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Adaptation of Artificial Intelligence Attitude Scale (AIAS-4) into Turkish: a validity and reliability study

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Abstract

The integration of Artificial Intelligence (AI) into all areas of our lives has been creating substantial changes. There certainly is an ever-growing need to assess the way public attitudes towards AI have taken shape. This study aims to adapt the Artificial Intelligence Attitude Scale (AIAS-4) (Grassini, 2023) into Turkish, where there are no measures that can be used in different contexts and by different organizations to assess the overall attitude towards AI and test its validity and reliability. The scale adaptation was conducted in two phases. The study was carried out with the participation of 422 undergraduate students during the 2023–2024 academic year. To verify the construct validity of the scale, exploratory factor analysis was conducted with 221 undergraduate students. With another group of 201 undergraduate students, confirmatory factor analysis, test-retest reliability and measurement invariance tests were computed. As in the original scale, results from exploratory and confirmatory factor analyses justified the single-factor structure of the scale with four items explaining 63.03% of the total variance, and item loadings were in the range of 0.70–0.89. The model fit values were in a good fit range (CFI: 0.998, TLI: 0.993, RMSEA: 0.048). Also, the model was strictly invariant between genders. The scale demonstrated good internal consistency in two studies, with Cronbach's alpha of 0.86 and 0.86; and McDonald's omega of 0.87 and 0.86. The results indicated that all items had discriminative power and therefore, the Turkish version of the scale proves to be valid and reliable and thus could be used by researchers in the Turkish context.

Keywords Artificial intelligence · Attitudes · Scale adaptation

Introduction

Artificial intelligence (AI) is defined by the European Commission as "systems that display intelligent behavior by analyzing their environment and taking action– with some degree of autonomy– to achieve specific goals" (Boucher, 2020, p. III). AI has rapidly made its way into all areas of our lives, and AI applications are now used in various sectors including the automotive industry, healthcare, housing, education, chemistry, e-commerce, food science, transportation, logistics, gaming etc. (Bharadiya et al., 2023). Grasping public opinions and viewpoints on AI has become more crucial as AI technologies are rapidly integrated. in various aspects of society (Cao et al., 2021; Chen et al., 2023; Kelly et al., 2023). The impact that AI technologies make on fields such as healthcare, transportation, and employment has raised various concerns and has become a topic of debate, making it necessary to assess public attitudes to address potential challenges and explore opportunities for improvement (Balakrishnan & Dwivedi, 2024; Harari, 2017; Langer & Landers, 2021).

Public perceptions of AI to this day have been the subject of extensive research, with studies revealing a diverse range of attitudes towards this ever-advancing technology. Positive views often highlight the ability of AI to transform industries, boost productivity, and elevate living standards (Araujo et al., 2020; Balakrishnan & Dwivedi, 2024; Chen et al., 2023). Among the benefits are increasing productivity by automating processes, using customers' certain shopping patterns to better respond to their needs, enhancing

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customer service, expanding operational capability, and reducing expenditures in the hospitality sector (Limna, 2022); data mining in the health sector to make precise diagnoses, medical image processing, hospital operations, treatment of various diseases etc. (Bharadiya et al., 2023). On the other hand, negative perceptions often refer to concerns loss of jobs, the possible invasion of privacy as well as certain ethical implications (Langer & Landers, 2021; Wachter et al., 2021). A report by the European Network Against Racism (ENAR) indicates that companies have been actively using AI for various HR tasks, including candidate engagement, promotion, and disciplinary procedures since 2015. Concerns in this regard focus on AI, possibly exacerbating biases in recruitment and HR practices. Algorithms can perpetuate existing biases, leading to discrimination and reduced diversity in the workforce, which are key elements of a modern office environment (ENAR, 2020). One key factor influencing public attitudes towards AI is its impact on job displacement. Studies have shown that AI technologies have the potential to automate a number of job tasks, leading to concerns about job loss and unemployment (Brynjolfsson & McAfee, 2014; Mutascu, 2021; Nguyen & Vo, 2022). Similarly, in a recent study, Gándara et al. (2024) examined the accuracy and fairness of success predictions among college students belonging to different racial/ethnic groups and found that the predictive models are less accurate for Black and Hispanic students, often predicting failure for those who succeed and underestimating their success rates compared to White and Asian students.

