia. *J@ti Undip: Jurnal Teknik Industri*, 15(2), 122-133. https://doi.org/10.14710/jati.15.2.122-133.

Robertson, J. (2014). Human rights vs. robot rights: Forecasts from Japan. *Critical Asian Studies*, 46(4), 571-598. https://doi.org/10.1080/14672715.2014.960707.

Singh, S., Sharma, P. K., Yoon, B., Shojafar, M., Cho, G. H., & Ra, I. H. (2020). Convergence of blockchain and artificial intelligence in IoT network for the sustainable smart city. *Sustainable Cities and Society*, 63, 102364.

Steiger J. H. (1990). Structural model evaluation and modification: an interval estimation approach. *Multivariate behavioral research*, 25(2), 173–180. https://doi.org/10.1207/s15327906mbr2502_4

Terzi, R. (2020). An adaptation of artificial intelligence anxiety scale into Turkish: Reliability and validity study. *International Online Journal of Education and Teaching* (IOJET), 7(4). 1501-1515. http://iojet.org/index.php/IOJET/article/view/1031.

Tucker, L. R., & Lewis, C. (1973). A reliability coefficient for maximum likelihood factor analysis. *Psychometrika*, 38, 1-10. https://doi.org/10.1007/BF02291170

Tuomi, I. (2018). The Impact of artificial intelligence on learning, teaching, and education. *Policies for the future, Eds. Cabrera, M., Vuorikari, R & Punie, Y., EUR 29442 EN, Publications Office of the European Union, Luxembourg*, ISBN 978-92-79-97257-7, https://doi.org/10.2760/12297 JRC113226.

Visintin, F, Porcelli, I, & Ghini, A (2014). Applying discrete event simulation to the design of a service delivery system in the aerospace industry: a case study. *Journal of Intelligent Manufacturing, Springer*, https://doi.org/10.1007/s10845-013-0742-1.

Vroom, V. (1964). *Work and Motivation*. Wiley and Sons, New York.

Wang, Y., & Wang, Y. (2019). Development and validation of an artificial intelligence anxiety scale: An initial application in predicting motivated learning behavior. *Interactive Learning Environments*, 30(4), 619-634. https://doi.org/10.1080/10494820.2019.1674887.

Wheaton, B., Muthen, B., Alwin, D. F., & Summers, G. F. (1977). Assessing reliability and stability in panel models. *Sociological Methodology*, 8, 84-136. https://doi.org/10.2307/270754

ADDITIONAL INFORMATION

Correspondence All inquiries and requests for additional materials should be directed to the Corresponding Author.

Publisher's Note Utan Kayu Publishing maintains a neutral stance regarding territorial claims depicted in published maps and does not endorse or reject the institutional affiliations stated by the authors.

APPENDIX

Final Version of the Artificial Intelligence Anxiety Adaptation Scale (Wang and Wang, 2019)

Dimensions	Item Code	No	Item Description	
			Original Version	Adapted Version
Learning	L1	1	Learning to understand all of the special functions associated with an AI technique/product makes me anxious	Belajar memahami semua fungsi khusus terkait dengan teknik/produk kecerdasan buatan (AI) membuat saya cemas.
	L2	2	Learning to use AI techniques/products makes me anxious	Belajar menggunakan teknik/produk kecerdasan buatan (AI) membuat saya cemas.
	L3	3	Learning to use specific functions of an AI technique/product makes me anxious	Belajar menggunakan fungsi tertentu dari suatu teknik/produk kecerdasan buatan (AI) membuat saya cemas.
	L4	4	Learning how an AI technique/product works makes me anxious	Mempelajari cara kerja teknik/produk kecerdasan buatan (AI) membuat saya cemas.
	L5	5	Learning to interact with an AI technique/product makes me anxious	Belajar berinteraksi dengan teknik/produk kecerdasan buatan (AI) membuat saya cemas.
	L6	6	Taking a class about the development of AI techniques/products makes me anxious	Mengikuti kelas tentang pengembangan teknik/produk kecerdasan buatan (AI) membuat saya cemas.
	L7	7	Reading an AI technique/product manual makes me anxious	Membaca panduan penggunaan teknik/produk kecerdasan buatan (AI) membuat saya cemas.
	L8	8	Being unable to keep up with the advances associated with AI techniques/products makes me anxious	Ketidakmampuan mengikuti kemajuan teknik/produk kecerdasan buatan (AI) membuat saya cemas.
Job Replacement	J1	9	I am afraid that an AI technique/product may make us dependent	Saya khawatir teknik/produk kecerdasan buatan (AI) dapat membuat kita ketergantungan.
	J2	10	I am afraid that an AI technique/product may make us even lazier	Saya khawatir teknik/produk kecerdasan buatan (AI) dapat membuat kita semakin malas.
	J3	11	I am afraid that an AI technique/product may replace humans	Saya khawatir teknik/produk kecerdasan buatan (AI) dapat menggantikan manusia.
	J4	12	I am afraid that widespread use of humanoid robots will take jobs away from people	Saya khawatir meluasnya penggunaan robot berbasis artificial intelligence (AI) yang menyerupai manusia, akan mengambil alih pekerjaan manusia.
	J5	13	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	Saya khawatir jika saya mulai menggunakan teknik/produk kecerdasan buatan (AI), saya akan ketergantungan dan kehilangan sebagian kemampuan penalaran saya.
	J6	14	I am afraid that AI techniques/products will replace someone’s job	Saya khawatir teknik/produk kecerdasan buatan (AI) akan menggantikan pekerjaan seseorang.
Sociotechnical Blindness	S1	15	I am afraid that an AI technique/product may be misused	Saya khawatir teknik/produk kecerdasan buatan (AI) akan disalahgunakan.
	S2	16	I am afraid of various problems potentially associated with an AI technique/product	Saya khawatir dengan berbagai masalah yang mungkin muncul akibat teknik/produk kecerdasan buatan (AI).
	S3	17	I am afraid that an AI technique/product may get out of control and malfunction	Saya khawatir teknik/produk kecerdasan buatan (AI) menjadi tidak terkendali dan tidak berfungsi sebagaimana mestinya.
	S4	18	I am afraid that an AI technique/product may lead to robot autonomy.	Saya khawatir teknik/produk kecerdasan buatan (AI) dapat mengarah pada munculnya robot yang bekerja secara mandiri tanpa campur tangan manusia.
AI Configuration	C1	19	I find humanoid AI techniques/products (e.g. humanoid robots) scary.	Menurut saya, teknik/produk artificial intelligence (AI) berupa robot yang menyerupai manusia, menakutkan.
	C2	20	I find humanoid AI techniques/products (e.g. humanoid robots) intimidating.	Saya menganggap teknik/produk artificial intelligence (AI) berupa robot yang menyerupai manusia, mengintimidasi.
	C3	21	I don’t know why, but humanoid AI techniques/products (e.g. humanoid robots) scare me.	Saya tidak tahu mengapa, tetapi teknik/produk artificial intelligence (AI) berupa robot yang menyerupai manusia, membuat saya takut.