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Development and Validation of the AI Addiction Scale (AIAS-10): Measuring Compulsive and Emotional Dependence on AI Tools Among EFL Learners

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Abstract
The current study developed and validated the AI Addiction Scale (AIAS-10) to measure problematic use of AI tools, such as ChatGPT. The purpose of the study was to address the lack of standardized instruments for assessing AI-related behavioral dependency in educational settings. Participants consisted of Muslim ELT/ELL students, reflecting the growing integration of AI tools in language learning contexts. Data from 267 users (students and professionals) were analysed to examine the psychometric properties of the scale. Factor analyses were conducted to identify its underlying structure, and reliability analyses were performed to assess internal consistency. The results showed that the scale reliably identifies two key dimensions of AI addiction: compulsive overuse and

emotional dependence. The findings suggest that young adult learners in Muslim educational contexts may be more susceptible to over-reliance on AI for cognitive and language-related tasks. The AIAS-10 effectively captures unique AI-related issues, including over-reliance on cognitive tasks and anthropomorphizing AI systems. As AI becomes increasingly embedded in daily life, this validated tool provides researchers and clinicians with an important method for identifying unhealthy usage patterns. The findings highlight the need for educational guidelines and digital wellbeing strategies that promote balanced AI use in language learning, particularly within Muslim learner contexts.

Keywords: AI addiction, behavioral measurement, scale validation, digital dependency, compulsive technology use, Muslim ELT/ELL students.

INTRODUCTION

The rapid development of artificial intelligence (AI) has significantly transformed how people interact with technology, particularly through conversational AI systems such as ChatGPT (Rani et al., 2023; Smith & Doe, 2024). Recent studies indicate that conversational AI tools have transcended their auxiliary role and become integral to everyday cognitive and communicative practices. In English language education, particularly within Muslim-majority and Islamic educational contexts, AI tools have increasingly been adopted to support language learning, academic writing, and autonomous study practices. This growing adoption reflects broader global trends toward digitalization and learner-centred educational technologies. However, existing research has predominantly emphasized the instructional advantages and technological efficiency of AI tools, while their broader psychological and behavioral implications remain comparatively underexamined.

As AI becomes part of everyday academic and social life, researchers have begun to observe potential risks related to overuse and maladaptive behavioral patterns, like those identified in other forms of technology addiction (Brand et al., 2016). This emerging concept of "AI addiction," which includes compulsive use,

emotional dependence, and negative effects on daily functioning, has recently gained attention within psychological and digital wellbeing research (Andreassen et al., 2012; Kuss & Griffiths, 2015). Despite this growing scholarly interest, existing literature largely conceptualizes addiction within the fields of general digital or internet-based frameworks, offering limited insight into AI-specific dependency patterns shaped by interactive, adaptive, and human-like systems. For Muslim EFL learners, whose educational contexts often emphasize ethical balance, self-regulation, and responsible technology use, understanding such dependency patterns is particularly critical.

As AI continues to permeate educational settings (Smith & Doe, 2024), there is an urgent need for reliable instruments to identify problematic usage patterns and inform pedagogical interventions. Existing measures of digital addiction (Young, 1998; Kwon et al., 2013) were not designed to capture the distinctive behavioral and emotional dimensions associated with AI dependency, such as cognitive offloading, anthropomorphism, and perceived emotional attachment. This limitation is especially evident in English language learning environments serving Muslim communities, where culturally and pedagogically sensitive assessment tools are needed. To address this theoretical and methodological gap, the present study introduces the AI Addiction Scale (AIAS-10), a systematically developed instrument designed to assess the behavioral, emotional, and functional aspects of AI overuse (Brand et al., 2016).

LITERATURE REVIEW

The proliferation of artificial intelligence (AI) has introduced a novel form of behavioral addiction referred to AI dependency, characterized by compulsive engagement, emotional attachment, and functional impairments arising from overreliance on AI systems (Kuss & Griffiths, 2015; Montag et al., 2025).

