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Psychometric Evaluation of the Turkish Version of the AI Chatbot Dependence Scale (AICD-8)

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Abstract

The rapid integration of generative artificial intelligence-based chatbots into daily life has intensified discussions about their potential association with problematic use and addiction-like behaviors. In this context, several psychometric scales have been developed to assess problematic chatbot use including the AI Chatbot Dependence Scale (AICD-8). However, the AICD-8 has not been validated into Turkish. Therefore, the present study translated the AICD-8 into Turkish, and its psychometric properties were evaluated. The sample comprised 600 individuals (249 employees and 351 university students). Descriptive statistics, reliability indicators (Cronbach's alpha, McDonald's omega, and composite reliability), Pearson correlation coefficients, and confirmatory factor analysis (CFA) were conducted to examine the psychometric properties of the scale. The Turkish version of the scale (AICD-8-T) demonstrated good internal consistency, and CFA confirmed that the single-factor model exhibited acceptable fit. Convergent validity was supported through strong associations between the AICD-8-T and the Problematic ChatGPT Use Scale. Nomological validity was evidenced by expected correlations with social media addiction, loneliness, and internet addiction. Criterion-related validity was supported by strong positive correlations with daily ChatGPT use and chatbot use. Overall, the findings indicate that the AICD-8-T possesses robust psychometric qualities and can be reliably used in future psychological research in Türkiye.

Keywords: Artificial intelligence, AI chatbot dependence, problematic technology use, psychometrics, Turkish validation

Declarations

Conflict of interest

Emrah Özsoy is an Editorial Board Member of Discover Psychology. He was not involved in the editorial handling, peer review process, or decision-making regarding this manuscript. The remaining authors declare that they have no competing interests.

Data availability

The dataset from the present study is available upon reasonable request from the corresponding author.

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Ethics

Ethical approval for this study was obtained from the Sakarya University Social and Human Sciences Ethics Committee (Approval No: E-61923333-050.99-479650). The study was conducted in accordance with the ethical principles of the Declaration of Helsinki.

Consent to Participate

Informed consent for participation and publication was obtained electronically from all participants prior to data collection.

Consent to Publish

Not applicable

Authors' contribution

Conceptualization: Emrah Özsoy. Data curation: Büşra Yiğit. Methodology: Ömer Alperen Onay. Writing—original draft: Emrah Özsoy, Şeyma Arslan, Sümeyya Koç, Ömer Alperen Onay, Büşra Yiğit, Mark Griffiths. Writing—review & editing: Emrah Özsoy, Mark Griffiths.

Introduction

Generative artificial intelligence (AI)-based chatbots have rapidly become integrated into daily life in recent years (Ahmadi, 2023). These systems are advanced AI tools capable of engaging in natural dialogue with humans and providing user-specific content through deep learning and natural language processing techniques (Shawar & Atwell, 2005; Lo, 2023). In particular, chatbots, such as ChatGPT, have begun to be widely used in areas such as education, information retrieval and question answering, work life, personal development, healthcare, and daily life assistance (Argan et al., 2024; Lund et al., 2023).

The widespread adoption of chatbots is primarily driven by their potential benefits, such as time saving, quick access to information, and increased efficiency (Skjuve et al., 2024). However, excessive and dysfunctional interaction with these systems can lead to problematic use (Xie et al., 2023).

Although the concepts of 'problematic use' and 'dependence' are sometimes used interchangeably, they conceptually represent different levels of severity (Huang et al., 2025). Problematic use refers to maladaptive and excessive involvement, whereas dependency reflects more structured addiction-like symptoms (Caplan, 2010; Carbonell & Panova, 2017). In contrast, the 'dependency' structure operationalized in the present study is theoretically based on Griffiths' (2005) components model and reflects addiction-like symptoms such as loss of control, tolerance, withdrawal, and relapse of behavior despite adverse consequences. It is important to note that this conceptualization does not claim to be a formal clinical diagnosis. It only aims to evaluate structured dependency-like patterns that go beyond high-frequency use or general problematic use.