Another aspect that shapes public attitudes towards AI is ethics. Ethical issues surrounding AI, such as bias in algorithms, decision-making transparency, and the potential for AI to be used unethically or maliciously can shape public perceptions (Coeckelbergh, 2019; Huang et al., 2023). Trust in AI technologies also plays a significant role in shaping public attitudes (Gao et al., 2020; Zhang & Dafoe, 2019). In a study by Vaccino-Salvadore (2023), the use of ChatGPT for language learning is discussed. It is indicated that while this technology offers interactive language learning experiences for people, it raises several ethical concerns such as data privacy and security, bias and lack of diversity, accessibility and reliability, authenticity, and academic dishonesty.

To effectively understand public attitudes towards AI, it is of significant importance to implement valid and reliable instruments for measurement. Numerous tools exist for measuring the acceptance of technology among individuals, such as those proposed by Davis (1989) and Parasuraman and Colby (2015). However, these tools often fail to take the distinct nature of AI into account (see Grassini, 2023 for review). The existing scales used to measure attitudes toward technology, such as the Media and Technology Usage and Attitudes Scale (MTUAS) developed by Rosen et al. (2013), do not exclusively address the interaction with modern AI systems like OpenAI's ChatGPT or AI-powered image generation services such as Dall-E. A few scales have been designed with the intention of measuring AI attitudes though, e.g. Schepman and Rodway (2020)'s 20-item General Attitudes Toward Artificial Intelligence Scale. The Attitude Toward Artificial Intelligence Scale (ATAI) introduced by Sindermann et al. (2021), on the other hand, is a 5-item instrument that specifically measures the acceptance and fear associated with AI. Despite these developments, challenges remain regarding their practicality in broader contexts. The comprehensive GAISS may be impractical due to its length, especially for widespread surveys or situations where time is a constraint. The ATAI, although more somewhat manageable, tends to focus on extreme opinions which may not accurately reflect the more nuanced views that people hold, including a mix of optimism, skepticism, and particular concerns (Grassini, 2023). With the swift advancement and integration of AI systems, public attitudes are likely evolving, which underscores the need for a more current, concise, and valid measure to assess these attitudes. Having established the necessity for a scale that effectively measures public attitudes towards AI in a nuanced and practical manner, Grassini (2023) developed AIAS-4 as a short, concise, reliable and valid scale that can help researchers from a variety of sectors understand public perception of AI.

Recognizing the imperative for an innovative and practical AI attitudes scale that accurately captures the complexities of contemporary perceptions, the AIAS-4, the next logical step would be to ensure that such a tool is not confined by language barriers.We sought a Turkish version of the assessment to ensure a culturally and linguistically nuanced understanding of attitudes toward AI. Given that AI has become a prominent topic among various groups in Türkiye, evaluating these attitudes will be an important focus for the Turkish community in the coming years. In Türkiye, AI has also attracted researchers' interest and has, therefore, led to several empirical and theoretical studies (e.g. Akdeniz & Özdinç, 2021; Gültekin & Şahin, 2024; İçen, 2022). However, to our knowledge there are only a few scale studies in the Turkish context which focus on either development or adaptation. In a recent one, Karaoglan-Yilmaz et al. (2023) developed an acceptance scale for generative AI, assessing students' acceptance of generative AI applications. Their research was conducted in a sample of 627 university students who used generative AI tools. The instrument involved four factors: performance expectations, effort expectations, financial status, and social impact, with 20 items in total. In another study, Ferikoğlu and Akgün (2022) measured the AI awareness of teachers using 51 items representing four dimensions: practical knowledge, belief-attitude, ability to associate,

and theoretical knowledge. Kaya et al. (2024) conducted an adaptation study on the General Attitudes Towards Artificial Intelligence Scale in Turkish, where items were divided into positive and negative attitudes towards AI. Akkaya et al. (2021) adapted the AI Anxiety Scale (originally developed by Wang & Wang, 2022), targeting undergraduate students, and Terzi (2020) narrowed it down to Turkish teachers in terms of adapting the AI Anxiety Scale.

AIAS-4 is one of the most concise scales developed, and it includes only four items that can help researchers assess overall attitude toward AI both validly and precisely. This is contrary to other scales used in Türkiye, which, while being comprehensive, often tend to be quite lengthy and complex as they often involve multiple factors and a greater number of items. The single-factor structure of the AIAS-4 combines to be unusually practical for large-scale surveys and diverse participant groups. Adapting AIAS-4 into Turkish would provide scientists and practitioners with a culturally sensitive, time-saving tool for scoring public attitudes towards AI, thus promoting large-scale data collection and evidence-based policy and educational measures. It is believed that this adaptation is crucial in fostering a nuanced understanding of AI perceptions in Türkiye, which the scale can help promote the responsible development and integration of AI applications within society.