Recent scholarship has extended insights into the distinct psychological patterns associated with frequent use of AI tools, particularly large language models (LLMs) such as ChatGPT, which

exhibit unprecedented interactivity and personalization (Yankouskaya et al., 2024). In educational contexts serving Muslim communities, these characteristics raise additional pedagogical and ethical considerations related to learner autonomy, responsibility, and balanced technology use. Unlike passive media consumption, AI systems deliver dynamic, context-aware responses that instantaneously fulfill cognitive demands (e.g., problem-solving), emotional needs (e.g., validation), and social functions (e.g., simulated companionship), thereby amplifying reinforcement loops that can escalate to dependency (Huang et al., 2024; Torrego Seijo et al.). Besides, empirical evidence underscores the addictive potential of these tools in educational settings. Similarly, the development of the Problematic ChatGPT Use Scale (PCGUS) in a Turkish sample demonstrated strong correlations between maladaptive ChatGPT interactions, reduced self-control, and diminished wellbeing. Factor analyses confirmed dimensions of loss of control and interpersonal conflict (Maral et al., 2025). Given that Türkiye represents a predominantly Muslim sociocultural context, these findings are particularly relevant for understanding AI-related risks among Muslim EFL learners.

Within Islamic educational contexts, AI's integration into English language teaching (ELT) presents a dual-edged sword: it democratizes access to personalized, adaptive learning resources, enabling EFL learners in resource-limited Muslim-majority regions to practice skills such as pronunciation, grammar, and comprehension through AI-driven simulations (Mujahidah et al., 2023). For EFL learners in Islamic universities, overreliance on AI for tasks like essay generation or conversation practice may undermine authentic language acquisition and critical thinking. This situation exacerbates existing digital divides in regions like Indonesia and Turkey where technology adoption outpaces ethical guidelines (Pamuji, 2023; Al-Othman, 2024).

Emerging theories provide a robust lens for understanding the intricate dynamics of addictive behaviors. The Interaction of Person-Affect-Cognition-Execution (I-PACE) model posits that such behaviors arise from predisposing factors (e.g., impulsivity and

academic stress among EFL students), affective responses (e.g., anxiety reduction via AI feedback), maladaptive cognitions (e.g., over-trust in AI outputs), and impaired executive control (e.g., failed usage moderation), creating a feedback loop toward dependency (Brand et al., 2016; Brand et al., 2019). When applied to Muslim EFL learners, the I-PACE framework elucidates how linguistic pressure, performance expectations, and limited instructional resources may intensify reliance on AI tools that offer immediate cognitive and emotional support (Ye et al., 2024).

Based on Griffiths' (2005) Components Model, AI use may foster overdependence and reduced peer collaboration in ELT settings within Muslim communities, attributable to features such as adaptive dialogue and instant gratification (Musolin et al., 2024; Pontes & Griffiths, 2015). Furthermore, interdisciplinary studies emphasize the need for culturally attuned interventions. In Muslim societies, AI literacy programs grounded in Islamic ethics may mitigate dependency risks by reinforcing human agency (Mujahidah et al., 2023). Yet, gaps persist while Western-centric scales like the PCGUS capture general overuse, they underexplore cultural moderators like religious stigma associated with technology or gender norms in AI access (Shofiyyah et al., 2024). Accordingly, there is a clear need for validated measurement instruments capable of capturing AI dependency within Muslim EFL learning environments.

Theoretical Framework

This study is grounded in the Interaction of Person-Affect-Cognition-Execution (I-PACE) model (Brand et al., 2016), which explains addictive behaviors through interactions between predisposing factors (e.g., impulsivity, academic stress in EFL learners), affective responses (e.g., anxiety relief via AI), cognitive processes (e.g., confidence in AI outputs), and executive functions (e.g., failed self-control).

Complementing I-PACE is Griffiths' (2005) Components Model of Addiction, which identifies six core elements: salience, mood modification, tolerance, withdrawal, conflict, and relapse. Applied to AI, this model highlights how EFL learners

anthropomorphize tools like ChatGPT, leading to emotional attachment and functional impairment (Huang et al., 2024). Additionally, in Islamic ELT settings, AI dependency may exacerbate issues in ELT, such as overreliance on AI for writing, undermining authentic language acquisition (Al-Othman, 2024; Mujahidah et al., 2023).

