

**Adaptation Study of the Problematic ChatGPT Use Scale into Turkish***

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30.04.2026**ABSTRACT**

The purpose of this study is to examine the validity and reliability of the Turkish form of the Problematic ChatGPT Use Scale developed by Yu et al. (2024). Unconscious and excessive use of technology may lead to negative psychological, social, and academic outcomes, and the scale was designed to identify whether individuals engage in unhealthy or maladaptive patterns of ChatGPT use. Following the linguistic and conceptual adaptation procedures, the scale was administered to adult participants aged 18–60. A total of 301 adults participated in the study (204 women, 97 men). Exploratory and confirmatory factor analyses indicated that the scale has a single-factor structure consisting of 11 items rated on a five-point Likert format. Factor loadings ranged from 0.52 to 0.87. In the confirmatory factor analysis, the chi-square value was significant ($\chi^2 = 2319.736$, $df = 55$, $p = .00$), and the fit indices were CFI = 0.819, TLI = 0.774, RMSEA = 0.178, and SRMR = 0.107. Internal consistency analysis yielded a Cronbach's alpha coefficient of 0.91. Criterion validity was supported by a significant correlation with the Artificial Intelligence Dependence Scale, indicating conceptual overlap between the two constructs. Overall, the findings show that the Turkish version of the Problematic ChatGPT Use Scale is a valid and reliable instrument for assessing problematic ChatGPT use among adults.

Keywords: Problematic ChatGPT Use, Artificial Intelligence Addiction Scale, Validity, Reliability.

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1. INTRODUCTION

Developing artificial intelligence technologies are significantly contributing to how people interact with digital environments. This transformation is part of a broader shift in Industry 4.0, which has introduced new approaches across various sectors, including production management and marketing (Tehci & Ersoy, 2018). This process can lead to the development of problematic use habits in some individuals. Digital addiction and problematic technology use are defined as excessive and uncontrolled attachment to tools such as digital games, AI-powered chatbots, social media, and the internet (Meng et al., 2022). These types of habits can negatively affect people socially, psychologically, and academically, and can impair their functioning (Griffiths et al., 2014; Young, 1998). The impact of digital technologies is not just an external change; it has become a factor that directly affects the quality of life for individuals.

Today, the rapid proliferation of AI-powered chatbots has brought the issue of technology addiction back to the forefront. Developed by Open AI, ChatGPT has rapidly gained popularity in daily and academic life due to its ability to generate human-like responses and provide information on a wide range of topics (Feuerriegel et al., 2024). However, this rapid proliferation can lead some individuals to become overly reliant on AI-based systems like ChatGPT. This situation can negatively impact individuals' social and cognitive abilities and weaken their real-world interaction and thinking skills (Xie et al., 2023). A life intertwined with artificial intelligence can actually reinforce individuals' dependence on technology, disrupting the balance in their relationship with the digital world.

The purpose of this study is to adapt the "Problematic ChatGPT Use Scale" developed by Yu et al. (2024) into Turkish and to test its linguistic equivalence, validity, and reliability. The adaptation process was carried out in accordance with international scale adaptation standards, considering both linguistic and cultural requirements to ensure psychometric appropriateness for

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individuals in Turkey. This study aims to determine individuals' levels of problematic ChatGPT use and contribute to future research on digital addiction.

The focus of the study has been shaped around the following questions.

RQ1: Is the Turkish version of the Problematic ChatGPT Use Scale linguistically and conceptually equivalent to the original scale?

RQ2: Does the Turkish form demonstrate an adequate factor structure consistent with the original instrument?

RQ3: Are the reliability coefficients of the Turkish version (e.g., Cronbach's alpha, CR) within acceptable ranges?

RQ4: Does the scale demonstrate sufficient convergent, discriminant, and criterion validity in the Turkish sample?

These research questions directly guided the methodological process and were addressed through the analyses presented in the findings section.

