e-Kafkas Journal of Educational Research

e-KJER

Research Article

Turkish Adaptation of Artificial Intelligence Attitude Scale-4: Investigating General AI Attitudes through Various Factors

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To cite this article:

Balıkçı H. C., & Alpsülün M. (2025). Turkish adaptation of the Artificial Intelligence Attitude Scale-4: Investigating general AI attitudes through various factors. *e- Kafkas Journal of Educational Research, 12*, 444-457. doi:10.30900/kafkasegt.1509077

Research article **Received:**02.07.2024 **Accepted:**09.05.2025

Abstract

This study aimed to evaluate the validity and reliability of the Artificial Intelligence Attitude Scale (AIAS-4), originally developed by Grassini (2023) and subsequently adapted into Turkish. In addition, the study examined participants' attitudes toward artificial intelligence (AI) across various demographic and usage-related factors. Following the translation and cultural adaptation of the scale, analyses were conducted to assess its psychometric properties. A total of 315 individuals voluntarily participated, and data were collected via an online platform. Statistical analyses confirmed that the Turkish version of the AIAS-4 is a valid and reliable instrument. The study also explored differences in AI attitudes based on gender, age, education level, and daily internet use. The results indicated significant differences in attitudes depending on gender, education level, and internet usage duration, whereas age did not have a significant effect. Overall, participants exhibited positive attitudes toward AI, with most reporting usage in areas such as digital assistants and language translation tools. This study contributes to a deeper understanding of AI attitudes and highlights demographic differences in these perceptions.

Keywords: Artificial intelligence, attitude, adaptation

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Introduction

Artificial intelligence (AI) has become an integral part of modern life, significantly influencing a wide range of domains, including communication, transportation, and entertainment (Ramírez & Islam, 2024). Its integration into these areas has profoundly affected how individuals interact with digital systems, access services, and make decisions. AI technologies can enhance productivity, support more informed decision-making, and transform numerous industries (Khadem, Khadem, & Khadem, 2023). These advantages are particularly evident in contexts that require predictive analysis and the processing of large volumes of data, where AI contributes to increased efficiency and reduced human error. For instance, in the field of education, Er et al. (2023) demonstrated that AI-based regression algorithms can effectively predict students' national exam scores by analyzing a combination of academic and socio-demographic variables, thereby facilitating data-driven decision-making. Nevertheless, despite these benefits, the integration of AI into everyday life also gives rise to new forms of uncertainty and concern (Konda, 2019). In this context, Yıldız Durak and Balıkçı (2025) developed a Turkish adaptation of the AI Chatbot Dependence Scale, emphasizing the emotional and behavioral risks associated with the excessive use of conversational AI technologies.

Individuals may be concerned with the transparency, reliability, or ethical nature of AI-driven systems. With AI being progressively incorporated into decision-making situations, ranging from medicine to education, users are increasingly likely to have to contend with algorithms they do not completely understand. Such ambiguity may influence the degree of confidence citizens have in these types of systems and influence their acceptance and use of them. In this context, Balıkçı and Yıldız Durak (2025) adapted a scale to examine teachers' acceptance of AI technologies in educational environments, revealing key factors such as perceived usefulness, ease of use, self-efficacy, and trust that shape user acceptance. To that end, understanding public sentiments about AI not only becomes relevant but also becomes essential.

Researchers have conducted numerous studies to measure attitudes toward artificial intelligence and have developed various scales for this purpose. In a cross-cultural study conducted in Germany, China, and the United Kingdom, a short five-item scale was developed and administered to participants in each country. The findings revealed a consistent two-factor structure across all three languages (Sindermann et al., 2021). Suh and Ahn (2022) designed a comprehensive 26-item scale with three dimensions to assess Artificial Intelligence Attitude (AIA) among K–12 students. Similarly, Mukherjee and Dasgupta (2024) developed a 30-item scale consisting of four dimensions to evaluate individuals' attitudes toward AI.

These studies highlight the importance of understanding people's views on AI and provide useful insights into the determinants that shape these beliefs. Gaining insight into individuals' viewpoints on AI is crucial for successfully incorporating this technology into our everyday lives. This understanding enables the formulation of strategies to tackle concerns and foster a favorable perception of AI among people (Brauner, Glawe, Liehner, Vervier, & Ziefle, 2024). By investigating these variables, we can gain insights into how factors such as age, education level, and previous exposure to AI influence individuals' attitudes towards this technology. By researching people's AIA, one can identify potential barriers to its adoption and develop strategies to overcome them (Baker-Brunnbauer, 2021). These findings can provide valuable insights for policymakers, AI developers, and educators in creating interventions and instructional programs that effectively tackle concerns and foster a favorable perception of AI. Understanding people's viewpoints on AI is essential for its successful incorporation into society. Researching individuals' AIA is crucial for comprehending the determinants that shape these views and successfully incorporating AI into our everyday existence.

