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A validity and reliability study of the artificial intelligence attitude scale (AIAS-4) and its relationship with social media addiction and eating behaviors in Turkish adults

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Abstract

Background In recent years, there has been a rapid increase in the use of the internet and social media. Billions of people worldwide use social media and spend an average of 2.2 h a day on these platforms. At the same time, artificial intelligence (AI) applications have become widespread in many fields, such as health, education, and finance. While AI has the potential to monitor eating behaviors and provide personalized health support, excessive use of social media and AI can lead to negative effects. These include addiction and reduced quality of life. It is important to examine the attitude toward AI and its relationship with social media addiction, eating behavior, and life satisfaction. Research on the connection between AI attitudes and eating habits is lacking, which emphasizes the necessity of validating AIAS-4 in Turkish in order to ensure its efficacy in this context. The first stage of the study aimed to adapt Grassini's (2023) Artificial Intelligence Attitude Scale (AIAS-4) into Turkish and assess its validity and reliability. In the second stage, it was aimed to examine the relationship between artificial intelligence attitude and social media addiction, eating behavior, and life satisfaction.

Methods This study cross-sectional and methodological study was conducted in two stages in Türkiye. 172 adult individuals underwent a validity and reliability study in the first stage (43% of them were men and 57% were women), which involved adapting the AIAS-4 into Turkish. In the second stage, the relationships between artificial intelligence attitude, social media addiction, eating behavior, and life satisfaction of 510 individuals were evaluated with an average age of 24.88 ± 7.05 years (30.8% male, 69.2% female). Using the snowball sampling technique, the survey was carried out on adults by reaching out to staff and their families from both universities (Gazi University and Tokat Gaziosmanpaşa University) as well as students and their relatives. A face-to-face survey approach (delivered by an interviewer) was used for the study. In this study, the Social Media Addiction Scale-Adult Form(SMAS-AF) was used to assess social media addiction, the Scale of Effects of Social Media on Eating Behavior (SESMEB) was used to measure the impact of social media on eating behavior, the Contentment with Life Assessment Scale was used to evaluate life satisfaction, and the Eating Disorder Examination Questionnaire (EDE-Q total) was used to assess eating disorder

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symptoms. Pearson Correlation and Spearman Correlation according to normality and Linear regression analysis were used to analyse variables.

Results AIAS-4 was a valid and reliable instrument in this study conducted in Türkiye (Cronbach's alpha = 0.90 and McDonald's omega = 0.89). Individuals spend an average of 3.7 ± 1.99 h per day on social media. All participants used WhatsApp, while 89.8% used Instagram. A negative correlation was found between AIAS and EDE-Q total, (r=-0.119 $p < 0.05$). BMI correlated positively with EDE-Q total ($r = 0.391$, $p < 0.01$). Higher AIAS scores were associated with increased time spent on social media ($r = 0.129$, $p < 0.001$). Conversely, higher AIAS scores were associated with lower EDE-Q total scores (r= -0.119, $p < 0.001$). SESMEB correlated positively with EDE-Q total ($r = 0.169$; $p < 0.001$). The model showed that BMI (β = 0.311; $p < 0.001$), AIAS (β =-0.157, $p = 0.005$), SMAS-AF (β = 0.036; $p = 0.002$) and SESMEB (β = 0.022; $p = 0.038$) affected EDE-Q total ($p < 0.001$ $R^2 = 0.198$).

Conclusion This study revealed that the Artificial Intelligence Attitude Scale (AIAS) is valid and reliable for Turkish adults. The results show that BMI, social media addiction have positive, and AI attitude has negative impact on eating behaviors. These findings emphasize the importance of multidisciplinary approaches and awareness programs in the prevention and management of eating disorders.

Keywords Artificial intelligence attitude, Eating disorder, Social media addiction, BMI, Eating behavior

Introduction

The widespread use of the internet in recent years has become a part of life, from shopping to information sharing, from the frequent use of search engines to the use of social media and artificial intelligence [1]. Artificial Intelligence (AI) applications, which have become as widespread in recent years as the use of social media, have started to be used in many areas of modern society, including health, transportation, finance, and education [2]. AI often means a computerized system (hardware or software) capable of conducting physical tasks and cognitive functions, resolving numerous issues, or making decisions autonomously, without direct human guidance [3]. These technologies have undoubtedly made our lives easier and more efficient by bringing convenience, connectivity, and speed. A quick tap on a screen enables us to effortlessly access information, engage with others, and perform many tasks. Social media platforms have transformed our interactions and information sharing, enhancing global connectivity and fostering societal development [1].

In addition, AI tools have automated many processes, facilitated workflow in many sectors such as health and education [4, 5], and increased productivity [1]. It is thought to contribute positively to improving eating behavior, quality of life, and health when AI is used consciously. For instance, utilizing AI, clinicians and researchers can assess individuals' progress across various mental health (triggering experiences mood, eating disorder symptoms) and physical (sleep, heart rate, activity level) and) fields through smartphones, enabling real-time tracking of each individual's risk for eating disorders and utilizing personal data to enhance health outcomes [6]. Evaluations on artificial intelligence and eating behavior have increased in the last decade. In addition to clinical applications, AI can help tackle challenges commonly encountered in Eating Disorder (ED) research, which will promote the improvement of overall knowledge acquisition and dissemination [7]. Individuals with a more favorable perspective on artificial intelligence (AI) may be more inclined to utilize AI-based health interventions, including personalized diet plans and monitoring systems. These tools offer evidence-based guidance, which may enhance dietary choices and foster healthier eating behaviors [8]. AI attitude with usage of AI may help individuals ecognizing and addressing symptoms of eating disorders, providing early intervention, and encouraging healthier eating habits [7]. If accurate and generalizable AI applications can be established in the field of eating disorders in the coming years, it is thought that this may improve the way eating disorders are identified, prevented, and treated [9].