Problematic digital technology use can be defined as individuals becoming uncontrollably and excessively dependent on technology, and this can be divided into different subcategories. These categories include areas such as problematic internet use (PIU), problematic social media use (PSMU), internet gaming disorder (IGD), and problematic chatbot use. The increasing prevalence of advanced chatbots like ChatGPT has led to the emergence of a new form of problematic technology use, increasing the risk of dependence on these systems (Ramadan, 2021; Xie et al., 2023). This new type of addiction can negatively impact individuals' daily lives, mental health, and social relationships. This evolving technology can also change human interactions and social bonds, making it difficult to understand and prevent new types of addiction.

Problematic Internet Use (PIU) is defined as individuals using the internet in an uncontrolled and overly dependent manner, which can negatively impact a person's academic, social life, and work (Chou et al., 2005; Young, 1998). Similarly, problematic social media use (PSMU) is a condition where individuals can impair their mental health by excessively using social media platforms (Andreassen, 2015). AI-powered chatbots, on the other hand, have the potential to replace social interactions because they offer customized responses to users. This can also lead individuals to withdraw from social relationships and even experience social isolation (Kim et al., 2022). These AI-based systems, by replacing human interactions, can lead individuals to experience emotional states such as loneliness and depression more frequently. Excessive use of such technologies can weaken individuals' real-life social connections and increase their sense of loneliness.

Chatbot addiction is characterized by people replacing human interaction with digital tools (Skjuve et al., 2021). It is possible for individuals to form emotional attachments to advanced AI-powered chatbots like ChatGPT because they make users feel understood (Pentina et al., 2023). These chatbots can encourage users to use them more by making them feel like a personal touch. According to Xie et al. (2023) study, people form safer and less anxious relationships with chatbots. Therefore, people can communicate with chatbots more easily and become more dependent on these technologies over time. However, preferring ChatGPT over social interaction can harm individuals' real-world interpersonal relationships.

The psychological effects of using ChatGPT on individuals should be comprehensively examined. Excessive interaction with AI-powered chatbots can lead to depression and anxiety (Huang et al., 2024). The 24/7 accessibility of platforms like ChatGPT could lead individuals to turn to these platforms exclusively during stressful and difficult moments. This situation can lead to social isolation and detachment from real human relationships over time (Ramadan, 2021). When individuals turn to digital chatbots for emotional support and comfort, they may lack genuine human interaction, which could jeopardize their psychological well-being. Using ChatGPT can reinforce cognitive biases and weaken critical thinking skills (Feuerriegel et al., 2024). ChatGPT can help acquire information with less cognitive effort, especially in academic and professional settings. Individuals who rely on ChatGPT's responses may experience a decline in their decision-making skills and problem-solving abilities (Khan, 2025; Zhou et al., 2024). When people constantly rely on external information, they can lose their critical thinking and analytical skills. Over-reliance on ChatGPT, especially in academic settings, can passively students' learning process and lead to cognitive laziness (Marriott & Pitardi, 2024).

The aim of this study is to adapt the Problematic ChatGPT Use Scale into Turkish and examine its psychometric properties. As AI-powered chatbots become increasingly integrated into daily life, concerns about excessive or maladaptive use have grown, given its potential negative effects on individuals' social, academic, and psychological functioning. Accordingly, this study evaluates the scale's factor structure, reliability, validity, and linguistic-cultural compatibility within the Turkish context. In addition, the relationships between problematic ChatGPT use and relevant psychological variables are explored to provide a clearer understanding of how AI-supported chatbots may influence individuals. This research is expected to contribute to the literature and offer a solid foundation for future studies in this emerging field.

2. LITERATURE REVIEW

2.1. Problematic ChatGPT Use

The rapid expansion of generative artificial intelligence tools such as ChatGPT has introduced new patterns of digital behavior, including the potential for excessive or maladaptive use. Unlike traditional digital platforms, ChatGPT provides continuous, personalized, and human-like conversational interaction, which may increase the risk of psychological dependence (Xie et al., 2023). Studies indicate that frequent and emotionally charged interactions with AI systems can reduce real-world social

engagement, reinforce avoidance-based coping strategies, and increase psychological reliance (Huang et al., 2024; Pentina et al., 2023).