Mukherjee and Dasgupta (2024) examined the research on AIA and found that both male and female students had positive AIA. The research of Sindermann et al. (2021) supports this finding by revealing the connection between people's AIA and their propensity to use various AI products. Hajam and Gahir (2024) conducted a study with the objective of comprehending the AIA of university students. Their findings indicate that students generally hold favorable AIA. Hajam and Gahir examined the adapted scale about various variables. The results of this survey indicate that there is no statistically significant disparity in opinions towards AI among male and female university students. Moreover, the study examined the influence of educational achievement on AIA, finding no significant difference in sentiments among university students with different levels of education. Kaya et al. (2022) found no significant difference between gender variables and AIA in their study. Age and education level did not predict AIA. In this research, the scale used for the adaptation study was adapted for Peruvian nurses (Morales-García, Sairitupa-Sanchez, Morales-García, & Morales-García, 2024). The study evaluated the psychometric properties of the “AIAS-4” instrument in a sample of Peruvian nurses. The findings demonstrated that the AIAS-4 is a reliable and valid instrument for measuring AIA among Peruvian nurses.

A review of the literature in Turkey revealed only one general attitude study adapted by Kaya et al. (2022), highlighting the limited availability of AIA scales in the Turkish context. The current study was initiated in response to this gap. It was carried out in two stages. In the first stage, the aim was to adapt the AIAS-4 originally developed by Grassini (2023) and consisting of four items into Turkish and to conduct a validity and reliability analysis of the scale. In the second stage, participants’ attitudes toward artificial intelligence were examined with various demographic and behavioral variables.

In this context, the study sought to answer the following research questions:

1. What are the participants’ attitudes toward artificial intelligence (AIA)?
2. Do participants' AIA scores differ significantly according to gender, age, education level, and daily internet use (DIU)?
3. In what ways have participants previously used artificial intelligence applications?

Method

Both phases of this two-stage study employed quantitative research methods. In the first phase, a scale adaptation study was conducted. In the second phase, a descriptive survey model was used to examine participants’ AIA and to investigate the relationships between AIA and variables such as gender, age, education level, and DIU. The descriptive survey model is a research approach designed to identify participants' tendencies and attitudes regarding a specific topic and is well-suited for studies involving larger sample sizes (Büyüköztürk, Akgün, Karadeniz, Demirel, & Kılıç-Çakmak, 2017).

This model aims to evaluate the current state of the phenomenon under investigation and to identify potential relationships or differences among the variables (Creswell, 2017).

Participants

The participants were individuals from various backgrounds and age groups. We selected the participants based on their availability and willingness to participate in the study. In adaptation studies, the sample size suitable for data collection should be at least 5-10 times the number of scale items (Büyüköztürk, 2018), or the number of participants should be at least 200 (Tinsley & Tinsley, 1987). Although the number of scale items was four, and at least 20-40 participants were sufficient, 315 participants were reached. In addition, more participants were reached because an examination was conducted according to different variables in the context of the research purpose. Convenience sampling was used to determine the individuals participating in the study. The convenience sampling method was chosen because of its ease of access and convenience in reaching various participants (Etikan, Musa, & Alkassim, 2015; Yıldırım & Şimşek, 2016). We collected data from participants using an online application. The study involved a total of 327 individuals, out of whom 315 individuals consented to participate voluntarily by submitting the participation form. Table 1 displays the descriptive characteristics of the individuals involved in the study.

According to Table 1, 48.3% of the participants were female and 51.7% were male. Participants’ ages were grouped in 10-year intervals, with the highest participation rate (47.3%) observed among those aged 19-28. Regarding educational level, the majority were undergraduate students, accounting for 41.6% of the sample. Additionally, 27.0% of participants reported using the internet for less than one hour per day.

Table 1.
Descriptives

Variable	Groups	f	%
Gender	Female	152	48.3
	Male	163	51.7
Educational level	High school	50	15.9
	Associate degree	95	30.2
	Undergraduate	131	41.6
	Master's degree	26	8.3
	PhD	13	4.1
Age	18 and under	30	9.5
	19-28	149	47.3
	29-38	90	28.6
	39 and over	46	14.6
DIU*	Less than 2 hours	46	27
	2-3	63	20
	3-4	72	22.9
	4-5	42	13.3
	5-6	40	12.7
	6-7	21	6.7
	More than 7 hours	31	9.8

* hours

Data collection tool

The researchers adapted Grassini's (2023) Artificial Intelligence Attitude Scale into Turkish and collected data using a personal information form they had prepared. The personal information form included questions about gender, education level, age, and DIU status for research purposes. The Artificial Intelligence Attitude scale, developed by Grassini (2023), which aims to adapt to Turkish, has one factor and four items. The measure comprises a Likert-type scale with 10 points, ranging from "(1) Strongly Disagree" to "(10) Strongly Agree." The average of all item scores should be taken as the basis for calculating the attitude scores for the scale.

Language equivalence

The adaptation process began with obtaining permission from the original researcher to translate the scale into Turkish. The researchers translated, after which three language experts and three content experts reviewed it. To ensure language equivalence, we gave both the original and translated versions of the scale to 23 English teachers at two-week intervals. We conducted Pearson product-moment correlation analysis on the data collected from the 23 EFL teachers for language equivalency assessments. The results showed a strong positive correlation ($r = .912$, $p < .01$) between the original English version of the scale and its Turkish version. Following this validation, more than 300 participants completed the Turkish version of the scale for further assessment.