Although it is thought that the use of social media and AI is beneficial for the desired information, product, socialization, and scientific development, it is reported that excessive and unconscious use may cause addiction and may also negatively affect the quality of life [6, 10]. Social media addiction can be seen as a form of internet addiction in which individuals exhibit the urge to overuse social media. Individuals with social media addiction are usually overly interested in social media and are driven by an uncontrollable urge to log on and use social media [11]. Social media addiction may promote eating behavior disorders, disturbances in body perception, quality of life, and sedentary life in individuals [10, 12]. Social pressures about body weight, body image, facial features, fashion, self-esteem, and socio-economic comparisons on social media platforms can adversely impact wellness [10, 13]. Although social media provides positive contributions in areas such as communication and information sharing [14], the presence of inaccurate nutrition information not based on evidence on social media platforms may be associated with individuals adopting incorrect eating behaviors or nutrition models [15]. Similarly, although the positive effects of AI applications are considered [6, 7, 9], it has been reported that information on nutrition in artificial intelligence applications needs to be improved [16]. Nutrition recommendations especially for individuals with chronic diseases (such as chronic kidney failure) may be misleading [17]. Advanced applications that will enable individual assessment in the future may contribute to this context.

Prolonged social media engagement can lead to low self esteem [18]. It may contribute to feelings of loneliness, anxiety, or depression, which directly impact life satisfaction. The constant stream of idealized content and the pursuit of social validation may reduce overall life satisfaction [19].

Positive AI perceptions may help people take advantage of its useful uses, including tailored health monitoring or enhanced wellness initiatives, which can enhance their quality of life and general well-being [20]. Because AI promotes healthy lifestyles such as physical activity and healthy diet, smoking cessation [21], it may encourage healthier habits, detect health problems early, and increase life satisfaction.

Social media use may affect individuals' perceptions of artificial intelligence technology. The number of studies examining this relationship is limited [22]. Individuals with positive attitudes towards artificial intelligence (AI) may be able to mitigate the negative effects of social media on their eating behaviors by utilizing AI-based health tools. Conversely, individuals with negative attitudes towards AI may rely on social media for dietary advice, which could potentially exacerbate unhealthy eating patterns.

AI tools may have the potential to counteract the detrimental effects of social media by providing more accurate, personalized, and health-oriented information [23]. This information may influence individuals to make informed dietary choices, even in the face of social media pressures.

Nowadays, there are scales in the literature evaluating the attitude toward artificial intelligence, and the Turkish validity and reliability of these scales have been conducted [24–26]. While one of these scales determines not only attitude but also knowledge, awareness, attitude, and anxiety levels towards artificial intelligence [26], the other scale includes questions about general attitude, including 20 items [24, 25]. However, the scale developed by Grassini [27] in 2023 includes 4 items. The AIAS-4 scale offers a concise yet effective measure of individuals' attitudes toward artificial intelligence, making it particularly useful for studies requiring efficient data collection.

The other scales, which have been validated and reliable in Turkish, have different contexts in terms of practicality and in terms of measuring the general attitude towards artificial intelligence. For example, GAIAS will be both time-consuming and impractical in studies with large samples. In addition to reflecting the general attitude, it includes emotions such as fear and anxiety about artificial intelligence [24, 25]. Validation a reliable and a practical scale for assessing AI attitudes would facilitate research and practice in comprehending and addressing public perceptions of artificial intelligence. This scale differs from other scales due to its short and practical features. It is thought that a scale that will quickly evaluate the attitude towards the use of artificial intelligence, which has been popular recently, will contribute to the literature.

Accordingly, this study primarily aims to establish the Turkish validity and reliability of the AI attitude scale. Secondarily, it aimed to investigate the relationship between artificial intelligence attitude and social media addiction, eating behavior, and life satisfaction. This study consists of two-step processes. For the 1st step of the study Turkish validity and reliability of AIAS-4 were conducted. For the 2nd step of the study, the relationship between AI attitude and social media addiction, eating behavior, and life satisfaction was examined.

Methods

Participants

This study consists of 2 phases (Fig. 1). In step 1 of the study, the adaptation of AIAS-4 into Turkish and its validity and reliability were conducted with 172 adult individuals. Validity and reliability studies have reported that the sample size should be 5–10 times the number of scale items [28]. The scale used in this study consists of 4 items; therefore, we aimed to reach at least 20–40 individuals for conducting the study. A total of 172 adults aged between 18 and 64 years, males (43%) and females (57%), participated in this study. In step 2 of the study, the relationship between artificial intelligence attitude, social media addiction, dietary habits and life satisfaction of 510 different individuals was evaluated. Based on the efect size$|\rho|=0.20$, $\alpha = 0.05$, $1\text{-}\beta = 0.80$, the sample size was calculated 312. Considering the data loss, the sample was increased by 20% and the study was required 377 individuals [29].