Problematic ChatGPT use refers to excessive, uncontrolled, and maladaptive engagement with ChatGPT that disrupts individuals' social, academic, and psychological functioning (Yu et al., 2024). This includes symptoms such as preoccupation, loss of control, withdrawal-like reactions, and interference with daily activities. Given that this form of AI-specific behavior is relatively new, measurement tools are needed to systematically examine its psychological correlates.

2.2. Related Constructs: Digital Addiction and AI Dependence

Problematic ChatGPT use shares certain features with established forms of digital addiction—such as problematic internet use (Young, 1998), problematic social media use (Andreassen, 2015), and AI dependence (Morales-Garcia et al., 2024)—including loss of control, excessive engagement, tolerance, and functional impairment. However, ChatGPT differs due to its interactive depth and generative capacity, which enable users to receive instant information, emotional support, and personalized responses.

Research shows that overreliance on AI-based chatbots can increase loneliness, social withdrawal, and reductions in decision-making and critical thinking (Duong et al., 2024; Ramadan, 2021). These findings demonstrate the importance of developing tools capable of assessing AI-specific maladaptive behaviors rather than relying solely on general internet-related measures.

2.3. Need for a Valid and Culturally Appropriate Measurement Tool

Yu et al. (2024) developed the Problematic ChatGPT Use Scale to assess psychological dependence and loss of control specifically associated with ChatGPT. However, no validated Turkish instrument existed. Considering the rapid adoption of AI tools in Türkiye across academic, professional, and personal contexts, there is a need for a culturally adapted, psychometrically sound scale.

Adapting the scale into Turkish provides researchers with a standardized tool for investigating problematic ChatGPT use and examining its associations with cognitive, emotional, and behavioral variables.

3. METHOD

The study primarily focused on the linguistic and cultural adaptation of the scale and followed internationally recognized guidelines for test adaptation (e.g., ITC and Hambleton-based procedures). In the first stage, a forward-backward translation process was implemented. Five independent bilingual translators, all fluent in both Turkish and English and familiar with psychological terminology, translated the original items into Turkish. These versions were compared and synthesized into a single preliminary Turkish form by a small reconciliation team. Next, this preliminary form was back-translated into English by another five bilingual translators who were blinded to the original scale.

All forward and backward translations were then reviewed by a panel of three field experts (academics in psychological counseling and educational sciences with experience in scale development and digital addiction research). The expert panel evaluated each item in terms of semantic equivalence, conceptual consistency, and cultural appropriateness for adults in Türkiye and suggested minor wording changes where necessary. Following this expert review, cognitive interviews were conducted with a small group of participants ($n = 20$) to check item clarity, interpretability, and perceived relevance. Based on their feedback, minor linguistic refinements were made.

Subsequently, a pilot study was carried out with a separate group of participants to examine the functioning of the items (e.g., response distributions, initial internal consistency). After confirming that the Turkish items operated adequately, the main data collection was conducted. For the main study, data were obtained from 301 adult volunteers residing in Türkiye, and the psychometric analyses of the Turkish version of the Problematic ChatGPT Use Scale were performed. After data collection, a construct validity study was conducted (EFA and CFA), criterion validity was examined using the Turkish version of the Artificial Intelligence Dependence Scale (Savaş, 2024), and reliability analyses (e.g., Cronbach's alpha, CR) were carried out. In addition to exploratory and confirmatory factor analyses, internal consistency coefficients were calculated to evaluate the reliability of the adapted scale.

3.1. Scales Used in the Study

Artificial Intelligence Dependence Scale (Morales-Garcia et al., 2024; Turkish adaptation by Savaş, 2024) is a five-item scale. Participants can score from 1 to 5, meaning they strongly disagree or strongly agree. High scores indicate an increasing dependence on artificial intelligence. In the study conducted by Morales-Garcia et al. (2024), the internal consistency coefficient of the scale created by 528 university students is a Cronbach Alpha value of 0.87. In a study conducted by Savaş (2024), there were 584 students, and the internal consistency coefficient, Cronbach's Alpha value, was 0.82. The method was applied to participants voluntarily, and the response time varied between three and four minutes.