Data analysis

We used appropriate software to analyze the collected data for scale adaptation, the main focus of this study. In the adaptation phase, we used CFA to check validity and Cronbach's alpha coefficients to check internal consistency to test reliability. We preferred CFA for scale adaptation because we did not add any new items or remove any items from the scale (Büyüköztürk et al., 2017; Tabachnick, Fidell, & Ullman, 2013), thus eliminating the need for exploratory factor analysis.

Before conducting the data analysis, we assessed the assumptions required for CFA and met these requirements. The Participants section provides a detailed explanation of the sample size required for CFA. We fulfilled this adequate sample size requirement with 315 participants.

The second aim of the study involved analyzing the data collected for the research questions. We used descriptive statistical methods to analyze frequency and percentage distributions of participants' demographic characteristics. Before selecting tests for data analysis, we conducted an assessment to determine the normality of the scales.

Table 2.

Descriptive Data Related to a Normal Distribution

	N	Mean	Median	Mod	Skewness	Kurtosis
AIAS-4	315	7.11	7.5	10	-.566	-.461

Table 2 shows the normal distribution of data on the artificial intelligence attitude scale. The skewness and kurtosis values of both scales were within the acceptable ranges (–1.5 to +1.5; Tabachnick et al., 2013; –2 to +2; George & Mallery, 2010), indicating normal distribution. Therefore, we can conclude that using parametric tests to analyze the data is appropriate. The study analyzed data using frequency, arithmetic mean, and standard deviation, using t-tests for two-group comparisons and ANOVA for three or more-group comparisons.

Ethics committee permission

We obtained permission from the researcher via email before using the scale for adaptation in the study. The Harran University Social Sciences and Humanities Ethics Committee dated February 15, 2024, and numbered 2024/65, decided that the research aligned with scientific ethical rules.

Findings

The data analysis began with findings about the scale's validity and reliability in Turkish, followed by findings about the research questions.

Validity

Confirmatory factor analysis was conducted using appropriate statistical software to assess the validity of the Turkish version of the scale. Several model fit indices were examined to evaluate the adequacy of the model. These included the Goodness-of-Fit Index (GFI), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA).

Table 3.

CFA fit indices for the AIAS-4

Goodness of Fit Values	E.V	A.V	O.S	A.S
χ^2/df	≤3	≤5	2.49	1.24
RMSEA	≤.05	≤.08	.028	.028
SRMR	≤.05	≤.08	-	.006
TLI	≥.95	≥.90	.99	.99
CFI	≥.95	≥.90	.99	.99
GFI	≥.95	≥.90	-	.99
NFI	≥.95	≥.90	-	.99

E.V.: Excellent value; A.V.: Acceptable value; O.S.: Original Scale; A.S.: Adapted Scale

In the initial CFA conducted without any modifications, the one-factor structure of the AIAS-4 did not adequately fit the data. The model fit indices were χ^2/df = 10.45, $p < 0.001$, RMSEA = 0.174, SRMR = 0.033, TLI = 0.93, CFI = 0.977, GFI = 0.967, and NFI = 0.975. While CFI, TLI, GFI, NFI, and SRMR values were within acceptable ranges, RMSEA and χ^2/df exceeded the recommended cut-off points (Çokluk, Şekercioğlu, & Büyüköztürk, 2010), indicating that the initial model generally exhibited poor fit.

Subsequently, modification indices were examined to identify potential improvements. Based on theoretical justification, the error covariance between Item YT1 and Item YT4 (e1 ↔ e4) was freed to account for shared variance attributable to content similarity rather than the latent construct. Following this modification, model fit improved substantially, with indices of χ^2/df = 1.24, $p < 0.01$, RMSEA = 0.028, SRMR = 0.006, TLI = 0.99, CFI = 0.99, GFI = 0.99, and NFI = 0.99 (see Table 3). All post-modification indices met or exceeded the thresholds for excellent fit (Çokluk et al., 2010; Tabachnick et al., 2013), indicating that the adapted scale retained its original factor structure and demonstrated strong construct validity (see Figure 1).