For the first stage of the study, data collection took place between February and March 2024, and for the second stage, it was conducted between April and June 2024. This cross-sectional study was conducted with volunteer individuals between the ages of 18–64 using the snowball sampling method. For the sample of the study, announcements were made on social media (Facebook, Twitter and Instagram) and recruitment of participants was provided. The study was conducted on adult individuals by reaching students and their relatives, as well as employees and

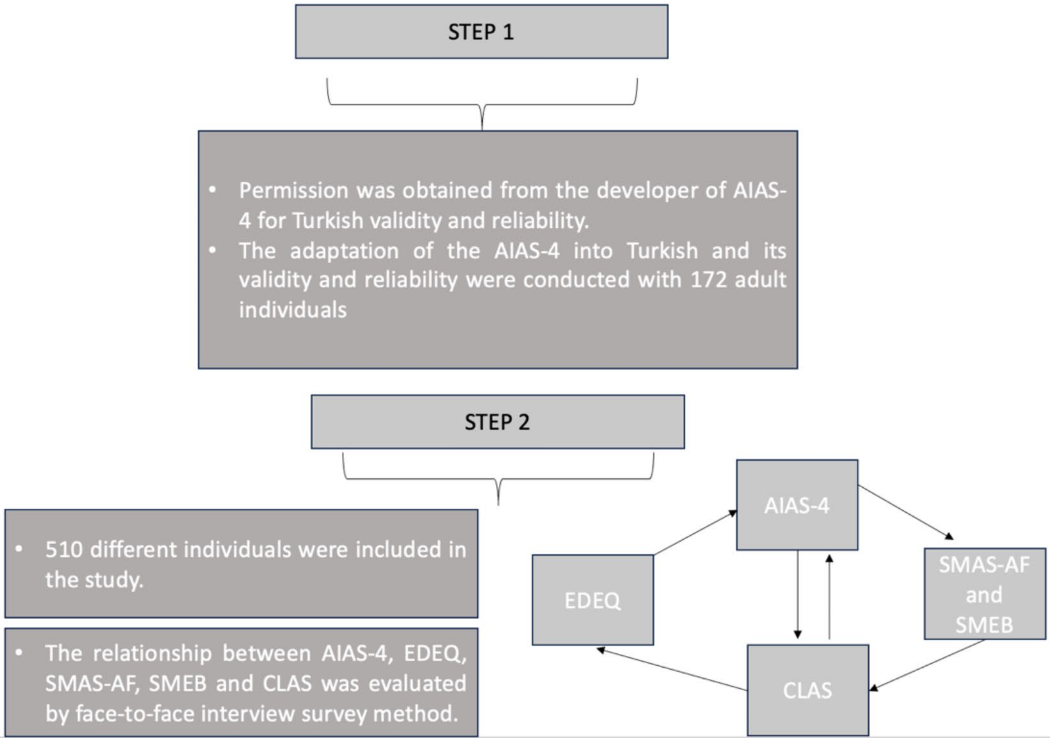

Fig. 1 Stages of work
(BMI: Body mass index; AIAS: Artificial Intelligence Attitude Scale SMA S-AF: Social media addiction scale-adult form; EDE-Q: The Eating Disorder Examination Questionnaire; CLAS: Contentment With Life Scale; SESMEB: Social Media on Eating Behavior)

their relatives, from both universities using the snowball sampling method. The study was conducted using a face-to-face survey method (interviewer-administered). Individuals with eating disorders and psychiatric disorders were not included in the study (self-reported health history). The questionnaire included sociodemographic data such as age, gender, socioeconomic status, education, marriage, height, and body weight, and scales of the artificial intelligence attitude scale, social media addiction scale (adult form), the scale of effects of social media on eating behavior, contentment with life scale, eating disorder examination questionnaire (EDE-Q-13). The questionnaire form consists of a total of 97 questions, including 19 sociodemographic questions and 78 scale questions. In this study, approximately 726 people were applied for a questionnaire and 98 people were excluded from the study because they were diagnosed with psychiatric illness and 58 people were diagnosed with eating disorders. In addition, 60 people were excluded from the study because they did not complete the study questionnaire, and a total of 510 people were included.

Artificial intelligence attitude scale (AIAS-4 scale)

The scale is a short self-report instrument designed to assess public perceptions of AI technology. The scale was developed and validated by Grassini (Cronbach's alpha = 0.830) [27]. The scale is one-dimensional and consists of 4 questions. Participants rated their agreement with each item using a 10-point Likert scale (1 = Not at all, 10 = Completely Agree). All item scores are averaged for the total score. The higher the score, the more positive attitude and higher level of acceptance individuals will have towards AI technology.

Turkish adaptation of artificial intelligence attitude scale (AIAS-4 scale)

To adapt the Artificial Intelligence Attitude Scale into Turkish, permission was obtained from the researchers who developed the test via e-mail. The translation of the scale was done according to the guide created by Beaton [30]. The original English version of the questionnaire was translated into Turkish by two independent translators who were fluent in both Turkish and English. One of the translators was an individual with a medical or clinical background and the other was an individual without a medical or clinical background. The translations of the two translators were evaluated and a single form was created according to Turkish culture. This final Turkish version of the questionnaire was translated into English and compared with the original version by two native English speakers who were also fluent in Turkish. A team of translators and researchers (a dietician, a native language professional and a translator) finalized the Turkish version. To investigate the test-retest reliability, 30 participants were evaluated. The test-retest method to determine the invariance of the questionnaire over time was applied to the participants at 15-day intervals.

Body mass index
The body weight and height were obtained from participants. Body mass index (BMI) was calculated as weight (kg)/height (m^2), and subjects were classified according to WHO classification [31]. The obtained BMI values were classified as underweight (≤ 18.5 kg/m^2), normal (18.5–24.99 kg/m^2), overweight (25–29.99 kg/m^2), and obesity (≥ 30 kg/m^2).