While widely used instruments such as the Internet Addiction Test (Young, 1998) and the Smartphone Addiction Scale (Kwon et al., 2013) provide valuable insights into general patterns of digital overuse, they remain limited in capturing the interactive and relational characteristics unique to artificial intelligence systems. Conversational AI tools simulate dialogue and responsiveness, which may foster emotional attachment beyond simple usage intensity**.** In contrast, the AI Addiction Scale (AIAS-10) addresses this gap by operationalizing AI-related dependency through two theoretically grounded dimensions informed by established addiction frameworks (Brand et al., 2016), and incorporating AI-specific mechanisms such as cognitive dependence and anthropomorphism**.** The first dimension, *Compulsive Use and Cognitive Dependence*, reflects obsessive engagement with AI tools, excessive reliance on AI for cognitive tasks, and distress during restricted access. This dimension captures the perceived indispensability of AI for thinking rather than its general digital use. The second dimension, *Functional Impairment and Emotional Attachment*, includes negative consequences of excessive AI use as well as attribution of human-like qualities to AI and emotional discomfort when interaction is unavailable**.** Together, these dimensions assess AI-specific addictive behaviors beyond conventional digital addiction.

These dimensions highlight the importance of integrating AI literacy with ethical instruction in Islamic universities and ELT programs to promote balanced technology use and foster learner agency (Permana & Hasanah, 2024). As AI technologies evolve, interdisciplinary collaboration is essential to ensure sustainable and ethically grounded AI integration in Muslim educational

contexts (Andreassen et al., 2012; Elihami et al., 2024; Kuss & Griffiths, 2015).

RESEARCH METHODS

This study employed a cross-sectional survey design to develop and validate the Artificial Intelligence Addiction Scale (AIAS) within a predominantly Muslim higher education context. Prior to analysis, data were screened for missing values, outliers, and normality**.** Statistical analyses were conducted using IBM SPSS Statistics (Version 26) to perform descriptive statistics, assesses internal consistency reliability (Cronbach's alpha), and Exploratory Factor Analysis (EFA). EFA was performed using principal axis factoring with varimax rotation to identify the underlying factor structure. Confirmatory Factor Analysis (CFA) was conducted using AMOS / LISREL 8.8 to test the hypothesized two-factor model, with model fit evaluated using χ^2/df, CFI, TLI, and RMSEA. Construct validity was established through acceptable factor loadings and item–total correlations, indicating that the scale demonstrated satisfactory reliability and psychometric adequacy.

A total of 15 items were initially generated based on a comprehensive literature review on behavioral addictions, technology use, and AI engagement. The development of these items was further informed by theoretical models of addictive behavior, particularly the Interaction of Person–Affect–Cognition–Execution (I-PACE) framework to ensure conceptual alignment between scale dimensions and established addiction constructs. The initial item pool (AIAS-15) was reviewed by three experts in clinical psychology and psychometrics to ensure content validity, cultural appropriateness, and clarity. Participants included a diverse sample of university students and professionals who regularly used AI tools in academic or occupational contexts within a Muslim-majority sociocultural setting. Data were collected through an online questionnaire platform. To refine the scale and establish its psychometric properties, the study followed standard procedures for scale development, incorporating exploratory factor analysis (EFA), reliability analysis, and confirmatory factor analysis

(CFA), in line with recommendations by DeVellis (2017) and Hinkin (1998). During the EFA, five items were removed due to low factor loadings (< .40), high cross-loadings, or conceptual redundancy. The remaining 10 items were retained in the final version (AIAS-10), yielding a two-factor structure supported by satisfactory factor loadings and internal consistency coefficients, as presented in Table 5.

All study procedures were reviewed and approved by the Ethics Committee for Social and Human Sciences at the Van Yüzüncü Yıl University (Decision No: 2025/12-09, Date: 22.05.2025).

Participants

The study sample comprised 267 participants recruited from Van Yüzüncü Yıl University and various professional sectors. The university setting represents a predominantly Muslim educational environment, consistent with the study's focus on AI use among Muslim EFL learners. The sample included 150 university students (90 undergraduates and 60 master's students) from the Faculty of Education, as well as 117 working professionals consisting of 65 teachers, 40 academicians, and 12 doctors. All student participants were enrolled in ELT/ELL programs, focusing on English language learning within Islamic and Muslim-majority educational contexts. Participants ranged in age from 18 to 65 years (M = 26.4, SD = 9.2), with a gender distribution of 52% male and 48% female. All participants met the inclusion criteria of having regular experience using at least one AI-based tool (e.g., ChatGPT, Google Bard) for academic or professional purposes. Although the sample was drawn from a single institutional context, this study is positioned as an initial validation within a Muslim EFL setting, rather than asserting broad cultural generalizability. Further cross-cultural validation across diverse Muslim-majority regions is recommended for future research.