The endeavor to adapt an AI attitude scale into Turkish is underpinned by several other scientific imperatives. Firstly, cultural specificity necessitates the consideration of unique societal norms and values that impact the public's perception and acceptance of AI within the Turkish milieu. Secondly, linguistic precision is crucial; a mere linguistic translation does not suffice, as it may overlook the semantic nuances inherent to the Turkish language. Thirdly, the accessibility factor is paramount, as it democratizes the participation of non-English-speaking Turkish respondents, thus, enhancing the representativeness of the sample. Finally, the provision of a linguistically adapted scale facilitates comparative studies, allowing for the exploration of cross-cultural patterns in AI acceptance. Therefore, the adaptation of AIAS-4 into Turkish will be a valuable contribution for researchers looking into attitudes towards AI in different contexts.

Method

Original scale

The AIAS-4 was developed by Grassini (2023) and consists of 4 items (see Appendix). The scale is designed to use a 10-point Likert scale. This scale was preferred by Grassini (2023) due to its high test-retest reliability and ease of use. The items aim to comprehensively capture the most important aspects of attitudes toward AI, drawing on established theories and methods in the fields of technology acceptance and risk perception.

Participants

According to the literature, a sample size of greater than 200 is typically regarded as appropriate (Comrey & Lee, 2013). The number of variables analyzed in this study determined the sample size. Thus, two separate convenience samples of greater than 200 Turkish undergraduate students were used in two studies. Prior to data collection, participants' informed consents were obtained. The initial study assembled a sample of 221 Turkish city-born undergraduate students (47.9% women, 52.1% men) aged 18 to 25 (M = 20.69, SD = 2.78) from different undergraduate programs (33 Turkish Language Education, 30 Social Studies Education, 32 Elementary Mathematics Education, 27 Science Education, 33 Guidance and Psychological Counseling, 32 English Language Teaching, 34 Primary School Education).

Study 2 includes a different sample of 201 Turkish city-born undergraduate students (59.2% women, 40.8% men) aged 18 to 25 (M = 20.59, SD = 2.56) from different undergraduate programs (29 Turkish Language Education, 31 Social Studies Education, 30 Elementary Mathematics Education, 24 Science Education, 29 Guidance and Psychological Counseling, 28 English Language Teaching, 30 Primary School Education).

Language adaptation

After getting approval from the original scale's author for the adaptation of the scale into Turkish, the initial phase was the forward translation of the items of AIAS-4 from source language (English) to the target language (Turkish) by three independent language experts who were native speakers of Turkish with native-like proficiency in English. Following the initial translation of the instrument, the three translations were compared by the researchers for ambiguities until a consensus had been reached. The third phase of the translation involved blind back translation of the preliminary translation of the instrument from target language (Turkish) to source language (English) by three different independent language experts and finally, the three versions were cross checked by the researchers and final consensus had been achieved for the Turkish version of the instrument. In order to examine the item in terms of comprehensibility, the reviews of 3 faculty members (1 Computer Education and Instructional Technology, 1 Turkish Language and 1 Educational Measurement and Evaluation) and 5 undergraduate students were taken, and it was seen that there was no issue in terms of comprehensibility.

Validity

Content validity

Content validity was investigated by taking expert reviews. Based on the reviews, content validity ratio (Lawshe, 1975) and content validity index (Lawshe, 1975) were calculated.

Construct validity

In Study 1, exploratory factor analysis (EFA) was used to reveal the existing structure of observed variables. This method relies on data and provides adaptability in model formulation. The items were created from theoretical perspectives, but EFA determines the fundamental factor structure, enabling an unbiased examination of the data. The initial study assembled a sample of 221 Turkish undergraduate students from different undergraduate programs using paper-pencil forms.

After EFA, in Study 2, confirmatory factor analysis (CFA) was performed to investigate whether the model was specified before fitting the data, with a different sample of 201 Turkish undergraduate students from different undergraduate programs.