The Problematic ChatGPT Use Scale was first developed in a study by Yu et al. (2024). Participants can answer this scale with 11 questions, ranging from 1 to 4. High scores indicate problematic ChatGPT usage.

This study examined the relationship between the widely used and validated Artificial Intelligence Addiction Scale and the Problematic ChatGPT Use Scale. The analysis focused on how the new scale related to the AI Addiction Scale, indicating that both instruments measured conceptually similar constructs. The reliability and validity of the scale were tested using several statistical techniques. First, Cronbach's alpha was calculated to assess internal consistency. This coefficient served as an indicator of the scale's reliability. In addition, the compatibility of the factor structure with the theoretical model was evaluated through confirmatory factor analysis (CFA) to test construct validity. These analyses assessed the psychometric properties of the Problematic ChatGPT Use Scale and demonstrated whether it functioned as a reliable and valid measurement tool.

3.2. Data Collection Process

The survey design of the study was approved by the Scientific Research and Publication Ethics Committee of Nevşehir Hacı Bektaş Veli University. Before the final administration, the survey was pilot-tested with 310 adult participants, and the survey was revised based on their feedback. For the main study, data were collected from adult volunteers aged 18–60 residing in Türkiye. The Problematic ChatGPT Use Scale, developed by Yu et al. (2024), was included in the final survey form as an 11-item measure.

3.3. Data Analysis

Reliability and validity analyses were carried out based on established methodological guidelines in the literature. In addition to construct validity procedures, extensive validity steps were followed in accordance with recommendations by DeVellis (2017), Kline (2015), and Tabachnick & Fidell (2019). Expert opinions were obtained, and a detailed literature review was conducted as part of the content validity process (Lawshe, 1975). The suitability of the data for factor analysis was examined using the Kaiser–Meyer–Olkin (KMO) coefficient and Bartlett's Test of Sphericity (Kaiser, 1974). Following this, exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were conducted in line with the guidelines of Byrne (2016) and Worthington & Whittaker (2006). Item–total correlations and item discrimination indices were calculated. Internal consistency reliability was assessed using Cronbach's alpha (Cronbach, 1951). All analyses were performed using SPSS 22, R, and AMOS 24 software.

3.4. Sample Characteristics

Adults aged 18 to 60 constituted the study group. Participants were recruited through online announcements shared on social media platforms (Instagram, WhatsApp groups, and Telegram channels) and through university community networks. Individuals who volunteered to participate and confirmed that they were active ChatGPT users were included in the study. Inclusion criteria were: (a) being between 18 and 60 years old, (b) residing in Türkiye, and (c) voluntarily agreeing to participate. Exclusion criteria were incomplete responses and failure to provide informed consent. A total of 310 adults responded to the survey, but 9 forms were excluded because they did not meet the data-quality requirements; thus, 301 valid responses were used for analysis. Simple random sampling was applied among volunteers who met the inclusion criteria. Of the participants, 97 (32.2%) were male and 204 (67.8%) were female. Sample size was deemed sufficient based on the criterion that the number of participants should be at least five times the number of items (Tavşancıl, 2006). In the first application, all 301 adult participants were included in the exploratory factor analysis (EFA), and in the second application, the same participants were included in the confirmatory factor analysis (CFA). In addition to these guidelines, recent literature suggests that employing efficient estimation methods in sampling designs can further improve the reliability of statistical outcomes (Zaman, 2019).

Table 1.