Problematic use of chatbots or chatbot dependence may differ from other widely accepted classical behavioral addictions associated with technology, such as addictions to the internet, social media, and smartphones (Andreassen, 2012; Griffiths, 2013). This is because chatbots can engage in one-to-one and personalized interactions with users and can provide (to some degree) empathetic responses (Ahmadi, 2023; Skjuve et al., 2024). Therefore, evaluating problematic chatbot use using classical digital addiction scales may be insufficient, and assessment tools developed explicitly for this new potential form of digital addiction are required (Zhang et al., 2024).

Currently, several instruments have been developed that assess problematic chatbot use. These include the AI Chatbot Dependence Scale

(AICD-8) (Zhang et al., 2024), PUCAI-6 [Problematic Use of Conversational AI] (Hu et al., 2023) (adapted from the Bergen Social Media Addiction Scale (BSAMS) [Andreassen et al., 2016]); the three-item GAA-3 [Generative AI Addiction] (Zhou & Zhang, 2024), the AI Dependence Scale (Huang et al., 2024) (derived from existing smartphone addiction measures such as the Smartphone Addiction Proneness Scale (SAPS; Kim et al., 2014) and the Smartphone Addiction Scale–Short Version (SAS-SV; Kwon et al., 2013), the DAI Scale [Dependency on Artificial Intelligence] (Morales-García et al., 2024), and the Problematic ChatGPT Use Scale (PCUS) (Yu et al., 2024) (specifically designed to assess ChatGPT-related problematic use).

The AICD-8 (Zhang et al., 2024) differs from other assessment tools in that it covers all AI chatbots and was specifically developed for assessing chatbot dependence, rather than being adapted from other instruments. It covers core components of addiction (e.g., excessive use, withdrawal, tolerance, loss of control, escape). During scale development, original expressions derived from the literature on AI-based chatbots and in-depth interviews with users were utilized. Subsequent analyses resulted in an eight-item, single-factor structure. This structure had good explained variance (58.42%) and very good internal consistency (Cronbach's α = 0.88). Therefore, due to its originality and development approach, it can be considered a comprehensive tool for assessing dependence on generative AI chatbots.

On the other hand, the AICD-8 is relatively new in the literature, and there is some debate regarding its conceptual scope. In particular, some researchers have pointed out limitations regarding whether the items equally represent all components of addiction (Ciudad-Fernández et al., 2025). Therefore, validation studies across different cultural contexts are important for assessing the scale's structural and measurement robustness. Therefore, the purpose of the present study was to adapt the AICD-8 into Turkish and to provide a valid and reliable tool for assessing AI chatbot dependence–related behaviors among the Turkish population. This adaptation was also expected to offer additional evidence regarding the psychometric performance of the AICD-8 across cultures and to contribute to the growing body of research on the problematic use of chatbots in Türkiye.

To determine whether the Turkish form (AICD-8-T) of the AICD-8 is psychometrically valid and reliable, several expectations must be met. First, the AICD-8-T should demonstrate adequate internal consistency. Second, the original factor structure of the scale must be tested using confirmatory factor analysis (CFA) to examine whether the factor structure is retained in the Turkish version. For convergent validity, the AICD-8-T is expected to show a strong positive correlation with the Problematic ChatGPT Use Scale (PCUS), because both instruments assess constructs related to problematic use of generative AI chatbots. For nomological validity, the AICD-8-T total score is expected to exhibit significant positive associations with related constructs (i.e., social media addiction, internet addiction), as well as loneliness.

Although the relationships between chatbot/ChatGPT dependence and these variables have been examined only to a limited extent, prior research has shown that problematic ChatGPT use is positively associated with internet addiction (Maral et al., 2025), and that daily AI chatbot use is positively associated with loneliness (Fang et al., 2025).

Moreover, social media addiction, internet addiction, and loneliness share similar psychosocial foundations with AI-based digital addictions (e.g., social isolation, low self-esteem, poor self-regulation skills) (Andreassen et al., 2017; Boursier et al., 2020; Caplan, 2002; Kim et al., 2008). Finally, in terms of criterion-related validity, the AICD-8-T was expected to be positively associated with the daily frequency of chatbot or ChatGPT use.