Convergent validity

A survey comprising the AIAS-4 items as well as additional measures of technology attitudes and demographic data was filled out by study participants. The positive attitudes, negative attitudes and anxiety subscales of the Turkish version of MTUAS (Özgür, 2016) was employed to examine convergent validity in two studies. The original MTUAS (Rosen et al., 2013) is a psychometric instrument that assesses individuals' attitudes and usage patterns concerning different types of media and technology. It has demonstrated strong validity as a psychological assessment tool (Sigerson & Cheng, 2018). The scale encompasses various aspects, focusing on both positive and negative attitudes towards technology, and the anxiety associated with technology use. Also, the average variance extracted (AVE) was computed to assess the convergent validity of the scale.

Reliability

The scale's internal consistency was assessed by calculating Cronbach's alpha coefficient (Cronbach, 1951). McDonald's omega coefficient was used for the structural reliability of the scale (Shrout & Fleiss, 1979).

Test-retest reliability

Test-retest reliability was evaluated to test the stability of the construct against time effect (Vilagut, 2014). 201 undergraduate students completed AIAS-4 twice, 21 days apart. The Pearson Correlation Coefficient was computed between two measures for test-retest reliability.

Measurement invariance

Measurement invariance is the condition under which the latent variables relate similarly to observed variables across all subgroups (Widaman & Reise, 1997). It is a construct validity concept that is used as a method of proof of validity. A measurement invariance test through multi-group confirmatory factor analysis (MGCFA) is typically performed by sequentially evaluating four hierarchical models between subgroups: configural invariance, metric invariance (for the equity of the factor loadings), scalar invariance (for the equity of the item intercepts), and strict invariance (for the equity of the error variances) (Bialosiewicz et al., 2013). $\Delta CFI \leq 0.01$ value (Cheung & Rensvold, 2002) was the cutoff criterion in testing measurement invariance between models.

Ethical considerations

The research was carried out in line with the ethical guidelines established by the Declaration of Helsinki. Approval from the ethics committee was obtained at Bartın University (Decision no: 2023-SBB-0866). No personally identifying information was collected from those participating.

Data analysis

Before analyses, the descriptive statistics were calculated, and the assumptions were checked. EFA was performed on the data collected in Study 1 to examine the construct validity and factor structure of the AIAS-4. This structure was further justified by the CFA and MGCFA results in Study 2. In two studies, the correlation matrices were estimated to investigate the convergent validity of the AIAS-4 with the MTUAS, specifically the positive views toward technology, negative views toward technology, and anxiety associated with being without technology subscales. The data analysis was conducted using Jamovi 2.4.12 (The Jamovi Project, 2024).

Table 1 Descriptive statistics

Items	Mean	Median	SD	Skewness	Kurtosis
Item 1	7.281	8	2.156	−0.579	−0.152
Item 2	7.081	8	2.371	−0.571	−0.396
Item 3	8.380	9	2.007	−1.411	1.731
Item 4	6.394	6	2.494	−0.068	−0.798

Table 2 Factor loadings

Items	Loading	Uniqueness
I-1	0.865	0.252
I-2	0.863	0.256
I-3	0.782	0.388
I-4	0.646	0.583

Table 3 Descriptive statistics

Items	Mean	Median	SD	Skewness	Kurtosis
I-1	7.811	8	1.948	−0.945	0.782
I-2	7.557	8	2.102	−0.856	0.297
I-3	8.209	9	2.068	−1.239	1.017
I-4	6.801	7	2.274	−0.287	−0.446

Table 4 CFA results

Items	Estimate	SE	Z	*p*	Std. Estimate
Item 1	1.725	0.115	15.061	<0.001	0.888
Item 2	1.684	0.129	13.048	<0.001	0.803
Item 3	1.520	0.131	11.606	<0.001	0.737
Item 4	1.593	0.147	10.800	<0.001	0.702

Results

Validity

Content validity

For content validity, CVR and CVI were calculated by taking the opinions of 10 experts. CVR was calculated as 1 for items 1, 2 and 3; and 0.8 for item 4, and CVI was calculated as 0.95. Since these values were equal to or greater than the cut-off value of 0.8 (Ayre & Scally, 2014) for 10 experts, the content validity of all items was statistically significant ($p<.05$).

Construct validity

First, descriptive statistics of the items were checked out. The descriptive statistics for the AIAS-4 items are demonstrated in Table 1. The skewness values indicate that the data is approximately symmetrical, while the kurtosis values suggest that it is mesokurtic.