Demographic characteristics of the study group

Gender		Frequency	Percentage	Valid Percentage	Cumulative Percentage
Gender	Woman	204	67,8	67,8	67,8
	Male	97	32,2	32,2	100,0
	Total	301	100,0	100,0	
Civil Status	Single	240	79,7	79,7	79,7
	Married	61	20,3	20,3	100,0
	Total	301	100,0	100,0	
Age	Between 18 and 28	220	73,1	73,1	79,1
	Between 29 and 39	58	19,3	19,3	92,4
	Between 40	18	6,0	6,0	98,3

	and 50 51 years and older	5	1,7	1,7	100,0
	Total	301	100,0	100,0	
ChatGPT Usage Hour	0	105	34,9	34,9	34,9
	1	137	45,5	45,5	80,4
	2	33	11,0	11,0	91,4
	3	11	3,7	3,7	95,0
	4	8	2,7	2,7	97,7
	5	4	1,3	1,3	99,0
	6	1	,3	,3	99,3
	7	2	,7	,7	100,0
	Total	301	100,0	100,0	

4. FINDINGS

4.1. RQ1: Assessment of the Linguistic and Conceptual Equivalence of the Turkish Version

The linguistic and cultural adaptation of the scale was carried out in accordance with internationally accepted guidelines for test adaptation (e.g., ITC and Hambleton procedures). First, a forward-backward translation approach was employed. Five independent bilingual experts translated the original items into Turkish, and these translations were synthesized into a unified preliminary version. This version was then back-translated into English by a different group of five bilingual translators who were not familiar with the original instrument. All translation forms were subsequently evaluated by a panel of three experts in psychological counseling and educational sciences who had experience in scale development and digital technology-related behavioral research. The panel reviewed each item for semantic and conceptual equivalence, clarity, and cultural appropriateness for adults in Türkiye. Minor wording adjustments were made in line with their recommendations. To further ensure linguistic and conceptual equivalence, cognitive interviews were conducted with a small group of participants ($n = 20$). These interviews examined item clarity, comprehensibility, and perceived relevance. Participants' feedback indicated that the items were understandable and contextually appropriate, requiring only minor refinements. Finally, a pilot study was conducted to evaluate item functioning in practice, including response patterns and initial reliability indicators. The results confirmed that the Turkish items were linguistically and conceptually equivalent to the original scale and suitable for use in the main study.

4.2. RQ2: Evaluation of the Factor Structure Exploratory factor analysis

Principal Component Analysis was used to verify the construct validity. The single-factor analysis was performed without rotation. For example, the KMO test value was found to be 0.914 and the Bartlett's test value was found to be 2319.736 ($df=55$, $p=0.00$). These results indicate that the scale data is suitable for factor analysis (Kalaycı, 2009; Sönmez & Alacapınar, 2014). Following these results, principal component analysis was performed to determine the elements of the scale. As a result of factor analysis, only one factor with an eigenvalue above 1 was found. This accounts for 56.14% of the total variance. All items are at an acceptable level in terms of factor loadings, and the factor loadings range from 0.521 to 0.875. The analysis reveals that the scale has a one-dimensional structure. Factor analysis linked all components of the scale to a single factor, which accounted for 56.14% of the total variance. This finding indicates that the scale is unidimensional. Additionally, the common variances of the items, i.e., the communalities, are generally at an acceptable level. Although I1 (0.271) and I2 (0.296) have relatively low common variance, they were deemed suitable for inclusion in the analysis due to sufficient factor loadings.

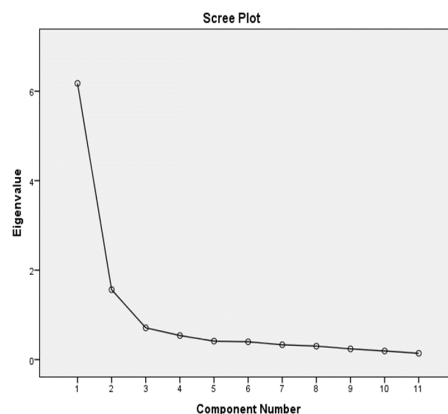


Figure 1. Factor line graph.

Table 2.