Based on the aforementioned literature, it was hypothesized that (i) internal consistency values of the AICD-8-T would be within the acceptable range (H_1), (ii) the single-factor structure of the AICD-8-T would be supported (H_2), (iii) convergent validity of the AICD-8-T would be supported (H_3), (iv) AICD-8-T scores would be positively related to scores on scales assessing social media addiction, internet addiction, and loneliness (H_4), and (v) the AICD-8-T scores would be positively associated with daily chatbot use and daily ChatGPT use, supporting criterion-related validity (H_5).

Method

Participants and recruitment procedure

A total of 641 individuals initially participated in the study, comprising employees from the public and private sectors and university students in

Türkiye. After excluding incomplete surveys, responses failing three attention-check items (e.g., *"If you are reading this item, please mark 54"*), and straightlining responses (e.g., marking all items the same at either end of the response options), 41 cases were removed, resulting in a final sample of 600 participants. Of these participants, 70.5% were female, 68% were single, and 53.5% had completed high school education. Additionally, 41.5% were employed in the public or private sector. Among the employees, 62.7% were white-collar workers, 58.2% were mid-level employees, 27.7% held managerial roles, and 28.5% were mid-level managers. The mean age of the participants was 27.62 years (SD = 9.57; range = 18–62). Their average work experience was 9.84 years (SD = 9.49), and they worked an average of 33.06 hours per week (SD = 18.98).

The data were collected using an online survey designed to assess the study variables and gather demographic information. For students, the survey link was distributed through the first author's university's academic information system and via direct communication between the researchers and the students. For employees, the survey was shared through the researchers' professional networks. Participants were informed that their participation was voluntary, and informed consent was obtained prior to data collection. The study was conducted in accordance with the Declaration of Helsinki, and ethical approval was granted by the ethics board of Sakarya University (Ethics approval number: E-61923333-050.99-479650).

Translation Procedure of the AICD-8

Permission was obtained from the developers of the scale to adapt it into Turkish. Subsequently, the required steps were carried out in accordance with an internationally standardized translation protocol (Beaton et al., 2000). First, the scale was independently translated into Turkish by two of the study authors. Second, the translations were reviewed by a group of academics with high English proficiency. Third, based on their recommendations, the authors synthesized the translations into a single version. Fourth, a small group of six doctoral students were asked to examine the items using the think-aloud method (van Someren et al., 1994) to evaluate clarity and meaning. Fifth, a bilingual faculty member with no prior knowledge of the original scale performed a back-translation. The back-translated form was compared with the original, and no conceptual discrepancies requiring revision were identified. In the final step, the Turkish version of the scale was finalized (see Appendix).

Measures

AI Chatbot Dependence Scale (AICD-8). The AICD-8 (Zhang et al., 2024) was used to assess chatbot dependence. It comprises eight items (e.g., *"I need to open AI chatbots before starting work or tasks"*). Participants rate the items on a five-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). Higher scores indicate a greater level of dependence on AI chatbots. In the present study, Cronbach's alpha for the AICD-8-T was .86.

Problematic ChatGPT Use Scale (PCUS). The PCUS (Yu et al., 2024; Turkish translation: Hoşgör & Güngördü, 2025) was used to assess problematic ChatGPT use. It comprises 11 items (e.g., *“I constantly have thoughts related to ChatGPT lingering in my mind.”*). Participants rate the items on a five-point Likert scale ranging from 1 (*never*) to 5 (always). Higher scores indicate greater levels of problematic ChatGPT use. In the present study, Cronbach’s alpha for the PCUS was .88.

Bergen Social Media Addiction Scale (BSMAS). The BSMAS (Andreassen et al., 2016; Turkish version: Demirci, 2019) was used to assess problematic social media use. It comprises six items (e.g., “*You become restless or troubled if you are prohibited from using social media.”*). Participants rate the items on a five-point Likert scale ranging from 1 (*very rarely*) to 5 (*often*). Higher scores reflect greater risk of problematic social media use. See Table 1 for internal consistency scores. In the present study, Cronbach’s alpha for the BSMAS was .88.