Social media addiction Scale- adult form (SMAS-AF)
It was developed by Şahin and Yağcı (2017) [32] to determine the social media addiction levels of adults aged 18–65. It was determined that the SMBI-SF has a five-point Likert-type structure (each of the items is scaled as Not at all suitable for me-1, Not suitable for me-2, Undecided-3, Suitable for me-4, Very suitable for me-5), 2 sub-dimensions (virtual tolerance and virtual communication) and 20 descriptions. The virtual tolerance sub-dimension consists of items 1–11 and virtual communication consists of items 12–20. Items 5 and 11 are reverse-scored. Cronbach alpha (α) internal consistency coefficient for the overall scale is 0.94. In this study, it was found to be 0.84. The analyses revealed that the SMBS-SF is a valid and reliable scale for determining adults' social media addiction. The highest score that can be obtained from the scale is 100 and the lowest score is 20. A higher score indicates that the individual perceives himself/herself as a "social media addict". Scoring is categorized as no addiction between 20 and 35, low addiction between 36 and 41, medium addiction between 42 and 57, high addiction between 58 and 73, and very high addiction between 74 and 100.

The scale of effects of social media on eating behavior (SESMEB)
SESMEB, comprising one subscale and eighteen items, is assessed using a five-point Likert scale. Each item is assessed as follows: 'always' receives five points, 'often' four points, 'occasionally' three points, 'seldom' two points, and 'never' one point. No reverse-coded material exists. The overall score can be computed, as indicated in the item analysis section. The overall score can range from a minimum of eighteen to a maximum of ninety points on the SESMEB scale. A higher scale score is associated with a greater effect of social media on the individuals' eating behaviors(Cronbach α = 0.92) [33] Cronbach α in this study has been found 0.88.

Contentment with life assessment scale (CLAS)
The Life Assessment Scale was used to evaluate life satisfaction developed by Lavallee et al. [34] in 2007 and its Turkish validity and reliability study was conducted by Akın and Yalnız [35] (Cronbach α = 0.73). In this study, Cronbach α = 0.72. The scale consists of five one-dimensional items and has a 7-point Likert-type rating (Strongly Disagree = 1, Disagree = 2, Sometimes Disagree = 3, Undecided = 4, Sometimes Agree = 5, Agree = 6, Strongly Agree = 7). Items three and four are reverse-scored. High scores indicate a high level of life satisfaction.

Eating disorder examination questionnaire (EDE-Q-13)
This scale was developed by Lev Ari [36] to be used in identifying eating disorder symptoms. The validity and reliability of the Turkish scale in adult participants were examined by Esin et al. [37]. According to this study, the Turkish version of the original EDE-Q-13 total score had a Cronbach's α value of 0.89. In the present study, it has been found that Cronbach's α = 0.90. The overall score of each item on the entire scale as well as each sub-dimension of the scale is used to evaluate the EDE-Q-13 scoring. To calculate the score, the total score is divided by the number of sub-dimensions, and sub-dimension scores are divided by the number of items. A higher score denotes a higher degree of psychopathology connected to eating.

Statistical analysis
The data obtained in this study were analyzed using the SPSS (Statistical Package for the Social Sciences) for Windows 29.0 program. Descriptive statistical methods were used for data analysis. To determine the normality of the distribution of the data, Skewness and Kurtosis Tests and Z-values were used. A p-value smaller than 0.05 was considered statistically significant. "Pearson" correlation coefficient was used for the relationships of two quantitative data with normal distribution; "Spearman" correlation coefficient was used when at least one of the two quantitative data did not show normal distribution. A linear regression model (Enter) was used to predict the EDE-Q total by using independent variables such as BMI, AIAS-4, SMAS-AF and SESMEB. To make sure the assumptions of normality, linearity, multicollinearity, and homoscedasticity were not damaged, preliminary tests were performed before beginning all of the basic linear regression analyses. Each of these variables was selected for inclusion based on their relevance to the study's aims. SESMEB is included due to its potential influence on individuals' nutrition behaviors and eating habits. BMI is considered because it is a key indicator of physical health and is often associated with eating behaviors. AIAS is included to examine the impact of attitudes toward artificial intelligence on nutrition-related decisions. SMAS-AF

was chosen to assess the role of social media addiction in influencing eating behaviors. Finally, the EDE-Q total score is used as the dependent variable to measure the severity of eating-related concerns, as it captures a range of disordered eating behaviors.

The reliability and internal consistency of the Turkish version AIAS-4 were assessed using Cronbach's alpha and McDonald's omega coefficients with values above 0.60 and 0.70 indicating acceptable and good fits, respectively [28]. To assess reliability and construct validity of the adapted scale Explanatory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) were performed. AMOS28 software was used to perform CFA in this study. Within the scope of CFA, several parameters were examined: Kaiser-Meyer-Olkin (KMO) value and multiple fit indices, including Root Mean Square Error of Approximation (RMSEA), Goodness-of-Fit Index (GFI), Adjusted Goodness-of-Fit Index (AGFI), Comparative Fit Index (CFI), Normed Fit Index (NFI), Tucker-Lewis Index. An acceptable fit is indicated by $0.05 \leq RMSEA \leq 0.08$, $3 \leq \chi2/df \leq 5$, $0.80 \leq GFI \leq 0.90$, $0.85 \leq CFI \leq 0.95$, $0.85 \leq AGFI \leq 0.95$, $0.80 \leq TLI \leq 0.95$ and $0.80 \leq NFI \leq 0.95$, while a good fit in CFA is indicated by $RMSEA \leq 0.05$, $\chi2\ /df \leq 3.0$, $0.90 \leq GFI$, $0.95 \leq CFI$, $0.95 \leq AGFI$, $0.95 \leq TLI$ and $0.95 \leq NFI$ [38]. The assessment was conducted based on the Average Variance Extracted (AVE) and Construct (composite) Reliability (CR) values. In the measurement model, the CR value of the latent variables should exceed 0.70, while the AVE value should be greater than 0.50 [39].