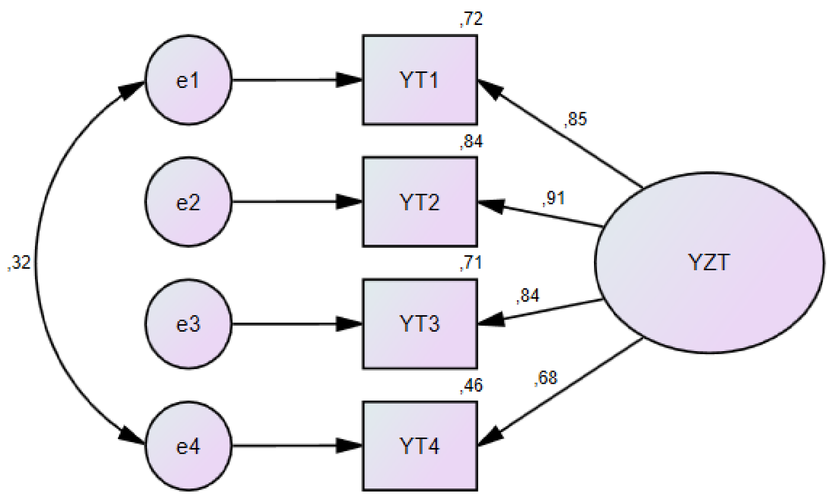

Figure 1. Item-factor Structure of AIAS-4

Examination of the item-structure parameters in Figure 1 indicates that the model's standardized factor loadings range from 0.46 to 0.91, all of which were statistically significant according to the t-test. In line with Costello and Osborne (2005), factor loadings above 0.40 are considered acceptable in the social sciences, while Velicer and Fava (1998) note that loadings greater than 0.80 are highly desirable. The CFA results for the model were consistent with the item-structure pattern of the original scale developed using a European sample, providing support for the factorial validity of the scale.

Reliability

To assess the internal consistency of the adapted scale, Cronbach's alpha was computed, yielding a value of 0.90, indicating a high level of reliability. Corrected item–total correlations ranged from 0.696 to 0.829, all exceeding the recommended threshold of 0.30 (Büyüköztürk, 201**8**), suggesting that each item is strongly related to the overall scale score: 0.829 for YT1, 0.814 for YT2, 0.773 for YT3, and 0.696 for YT4.

Item discrimination analysis, conducted by comparing the upper 27% and lower 27% of participants based on total scale scores, revealed a statistically significant difference between the two groups ($t_{(170)} = 39.94$, $p < 0.001$). The mean difference was 22.74 points, with a 95% confidence interval of 21.62 to 23.87. These findings indicate that the adapted scale demonstrates both strong internal consistency and a high capacity to differentiate between individuals with high and low levels of the measured construct.

Findings related to the research questions

The first research question in the second stage of the study is, "1. What are the participants' AIA?". This question aims to identify and summarize the overall attitudes, impressions, or awareness levels (AIA) that participants hold regarding the subject of interest. Establishing this baseline is essential for understanding the general tendencies within the sample before conducting more complex statistical analyses. To address this question, Table 4 presents the descriptive statistics (e.g., means, standard deviations) for the participants' AIA scores. These descriptive indicators provide a preliminary understanding of how participants perceive or relate to the measured construct and guide the interpretation of further findings in the study.

Table 4.
Descriptive Statistics for AIAS-4

Scale	N	$\bar{X}$	SD
Attitudinal Trends in Artificial Intelligence	315	7.11	2.29

Table 4 reveals that the participants' average score on the artificial intelligence attitude scale was X = 7.11. Based on the classification by Ata and Alpaslan (2019), scores between 1.00 and 4.00 indicate a low level, 4.01 to 7.00 a medium level, and 7.01 to 10.00 a high level of AI attitudes. According to this classification, participants demonstrated a high overall level of AI attitudes.

The second research question was stated as: “Is there a significant difference between participants’ AIA scale scores and variables such as gender, age, education level, and daily Internet use?” An independent samples t-test was conducted to examine differences in scale scores by gender. The findings are in Table 5.

Table 5.
Results of the T-Test on the Gender of Participants

Scale	Variable	Groups	N	$\bar{X}$	SD	df	t	p
AIAS-4	Gender	Female	52	6.68	2.27	313	3.26	0.01*
		Male	63	7.51	2.25			

As shown in Table 5, a significant difference in AIA scores was observed based on gender ($t_{(313)} = 3.26$, $p < .05$), indicating that males reported higher average attitudes toward artificial intelligence than females. Table 6 and Figure 2 present the AI Attitude Scale results stratified by participants’ age.

