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Psychometric properties and Turkish adaptation of the artificial intelligence attitude scale (AIAS-4): evidence for construct validity

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Abstract
Artificial intelligence (AI) attitude scales can be used to better evaluate the benefit and drawback cons of AI. This article consists of two different studies examining attitudes towards AI. In Study I ($N=370$), the four-item Artificial Intelligence Attitude Scale-4 (AIAS-4) has a one-dimensional structure as a result of confirmatory factor analysis and the fit index values are at an acceptable level [Comparative Fit Index (CFI) = 0.991; Goodness of Fit Index (GFI) = 0.989; Normed Fit Index (NFI) = 0.988; Tucker-Lewis Index (TLI) = 0.973; Standardized Root Mean Square Residual (SRMR) = 0.018]. Additionally, according to the results of the item response analysis conducted to support construct validity at this stage, the scale items have sufficient discrimination (discrimination value range = 2.22–3.80). Later, measurement invariance analysis revealed that the scale measured the same construct in females and males. In Study II ($N=331$), the reliability of AIAS-4 was reached by calculating different reliability coefficients. Then, AI attitude was found to be associated with depression, anxiety, and stress, as well as mental health variables such as mental wellbeing and flourishing. Moreover, openness to experience, conscientiousness, extraversion, and neuroticism are significantly related to an AI attitude. Lastly, psychological distress has a significant mediating role in the relationship between AI attitude and mental health. The findings of this pioneering research on AI attitudes were discussed and interpreted in light of the literature.

Keywords Artificial intelligence, Personality traits, Psychological distress, Mental wellbeing, Flourishing

Introduction

The rapid advancement of technology is posed to drastically change human life. Artificial intelligence (AI) stands as one of the leading innovations. However, it must also be recognized that AI is just one innovation in a long process of technological advances that have followed previous milestones such as personal computers, the internet, smartphones, social media, and virtual reality. In other words, AI is an innovation that builds on the foundations of previous breakthroughs. There are many different definitions of AI in the literature. For instance, according to Fetzer and Fetzer's definition, AI is a major technological

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advancement explained as the imitation of human intelligence by machines and software [1]. In another more recent study, AI is defined as a technological revolution that makes human life easier and arises to assist people [2]. Based on these definitions, it can be said that AI is becoming a widespread technology and is an important development that can change human history. Therefore, when AI is placed within a broader historical trajectory, each successive wave of innovation not only transforms human life but also paves the way for subsequent inventions [3]. This clarifies AI's position within the developmental technology trajectory, making it clear how it can form the basis for future innovations.

In recent years, AI has been introduced in many aspects of life, influencing almost all aspects of society. Research demonstrates that these areas include health, education, economy, art, transportation, informatics, and politics [4–7]. In addition, it has been reported that AI technology is frequently used for social benefit. For example, Brooks's study revealed that AI technology was used to control the use of environmental resources or predict natural disasters [8]. Similarly, Brill et al. reported that AI-based products on phones make it simple to give navigation support or weather forecasts [9]. According to Evans' study, it was stated that banking services have become easier with the support of AI [10]. Apart from this, recent research by Luan et al. revealed that AI technology is used to prevent social violence and ensure occupational health and safety [11]. In summary, research emphasizes that AI may improve efficiency in life and reduce human-made mistakes, thus reducing problems and increasing the quality of life of individuals [12, 13]. All these studies prove the importance of AI for humanity and reveal that individuals can have a positive attitude towards AI as it provides convenience in many different areas of life.

Despite all these positive aspects and exciting developments, there are some characteristics of the technology that may cause individuals to have negative attitudes towards AI. Several studies in the literature mention concerns about AI [14–16]. One of the most promiment concern is related to the possibility of AI to create jobs displacement in several sectors. It is stated in research that the automation system developed with the support of AI has replaced humans, and this situation triggers the unemployment problem [17, 18]. Similarly, in a recent study by Tschang and Almirall, it was reported that AI increased the anxiety of being unemployed in individuals [19]. For this reason, the psychological health of people who lose their jobs and experience an economic crisis is negatively influenced, and they may adopt a negative attitude towards AI.

A further factor that causes concern and shape attitudes towards AI is related to personal and social security. For instance, in the research of Gillespie et al., it was found that individuals experience anxiety due to possible uses of AI that violates human rights, promote is racism, discrimination, and prejudiced [20]. There are other studies in the literature that reveal security problems [21, 22]. These aforementioned studies reveal that AI poses a danger both socially and politically. Apart from this, the widespread use of attacks on the privacy of personal data with the support of AI plays a role in individuals' negative attitudes towards AI [23, 24]. Recent deployment of AI technology have shown the necessity of examining attitudes towards AI. Especially in recent years, attitudes towards AI and concepts associated with this attitude have been investigated in the scientific literature [25–27]. All these studies examine the benefits and risks that the widespread use of AI will provide to individuals. Like these studies, similar benefits and risks related to AI were discussed in Eitel-Porter's research [28]. In the aforementioned research, it was examined why individuals accept or do not accept AI and how they resist AI when they do not accept it. In summary, research attempts to determine what kind of attitude individuals have towards AI.

AI attitude

AI attitude is a concept that reveals individuals' perceptions and feelings toward technologies based on AI [29]. In Grassini's scale development study, thoughts on technological developments are explained as AI attitude [30]. This attitude includes evaluations about AI's social impacts, ethical dimensions, reliability, and usage practices [31]. In addition, it refers to the sum of individuals' cognitive (beliefs and thoughts), affective (felt emotions), and behavioral (tendencies to act) responses to AI technologies and applications [32]. These attitudes are significantly influenced by individuals' perceptions and feelings about the social and personal impacts of AI [33]. For instance, a person may believe that AI will increase work efficiency (cognitive), be excited about it (affective), and consequently be willing to use AI-based tools (behavioral).

The literature emphasizes that people's attitudes towards AI influence the pace of societal acceptance of new technologies, policy organization, and innovation processes [34]. Therefore, understanding AI attitudes can enable the development of healthier policies and strategies regarding technological developments in individual and social terms. In particular, beliefs about AI's potential to improve both individual and social living conditions strengthen the acceptance of technology [35]. Moreover, predictions about the use of these technologies in the future can ensure that people are ready to adopt innovative applications related to AI. As a result, research on AI attitudes makes it possible to better understand and manage developments related to AI.