Results

In Stage 1 of the study, the AIAS-4 was adapted to Turkish, and its validity and reliability were established. In this phase, 172 adult individuals (43% male, 57% female) with an average age of 26.4 ± 6.75 years participated. The mean age of the participants in the retest was 24.2 ± 4.88 years. Of the 30 participants, 46.7% ($n = 14$) were male, and 53.3% ($n = 16$) were female. Regarding educational background, 36.7% of the participants were high school graduates, while 63.3% were university graduates.Confirmatory factor analysis (CFA) was performed after Explanatory factor analysis (EFA) and reliability were performed.

Explanatory factor analysis (EFA) and reliability

Table 1 shows EFA and internal consistency analysis of AIAS-4. The KMO test was applied to test suitability of the sample size for factor analysis before EFA. As per this analysis KMO value was found to be 0.79. The sample size was deemed sufficient for factor analysis based on this finding [40]. The acceptable level for factor loading values in the EFA was found to be 0.40 [28, 41]. Furthermore, the Chi-squared value in the Bartlett's test of sphericity results was shown to be significant ($\chi2$ [6] = 448.69; KMO = 0.79 $p < 0.01$). As a result, a multivariate normal distribution was assumed for the data. The factors accounted for 76.9% of the total variation. In the current investigation, McDonald's omega was 0.89 and the Cronbach's alpha coefficient was 0.90. In this study, the AVE was found to be 0.67 and the CR was 0.89, indicating that both values are at the desired level. The scale's test-retest reliability coefficient was determined to be 0.90.

Confirmatory factor analysis (CFA)

Confirmatory factor analysis of AIAS-4 was given in Fig. 2. Based on the following suggested thresholds, the scale's model good fit statistics achieved good fit: CMIN/Df = 0.40, GFI = 0.99, AGFI = 0.98, CFI = 1.00, RMSEA = 0.01; NFI = 0.98; and TLI = 1.00. All of the items were significant, according to the t-statistics.

In Stage 2 of the study, 510 adult individuals (30.8% male, 69.2% female) with an average age of 24.88 ± 7.05 years were evaluated for the relationship between artificial intelligence attitude, social media addiction, eating behaviors and contentment with life. The general characteristics of these individuals and data on social media use are shown in Table 1. It was seen that all of the participants in the study used social media. The average duration of social media use was 3.7 ± 1.99 h/day. While all of the individuals use WhatsApp, 89.8% of them use Instagram. The mean age of the individuals was 24.8 ± 7.05 years. The mean BMI of the individuals was 22.9 ± 3.55 kg/m^2. 9.4% of the individuals were

Table 1 The results of the EFA and internal consistency analysis of AIAS-4 (n:172)

Factors and Items	Total variance (%)	Factor loading	X ± SD	Cronbach' alpha	McDonald's omega	AVE	CR	*r*
		Total	*6.6 ± 2.04*	0.90	0.89	0.67	0.89	0.90
I1	76.9%	0.90	6.0 ± 2.45					
I2		0.89	6.5 ± 2.43					
I3		0.83	7.0 ± 2.36					
I4		0.88	6.1 ± 2.49					

I: Item, Kaiser–Meyer–Olkin (KMO) = 0.79; χ2 (6) = 448.69; Barlett test of sphericity (p) < 0.01, AVE: Average Variance Extracted, CR: Construct (composite) Reliability, r: Retest correlation coefficient

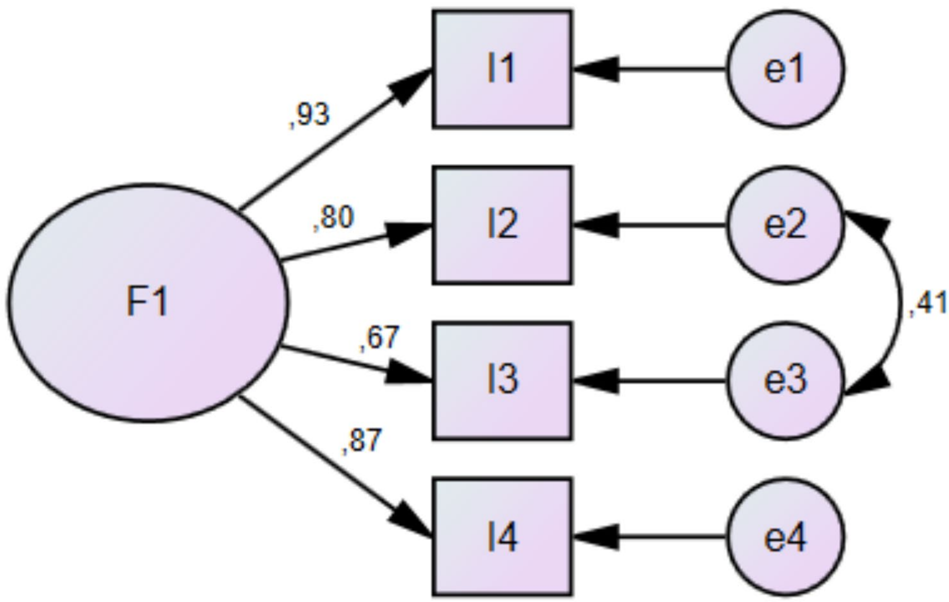

Fig. 2 Confirmatory factor analysis of AIAS-4

underweight, 61.0% were normal, 26.1% were overweight and 3.5% were obese.