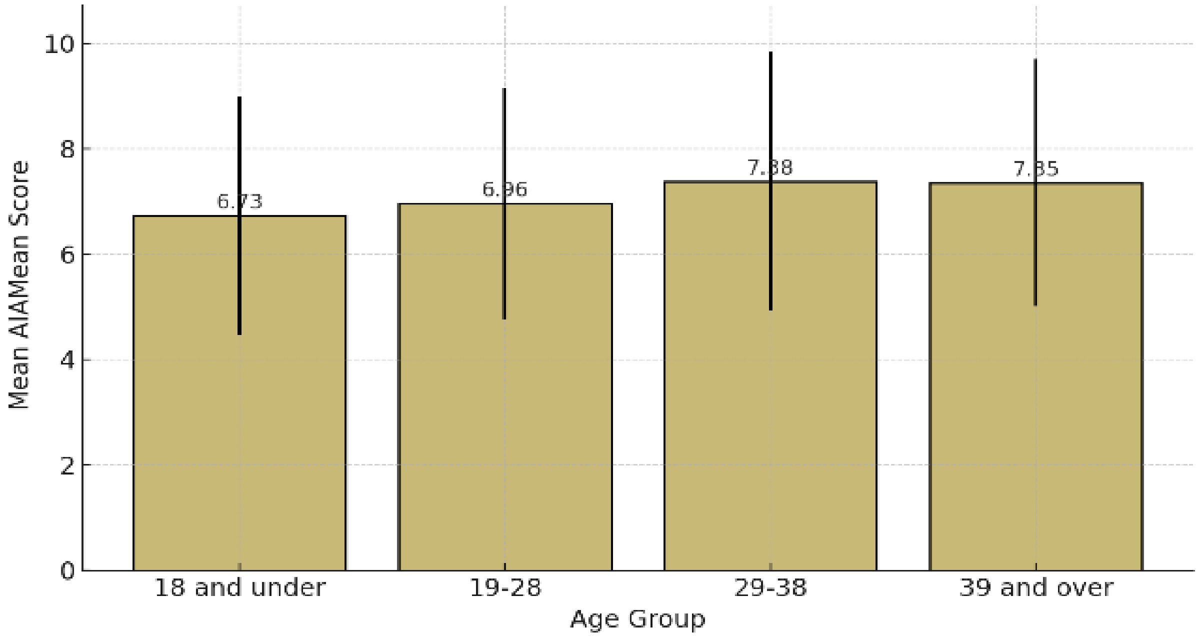

Figure 2. Mean AIAMean Scores by Age Group (±SD).

According to Figure 2, the mean AIAS-4 score was 6.73 (SD = 2.2) for participants aged 18 and under, 6.96 (SD = 2.2) for those aged 19–28, 7.38 (SD = 2.3) for those aged 29–38, and 7.35 (SD = 2.3) for those aged 39 and above. Although there are small differences in the means, ANOVA results showed that these differences were not statistically significant (p > .05).

Table 6.
ANOVA results according to the participants' age variable

Scale	Source of Variance	Sum of Squares	Sd	Mean Squares	F	p
AIAS-4	Intergroup	17,13	3	5.711	1.081	.357
	Intragroup	1642,63	311	5.282		
	Total	1659,77	314			

As shown in Table 6, the variance in AIAS-4 scores between age groups was not statistically significant ($F_{(3, 311)} = 1.081$, $p = .357$), indicating that age did not have a meaningful effect on participants’ attitudes toward artificial intelligence. Table 7 and Figure 3 present the ANOVA results for the AIA scale by participants’ educational background.

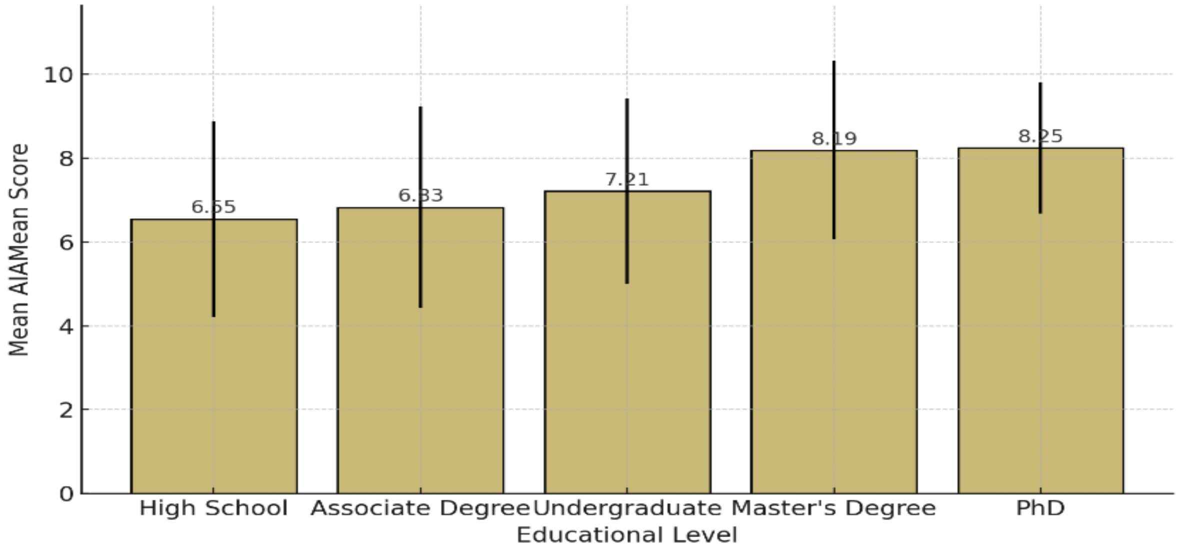

Figure 3. Mean AIAMean Scores by Educational Level (±SD).

According to Figure 3, the mean AIAS-4 score was 6.55 (SD = 2.3) for high school graduates, 6.83 (SD = 2.2) for associate degree holders, 7.21 (SD = 2.2) for undergraduates, 8.19 (SD = 2.3) for master's degree holders, and 8.25 (SD = 2.3) for participants with a PhD. The results show an upward trend in mean scores with increasing education level.

Table 7.