Before the EFA, it was determined if the assumptions required for conducting an EFA were met. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy, a crucial indicator for assessing the appropriateness of the dataset for the EFA, was calculated. The data exhibited excellent sampling adequacy with a KMO value of 0.816, verifying its suitability for EFA (Tabachnick & Fidell, 2013). Additionally, to assess the presence of significant correlations among the items, Bartlett's test of sphericity was performed. The test yielded a significant result [$\chi2(6)=439.921$, $p<.001$], confirming the validity of continuing with the EFA.

EFA utilized the principal axis factoring method and oblimin rotation. Parallel analysis extracted one factor, as shown in Table 2, where all items had high loadings. The single-factor model explained 63.07% of the total variance.

In Study 2, we tested the AIAS-4 that was validated in Study 1 and conducted a confirmatory factor analysis (CFA). We calculated descriptive statistics for each of the four items in the scale, which are presented in Table 3.

CFA was performed to investigate the factor structure of the AIAS-4 using the sample from Study 2. Upon examining the univariate and multivariate normality values, we found that most of the standardized univariate skewness and kurtosis values fell inside the range of ±1.96, and the multivariate skewness and kurtosis values were statistically non-significant ($p>.05$). Therefore, we applied a maximum likelihood estimation method for the CFA. All factor loadings showed significance ($p<.001$), indicating that the items effectively represented the underlying structure. The results, including standardized estimates, are reported in Table 4.

The model's fit was evaluated by various fit indices. The chi-square test for precise fit was not significant, which indicated a good model fit ($\chi2(2)=2.92$, $p=.232$) (Hu & Bentler, 1999). The Comparative Fit Index (CFI) and the Tucker-Lewis Index (TLI) were CFI = 0.998, TLI = 0.993. The values were above the recommended threshold of 0.95 (Byrne, 2016). These results suggest a good fit between the proposed model and the data. The Root Mean Square Error of Approximation (RMSEA) value of 0.048 indicates a good model fit, as the value is below 0.05 (Hu & Bentler, 1999). After confirming the model, we analyzed the measurement invariance of the structure by gender using MGCFA (Table 5).

Table 5 MGCFA results

Model	χ2	df	*p*	TLI	CFI	ΔCFI
Configural	9.43	4	<0.05	0.957	0.986	
Metric	10.046	7	<0.05	0.968	0.981	0.005
Scalar	15.78	10	0.106	0.982	0.985	−0.004
Strict	22.707	14	0.074	0.982	0.978	0.007

Table 6 Correlation matrix

	I-1	I-2	I-3	I-4	AIAS-4 Total Score
I-2	0.728***				
I-3	0.645***	0.651***			
I-4	0.589***	0.593***	0.487***		
AIAS-4 Total Score	0.874***	0.894***	0.783***	0.803***	
Positive Attitudes	0.368***	0.350***	0.379***	0.405***	0.439***
Negative Attitudes	−0.220***	−0.239***	−0.158**	−0.244***	−0.250***
Anxiety	0.115	0.115	0.233***	0.091	0.154*

*: $p<.05$; **: $p<.01$; ***: $p<.001$

Table 7 Correlation matrix

	I-1	I-2	I-3	I-4	AIAS-4 Total Score
I-2	0.716***				
I-3	0.667***	0.563***			
I-4	0.606***	0.590***	0.528***		
AIAS-4 Total Score	0.880***	0.851***	0.815***	0.820***	
Positive Attitudes	0.402***	0.346***	0.286***	0.323***	0.402***
Negative Attitudes	−0.148*	−0.071	−0.028	−0.197***	−0.134
Anxiety	0.086	0.044	0.061	0.084	0.082

*: $p<.05$; **: $p<.01$; ***: $p<.001$

The configural model, which was established without constraints, demonstrated a high CFI of 0.986, indicating a perfect fit. In the metric invariance, the CFI decreased to 0.981, with a ΔCFI of 0.005. This indicates that the scale measures the construct equivalently across genders. In the scalar invariance, wherein also the intercepts are equalized, the CFI increased to 0.985 with a ΔCFI of −0.004, indicating that measurement equivalence between groups remains still. Finally, in the strict invariance, which also includes equality of error variances to the previous constraints, a CFI of 0.978 with a ΔCFI of 0.007 was obtained. This indicates that the strict invariance was met.

Convergent validity

The AVE value was 0.63, which indicates an acceptable level of convergent validity (Fornell & David, 1981). Pearson correlation coefficients (r) were calculated between the AIAS-4 and the MTUAS subscales. Table 6 presents the correlation matrix in Study 1.