Table 3 shows the correlation matrix between variables. The study found that age was positively correlated with BMI ($r = 0.260$, $p < 0.01$) and negatively correlated with time spent on social media (r = -0.272, $p < 0.01$), SMAS-AF (r=-0.118, $p < 0.001$).

BMI showed positive correlations with EDEQ total ($r = 0.391$, $p < 0.01$) Time spent on social media positively correlated with AIAS ($r = 0.129$, $p < 0.01$), SMAS-AF ($r = 0.378$, $p < 0.01$), but negatively with CLAS (r = -0.137, ($p < 0.01$). SMAS-AF total was positively correlated with EDEQ total ($r = 0.129$, $p < 0.01$), while negatively correlated with CLAS (r=-0.280 $p < 0.001$). SESMEB showed a positive correlation with time spent on social media ($r = 0.216$, $p < 0.001$), SMAS-AF ($r = 0.326$, $p < 0.001$), EDEQ ($r = 0.169$, $p < 0.001$).

The linear regression analysis was shown in Table 4. The linear regression model established to understand the relationship between the variables and the eating disorder score was significant ($R^2 = 0.198$, Adjusted $R^2 = 0.192$, $p < 0.001$). A 1 kg/m^2 increase in BMI increased the EDE-Q Total score by 0.311 units. A 1-point increase in AIAS-score decreases the EDE-Q total score by 0.157 points. A 1 unit increase in SMAS-AF increases the EDE-Q total score by 0.036 points, 1 point increase in SESMEB increases the EDE-Q total by 0.022 points.

Discussion

This study aimed to establish the validity and reliability of the AI attitude scale and to reveal the relationship between AI attitude and social media addiction, eating behavior and life satisfaction. Artificial intelligence has recently been frequently used in sectors such as education and health [42, 43]. While the widespread use of such applications may make people's lives easier, it may also increase anxiety and anxiety levels due to the fear that it may replace their jobs [44]. It has been shown that artificial intelligence may have positive or negative effects on accessing health-related information [45]. Chew et al. [46] reported that artificial intelligence (AI)-assisted body weight management applications to improve eating behaviors may contribute positively in the fight against obesity. In fact, in recent years, the integration of AI techniques, especially Machine Learning and Deep Learning, has shown promise in the development of both diagnostic and treatment strategies for eating disorders [47]. However, malpractice risk and lack of accountability are negative aspects of the use of AI in health. Therefore, the responsibility of the healthcare professional is crucial. The data used to train AI models can be biased, which can compromise the quality of care for vulnerable or minority patient groups [48]. The attitude of AI users or non-users toward AI is significant, not just for medical professionals. Because when considered from the perspective of users, a high level of positive attitude towards AI may cause individuals to have unhealthy behaviours, while a low level of the opposite attitude may lead to situations such as rejection of scientific information. Evaluation of attitudes towards artificial intelligence can be conducted with different scales [24–27]. The AIAS-4 [24], which is used quickly and practically in the evaluation of this attitude, was shown to be a valid and reliable scale in Turkish in this study (Cronbach alpha = 0.90).

Engagement with social robots or AI chatbots can influence our perceptions, attitudes, and social interactions

Table 2 General characteristics of individuals and data on social media use (n:510)

Gender	*n*	%
Male	157	30.8
Female	353	69.2
Education level		
Primary	3	0.6
Secondary	12	2.4
Highschool	229	44.9
University	266	52.2
Working status		
Yes	132	25.9
No	378	74.1
Social media use		
Yes	510	100
Social media addiction level		
Non addicted	52	10.1
Low addicted	47	9.2
Moderately addicted	262	51.3
High addicted	139	27.2
Very high addicted	10	1.9
Social media platforms*	**n**	**%**
Facebook	88	17.3
Instagram	458	89.8
Twitter	301	59.0
Snapchat	196	38.4
Youtube	422	82.7
TikTok	116	22.7
Linkedin	102	20.0
WhatsApp	510	100.0
Pinterest	153	30.0
Spotify	148	29.0
Discord	81	15.9
Others**	52	10.1
BMI(kg/m^2)(X ± SD)	22.99	3.5
BMI Classification		
Underweight	48	9.4
Normal	311	61.0
Overweight	133	26.1
Obesity	18	3.5

* One person can use more than one platform. ** Tumblr, Twitch, Kick, Telegram

BMI: Body mass index; SD: Standard deviation

[49]. Social media addiction, defined as excessive use leading to negative consequences, has become a growing concern among researchers [50]. Extreme engagement in digital activities, particularly social media, has been demonstrated to stimulate addictive behaviors by triggering the brain's reward pathway [51]. In parallel with the literature [10], a positive correlation was found between time spent on social media and social media addiction in this study (Table 3). In this study, it was determined that as the time spent on social media increased, the positive attitude toward artificial intelligence also increased (Table 3). However, no relationship was found between social media addiction and attitude towards artificial intelligence. This implies that while engagement with digital technologies may facilitate familiarity and acceptance of artificial intelligence, addiction itself may not necessarily correlate with AI attitudes.