Factor loadings and common variances of scale items

Item	Factor Loading	Communality
I1	0,521	0,271
I2	0,544	0,296
I3	0,745	0,555
I4	0,707	0,500
I5	0,846	0,716
I6	0,804	0,647
I7	0,812	0,659
I8	0,875	0,765
I9	0,824	0,678
I10	0,809	0,655
I11	0,658	0,432

In factor analysis, common variances of items close to 1.00 or above 0.66 are considered a good model fit (Büyüköztürk, 2007). Table 3 shows the inter-item correlations. In this context, fundamental information regarding the use of R software is addressed in Bulut (2023).

Table 3.

Inter-item correlations

N=301	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11
I1	1	0,534	0,444	0,474	0,373	0,348	0,315	0,332	0,238	0,258	0,29
I2		1	0,551	0,625	0,336	0,304	0,328	0,308	0,199	0,266	0,364
I3			1	0,649	0,563	0,472	0,507	0,578	0,478	0,449	0,508
I4				1	0,504	0,44	0,544	0,484	0,375	0,364	0,521
I5					1	0,706	0,67	0,751	0,694	0,732	0,447
I6						1	0,659	0,745	0,691	0,661	0,403
I7							1	0,728	0,704	0,617	0,431
I8								1	0,799	0,748	0,494
I9									1	0,823	0,5
I10										1	0,507
I11											1

Table 4.

Average, Standard Deviation, Corrected Item-Total Correlations, Cronbach's Alpha values if the item is deleted, and the total variance explained by the scale

N=301	Average	Standard Deviation	Skewness	Kurtosis	Corrected Item Total Correlation	When the item is deleted, Cronbach's Alpha	Total Variance Explained and Eigenvalue
I1	1,76	0,718	,554	-,316	,493	,911	56,137
I2	1,88	0,890	,637	-,573	,522	,914	(6,165)
I3	1,54	0,655	,967	,443	,715	,899	
I4	1,71	0,778	,803	-,094	,690	,900	
I5	1,49	0,587	,844	,277	,766	,897	
I6	1,46	0,596	1,124	1,229	,712	,900	
I7	1,49	0,625	1,144	1,391	,728	,898	
I8	1,46	0,591	,978	,483	,788	,896	
I9	1,39	0,564	1,231	1,163	,712	,900	
I10	1,40	0,566	1,198	1,076	,706	,900	
I11	1,54	0,704	1,265	1,458	,594	,905	

Looking at the relevant data in Table 4, it can be seen that the corrected item-total correlation coefficients range from 0.493 to 0.788, and that 56.1% of the total variance on the scale is explained (eigenvalue = 6.165). Whether the preconditions for parametric tests were met was evaluated based on the skewness and kurtosis values of the data (measures of normal distribution) and the results of the Levene test (homogeneity of variances) (Büyüköztürk, 2010). The fact that the skewness and kurtosis values are within the specified limits indicates that the data is normally distributed.

4.3. Confirmatory factor analysis

Confirmatory Factor Analysis (CFA) was conducted to test the construct validity. In addition, covariance was defined between the errors of the observed values to achieve the recommended values for the fit indices (Şimşek, 2007). When the fit indices of the one-dimensional model were examined, they were found to be CFI = 0.819, TLI = 0.774, RMSEA = 0.178, and SRMR = 0.107. These values indicate that the model's fit is weak to moderate. The highest factor loadings were observed for items I5 (0.842), I8 (0.901), and I9 (0.862), while the loadings for items I1 and I2 were relatively low (0.405 and 0.400, respectively). Modification indices, particularly between I2–I4, I3–I4, and I1–I2, indicate that adding error covariances can improve the model's fit. Although Items I1 and I2 exhibited relatively lower factor loadings compared to the remaining items, they were retained based on theoretical relevance and psychometric acceptability. Importantly, the original study by Yu et al. (2024) also reported lower yet acceptable loadings for these items, emphasizing their conceptual contribution to the construct of problematic ChatGPT use. Furthermore, item–total correlations obtained in this study were above recommended thresholds, and removing these items did not improve the reliability coefficients (Cronbach’s alpha, CR). Therefore, both items were preserved in order to maintain consistency with the original instrument and avoid compromising the conceptual integrity of the scale. Figure 1 shows the path analysis (path diagram) of the measurement model obtained from the data analyzes performed using the AMOS 24 program. The diagram shows standardized beta values on paths extending from dimensions to items. The error for each substance is shown next to the substances. The most important factor that makes structural equation modeling valuable is its ability to simultaneously perform confirmatory factor analysis and regression analysis, while also including and presenting the error terms for the items in the model (Ayyıldız & Cengiz, 2006). In addition, the correlation relationships between the dimensions can also be observed within the scope of the analysis.