Measuring AI attitude

Individuals' positive or negative opinions about AI can be determined quantitatively with various measurement tools. This study aimed to examine the psychometric properties of the Artificial Intelligence Attitude Scale-4 (AIAS-4) developed by Grassini in a Turkish sample [30]. This scale was designed to be administered to adults in the United Kingdom and was prepared to have a total of five items, one of which was a reverse item, prior to analysis. However, after the analysis, the final form of the scale consisted of four items because the reverse item did not have sufficient factor loading. The selection of scale items was inspired by theoretical and empirical research in the technology acceptance and risk perception literature covering the key factors of attitudes toward AI. Davis's Technology Acceptance Model and Venkatesh et al.'s Unified Theory of Acceptance and Use of Technology can be given as examples of these theoretical studies [35, 36]. For empirical studies, the study by Kaur et al., which examines the risks associated with AI, can be cited as an example [37]. AIAS-4 addresses the impact of AI on individuals' entire lives from different perspectives and focuses on the potential for future adoption in line with the possible benefits and risks of AI. When the scale items are examined, the first item is based on Davis's Technology Acceptance Model and aims to measure individuals' belief in the potential of AI to increase the quality of life. The second item aims to evaluate perceptions of the benefits that AI provides to the business environment, again based on the Technology Acceptance Model framework [36]. The third item is prepared with a focus on both Davis's Technology Acceptance Model and Venkatesh et al.'s Unified Theory of Acceptance and Use of Technology [35, 36]. This item aims to measure individuals' intention to adopt and use AI. The last item can be based on the study of Brynjolfsson and McAfee [38]. This item aims to measure the general belief in the broad benefits that AI offers to society and humanity. As a result, items that include elements such as perceived usefulness of AI, potential social impact, intention to adopt, risk perception, and assessment of the total impact of AI on humanity have emerged in this scale.

Measures of AI attitudes can shed light on how society will respond to technologies in the future, whether they will adopt or reject them. The examination of attitudes toward AI, a relatively new topic, has been inadequate, leaving a noticeable gap in the literature. This scarcity in research could be attributed to the lack of comprehensive tools for measuring attitudes towards AI. However, recent developments in the field have seen the creation of some measurement instruments [25, 26, 39]. In the scales developed in these studies, individuals' positive and negative approaches towards AI, their acceptance of AI or fear of AI, and whether AI is seen as a threat were examined. These scales primarily focus on general attitudes toward AI, emphasizing broad constructs such as fear, acceptance, and perception of threats. Additionally, the scales attempt to capture the influence of AI on various aspects of life, such as professional environments, education, health care, and social interactions, highlighting the potential benefits and challenges AI poses in these domains. As far as we know, the only measurement tool that measures attitudes towards AI adapted to the Turkish sample belongs to Kaya et al. [40]. All these measurement tools have made a significant contribution to the literature, but these measurement tools are thought to have some limitations. The first of these limitations is that many AI tools, especially ChatGPT, were not widely deployed at the time the scales were developed or adapted. In other words, it is a limitation that scales on this subject were developed or adapted in a period when people were less exposed to and less influenced by AI. However, this study addresses not only the timing of the scales but also their content limitations. This scale, unlike existing scales, aims to directly measure specific perceptions of AI in individuals' daily lives, business processes, and potential future use. In particular, it separately evaluates individuals' intentions toward technology and its general effects on humanity, with concrete contributions such as "improving life" and "increasing work performance". This content provides a more detailed and contextual understanding of individuals' attitudes toward AI and, consistent with the definition of "attitude," covers individuals' experiences, beliefs, and future expectations. This approach is different in that it addresses the direct effects of AI in the context of daily life and business life, as opposed to previous scales that generally focus on abstract and general perceptions. Another limitation is that these measurement tools are difficult in terms of applicability. That is to say, the large number of items on these scales is a limitation, as it may hinder scale usage especially outside the academic environment. These limitations make it necessary to develop or adapt new scales in different cultures. When the literature is examined, no other scale has been found that contains a small number of items and has strong psychometric properties to measure AI attitude. In addition, the fact that this scale has not yet been adapted to another language indicates that it has the potential to gain a more universal quality with future adaptations to different cultures and languages. At this point, the adaptation of the scale to Turkish culture in this study will both fill an important gap in the literature and make a meaningful contribution to the field by paving the way for comparative studies on a global scale.

The current study

Given the rapid integration of AI into various sectors today, understanding individuals' attitudes towards AI becomes important. This study aims to provide a comprehensive assessment of attitudes towards AI and investigate how these attitudes are related to factors such as technology/internet attitude or acceptance, personality traits, and mental health (depression, stress, anxiety, wellbeing, etc.). By doing so, insights can be provided into the nomological network surrounding attitudes towards AI, especially in the context of Turkish society, and a contribution can be made to the literature. In this context, the rationality between the variables discussed in this study and AI attitude is detailed below and the nomological network is presented.

The studies examining attitudes towards AI in the literature have determined that various factors play a role [26, 41, 42]. Research has shown that attitudes toward AI are significantly shaped by cultural influences, individual personality traits, and personal values. Individuals' trust and acceptance of the internet or technology may also be reflected in their attitude towards AI. Attitudes towards AI are closely related to factors such as technology acceptance level and openness to innovation [43]. For instance, individuals scoring higher in the personality trait of openness tend to be more receptive to innovative technologies, including AI, as they generally seek novelty and show a greater willingness to engage with emerging tools and systems. Apart from this, trust in technology can be a determinant of positive attitudes towards AI [44]. On the other hand, those with higher neuroticism may exhibit heightened apprehension towards AI, reflecting a sensitivity to perceived threats and uncertainties associated with automated systems. Specifically, personality characteristics can influence people attitudes toward AI. Supporting this view, the study by Gallego and Pardos-Prado revealed that the Big Five personality traits—openness, agreeableness, extraversion, conscientiousness, and neuroticism—affect people's views towards AI [45]. A different study also proposed that personality characteristics influence technology adoption [46]. These aligns with a growing body of evidence that personality not only shapes how individuals perceive emerging technologies but also influences their engagement, trust, and eventual adoption behaviors regarding AI-based solutions.