Given the speed at which social media platforms and technology are evolving to include new functionalities and features, AI applications such as machine learning models will need to be regularly reviewed and tested to ensure that they remain accurate predictors of users' eating disorder status [9]. No statistical difference was found between the normal and eating-disordered groups according to their technology use [15]. The negative correlation between AIAS and EDE-Q in this study (Table 3) suggests that the use of artificial intelligence in health may positively affect eating behaviors. Each 1 unit increase in AIAS score decreased the EDE-Q total score by 0.157 units, which may reflect the positive effect of positive attitudes towards AI on individuals' eating behaviors. AI may facilitate faster recognition of having symptoms specific to eating disorders or being an individual at extreme risk for eating disorders. Early detection is crucial to the effective management of eating disorders and can make a difference in the likelihood of treatment being more effective [52]. AI algorithms can analyze large amounts of data, including social media posts, online searches, and even patterns of smartphone use [53]. By recognizing behavioral patterns and language cues, AI can alert users and even inform healthcare professionals, enabling them to intervene at the earliest stages of the disorder [54]. Therefore, improving attitudes towards AI may contribute positively to the improvement of eating behavior. Physicians and psychotherapists should collaborate in the development of AI models to improve the learning machine's ability not to provide harmful information [54]. Artificial intelligence (AI)-assisted body weight management applications to improve eating behaviors may contribute positively to the fight against obesity [46].

In the regression model in the present study showed that increase in Artificial Intelligence Attitude Score (AIAS) was found to be associated with decreasing EDE-Q total score. This result suggests more positive attitudes toward AI might be associated with reduced eating disorder symptoms, potentially influenced by increased technological engagement and digital health applications in Türkiye. The negative relationship between AIAS score and EDE-Q total score may reflect the positive effect of positive attitudes towards AI on individuals' eating behaviors. AI may facilitate faster recognition of having symptoms specific to eating disorders or being an individual at extreme risk for eating disorders. Early detection is crucial to the effective management of eating disorders and can make a difference in the likelihood of treatment being more effective [59]. AI

Table 3 Correlation matrix

	1	2	3	4	5	6	7	8
1. Age(years)	1							
2. BMI	0.260**	1						
3. Time spent on social media	-0.272**	-0.069	1					
4. AIAS	-0.081	-0.044	0.129**	1				
5. SMAS-AF	-0.118**	0.009	0.378**	0.072	1			
6. EDE-Q Total	0.009	0.391**	0.000	-0.119**	0.129**	1		
7- CLAS	0.063	-0.037	-0.137**	-0.060	-0.280**	-0.072	1	
8- SESMEB	-0.073	0.021	0.216**	0.016	0.326**	0.169**	-0.139**	1

0.9-1 | 0.7-0.89 | 0.40-0.69 | 0.10-0.39 | 0.10-0 | 0- -0.10 | -0.39- -0.10 | -0.69- -0.40 | -0.89- -0.7 | -1.0- -0.9

BMI: Body mass index; AIAS: Artificial Intelligence Attitude Scale SMA S-AF: Social media addiction scale-adult form; EDE-Q: Eating Disorder Examination Questionnaire; CLAS: Contentment With Life Scale; SESMEB: Social Media on Eating Behavior
Age, Time spent on social media: Spearman; Others: Pearson
Correlation is significant at the 0.01 level (2-tailed).**
Correlation is significant at the 0.05 level (2-tailed).*

Table 4 Linear regression analysis of factors affecting EDE-Q total score

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
	B	Std. Error	Beta			Lower Bound	Upper Bound
(Constant)	-3.221	0.995		-3.236	0.001	-5.176	-1.265
BMI	0.311	0.032	0.384	9.616	< 0.001	0.248	0.375
AIAS-4	-0.157	0.056	− 0.112	-2.796	0.005	-0.267	-0.047
SMAS-AF	0.036	0.011	0.134	3.180	0.002	0.014	0.059
SESMEB	0.022	0.011	0.088	2.079	0.038	0.001	0.043

$p < 0.001$ R square = 0.198 Adjusted R square = 0.192

Dependent variable: EDE-Q Total Score (BMI: Body Mass Index; AIAS: Artificial Intelligence Attitude Scale; SMAS-AF: Social Media Addiction Scale-Adult Form, SESMEB: Social Media on Eating Behavior)

algorithms can analyze large amounts of data, including social media posts, online searches, and even patterns of smartphone use [60]. By recognizing behavioral patterns and language cues, AI can alert users and even inform healthcare professionals, enabling them to intervene at the earliest stages of the disorder [61]. Therefore, improving attitudes towards AI may contribute positively to the improvement of eating behavior. Physicians and psychotherapists should collaborate in the development of AI models to improve the learning machine's ability not to provide harmful information [61]. Artificial intelligence (AI)-assisted body weight management applications to improve eating behaviors may contribute positively to the fight against obesity [55].

Additionally, a 1-unit increase in the Social Media Addiction Scale–Adult Form (SMAS-AF) led to a 0.036-unit increase in the EDE-Q total score, while a 1-unit increase in the SESMEB score increased the EDE-Q total by 0.022 units These results align with prior research suggesting that individuals frequently exposed to idealized body images on social media experience heightened body dissatisfaction and are at a greater risk of developing disordered eating behaviors [55] The correlation between social media addiction and EDE-Q scores suggests that excessive social media engagement may reinforce unrealistic body standards, contributing to disordered eating patterns. The SESMEB score, which reflects the influence of social media on body image, further supports the idea that appearance-focused content may trigger negative self-evaluations and unhealthy eating behaviors [18, 55]. The SESMEB score which is a tool that shows that social media use affects eating behavior through body image further supports the idea that appearance-focused content may trigger negative self-evaluations and unhealthy eating behaviors [33, 56].