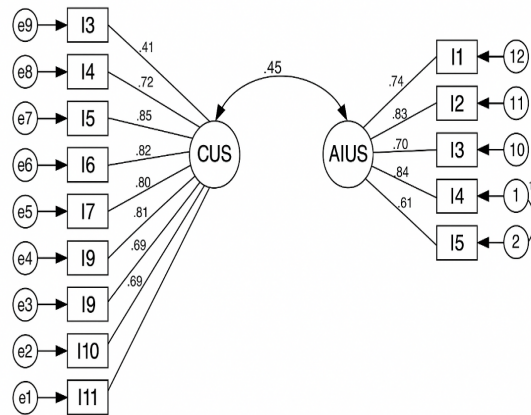


Figure 2. CFA correlation diagram (standardized).

When examining Figure 2, it is evident that the scale meets the fit indices frequently used in the literature. Based on the structural equation analysis and the findings obtained from the model, the structural validity of the measurement model consisting of 1 dimension and 11 items is at an acceptable level.

4.4. RQ3: Reliability and Validity Analyses

4.4.1. Item Validity

In the study, item mean scores were examined to test item validity and are shown in Table 5.

Table 5.
Item analysis results

Items	Average	Standard Deviation	t	p
Item 1	0.441	0.037	11.897	0.000
Item 2	0.654	0.055	11.892	0.000
Item 3	0.238	0.021	11.521	0.000
Item 4	0.402	0.034	11.682	0.000
Item 5	0.100	0.010	10.399	0.000
Item 6	0.121	0.011	10.699	0.000
Item 7	0.146	0.013	10.871	0.000
Item 8	0.065	0.007	8.988	0.000
Item 9	0.079	0.008	9.943	0.000
Item 10	0.095	0.009	10.454	0.000
Item 11	0.337	0.029	11.702	0.000

According to the analysis results, the fact that all z-values are above 4.392 indicates that the variances in the model are statistically significant.

4.4.2. Findings Regarding the Reliability of the Scale

Table 6.
Criterion validity

Correlations		ChatGPT Total	Artificial Intelligence Total
ChatGPT Total	Pearson Correlation	1	,517**
	Sig. (2-tailed)		,000
	N	301	301
Artificial Intelligence Total	Pearson Correlation	,517**	1
	Sig. (2-tailed)	,000	
	N	301	301

****.** Correlation is significant at the 0.01 level (2-tailed).

There is a positive, moderate, and statistically significant relationship between the total score of ChatGPT and the total score of Artificial Intelligence ($r = 0.517$, $p < 0.001$). This result indicates a significant relationship between attitudes toward ChatGPT use and general attitudes toward artificial intelligence.

Table 7.
CKÖ Reliability Analysis Results (Cronbach's Alpha), Average Variance Explained (AVE), and Composite Reliability (CR)

Number of Items	Cronbach's Alpha	AVE	CR
Scale total (11 items)	0,910	0.561	0.932

When Table 7 is examined, it is seen that the Cronbach's Alpha internal consistency coefficient is .910, the AVE value is .561, and the CR value is .932. According to Fornell & Larcker (1981), an AVE value above .50 demonstrates adequate convergent validity, while a CR value above .70 indicates acceptable composite reliability. These results show that the scale meets the recommended psychometric criteria.