Revised UCLA Loneliness Scale (RULS-6). The RULS-6 (Wongpakaran et al., 2020; Turkish version: Elbi et al., 2025) was used to assess loneliness. It comprises six items (e.g., *“How often do you feel alone?”*) with a single factor. Participants rate the items on a five-point Likert scale ranging from 1 (*never*) to 4 (*always*). Higher scores indicate greater loneliness. See Table 1 for internal consistency scores. In the present study, Cronbach’s alpha for the RULS-6 was .91.

Internet Addiction Test–Short Form (IAT-SF). The IAT-SF (Pawlikowski et al., 2013; Turkish version: Kutlu et al., 2015) was used to assess internet addiction. It comprises 12 items (e.g., *“How often do you choose to spend* *more time online over going out with others?"*). Participants rate the items on a five-point Likert scale ranging from 1 (*never*) to 5 (*very often*). Higher scores reflect greater risk of internet addiction. See Table 1 for internal consistency scores. In the present study, Cronbach's alpha for the IAT-SF was .91.

Daily technology use variables. Participants were asked open-ended questions regarding daily social media use (*"On average, how many hours per day do you spend on social media?"),* daily AI chatbot use (*"On average, how many hours per day do you use AI chatbots [ChatGPT, Gemini, Claude, Copilot, DeepSeek, etc.]?"*), daily ChatGPT use (*"On average, how many hours per day do you spend using ChatGPT?"*). Hour-based responses were used as continuous variables in all analyses. Daily chatbot use refers to the total daily time spent using all AI-based chatbots, including ChatGPT. In contrast, daily ChatGPT use refers only to time spent on the ChatGPT platform.

Demographics. Participants answered demographic questions as follows: gender (1 = male, 2 = female), marital status (1 = married, 2 = single), education level (1 = primary school, 2 = high school or equivalent, 3 = associate degree, 4 = bachelor's degree, 5 = master's degree, 6 = doctorate), age (open-ended), employment sector (1 = public sector, 2 = private sector), type of employee (1 = blue-collar, 2 = white-collar), and organizational position (1 = lower level, 2 = mid-level, 3 = upper level).

Data analysis

Descriptive statistics (means and standard deviations; frequencies and percentages), reliability analyses (Cronbach's alpha, McDonald's omega, and composite reliability), correlation analysis, and confirmatory factor analysis (CFA) were conducted. Model fit for the AICD-8-T was assessed using several widely recommended indices, such as the comparative fit index (CFI), Tucker–Lewis index (TLI), and the root mean square error of approximation (RMSEA). CFI and TLI > .9, and RMSEA < .08 indicate support for the factor structure (Hu & Bentler, 1999). The analyses were performed using SPSS software (version 24) and CFA was conducted using AMOS.

CFA was performed using the Maximum Likelihood (ML) estimation method in AMOS. Although the ML method has been criticized for ordinal data (Li, 2016), it has been shown to provide reliable results in Likert-type scales with five or more categories and among large samples (Rhemtulla et al., 2012). Therefore, in the present study, the ML method was preferred because the scales used a five-point Likert scale and the sample size was sufficient (N = 600). Although robust estimators such as WLSMV or DWLS are often recommended for ordinal data, these estimators are not available in AMOS.