Schepman and Rodway's recent study reported that personality traits may influence attitudes toward AI [47]. Research has shown that a negative attitude toward AI can cause anxiety, which in turn can impact an individual's mental health [29]. Moreover, negative perceptions of technologically advanced systems, including AI, may exacerbate levels of depression and stress, thereby further compromising psychological wellbeing [48]. Recent literature indicates that individuals' attitudes toward AI differ based on their ideologies and subjective norms, which shape their worldview. Studies such as those conducted by Gillespie et al. and Park & Woo report that these factors significantly influence perceptions of AI [20, 49]. In this context, individuals experiencing greater distress due to negative AI attitudes may exhibit lower life satisfaction and diminished mental wellbeing, reflecting a critical link between technology perceptions and mental health outcomes [48]. Previous studies suggest that individuals' personality traits, psychological structure, culture, and upbringing environment significantly influence their attitude towards AI. Therefore, it is relevant to examine attitudes toward AI in different cultures. In the literature, it has been determined that research has been conducted on the relevant subject in Türkiye in recent years, but these studies are limited in number [40, 50]. More research, especially on determining attitudes towards AI, can provide a richer and deeper understanding of Turkish society's attitude towards AI.

Based on this requirement, this research was designed as two separate studies with complementary objectives. The study I aimed to examine the psychometric properties of AIAS-4 in a Turkish sample to determine whether construct validity was achieved. The study II, based on the validated scale, aimed to investigate the relationships of AI attitude with psychological structures including mental health and personality traits in a different sample. This two-stage study can allow for a more systematic and in-depth examination from both psychometric and practical perspectives and can provide a comprehensive understanding of attitudes towards AI. In line with the purpose of the research, the scale to be examined will be presented at a time when society is more familiar and accustomed to AI and will be economical due to its short, easy-to-apply, and evaluable nature. With this scale, the approach of Turkish society to AI and the possibility of adopting AI in Turkish society in the future can be discussed. In addition, it is believed that this study will lead to more scientific studies and applications in understanding and addressing the perception and attitude of Turkish people towards AI. In this context, the following hypotheses will be answered in the study:

H1 AIAS-4 is psychometrically valid and reliable.

H2 There is a negative significant relationship between AI attitude and depression, anxiety, and stress.

H3 There is a positive significant relationship between AI attitude and mental wellbeing and flourishing.

H4 AI attitude is positively associated with openness to experience, conscientiousness, extraversion, and agreeableness, and negatively associated with neuroticism.

H5 Psychological distress has a mediating role in the relationship between AI attitude and mental health.

Study I

Study I was aimed at adopting the AIAS-4 into Turkish. For that purpose, Confirmatory Factor Analysis (CFA), measurement invariance, and Item Response Theory (IRT) analyses will be carried out at this stage of the research. Additionally, whether AIAS-4 provides criterion-related validity will be revealed by looking at its relationship with life satisfaction and internet attitude. Lastly, Cronbach's alpha, McDonald's omega, Guttman's lambda, and Composite reliability values will be calculated for the reliability analysis of the scale.

Method

Participants and procedure

In Study I, participants were recruited using the convenience sampling method. Using online surveys, a total of 370 [female = 240 (65%), male = 130 (35%)] participants from different provinces of Türkiye were recruited for the study. The age of these participants, who represent various education levels, ranged from 18 to 54 years, and the mean age was calculated as 22.52 (SD = 5.19). The education level of the majority of the participants was at the university level (n = 264, 70%), and the majority stated that they were of middle socio-economic status (n = 290, 78%). Participant information is presented in Table 1.

The link to the online form was shared in various social media groups from the social media accounts of Turkish authors, and the participants who received the link were asked to fill out the research scales. Before starting the study, all participants gave informed consent and participated in the research voluntarily. No fee was paid to the participants. The online form is designed so that participants can withdraw at any time and submit if all questions are answered. In this online form, participants were first asked for descriptive data regarding gender, age, socio-economic status, and education level. This information was followed by the three scales in Study I.

Since participants were reached online, some precautions were implemented to obtain high-quality responses. The first of these precautions was to add questions to the online form to identify careless participants. For instance, "*Please check the option I agree with in this question*" or "*Confirm that you have read the questions carefully*". Another precaution was to follow the response time. Responses from participants with extremely short completion times were not included in the data set. Third, entries to the online form were checked to prevent multiple submissions from the same person. Lastly, and most importantly, the importance of providing sincere and honest responses to all participants before starting the research was conveyed.

Translation process

Within the scope of this research, the co-author of the study was contacted via e-mail, and permission was obtained to examine the psychometric properties of AIAS-4 in a Turkish sample. The translation of the scale items was carried out using the translation-back translation method. Firstly, three individuals with both psychology field and English language knowledge translated the scale items into Turkish. All translations made separately for each item were compared, and the most understandable and fully meaningful items were determined, and the Turkish form was created. Three different experts with doctoral degrees in the fields of measurement and evaluation, Turkish language, and psychology examined this Turkish form and presented its final version. Then, the Turkish form was translated back into English by another expert who had not seen the original English form and was proficient in English language knowledge. The resulting English text was compared with the original text in terms of semantic integrity and consistency. As a result of this comparison, the Turkish form was reviewed again, and the application form was created. Finally, this form was applied to 15 adults within the scope of the pilot study, and the comprehensibility of the items was tested. After the necessary corrections were made, the main application process was started.

Measures

Artificial intelligence attitude scale (AIAS-4) The AIAS-4 was developed by Grassini to measure attitudes toward the technology of AI, and in this present study, it is adapted to Turkish [30]. The scale has four items (e.g., "*I believe that AI will improve my work*") on a 10-point scale (*1 = strongly disagree; 10 = strongly agree*) between 4 and 40. There is no reverse item. The internal consistency of the scale reported in the original validation study was of α = 0.90 [30]. In this study, the Cronbach's alpha value was of α = 0.86.

The satisfaction with life scale (SWLS) The SWLS was developed by Diener et al. to measure individuals' level

Table 1 Participants demographics

Sample	Gender		Age			Socioeconomic Status			Education Level		
	Female	Male	M	SD	Range	Low	Medium	High	High School	University	Postgraduate
Study I	240(65)	130(35)	22.52	5.19	18–54	56(16)	290(78)	24(6)	53(15)	264(70)	53(15)
Study II	232(70)	99(30)	20.89	4.01	18–65	41(13)	276(83)	14(4)	44(14)	243(72)	44(14)

Note. Information on gender, socioeconomic, educational level status is presented as n(%)

of life satisfaction and adopted into Turkish by Durak et al. [51, 52]. The scale consists of five items (e.g., "*The conditions of my life are excellent*"), which are rated from 1 (*strongly disagree*) to 7 (strongly *agree*). Higher scores mean higher satisfaction with life. In this study, CFA results indicated that the fit indices of the scale were at a sufficient level (χ^2/df = 3.422; CFI = 0.983; GFI = 0.983; NFI = 0.976; SRMR = 0.027). The internal consistency values of the original English form and the Turkish form are 0.87 and 0.81. In this study, Cronbach's alpha value was calculated as 0.84.