ANOVA Results According to the Participants' Education Level

Scale	Source of Variance	Sum of Squares	df	Mean Squares	F	p	Difference Source
AIAS-4	Intergroup	71.60	4	17.90	3.494	.008	
	Intragroup	1588.16	310	5.12			A-D
	Total	1659.77	314				

A: High School B: Associate-degree C: Undergraduate D: Master's degree E: PhD

As shown in Table 7, there was a statistically significant difference in AIAS-4 scores across education levels ($F_{(4, 310)} = 3.494$, $p = .008$). Tukey's HSD test revealed that participants with a master's degree scored significantly higher than those with a high school degree.

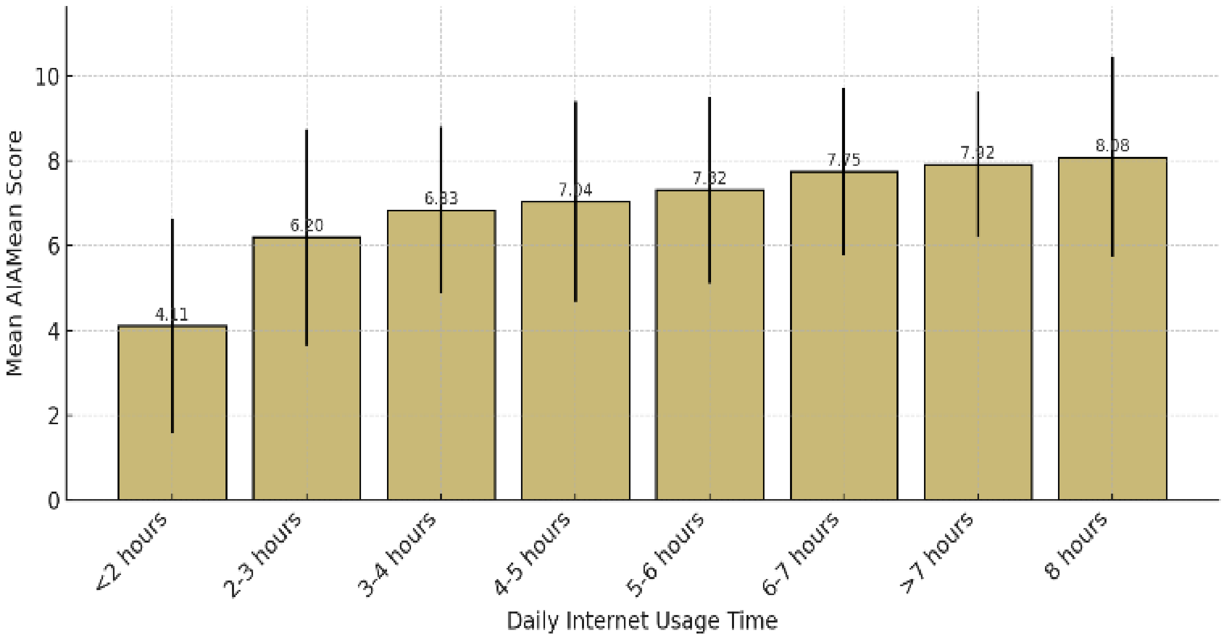

Figure 4. Mean AIAMean Scores by Daily Internet Usage Time (±SD).

According to Figure 4, the mean AIAS-4 score was 4.11 (SD = 2.4) for participants using the internet less than 2 hours daily, 6.20 (SD = 2.2) for 2–3 hours, 6.83 (SD = 2.2) for 3–4 hours, 7.04 (SD = 2.2) for 4–5 hours, 7.32 (SD = 2.3) for 5–6 hours, 7.55 (SD = 2.3) for 6–7 hours, 7.92 (SD = 2.3) for more than 7 hours, and 8.08 (SD = 2.3) for 8 hours of daily internet use. The results indicate a clear increase in mean scores with longer daily internet usage times.

Table 8.

ANOVA Results of the AIA Scale According to the Participants' DIU Time Variable

Scale	Source of Variance	Sum of Squares	df	Mean Squares	F	p	Difference
AIAS-4	Intergroup	161.858	7	23.12	4.739	.000	The order is A-B, C, D, E, F, G, B-F, H.
	Intragroup	1497.91	307	4.87			
	Total	1659.77	314				

A: Less than 2 hours B: 2-3, C: 3-4, D: 4-5 E: 5-6; F: 6-7; G: More than 7 hours

As shown in Table 8, there was a statistically significant difference in AIAS-4 scores according to daily internet usage time ($F_{(7, 307)} = 4.739$, $p < .001$). Tukey's HSD tests revealed significant differences between group A (<2 hours) and groups B, C, D, E, F, G, and H, as well as between groups B and F, and H.

The third research question was, "How have participants used artificial intelligence applications previously?". Figure 2 presents the findings corresponding to this research question based on the collected data.