Results

The internal consistency findings of the AICD-8-T (Cronbach's alpha, McDonald's omega, and composite reliability) indicated very good internal consistency (.86–.89), and the internal consistency coefficients of the other variables were also very good to excellent (.87–.93) (see Table 1). CFA results were as follows: $\chi^2 = 66.77$, $p < .001$, $\chi^2/df = 3.71$, TLI = 0.96, CFI = 0.97, RMSEA = 0.07. Factor loadings ranged from .50 to .77 (see Appendix). RMSEA (.07) was within acceptable limits (i.e., below .08), and when evaluated together with CFI and TLI values, the overall fit of the model was found to be good, especially given the model's parsimony and the small number of indicators. Alternative factor structures (e.g., multifactor or bifactor models) were not tested because the AICD-8 was theoretically and empirically developed as a single-dimensional structure in the original study, and the aim of the present study was to test this structure in a new cultural context. Significant positive correlations were found between the AICD-8-T scores and scores on scales assessing problematic ChatGPT use ($r = .68$, $p < .001$), problematic social media use ($r = .30$, $p < .001$), internet addiction ($r = .39$, $p < .001$), and loneliness ($r = .24$, $p < .001$) (see Table 2).

Measurement invariance across gender, job status, and marital status was examined using multi-group CFA. The configural model demonstrated acceptable fit (CFI = .947, TLI = .92, RMSEA = .061), indicating that the single-factor structure was comparable across groups. Although the χ^2 statistic was significant, evaluation primarily relied on incremental fit indices and RMSEA, which are recommended for large samples. Metric invariance was supported because constraining factor loadings to equality resulted in a negligible change in model fit (CFI = .949; ΔCFI = .002), remaining well below the recommended cutoff of .01. Scalar invariance was also supported because constraining item intercepts to equality did not deteriorate model fit

(CFI = .951; ΔCFI = .002; RMSEA = .051). These findings indicate that the scale operates equivalently across gender groups and supports meaningful latent mean comparisons. These findings suggest that the psychological mechanisms underlying AI chatbot dependence operate similarly across gender groups.

The configural model for job status groups showed acceptable fit (CMIN/DF = 5.521; CFI = 0.947; TLI = 0.926; RMSEA = 0.043), supporting the comparability of the factor structure across groups. Metric invariance was also supported because constraining factor loadings did not result in a meaningful deterioration in model fit (ΔCFI < 0.01). These findings indicate that the scale operates equivalently across job status groups.

Similarly, the configural model for marital status groups indicated acceptable fit (CMIN/DF = 5.521; CFI = 0.947; TLI = 0.926; RMSEA = 0.050), suggesting that the factor structure is consistent across groups. Metric invariance was supported because constraining factor loadings did not lead to a substantial decrease in model fit (CFI = 0.950; ΔCFI = 0.003). These results further indicate that the scale functions equivalently across marital status groups. Overall, these findings suggest that the factor structure of the AICD-8-T is stable across different demographic groups.

Table 1. *Descriptive statistics and internal consistency scores of the study variables*

Variable	Total (N = 600)				
	M	*SD*	*(α)*	*(ω)*	*CR*
AI Chatbot Dependence Scale	2.11	0.89	.86	.86	.89
Problematic ChatGPT Use Scale	1.54	0.62	.88	.87	.91

Bergen Social Media Addiction Scale	2.94	1.09	.88	.88	.91
Revised UCLA Loneliness Scale	2.34	0.97	.91	.91	.93
Internet Addiction Test–Short Form	2.34	0.83	.91	.91	.92
Daily social media use (hours)	4.08	2.51			
Daily chatbot use (hours)	0.74	0.97			
Daily ChatGPT use (hours)	0.78	1.23			

Note. M = mean, SD = standard deviation, α = Cronbach's alpha, ω = McDonald's Omega, CR = composite reliability.

Table 2. *Convergent and discriminant validity findings*

Variables	1	2	3	4	5	6	7	8	9	10
1. AI Chatbot Dependence Scale	-									
2. Problematic ChatGPT Use Scale	.68***	-								
3. Bergen Social Media Addiction Scale	.30***	.33***	-							
4. Revised UCLA Loneliness Scale	.24***	.36***	.46***	-						
5. Internet Addiction Test–Short Form	.39***	.47***	.78***	.51***	-					
6. Daily social media use (hours)	.24***	.28***	.50***	.30***	.51***	-				
7. Daily chatbot use (hours)	.51***	.54***	.19***	.22***	.26***	.29***	-			
8. Daily ChatGPT use (hours)	.39***	.43***	.12*	.20***	.19**	.16**	.67***	-		
9. Age	-.24***	-.26***	-.39***	-.23***	-.35***	-.44***	-.24***	-.15*	-	
10. Gender	-.02	-.06	.15*	.03	.07	.13**	-.05	-.05	-.15*	-

Note. ** *p*<0.01, ****p*<.001. Gender 1 = male, 2 = female.