Internet attitude scale (IAS) The IAS was developed by Karadeniz and Akpınar to evaluate individuals' attitudes toward the internet [53]. The scale has 17 items (e.g., "*I lose track of time when I'm online*") in three factors named as follows: "*enjoying the internet*", "*using the internet*", and "*believing the internet is useful*". The scale is five points, and 1 means "*strongly disagree*" and 5 means "*strongly agree*". In this study, the fit indices values of the scale are at an acceptable level: χ^2/df = 2.983; CFI = 0.907; GFI = 0.900; IFI = 0.908; SRMR = 0.078. Internal consistency values of the sub-dimensions were reported as 0.77, 0.71 and 0.63, respectively [53]. In this research, the internal consistency coefficient was found to be 0.89.

Data analysis

Firstly, CFA was carried out using maximum likelihood estimation to test the construct validity of the AIAS-4. This was chosen because the scale was rated on a 10-point Likert scale and consisted of four continuous items. In addition, the sample size was sufficiently large, and the data were normally distributed, making maximum likelihood estimation an appropriate choice [54]. Tucker-Lewis Index (TLI), Goodness of Fit Index (GFI), Comparative Fit Index (CFI), and Standardized Root Mean Square Residual (SRMR) were examined to determine if the data fits the model adequately. The acceptable values for TLI, GFI, and CFI are above 0.90 and for SRMR below 0.08 [55]. These analyses were utilized using the AMOS program [56]. After completing the CFA, IRT analyses were conducted to gain detailed insights into how participants interacted with each item. IRT is a statistical analysis used to learn more about how participants respond to questions on a scale [57]. In other words, IRT provides a framework for modeling the probability of endorsing each response category as a function of an underlying latent trait. This study used the Grade Response Model (GRM) in Stata, which is specifically designed for ordinal response categories and assumes that items measure a single underlying dimension of the construct. This model estimates item parameters such as discrimination and category thresholds using maximum likelihood estimation. The focus of the GRM on ordinal data is a significant advantage in this regard, as it is more compatible with the nature of our response format than the continuous variable assumptions often associated with CFA. By applying IRT (GRM), the relative contribution and function of each item across the latent trait can be better understood, thus providing complementary evidence to the factor structure identified in the CFA. Value ranges are categorized as follows: 0 (none), 0.01–0.34 (very low), 0.35–0.64 (low), 0.65–0.1.34 (moderate), 1.35–1.69 (high), 1.70 and above (very high), and + infinity (perfect). Following these analyses, a measurement invariance analysis was performed to determine whether the scale measured the same structure in males and females. For the criterion-related validity of AIAS-4, the relationship between life satisfaction and internet attitude was determined by correlation analysis. Then, reliability analyses of the scale were carried out. The reliability coefficients such as Cronbach's alpha (α), McDonald's omega (ω), Guttman's lambda ($\lambda 6$), and composite reliability were calculated. Lastly, AIAS-4 item-total correlation scores were calculated. These analyses were carried out with the SPSS statistical package program.

Ethics

Since this study involved human participants, ethical clearance was obtained from the institution to which one of the study authors is affiliated. The protocol for this study was approved by the Yıldız Technical University Human Research Ethics Committee (Report Number = 20240603076, Verification Code = 31d57). Additionally, this study was conducted in accordance with the ethical standards declared in the 1964 Declaration of Helsinki and subsequent updates. Professional ethical rules were followed throughout the research.

Results

CFA indicated that the fit metrics fell within acceptable thresholds, [(χ^2/df = 4.06; CFI = 0.991; GFI = 0.989; AGFI = 0.945; NFI = 0.988; TLI = 0.973; IFI = 0.991; SRMR = 0.018)]. It was observed that the factor loadings for the Turkish-AIAS-4 were significantly distributed, with values ranging between 0.755 and 0.853. Moreover, the item analysis for the Turkish-AIAS-4 is presented in Table 2.

The investigation into the factor structures of Turkish-AIAS-4 through CFA was extended to evaluate the scale's ability to uniformly measure distinct constructs across genders. To this end, CFA was applied to datasets segregated by gender, examining the scale's performance separately for female and male subjects. Analysis results demonstrated a statistically significant level of agreement for participants of all genders in the Turkish adaptation of the AIAS-4. Furthermore, while the fit indices for all levels of invariance remained within acceptable ranges,

Table 2 Factor Loadings, descriptive statistics and Item-Total correlations

Item	Factor Loadings	Mean	SD	Skewness	Kurtosis	Item Total Correlations
1. I believe that AI will improve my life. *Yapay zekanın hayatımı iyileştireceğine inanıyorum.*	0.853	6.15	2.20	-0.190	-0.482	0.767
2. I believe that AI will improve my work. *Yapay zekanın işimi iyileştireceğine inanıyorum.*	0.771	6.06	2.39	-0.279	-0.593	0.697
3. I think I will use AI technology in the future. *Yapay zeka teknolojisini gelecekte kullanacağımı düşünüyorum.*	0.755	7.71	2.01	-0.874	0.0522	0.697
4. I think AI technology is positive for humanity. *Yapay zeka teknolojisinin insanlık için olumlu olduğunu düşünüyorum.*	0.758	6.22	2.11	-0.155	-0.244	0.693

Note. N = 370

Table 3 Fit indices of gender invariance

Invariance	χ^2	df		GFI	NFI	TLI	ΔTLI	CFI	ΔCFI
Females	3.34	2	1.67	0.993	0.990	0.988	-	0.996	-
Males	8.63	2	4.31	0.967	0.968	0.924	-	0.975	-
Configural invariance	11.97	4	2.99	0.984	0.981	0.961	-	0.987	-
Metric invariance	23.83	7	3.40	0.966	0.962	0.952	0.009	0.972	0.015
Scalar invariance	27.87	10	2.78	-	0.955	0.965	0.013	0.971	0.001

Table 4 IRT results for the Turkish-AIAS-4

Item	a coefficient	SE	Confidence interval	z	$p>\lvert z\rvert$
Item 1	3.80	0.41	2.98–4.61	9.12	0.001
Item 2	2.60	0.22	2.15–3.05	11.34	0.001
Item 3	2.23	0.21	1.81–2.63	10.64	0.001
Item 4	2.22	0.19	1.83–2.61	11.34	0.001

the difference in ΔCFI between configural and metric invariance was higher than anticipated. However, the transition from metric to scalar invariance demonstrated acceptability (ΔCFI = 0.001). These results indicate that, within the Turkish cultural framework, the AIAS-4 can be deemed applicable across different genders, despite the unexpected elevation in the ΔCFI value between the configural and metric stages (see Table 3).