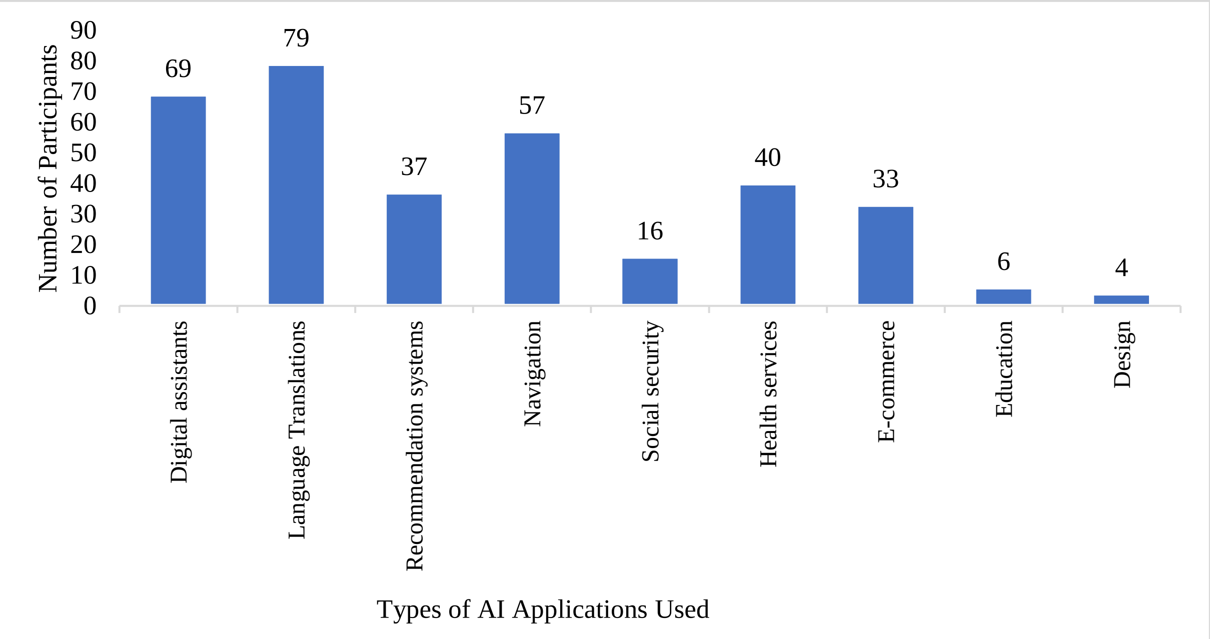

Figure5. Participants' Utilization of AI Applications

Figure 5 shows that most people used AI to develop digital assistants (f = 69) and language translations (f = 79). These findings demonstrate the growing integration of AI technologies into daily routines, emphasizing their role in enhancing digital interactions and language-related activities.

Discussion, Conclusion, and Suggestions

The purpose of this two-phase study was (a) to adapt and validate the AIAS-4 scale for a Turkish population and (b) to explore how demographic and usage variables shape general attitudes toward AI. In phase 1, we confirmed through CFA that the one-factor AIAS-4 structure holds in Turkish (χ^2/df=1.24, RMSEA=0.028, CFI=0.99). In phase 2, we found that while overall attitudes were positive, variables such as education level and daily Internet use significantly influenced AIA, whereas age did not.

The study first adapted the AIAS-4 scale to Turkish and investigated its validity and reliability using data collected from individuals from various backgrounds and age groups living in Turkey. According to CFA, the fit statistics of the 1-factor structure of the AIA scale were $\chi 2/df = 1.24$, $p < 0.01$, RMSEA = 0.28, SRMR = 0.006, TLI = 0.99, CFI = 0.99, GFI = 0.99, and NFI = 0.99. When the values were analyzed, the $\chi 2/df$, SRMR, TLI, CFI, RMSEA, GFI, and NFI fit index values were excellent. As a result, the model and factors obtained from the adapted scale's CFA results were the same as those of the original scale, ensuring its validity (Çokluk et al., 2010; Tabachnick et al., 2013). Examining the item-structure parameters revealed that the relevant model's standardized factor loadings ranged from 1 to 1.28. Factor loadings were found to be statistically significant according to the t-test. According to Costello and Osborne (2005), the accepted item factor loading in the social sciences is greater than 40. According to Velicer and Fava (1998), all item factor loadings greater than 80 are considered very good. Cronbach's α for the internal consistency reliability of the scale in the original study was 0.90 (Grassini, 2023). Analysis within the scope of the adaptation study yielded a similar result. Cronbach's α for this study was 0.90. A value above 0.70 is considered sufficient (Bland & Altman, 1997; Hair, 2011). In this sense, this study's findings indicate a high level of reliability.

The second stage of the study involved an analysis of the research questions. The first research question focused on examining the attitudinal levels of the participants and revealed that they had a positive perception of artificial intelligence. This finding is consistent with existing literature (Mukherjee & Dasgupta, 2024; Sindermann et al., 2021). However, there are also studies on negative attitudes and concerns regarding AI (Brewer, Bingaman, Paintsil, Wilson, & Dawson, 2022; Liao, Lin, Chen, & Pei, 2024; Zheng et al., 2021). Liao et al. (2024) stated that the collaborative work of AI with robots will cause unemployment, while Zheng et al. (2021) stated that the use of AI in the field of health creates a negative attitude due to ethical concerns. These contrasting perspectives underline the complexity and diversity of AIA in the research environment. To gain a more nuanced understanding of the multifaceted perspectives surrounding AI, we need to conduct further research and analysis.