Discussion

In the present study, the psychometric properties of the AICD-8-T were examined. The internal consistency coefficients (α, ω, and CR) of the AICD-8-T were found to be very good (in the range of .86–.89), also consistent with the Cronbach's alpha (.88) and composite reliability (.79) coefficients reported by Zhang et al. (2024) for the original form of the AICD-8. Therefore, H_1 was supported. The present study contributes to the emerging literature on AI chatbot dependence by providing a robust cross-cultural psychometric validation of the AICD-8 within a Turkish sample, including evidence for measurement invariance across multiple demographic groups.

The CFA results indicated that the single-factor structure of the AICD-8-T was confirmed with acceptable model fit. The fit indices obtained were largely consistent with those reported in the original development study ($\chi^2/df = 2.97$, CFI = .96, RMSEA = .08; Zhang et al., 2024). These results confirmed the single-factor structure of the scale, thereby providing support for H_2.

A strong positive relationship was found between the AICD-8-T scores and scores on the Problematic ChatGPT Use Scale ($r = .68$, $p < .001$). These findings support the convergent validity of the scale (supporting H_3). The high effect size suggests that (i) the scales capture a similar latent structure within the same context and (ii) they reflect behaviorally similar addiction constructs (construct alignment) (Fornell & Larcker, 1981).

In terms of nomological validity, the expected positive associations between scores on the AICD-8 and scores on scales assessing problematic social media use, internet addiction, and loneliness supported H_4 and were consistent with previous research (Maral et al., 2025; Robayo-Pinzon et al., 2025). This also suggests that AI chatbot dependence shares underlying psychosocial mechanisms with other forms of online addiction. These mechanisms include social compensation seeking, difficulties with self-regulation, escape motivations, and instant reward cycles (Andreassen et al., 2017; Boursier et al., 2020; Kim et al., 2008).

The moderate positive relationships found between AICD-8-T scores and both problematic social media use and internet addiction are consistent with previous research indicating that online addictions overlap to some extent (Ahmadi, 2023; Skjuve et al., 2024). These associations may be attributed to the structural and functional differences between AI chatbots and other digital technologies, such as social media and the internet (Hu et al., 2023). While internet and social media use often involve more passive activities, such as browsing, reading, or viewing content, AI chatbots operate through an interaction-based, turn-taking conversational process (Hu et al., 2023; Zhang et al., 2024). Therefore, AI chatbots possess distinctive features such as creating a sense of emotional closeness, providing empathetic responses (to some extent), and fulfilling social relationship or companionship needs (Morales-García et al., 2024; Skjuve et al., 2024; Xie et al., 2023). Therefore, the finding that these relationships are not excessively strong is expected and aligns with the existing literature.

The significant positive relationship between loneliness and AI chatbot dependence is consistent with recent research (Hu et al., 2023; Maral et al., 2025). This finding suggests that loneliness and clinical conditions associated with loneliness (e.g., depression, anxiety, deterioration in social relationships) may increase chatbot use and elevate the risk of chatbot dependence (Hu et al., 2023).

A critical finding supporting the criterion-related validity of the AICD-8-T was the strong positive association between the AICD-8-T and daily chatbot use, particularly daily ChatGPT use, which supports H_5. This demonstrates that the AICD-8-T successfully captures the behavioral expressions of ChatGPT dependence tendency.