IRT stands as a fundamental and widely adopted framework for the analysis and modeling of item responses, offering solutions to a variety of measurement challenges [58]. Unlike traditional methods that aggregate item scores, IRT focuses on the assessment of individual items [59]. For scales based on Likert responses, IRT facilitates a progressive understanding of the options provided to respondents [60]. Given the Likert format of the Turkish-AIAS-4, it is posited that an IRT approach will more precisely differentiate between response patterns. Baker posits that a α value exceeding 1 signifies substantial discriminative power [57]. In the conducted IRT evaluation, the α values for all Turkish-AIAS-4 items were observed to surpass this threshold, indicating high discrimination (see Table 4).

The assessment of criterion-related validity involved calculating Pearson's correlations between the Turkish-AIAS-4 and Internet Attitude Scale and Satisfaction with Life Scale (Table 5). In this analysis, the strength of the correlation results was interpreted by adhering to the threshold values determined by Evans [61]. These threshold values are very weak for correlations less than 0.20, weak for correlations between 0.20 and 0.39, moderate for correlations between 0.40 and 0.59, strong for correlations between 0.60 and 0.79, and very strong for correlations greater than 0.80. The Turkish-AIAS-4 has shown significant weak positive correlations with the subdimensions of enjoying the internet ($r = 0.349$, $p < 0.001$), using the internet ($r = 0.357$, $p < 0.001$), and believing the internet is useful ($r = 0.320$, $p < 0.001$) within the Internet Attitude Scale. In addition, there was a significant, very weak positive correlation observed between the Turkish-AIAS-4 Scale and life satisfaction ($r = 0.133$, $p < 0.01$).

Reliability analyses for the Turkish-AIAS-4, including Cronbach's alpha, McDonald's omega, Guttman's lambda, and Composite reliability, were performed. The outcomes of these analyses are documented in Table 6. These findings prove that the scale is a reliable tool for measurement.

Study II

Following the analyses of the psychometric properties of the AIAS-4, Study II aimed to investigate the relationships between the AIAS-4 and the Big Five personality traits, psychological distress (depression, anxiety, and stress), flourishing, and mental wellbeing, and to test these variables in a hypothetical model. The Big Five personality traits are an approach that emphasizes that there

Table 5 Descriptive statistics and correlations with Turkish AIAS-4

Variables	Mean	SD	Correlation with AIAS-4	
			r	*p*
Study I				
AIAS-4	26.14	7.35	-	-
Internet Attitude Scale	63.72	8.77	0.409	< 0.001
Enjoying the internet	22.36	3.79	0.349	< 0.001
Using the internet	21.51	3.70	0.357	< 0.001
Believing the internet is useful	19.85	2.94	0.320	< 0.001
Satisfaction with Life Scale	21.24	5.94	0.133	< 0.010
Study II				
AIAS-4	25.42	6.504	-	-
Depression	6.67	5.191	-0.194	< 0.001
Anxiety	7.05	5.015	-0.233	< 0.001
Stress	8.22	5.137	-0.176	< 0.001
Big five personality traits				
Openness to experience	7.35	1.689	0.122	0.026
Conscientiousness	6.93	1.617	0.124	0.024
Extraversion	6.60	2.108	0.196	< 0.001
Agreeableness	7.80	1.468	0.004	0.943
Neuroticism	6.15	1.788	-0.164	0.003
Mental wellbeing	25.02	4.618	0.322	< 0.001
Flourishing	39.99	7.835	0.349	< 0.001

Table 6 Reliability results of Turkish-AIAS-4

	Study I ($N = 370$)	Study II ($N = 331$)
Cronbach's alpha	0.863	0.855
McDonald's omega	0.866	0.856
Guttman's lambda	0.831	0.824
Composite reliability	0.865	0.858

are five fundamental characteristics that distinguish individuals from each other [62]. These five core traits are openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism. Yanto et al. state that this theoretical approach is used to understand individuals' reactions to any phenomenon, event, or situation [63]. At this stage, first the relationship between the variables will be revealed, and then an analysis will be made using structural equation modeling.

Method

Participants and procedure

As in Study I, participants were recruited using a convenience sampling method. Similarly, data was collected using an online form. In Study II, a total of 331 participants, 232 female (70%) and 99 (30%) male, were reached (M_{age} = 20.89 years, age range = 18–65 years, $SD = 4.01$). The education level of the majority of the volunteer participants at this stage is university level ($n = 243$, 72%). When socio-economic status was examined, the majority reported that it was at a medium level ($n = 276$, 83%). Participant information is given in Table 1.

In the second phase of the research, data was collected by sharing the online form link from social media accounts, in the same way as in Study I. The online form was designed to be completed only if all questions are answered, therefore avoiding missing data. Additionally, the form was designed so that participants could withdraw from the study at any time. Participants gave informed consent before participating in the study and declared that they participated voluntarily. No fee was paid to the participants. As in Study I, in this form, participants were first asked for descriptive data regarding age, gender, education level, and socio-economic status. Then, the participants filled out the five proposed scales.

Measures

The big five inventory (BFI-10) The BFI-10 was developed by Rammstedt and John and adopted by Türküm et al. to measure the Big Five dimensions of personality, which are extraversion, openness to experience, agreeableness, neuroticism, and conscientiousness [64, 65]. The scale has 10 items (e.g., "*I see myself as someone who is outgoing, sociable*"), which are rated on five points from 1 (*strongly disagree*) to 5 (*strongly agree*). The internal consistency of the original scale's sub-dimensions is 0.68, 0.73, 0.71, 0.73, and 0.71.