Table 8:
Fornell & Larcker Method

	CR	AVE	MSV	MaxR(H)	CUS	AIUS
CUS	0,925	0,586	0,196	0,944	0,765	
AIUS	0,862	0,558	0,196	0,879	0,442	0,747

In Table 8, the dark values represent the AVE, and the values with (***) indicate the correlation between variables. Since the AVE is greater than the inter-item correlations, the model's discriminant validity is established (Fornell & Larcker, 1981). A recent study stated that HTMT values should be examined for divergent validity (Henseler et al., 2015). According to the authors, if the variables in the model have a similar structure, the HTMT value should be below 0.80; otherwise, it should be below 0.90. Table 9 presents the HTMT coefficients.

Table 9.
HTMT Coefficients

	CUS	AIUS
CUS		
AIUS	0,509	

When Table 9 is examined, it is seen that all coefficients are below 0.90. According to Henseler et al. (2015), this indicates that the scale items successfully measure the constructs they are expected to measure. The VIF coefficients for the variables in the model were evaluated for multicollinearity. As a result of the analysis, it was determined that the VIF values for the sub-expressions of the variables ranged from 1.165 to 4.549. According to Hair et al. (2019), VIF values below 5 indicate that multicollinearity is not a problem in the model. In this context, the results obtained support the accuracy of the model.

5. CONCLUSION

The present study examined problematic ChatGPT use—a recently emerging construct in the field—and conducted comprehensive reliability and validity analyses to adapt the Problematic ChatGPT Use Scale (Yu et al., 2024) into Turkish. The findings demonstrated that the scale possesses acceptable psychometric properties, and the confirmatory factor analysis

confirmed the original single-factor structure. These results indicate that the Turkish version of the scale is a valid and reliable tool for assessing problematic ChatGPT use. Considering the rapidly increasing integration of AI-based systems into everyday life, the identification and measurement of problematic usage patterns have become increasingly important. This study contributes to the national literature by providing a standardized instrument that can help researchers and practitioners better understand the psychological, social, and cognitive effects associated with excessive reliance on AI-based tools.

Furthermore, the results align with previous research showing that excessive or emotionally charged interactions with AI systems can lead to dependence-like symptoms and reduced psychological well-being (Huang et al., 2024; Xie et al., 2023). The confirmation of a single-factor structure is also consistent with the initial validation study conducted by Yu et al. (2024). Given the rapid adoption of generative AI platforms such as ChatGPT, the measurement of problematic use remains a critical step for future studies exploring digital addiction, technology-induced cognitive load, and AI-mediated social withdrawal (Andreassen, 2015; Young, 1998).

While the current study provides strong initial evidence for the validity and reliability of the adapted scale, the findings are limited to the sample characteristics of the present research. Future studies may strengthen generalizability by applying the scale to broader and more diverse samples, including clinical, adolescent, or occupational groups. Alternative structural models, such as a two-factor structure, may also be tested. Additionally, items I1 and I2—identified as having relatively lower factor loadings—could be revised or reevaluated in future analyses. In the present study, these items were retained because their item-total correlations and overall reliability contributions were sufficient, and because the original scale developers also included them despite similar loading patterns. Thus, keeping I1 and I2 ensures conceptual alignment with the original scale and protects the theoretical breadth of the construct. Nevertheless, future studies using larger or different populations may consider revising these items to further enhance the model's fit. Model refinement using modification indices, including the addition of error covariances where theoretically justified, may further enhance model fit.

Overall, the validated Turkish form of the scale provides a solid foundation for future multidimensional research on AI-related behavioral tendencies. It is anticipated that the finalized version of the scale presented in the Appendix will serve as a useful instrument in future studies across diverse fields and contribute meaningfully to the expanding literature on problematic technology use.

Research and Publication Ethics Statement

The study has received ethical approval.

Contribution Rates of Authors to the Article

Author 1: %50 – Data analysis, methodology, writing

Author 2: %50 – Conceptualization, editing, review

Statement of Interest

The authors declare that there is no conflict of interest regarding the publication of this article.

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