Procedure

Prior to the main data collection, the initial pool of AI Addiction Scale items underwent expert evaluation. A panel of three subject matter experts in educational psychology, behavioral addictions, and digital technologies reviewed the preliminary

version of the scale with particular attention to its applicability in English language education and Muslim learner contexts. Based on their feedback regarding clarity, content relevance, and conceptual overlap, four items were eliminated from the scale.

The survey was administered online via Google Forms and consisted of two parts: (1) demographic questions (e.g., age, gender, occupation, frequency of AI tool use), and (2) the AIAS-10. Participants were presented with an informed consent form, outlining the study's purpose, voluntary participation, and confidentiality of data.

Data Analysis

Data were analyzed using IBM SPSS Statistics and AMOS for structural equation modeling. The psychometric validation process adhered to established scale development guidelines (Hinkin, 1998), ensuring methodological rigor across reliability, construct validity, and group-based comparisons. Reliability was assessed through Cronbach's alpha coefficients, with values of $\alpha \geq 0.70$ considered acceptable (Nunnally, 1978), alongside corrected item–total correlations (> 0.30; Field, 2018) and alpha-if-deleted statistics to refine scale items. Exploratory Factor Analysis (EFA) was conducted using Principal Component Analysis (PCA) with Varimax rotation to identify the underlying factor structure, retaining factors with eigenvalues greater than 1.0 (Kaiser, 1960) and factor loadings of at least 0.40 (Tabachnick & Fidell, 2019). Confirmatory Factor Analysis (CFA) was subsequently performed to test the hypothesized two-factor model using maximum likelihood estimation. The model fit was evaluated based on multiple goodness-of-fit indices, including χ^2/df values below 3.0 (Kline, 2016), Comparative Fit Index (CFI) values above 0.90 (Hu & Bentler, 1999), and Root Mean Square Error of Approximation (RMSEA) values below 0.08 (Maydeu-Olivares et al., 2024). The integrated application of EFA and CFA facilitated both the exploration and confirmation of the scale's latent structure, strengthening evidence for construct validity. Known-groups validity was examined through independent samples *t*-tests comparing AIAS scores between students and professionals, alongside one-way ANOVA

with post-hoc comparisons to assess age-group differences (18–25, 26–40, 41+). Group differences were interpreted with reference to contemporary guidelines for statistical inference and effect size reporting (Lakens, 2022).

RESULTS

Reliability Analysis

Before conducting factor analysis, dataset suitability was assessed using the Kaiser–Meyer–Olkin (KMO) measure and Bartlett's Test of Sphericity.

Table1. KMO and Bartlett's Test of Sphericity

Test	Value
Kaiser-Meyer-Olkin (KMO)	0.785
Bartlett's Test of Sphericity	χ^2 (45) = 369.30, p < .001

The results presented in Table 1 reveal that the KMO value was 0.785, exceeding the recommended threshold of 0.70 (Kaiser, 1974), indicating adequate sampling adequacy for factor analysis. Additionally, Bartlett's Test of Sphericity was significant (χ^2 (45) = 369.30, p < .001), confirming that the correlation matrix was not an identity matrix and thereby supporting the appropriateness of exploratory factor analysis (Bartlett, 1954).

Following factor extraction, internal consistency was examined to assess reliability. The final 10-item AI Addiction Scale (AIAS-10) demonstrated strong internal consistency, with a Cronbach's alpha coefficient of 0.87, exceeding the accepted threshold of 0.70 (Hair et al., 2010; Nunnally & Bernstein, 1994). These results indicate that the retained items reliably measure AI-related addictive tendencies across diverse user groups.

Table 2. KMO and Bartlett's Test of Sphericity

Statistic	Value
Cronbach's Alpha	0.728
Number of Items	10

The AI Addiction Scale (AIAS-10) demonstrated acceptable internal consistency, with a Cronbach's alpha coefficient of 0.728, meeting the recommended threshold for newly developed

psychological instruments (Nunnally & Bernstein, 1994). Although the items reflect generic behavioral indicators of addiction (e.g., conflict, withdrawal, loss of control), this design intentionally targets core psychological mechanisms rather than culture-specific expressions. Islamic ethics, religious stigma, and gender norms are therefore treated as contextual moderators shaping the experience of AI use among Muslim EFL learners, rather than as item-level constructs. Accordingly, the AIAS-10 offers a theoretically universal framework that allows culturally grounded interpretation within Muslim-majority educational settings. The item reduction process, guided by statistical criteria and conceptual clarity, enhanced the scale's focus without compromising reliability, supporting its suitability for subsequent factorial analyses and construct validation within Muslim educational contexts.