The absence of a relationship between the AICD-8-T and gender is consistent with the limited but recent evidence (Maral et al., 2025; Robayo-Pinzon et al., 2025). In contrast, age was negatively associated with all technology-related variables, including the AICD-8-T score, Problematic ChatGPT Use Scale score, Internet Addiction Test-Short Form score, Bergen Social Media Addiction Scale score, daily ChatGPT use, and daily chatbot use duration. This consistent negative pattern with age can be explained by prior findings showing that older adults report lower self-efficacy, higher anxiety, and various cognitive or physical barriers regarding technology use (Vaportzis et al., 2017). The finding also aligned with recent statistics indicating that ChatGPT use is far more prevalent among young adults (Pew Research Center, 2025). Therefore, the correlation pattern observed for age suggests that the AICD-8-T functions in the expected direction, further supporting the validity of the scale.

The mean AICD-8-T score was relatively low. This indicates that participants generally had a low level of dependency. However, the scale shows significant correlations with theoretically-related variables in the expected direction, suggesting that the AICD-8-T can sensitively distinguish individual differences in AI chatbot interactions. In this respect, despite the low mean scores, the AICD-8-T is functional in assessing the relative levels of dependency-like tendencies.

It is important to note that AI chatbot dependence is an emerging behavioral construct. The AICD-8 assesses dependency-like tendencies associated with excessive use rather than a clinical disorder. Therefore, the findings should be interpreted within the framework of behavioral patterns rather than formal psychopathology.

Limitations

The present study has several limitations. The relatively low mean age of the participants (27.62 years) suggests that the sample was not fully heterogeneous in terms of age. Because young adults are more inclined toward digital technologies, this may have contributed to higher scores for both online addictions and AI chatbot dependence. The recruitment strategy may have resulted in a sample that overrepresents individuals with higher digital literacy, which may have influenced the observed levels of AI chatbot dependence. In addition, the predominance of female participants reduced the heterogeneity of the sample. Collecting data through self-report measures makes the study susceptible to common measurement errors such as social desirability bias and subjective evaluations. Furthermore, daily usage variables were based on self-reported estimates, which may be subject to recall bias. Moreover, the use of convenience sampling limits the generalizability of the results. Test–retest reliability was also not assessed.

The study was conducted with a modest number of participants. Therefore, future research should include larger samples and participants from more diverse representative sociodemographic backgrounds and organizational levels to improve generalizability. Conducting measurement invariance analyses across different age groups and more gender-balanced samples would strengthen the scale's validity across diverse demographic structures. Test–retest applications should also be conducted to more comprehensively evaluate the reliability and temporal stability of the scale. Moreover, cross-cultural comparisons are needed to enhance the validity of the scale across different cultural contexts.

Conclusion

Overall, findings regarding strong internal consistency coefficients, the confirmation of the single-factor structure, and the expected relationships with theoretically relevant constructs collectively provide robust evidence for the psychometric properties of the AICD-8-T. Therefore, the AICD-8-T can be used to assess AI chatbot dependence among Turkish samples.

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Appendix

Turkish translation of the AI Chatbot Dependence Scale with factor loading

Items	**Factor Loading**
1. Yapay zekâ sohbet botlarını kullanamadığımda kendimi endişeli veya rahatsız hissederim.	0.50
2. İşe ya da bir göreve başlamadan önce yapay zekâ sohbet botlarını açmam gerekir.	0.67
3. Yapay zekâ sohbet botlarını kullanamadığımda, gerekli bilgilere ulaşmakta zorlanırım.	0.64
4. Kendi başıma rahatlıkla yapabileceğim işler ya da görevlerde bile, genellikle yapay zekâ sohbet botlarından yardım alırım.	0.71
5. Diğer insanlarla veya şeylerle vakit geçirmektense, zamanımı yapay zekâ sohbet botlarıyla geçirmeyi tercih ederim.	0.57
6. Yapay zekâ sohbet botlarını aktif olarak kullanmasam bile, onları oturum açık şekilde ya da arka planda çalışır durumda tutarım.	0.63
7. Yapay zekâ sohbet botlarında giderek daha fazla zaman harcıyorum.	0.72
8. Benim için yapay zekâ sohbet botları olmadan bir hayat çok zahmetli olurdu.	0.77

Note. The items reflect the same order as the original.