Depression anxiety stress scale (DASS-21) The DASS-21 was developed by Henry and Crawford and adopted into Turkish by Yilmaz et al. [66, 67]. This scale, which aims to measure psychological distress, consists of 21 items (e.g., "*I found it difficult to relax*"). The scale has three factors, which are "*depression*", "*anxiety*", and "*stress*". Every factor has seven items, and on four points from 0 (*did not apply to me at all*) to 3 (*applied to me very much or most of the time*). High scores indicate high levels of psychological distress. According to the CFA results of the scale, the fit index values are at an acceptable level in this study (χ^2/df = 2.837; CFI = 0.904; IFI = 0.905; RMSEA = 0.075; SRMR = 0.058. When the reliability coefficient was examined, it was reported that the sub-dimensions of the scale varied between 0.76 and 0.82. In this study, Cronbach's alpha coefficient was calculated as 0.87 for the depression sub-dimension, 0.83 for the anxiety sub-dimension, and 0.87 for the stress sub-dimension.

Flourishing scale (FS) The FS was developed by Diener et al. and adopted into Turkish by Telef [68, 69]. The scale, consisting of eight items (e.g., *"My social relationships are supportive and satisfying"*), is scored on a 7-point scale (*1 = strongly disagree, 7 = strongly agree*). Scores on the scale range from 8 to 56. Possible high scores indicate that the participants have high wellbeing. In this study, CFA results indicated that the fit indices of the scale were at a sufficient level (χ^2/df = 3.939; CFI = 0.949; GFI = 0.941; NFI = 0.933; SRMR = 0.043). The internal consistency value of the scale was reported to be 0.80. In this research, Cronbach's alpha value is 0.89.

The short Warwick-Edinburgh mental well-being scale short form (SWEMWBS The SWEMWBS was developed by Tennant et al. to measure wellbeing [70]. The short form of the scale was adapted into Turkish by Demirtaş and Baytemir [71]. The scale consists of seven items (e.g., "*I feel close to other people around me*") and is scored on a 5-point scale (*1 = never, 5 = always*). Scores range from 7 to 35 on the scale, and higher scores mean that the level of wellbeing increases. In this study, CFA findings revealed that the scale had acceptable fit indicators (χ^2/df = 3.535; CFI = 0.957; GFI = 0.963; NFI = 0.941; SRMR = 0.045). The Cronbach's alpha value of the scale was announced as 0.86. In this study, Cronbach's alpha internal consistency value was calculated as 0.82.

Data analysis

In Study II, descriptive findings regarding the variables of the study were first examined with the SPSS statistical package program. Then, correlation analysis was performed to determine the relationships between AIAS-4 and the Big Five personality traits (extraversion, openness to experience, agreeableness, neuroticism, and conscientiousness), depression, anxiety, and stress, mental wellbeing, and flourishing. After the relationships between the variables were revealed, structural equation modeling was used to test the hypothetical model, and the analyses were carried out with the AMOS statistical program. For mediation analysis, the measurement model was examined first and then the structural model [72]. Fit index values were examined in both models, and the threshold values specified by Hoyle and Panter were taken into account (CFI, GFI, TLI, and IFI > 0.90; SRMR and RMSEA < 0.08) [55].

Results

The Turkish-AIAS-4 exhibited significant, very weak negative correlations with depression (r = -0.194, $p < 0.001$) and stress (r = -0.176, $p < 0.001$) and significant, weak negative correlations with anxiety (r = -0.233, $p < 0.001$), suggesting that higher AIAS-4 scores are associated with lower levels of these negative emotional states. Conversely, very weak positive correlations were observed with several dimensions of the Big Five personality traits: openness to experience ($r = 0.122$, $p = 0.026$), conscientiousness ($r = 0.124$, $p = 0.024$), and extraversion ($r = 0.196$, $p < 0.001$). Agreeableness showed no significant correlation ($r = 0.004$, $p = 0.943$), while neuroticism was very weakly negatively correlated (r = -0.164, $p = 0.003$) with AIAS-4 scores. Additionally, the AIAS-4 was weakly positively associated with mental wellbeing ($r = 0.322$, $p < 0.001$) and flourishing ($r = 0.349$, $p < 0.001$), indicating that higher scores on the AIAS-4 are linked to better psychological flourishing and wellbeing (see Table 5). The strength of all these correlation results was interpreted in the context of Evans' threshold value [61].

The investigation into the mediating role of psychological distress in the relationship between AI attitude and mental health, while accounting for gender, utilized a structural equation modeling approach (see Fig. 1). Initially, a measurement model incorporating three latent constructs (AI attitude, psychological distress, and mental health) alongside nine observed variables was analyzed. The measurement model demonstrated satisfactory fit indices: χ^2 (24, N = 331) = 66.87, $p < 0.001$; χ^2/df = 2.78; GFI = 0.956; CFI = 0.970; IFI = 0.970; RMSEA = 0.074. All standardized factor loadings within this model were significant, ranging from 0.071 to 0.950 ($ps < 0.001$). Following the measurement model, the structural model was examined. According to the goodness-of-fit indices, the hypothesized mediation model demonstrated an acceptable fit: χ^2 (32, N = 331) = 157.37, $p < 0.001$; χ^2/df = 4.91; GFI = 0.915; CFI = 0.916; IFI = 0.917; RMSEA = 0.100. The model revealed a significant negative direct effect of AI attitude on psychological distress (β = -0.263, $p < 0.001$) and a significant negative direct effect of psychological distress on mental health (β = -0.444, $p < 0.001$). The statistical analysis further established that the indirect role was significant, as evidenced by a bootstrap estimate of 0.117 with a 95% confidence