All items in the AIAS-4 are strongly positively correlated with each other, and the AIAS-4 total score is also strongly positively correlated with all individual items. Positive attitudes have positive correlations with all items and the AIAS-4 total score, while the negative attitudes dimension has negative correlations with all items and the AIAS-4 total score, as expected. All of the correlation coefficients mentioned earlier are statistically significant ($p<.001$). However, anxiety shows mixed correlations, with Item 3 and the AIAS-4 total score having strong positive correlations (0.233, $p<.001$; 0.154, $p<.05$, respectively), while the correlations with other items are not significant or slightly positive (Item 1: 0.115, Item 2: 0.115, Item 4: 0.091).

Pearson correlation coefficients were computed between the AIAS-4 and the MTUAS subscales. Similar to Study 1, a further analysis was executed to determine the convergent validity between AIAS-4 and the MTUAS subscales. Table 7 shows the correlation matrix of the second study.

All items in the AIAS-4 are strongly positively correlated, and the AIAS-4 total score is also strongly positively correlated with all individual items. Positive attitudes have moderate positive correlations with all items and the AIAS-4 total score. The aforementioned correlation coefficients are statistically significant ($p<.001$). Negative attitudes have mostly weak negative correlations with the items and the AIAS-4 total score, with coefficients ranging from −0.028 to −0.197, with the correlation with Item 1 being significant at the 0.05 level and Item 4 being significant at the 0.001 level. Anxiety shows weak positive correlations with all items and the AIAS-4 total score, with coefficients ranging from 0.044 to 0.086. However, none of these correlations are statistically significant.

Reliability

The reliability of the scale was assessed through Cronbach's alpha (α) and McDonald's omega (ω) in Study 1. Cronbach's α of 0.862 and McDonald's ω of 0.871 were found, which demonstrated a strong internal consistency.

The reliability analyses were then computed in Study 2. The scale demonstrated a Cronbach's α of 0.860 and McDonald's ω of 0.861, indicating good internal consistency, similar to what was observed for Study 1.

Test-retest reliability

To test the stability of the construct against time effect (Vilagut, 2014), 201 undergraduate students completed AIAS-4 twice, 21 days apart. The test-retest reliability was found to be 0.71, indicating that the scores were stable.

Discussion and conclusion

In this study, AIAS-4 was adapted into Turkish, validating its reliability and relevance within the Turkish context. The results confirmed that the psychometric properties of the original AIAS-4 scale are maintained, making it valuable for use in the evaluation processes of attitudes toward AI among the Turkish-speaking population.

In the first study, an EFA was conducted to determine the factor structure, with the data of the 221 participants. The results suggested that the scale had a single-factor structure. The factor explains 63.07% of the total variance, and the item loadings were in the range of 0.65–0.87. According to Cronbach's α and McDonald's ω coefficient values (0.86 and 0.87, respectively), the model indicated higher internal consistency and reliability (Venkatesh, 2022), which were greater than 0.8. In subsequent analyses, the correlations among AIAS-4 scores and factors of MUTAS were analyzed. The positive attitudes have a positive correlation with all items and the AIAS-4 total score ($p<.001$), while the negative attitudes dimension has a negative correlation with all items and the AIAS-4 total score ($p<.001$). In the second study, a CFA was conducted as a step to validate the single-factor structure that was found in the EFA. The CFA was performed on a second sample of 201 individuals. The model fit values verified the single-factor structure and items. In subsequent analyses, the reliability and internal consistency values were high (0.86 of Cronbach's α and McDonald's omega), similar to the first study. As another reliability value, the test-retest reliability coefficient was computed as 0.71. Further analyses with positive, negative and anxiety factors of MUTAS showed similar results with the first study. As a result, the reported analysis confirms the single-factor structure of the scale with 4 items as in the original scale, and the adapted version of the AIAS-4 scale to Turkish proves to be valid and reliable.

The EFA and CFA consecutively confirmed a single-factor structure, which was consistent with Grassini's (2023) original scale, and which suggested that attitudes towards AI among Turkish undergraduate students could be understood as a unidimensional construct. The scale was also strictly invariant between genders. Further supporting evidence for Turkish AIAS-4's high internal consistency was established by Cronbach's Alpha and McDonald's Omega. The strong positive correlations between the adapted scale's scores and attitudes toward technology scores measured by the MTUAS indicate the convergent validity of the scale.