Consistent with previous research, BMI was found to be positively associated with disordered eating behaviors and body image concerns [57–59]. Specifically, each 1 kg/m^2 increase in BMI was found to increase the total score of the Eating Disorder Examination Questionnaire (EDE-Q) by 0.311 units (Table 4) further reinforcing the relationship between body weight and eating disorder symptoms. Additionally, BMI showed a significant correlation with EDE-Q total scores (Table 3), suggesting that body weight plays a key role in disordered eating patterns. Given the cultural emphasis on body image and dietary habits, these findings align with the broader literature on eating behaviors and body dissatisfaction.

Facebook, Instagram, Twitter, TikTok, Snapchat and Threads are also significant sources of distraction. Continuous notifications, updates, and scrolling feeds can cause individuals to lose focus on critical tasks and establish an endless cycle of partial attention [1]. A study by Kross et al. (2013) found that passive use of Facebook predicted decreased well-being and increased feelings of distraction and inattention [60]. AI tools enable quick responses and solutions to a wide range of questions and requests, which can be tempting for individuals to rely solely on them [1]. Over-reliance on ChatGPT or similar AI platforms can reduce an individual's ability to think critically and develop independent thought [61]. The influence of technological usage on young adults can affect numerous aspects of their lives, including mental health, academic achievement, and socio-emotional well-being [62]. In this study, individuals who spent more time on social media and showed higher addiction had lower life satisfaction (Table 3). In a study conducted in Poland on 381 Facebook users, the self-esteem and life satisfaction of addicts were found to be worse than non-addicts [18]. Similarly, it was supported by a study conducted in university students that found a negative relationship between life satisfaction and problematic Facebook use [63]. These findings reveal the necessity of awareness programs for social media use and emphasize the importance of interventions to improve quality of life. Of particular interest is the finding that CLAS scores decreased as social media addiction levels increased. This inverse relationship suggests that individuals with higher levels of social media addiction may experience a decline in overall life satisfaction. Excessive social media use may interfere with individuals' ability to engage in satisfying offline activities, reducing feelings of satisfaction and well-being. These results reflect previous studies showing how excessive use of social media can contribute to poorer mental health outcomes, such as lower life satisfaction and greater anxiety [18]. This association warrants further investigation of the long-term psychological effects of social media addiction on life satisfaction [1]. Frequent exposure to emotionally stimulating content, such as social media posts or online news, can disrupt emotional regulation processes and contribute to increased stress, anxiety, and depressive symptoms [64]. Young adults' mental health, academic achievement, and socio-emotional status are just a few areas that can and do be impacted by their heavy usage of digital media. Among young adults, there have been detrimental psychological impacts linked to excessive usage of social media platforms [62]. Given the speed at which social media platforms and technology are evolving to include new functionalities and features, AI applications such as machine learning models will need to be regularly reviewed and tested to ensure that they remain accurate predictors of users' eating disorder status [9].

Limitations and future directions

This study is the first study in Türkiye to reveal the relationships between artificial intelligence attitude, social media addiction, eating behavior, and life satisfaction. This research's strengths include the Turkish validation of the AI attitude scale and its assessment in relation to social media addiction, eating behavior, and life satisfaction. However this study has some limitations. At first this study, being cross-sectional, does not elucidate the cause-and-effect relationship. Second, the absence of an examination of the individuals' body composition is noteworthy. The distinct assessment of fat and fat free mass may prove beneficial in the evaluation of eating behavior. Another limitation of our study is the reliance on self-reported body weight and height, which may introduce bias. However, research comparing BMI derived from self-reported and directly measured values has shown strong correlations [65, 66] Lastly, women showed more interest in the announcements made on social media. Therefore, the number of women participating is higher than the number of men.

In future studies food consumption records from individuals and studies on diet quality may have a positive contribution. Validation of AIAS-4 with other scales measuring attitude towards artificial intelligence that have been validated in Turkish will contribute to the literature in future studies. Future research should consider examining measurement invariance across subgroups (e.g., age, gender) to account for potential differences in AI perceptions within the Turkish population. Conducting such analyses would enhance the robustness and generalizability of the findings.

Conclusion

In conclusion, in this study, AIAS was found to be a valid and reliable scale for measuring adults' attitudes towards artificial intelligence. The results show that BMI, social media use, and AI attitudes impact eating behaviors. The effects of different factors such as BMI, social media use, and artificial intelligence on eating behaviors provide important information about how individuals react to various environmental and technological factors. In this study, while social media use affects eating behavior negatively, attitude towards artificial intelligence affects it positively. In particular, awareness-raising programs to reduce the harmful effects of social media, the use of AI-supported health monitoring tools, and the education of individuals about body image may be important strategies in the prevention and management of eating disorders. Furthermore, educational initiatives on body image and digital consumption may help individuals develop healthier relationships with food and technology. Educational programs can provide individiuals with the abilities to critically assess digital content, utilize digital tools responsibly, and comprehend their own digital behaviors. In the future, there is a need for studies, programs, and training that will positively contribute to the evaluation of eating behavior and health through social media and artificial intelligence.

Abbreviations

BMI	Body mass index
AIAS	Artificial Intelligence Attitude Scale
SMAS-AF	Social media addiction scale-adult form
SESMEB	Social Media on Eating Behavior
CLAS	Contentment With Life Scale
EDE-Q 13	Eating Disorder Examination Questionnaire

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Data availability
The datasets used during the present study can be obtained from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
All procedures used in this study adhered to the World Medical Association's Helsinki Declaration (Ethical Principles for Medical Research Involving Human Subjects). Ethical approval of the study was obtained from the ethics commission of Tokat Gaziosmanpaşa University with decision number 390559 dated 25.01.2024. Informed consent to participate to the study was obtained from all of the participants.

Consent for publication
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Competing interests
The authors declare no competing interests.

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