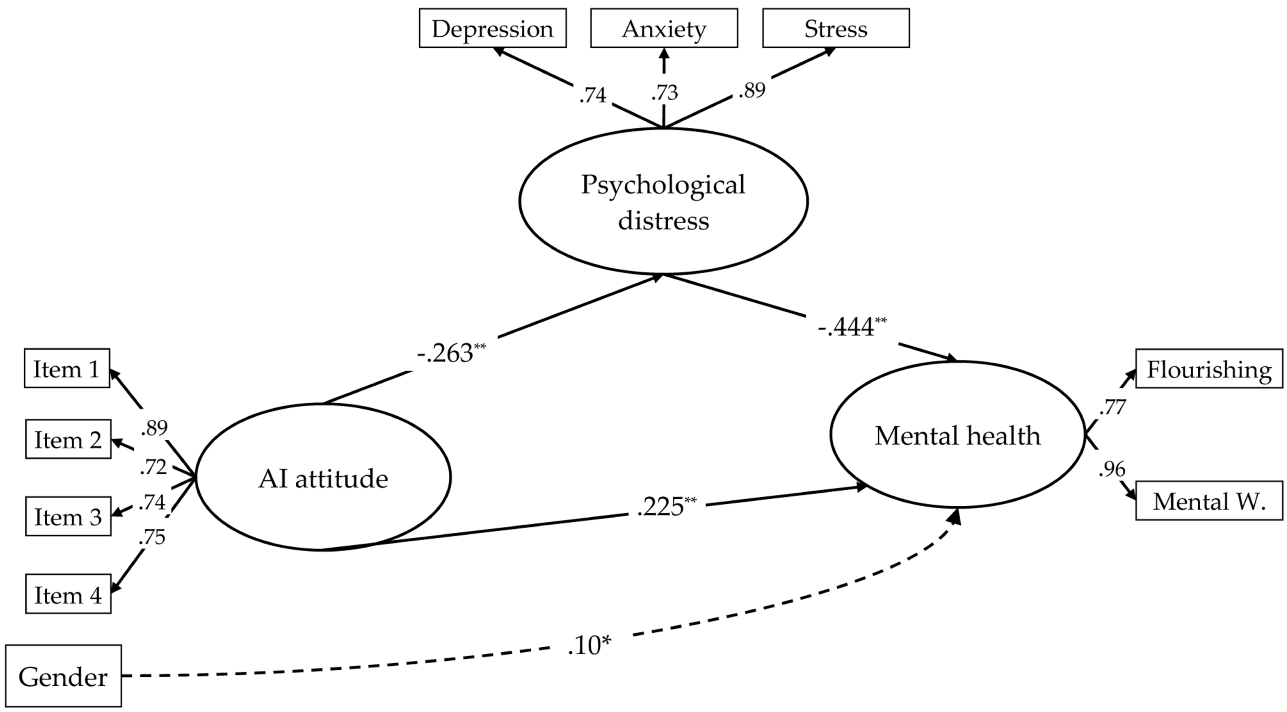

Fig. 1 Structural equation modeling for the mediation model. Note: * p <0.05, ** p<0.001

interval ranging from 0.054 to 0.199. Based on these findings, it is posited that the mediating effect of psychological distress play a significant role in the relationship between AI attitude and mental health.

Discussion

The rapid advancement of technology influences human life in many ways. In particular, the development of AI reveals innovations that transform human life. These innovations are also reflected in human mental health and make psychological health more important. In this context, it is important to examine people the attitude toward AI. New, useful, and efficient measurement tools are needed to examine attitudes towards AI. Meeting this need may enable people to determine positive and negative approaches to AI or to reveal the benefits and risks of AI more easily [26, 28]. That's why this study aims to evaluate the psychometric properties of AIAS-4 in Turkish society and examine the relationship between AI attitudes and a number of variables. The AIAS-4 was developed by Grassini, the items were derived from theories and empirical research on AI, technology acceptance, and risk perception [30, 73]. Therefore, this scale contains important statements about attitudes towards AI. In this context, this research was carried out as two separate studies. The discussion on the findings obtained from two separate studies is given below, and the research hypotheses are answered, respectively.

The finding obtained within the scope of Study I is that AIAS-4 is a psychometrically valid and reliable measurement tool. According to the CFA, the one-factor structure of AIAS-4 was supported for the Turkish adaptation of the scale, in line with the original validation study of the AIAS-4 in an English-speaking sample [30]. All fit index values are between the values stated in the literature [55]. Additionally, scale factor loadings were found to be at an acceptable level [74]. Apart from this, as a result of the gender-based measurement invariance analysis, AIAS-4 showed statistically significant fit for both male and female participants. This finding proves that AIAS-4 is applicable to different genders in Turkish society. Another finding obtained in Study I is related to IRT. IRT results indicate that all of the scale items were classified at a very high level according to Baker's standards [57]. Smalldon and Moffat explain the probability of distinguishing between two randomly obtained samples from participants as discriminatory power [75]. In this study, all items in AIAS-4 have high discrimination power. This finding means that the responses to all items are distinctive.

Within the scope of criterion-related validity, AIAS-4 was found to have a significant relationship with both internet attitude and life satisfaction. There are other research results that are similar to this finding [29, 46]. In these studies, attitudes towards AI were associated with individuals' wellbeing and technology adoption. Apart from this, other studies also demonstrate that attitudes towards AI are closely related to internet and technology usage habits. For instance, in the study by West and Allen, it was reported that people who adopted a positive attitude towards the internet and technology also approached AI positively [76]. This is due to the fact that these technologies offer fast access to information, social interaction and innovative solutions to problems. In another study, individuals who stay away from technology and focus on the risks of the internet may act more cautiously, thinking that AI comes with similar concerns [14]. Based on all these, this relationship between AI, internet and technology attitudes indicates that these technologies will develop together in the future and may deeply influence individuals' lives.

Lastly, in Study I, the reliability analysis of AIAS-4 was determined by making different measurements. Cronbach's alpha, McDonald's omega, Guttman's lambda, and Composite reliability values of the scale are above the reliability threshold stated in the literature [77, 78]. This finding reveals that AIAS-4 is a reliable measurement tool. As a result, it can be said that the one-factor structure of this scale is confirmed, measurement invariance is ensured, the response discrimination level is high, criterion-related validity is ensured, and the reliability level is at a sufficient level. Moreover, this scale has significant practicality in terms of its applicability to large samples.

In Study II, AI attitude was determined to be associated with depression, anxiety, and stress, as well as mental health variables such as mental wellbeing and flourishing. Moreover, openness to experience, conscientiousness, extraversion, and neuroticism are significantly related to an AI attitude. There are research results in the literature that are similar to these findings. For instance, in the study conducted by Hartwig, it was reported that people who have a positive attitude towards AI and think that AI increases efficiency in life have a higher quality of life [12]. Similarly, in Shabbir and Anwer's study, it was stated that AI attitude is related to life satisfaction [13]. In Gabriel's study on AI, it was reported that using AI improves individuals and increases their level of flourishing [79]. All these research findings prove that a positive attitude towards AI is related to wellbeing. Therewithal, there are also research results in the literature revealing the relationship between AI attitude and anxiety and stress. However, no findings have been found examining the relationship between AI attitude and depression. Studies demonstrate that people's attitudes towards AI are negative, especially due to employment problems and discriminatory and prejudiced use [14, 16, 21]. Kumar and Choudhury's recent study reported that unemployment was triggered by the development of AI, and therefore people became more anxious [15]. Similarly, Circiumaru's recent study reported that overcoming personal privacy with AI creates anxiety [23]. In the research conducted by Tschang and Almirall, it was stated that a negative attitude towards AI is associated with anxiety and stress [19]. All these studies prove that individuals experience more anxiety and stress if their attitude towards AI is negative. In this context, if people are made aware of the benefits and risks of AI by explaining them correctly, they may face less anxiety and stress.