The outcomes of the invariance testing offer compelling support for the gender-related measurement stability of the adapted AIAS-4. The consistently high Comparative Fit Index (CFI) values observed across configural, metric, scalar, and strict invariance assessments indicate that the scale effectively measures attitudes toward AI without exhibiting gender bias. The marginal reduction in CFI between the configural and metric models ($\Delta CFI = 0.005$) signifies that factor loadings are uniform across genders, which underscores the scale's reliability in equivalently measuring the construct for both male and female participants. Additionally, the scalar invariance results, highlighted by a CFI of 0.985 and a ΔCFI of -0.004, further validate that response patterns are comparable across groups when intercepts are standardized, implying that mean scores can be meaningfully compared. Even in the strictest invariance model, which examines the equality of error variances, the scale demonstrates an acceptable fit ($CFI = 0.978$, $\Delta CFI = 0.007$), reinforcing the notion that the AIAS-4 functions consistently across gender groups. These findings provide significant evidence for the validity of the adapted scale, emphasizing its appropriateness for gender-comparative research within the Turkish context.

The high loadings on the AIAS-4 items suggest that students perceive AI positively in terms of its potential to improve life and work and its overall benefit to humanity. This aligns with the fact that AI is increasingly seen as a transformative technology disposing of significant benefits, in spite of some concerns about unemployment and ethical considerations (Mutascu, 2021; Nguyen & Vo, 2022). The outcomes of this analysis complement the prior evidence regarding technology acceptance and AI attitudes. One more time, they show that the scores on the adapted AIAS-4 correlate positively with positive attitudes towards technology. This is consistent with the studies of Araujo et al. (2020) and Balakrishnan and Dwivedi (2024), where similar tendencies were also noticed in other cultural settings.

The results of this research have important implications for understanding the attitudes of Turkish undergraduate students towards AI. The sample primarily consisted of young individuals who are exposed to AI technologies across educational and social spheres. The positive attitudes indicated by high item loadings and strong internal consistency suggest that these students view AI as a driver of innovation and efficiency in their daily lives. This viewpoint aligns with worldwide trends among digitally savvy populations, while also highlighting the distinct cultural and educational influences that shape Turkish students' perceptions (e.g. Aykut et al., 2024). Furthermore, the results of the invariance testing, which affirmed the scale's validity across gender groups, provide further insights into the student population. The absence of notable differences in AI attitudes between genders suggests that exposure to and acceptance of AI concepts are relatively similar among Turkish undergraduates. The positive attitudes of Turkish undergraduate students towards AI, combined with the reliability of the adapted scale, highlight the importance of educational

and policy initiatives aimed at improving AI literacy and ethical understanding. By leveraging students' openness to AI, these initiatives can empower them to engage critically with AI technologies and contribute to their responsible development.

All in all, the demonstrated reliability and validity of the AIAS-4 adaptation underscore its potential as a tool for advancing research and practice. By providing a concise and effective measure of AI attitudes in Turkish, the scale enables researchers and policymakers to better understand public perceptions of AI in Türkiye. This understanding is critical for developing evidence-based policies and educational programs to address public concerns, enhance AI literacy, and promote ethical engagement with AI technologies. Furthermore, the availability of a validated Turkish scale opens avenues for cross-cultural research, facilitating comparisons that illuminate how cultural contexts influence AI perceptions. These insights could guide the development of culturally attuned AI applications, ensuring their relevance and acceptance across diverse user groups.

Limitations and future research

The results indicate that the Turkish version of AIAS-4 is a valuable tool for researchers and practitioners interested in understanding and assessing the public attitudes towards AI in the form of a short, concise and reliable scale. However, the current study has some limitations to be considered by the researchers. Although a systematic approach has been followed to ensure the validity and reliability of the instrument, the participants were undergraduate students. Future research could focus on administering this instrument to diverse groups to evaluate public attitudes towards AI to enhance the generalizability of the results. Additionally, cross-cultural comparative studies can be conducted to examine similarities and differences in AI perceptions in different cultures and societies. Future research may also explore the applicability of the scale to professionals in AI-related fields in order to understand how being familiar with AI shapes attitudes. Longitudinal studies could also track changes in public views over time to provide insights into the impact of exposure to AI technologies on attitudes.

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Data availability The datasets examined in this study can be obtained from the corresponding author upon a reasonable request.

Declarations

Conflict of interest The authors declare no financial interests or competing interests related to the content of this article.

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