The second research question aimed to investigate the relationship between participants' AIA and their demographic characteristics. The findings showed that there was no significant difference between age and AIA. Studies also indicate that there is no significant difference between age and AIA (Al-Ali, Polesie, Paoli, Aljasser, & Salah, 2023; Kaya et al., 2022; Polesie et al., 2020). These findings suggest that age may not be a determining factor in shaping individuals' AIA, suggesting that knowledge and experience in a particular field may override age-related effects. Hajam and Gahir (2024) emphasized that young people generally exhibit more positive AIA, highlighting that technological familiarity is more important in shaping AIA than age itself. The education level is another variable examined in this research question. Research findings revealed that participants with higher levels of education exhibited more positive AIA, which is consistent with existing literature on the subject (Kuznetsov, 2024). Kuznetsov (2024) pointed to a positive outlook on the desire of individuals with higher levels of education to use AI in educational settings to enhance their learning experience. DIU, which is considered in this question, has also emerged as a determinant of AIA. Participants with higher Internet usage reported more positive AIA. Research has shown that frequent Internet users tend to be more accepting of AI technologies because of their familiarity with digital platforms and exposure to technological developments. Research also demonstrates a positive correlation between Internet use and AIA, highlighting the likelihood of individuals who use the Internet extensively adopting AI applications across various fields (Kaya et al., 2022). These findings suggest that DIU plays an important role in shaping individuals' perceptions and AIA by promoting a sense of familiarity and comfort with technology. Gender was the last variable addressed in this research question. The findings showed a significant difference in AIA between male and female participants, with male participants exhibiting more positive attitudes. This finding is consistent with previous research in which men had a more positive AIA compared to women (Albarrán Lozano, Molina, & Gijón, 2021).

Addressing the third research question about whether the participants had previously used AI applications, the study's findings showed that the majority of the participants had primarily used AI applications for language translation and digital assistants. This finding is consistent with research that highlights the widespread use of AI technologies in language translation services (Adam, Wessel, &

Benlian, 2021; Pokrivcakova, 2019). It also demonstrated the various applications of AI in improving communication and task efficiency, underscoring the growing reliance on AI-powered digital assistants.

In conclusion, the findings of this study emphasize the successful adaptation of the AIAS-4 scale to Turkish, demonstrating high reliability and internal consistency. An analysis of participants' AIA revealed a predominantly positive perception, consistent with the existing literature, but contrasting perspectives from other studies underscore the complexity and diversity of AIA. The study also revealed that demographic characteristics such as age, education level, and DIU significantly influenced the participants' AIA. The results emphasize the role of familiarity and experience with technology in shaping AIA, with younger individuals, those with higher education, and frequent Internet users exhibiting more positive attitudes. In addition, the study identified a gender difference, with male participants exhibiting more positive AIA than female participants. Furthermore, the majority of participants reported using AI applications for language translation and digital assistants, highlighting the growing reliance on AI technologies to improve communication and task efficiency. Based on our findings, we offer the following concrete recommendations:

- Embed AI-awareness modules in secondary and higher-education curricula that allow students to interact directly with AI tools (e.g., chatbots, recommendation engines).
- Conduct workshops that demystify “black-box” algorithms by showing step-by-step how inputs become outputs, thereby reducing ambiguity and building trust.
- Implement transparent feedback features—such as short “explainability” blurbs—to clarify why an AI system made a particular decision.
- Undertake longitudinal research to determine whether positive attitudes toward AI persist after extended use.

Acknowledgment

Ethics statement: In this study, we declare that the rules stated in the "Higher Education Institutions Scientific Research and Publication Ethics Directive" are complied with and that we do not take any of the actions based on "Actions Against Scientific Research and Publication Ethics". At the same time, we declare that there is no conflict of interest between the authors, who all contribute to the study, and that all the responsibility belongs to the article authors in case of any ethical violations.

Author Contributions: Conceptualization, H.C.B. and M.A.; methodology, H.C.B.; validation, H.C.B. and M.A.; formal analysis, H.C.B.; investigation, M.A.; resources, H.C.B. and M.A.; data curation, H.C.B.; writing—original draft preparation, H.C.B. and M.A.; writing—review and editing, H.C.B.; visualization, M.A.; supervision, H.C.B.; project administration, M.A.

Funding: This research received no funding.

Ethics committee permission: We obtained permission from the researcher via e-mail before using the scale for adaptation in the study. The Harran University Social Sciences and Humanities Ethics Committee dated February 15, 2024, and numbered 2024/65, decided that the research aligned with scientific ethical rules.

Data Availability Statement: Data generated or analyzed during this study should be available from the authors on request.

Conflict of Interest: Authors should declare that there is no conflict of interest among authors.

Generative Artificial Intelligence Statement: The authors used OpenAI’s ChatGPT to support language editing during the manuscript preparation process. All AI-generated content was rigorously reviewed, modified, and approved by the authors, who take full responsibility for the final work.

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