Furthermore, our study shown an association between AI attitude and some personality traits. Many studies in the literature have examined the relationship between personality traits and attitudes towards AI [45, 47]. In these studies, it was emphasized that the big five personality traits may have an influence on attitudes towards AI. In this research, it was determined that there is a significant relationship between AI attitude and extraversion. This finding may be explained by the fact that individuals with high levels of extraversion accept technology more easily. Barnett et al.'s study also supports this prediction [80]. However, Schepman and Rodway reported a negative relationship between extraversion and attitude towards AI [47]. One reason for this contradiction may be cultural differences. Considering the unique characteristics of each culture, it is possible to have different personality traits. In this case, different results may arise regarding the attitude towards AI. The use of different personality scales may also be effective in revealing contradictory findings. Apart from this, it has been determined that AI attitude is related to conscientiousness. This finding may be explained in the literature by the fact that individuals with high levels of conscientiousness are better able to notice the negative effects of technology use [81]. This indicates that it is normal that it may be related to the attitude towards AI. Another finding is that AI attitude is related to openness to experience. This finding can be explained by the fact that people who are open to experience follow new technological developments more and actively use AI. Park and Woo's research supports this opinion [49]. The last finding is that there is a negative relationship between neuroticism and AI attitudes. This finding shows that a high level of neuroticism may affect the way people perceive technology [82]. In other words, the perception and use of technology may differ among people experiencing emotional instability [80]. The research result that parallels this finding belongs to Gallego and Pardos-Prado [45]. The aforementioned research also mentions a significant relationship between neuroticism and AI attitudes.

The last finding of the study relates to the third research hypothesis. As a result of the analyses conducted in Study II, it was found that psychological distress had a mediating role in the relationship between AI attitude and mental health. In this model, psychological distress includes depression, anxiety, and stress; mental health consists of mental wellbeing and flourishing variables. According to the tested model, individuals' attitudes towards AI predict mental health via psychological distress. For this reason, ensuring that the attitude towards AI is positive can reduce psychological distress and thus increase mental health. Recent research by Montag et al. supports this opinion [83]. The study in question addresses the relationship between AI and mental health, and it is stated that prioritizing the benefits of AI may strengthen mental health. In this context, further emphasizing the aspects of AI that make human life easier and explaining that its risks can be controlled, and anxiety-provoking situations can be prevented may increase the positive attitude towards AI. Thus, individuals' psychological distress can be reduced, and their level of wellbeing may increase.

Implications

Based on these research findings, significant implications can be drawn. Examining the psychometric properties of AIAS-4 in detail in the Turkish sample has become more important as AI enters our lives more and more every day. Especially in recent times, people have started to use AI more and have been influenced by AI in all areas of life, making it necessary to adapt this measurement tool. Since this scale has been examined with both CFA and IRT and many different reliability analyses have been conducted, this measurement tool can be used frequently. Apart from this, positively supporting the attitude towards AI can serve as a protective buffer against negativities such as depression, anxiety, and stress. In addition, it can positively impact mental health as it will make individuals' lives easier. Therefore, preventive and interventional studies should be designed by researchers for every age group to increase the positive attitude towards AI. These studies may also benefit practitioners in the field of mental health. In addition, positive attitudes can be gained by preparing informative content or providing training regarding AI technology. Apart from this, the opportunities that AI will offer in different fields should be explained to the public for potential AI users. Policymakers should reassure the public that the security vulnerabilities of AI technology can be eliminated.

Limitations and future research

The findings of this study should be interpreted taking into account some limitations. The first limitation is that research data were collected using self-report scales at both stages [84]. Self-report scales may cause participants to make social desirability errors. Therefore, data collection methods may be diversified in future studies. The second limitation of the research is that the study has a cross-sectional design. This makes it difficult to interpret the causal link between variables. In future studies, the relationships between these variables can be examined using different research designs (e.g., longitudinal or experimental). Thus, the social perception of AI can be better understood. The third limitation is that the study was conducted in a non-clinical population. In future research, studying the scale with a clinical sample may also provide important findings. The fourth limitation is that the findings obtained in this study may not be generalizable to different cultures and demographic characteristics [85]. Therefore, it may be recommended to conduct studies to validate the scale in groups with different cultures and demographic characteristics. So, the external validity of the scale will be increased. It should not be forgotten that cultural dimensions such as privacy or spirituality may play a role in the attitude towards AI in these studies. Therefore, in future studies, analyses can be repeated by including new additional items in this scale to further enrich the AI attitude measurement.

Conclusion

The concept of attitude towards AI has been examined in two separate studies in Turkish culture. The findings obtained in the first study revealed that Turkish-AIAS-4 is a valid and reliable measurement tool. In the second study, it was determined that positively supporting the attitude towards AI may reduce psychological distress in individuals and therefore strengthen mental health. This study will contribute to the literature as attitudes towards AI are addressed in a limited number of studies. Future experimental and longitudinal studies may provide a better understanding of this concept and its relationship with other variables.

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S.A.S., S.O., F.B.Y., and S.G. contributed to writing this paper. S.A.S. conducted and supervised the research. All authors reviewed and approved the manuscript.

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Data availability
The dataset that allowed us to obtain the findings of this research will be provided upon request. For this, the second author of the study should be contacted. The e-mail address of the said author is sinan.okur@msu.edu.tr.

Declarations

Ethics approval and consent to participate
The protocol for this study was approved by the Yıldız Technical University Human Research Ethics Committee (Report Number = 20240603076, Verification Code = 31d57). The study was performed in accordance with the ethical standards laid down in the 1964 Declaration of Helsinki and its following updates. Informed consent was obtained from all the individual participants that were included in the study.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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