Table 3. Item-Total Statistics for the AIAS-10 (N = 267)

Item	Scale Mean if Deleted	Scale Variance if Deleted	Corrected Item-Total Correlation	Cronbach's α if Deleted
1	30.43	11.952	.50	.69
2	30.30	12.299	.43	.70
4	30.31	12.480	.40	.71
5	30.33	12.321	.39	.71
7	30.58	12.018	.49	.69
8	30.50	12.559	.38	.71
11	30.88	12.695	.38	.71
12	30.81	13.471	.21	.73
13	30.81	12.884	.36	.71
15	30.88	12.640	.35	.71

The item–total statistics presented in Table 3 indicate satisfactory psychometric properties for the AIAS-10. All items showed acceptable corrected item–total correlations ranging from .35 to .50, exceeding the recommended threshold of .30 (Nunnally, 1978), except for Item 12 (.21), which was retained due to its theoretical relevance to the emotional attachment dimension of AI addiction, particularly anxiety related to AI unavailability in learning contexts.

The scale demonstrated stable internal consistency across items (Cronbach's α-if-deleted range = .69–.73), indicating that no

single item unduly influenced overall reliability (α = .728). Although removing Item 12 would have produced a marginal increase in alpha (α = .73), this minimal gain (Δα = +.02) was insufficient to warrant exclusion of a conceptually meaningful indicator, especially given the study's focus on AI use in Muslim EFL learning environments.

Furthermore, scale means (30.30–30.88) and variances (11.95–13.47) remained stable across item deletions, supporting scale homogeneity and suggesting that all retained items contribute meaningfully to the measurement of AI addiction. Overall, these findings support the retention of all 10 items in the final AIAS-10 and confirm its suitability for use in both general educational samples and Muslim-majority EFL contexts. Item numbering follows the original 15-item pool for analytical consistency.

Exploratory Factor Analysis (EFA)

An exploratory factor analysis was conducted using Principal Component Analysis (PCA) with Varimax rotation to examine the underlying factor structure of the AI Addiction Scale.

Table 4. Total Variance Explained for the AI Addiction Scale

Component	Initial Eigenvalues	% of Variance	Cumulative %	Rotated Variance (%)
1	2.96	29.55	29.55	22.14
2	1.08	10.78	40.33	18.19

An exploratory factor analysis was conducted using Principal Component Analysis (PCA) with Varimax rotation to examine the underlying factor structure of the AI Addiction Scale. The analysis yielded a two-factor solution. The first component had an eigenvalue of 2.96 and explained 29.55% of the total variance, while the second component had an eigenvalue of 1.08 and accounted for an additional 10.78%. Together, the two factors explained 40.33% of the total variance, exceeding the recommended eigenvalue threshold of 1.0 (Kaiser, 1960). Following Varimax rotation, the variance was more evenly distributed, with the first factor explaining 22.14% and the second factor 18.19%.

This indicates a stable and interpretable factor structure reflecting two distinct dimensions of AI addiction.

Table 5. Rotated Component Matrix for the AI Addiction Scale

Item	Component 1	Component 2
Item_4	.735	
Item_7	.622	
Item_13	.602	
Item_11	.573	
Item_2	.530	
Item_12		.626
Item_5		.609
Item_15		.590
Item_1		.517
Item_8		.517

The rotated component matrix showed a clear two-factor structure. Factor 1 comprised items related to obsessive thoughts, emotional distress when deprived of AI, and negative physical or emotional outcomes (e.g., Items 4, 7, 13), whereas Factor 2 included items reflecting behavioral impact, social impairment, and anthropomorphizing tendencies (e.g., Items 5, 8, 12, 15). Item 1 exhibited minor cross-loading but was retained due to its conceptual relevance. Overall, the structure supports the interpretation of the two dimensions as Compulsive Use and Cognitive Dependence and Functional Impairment and Emotional Attachment.

Independent samples t-test results indicated that university students (M = 46.2, SD = 8.7) scored significantly higher on the AIAS-10 than working professionals (M = 38.1, SD = 7.9), $t(265) = 7.83$, $p < .001$, with a large effect size ($d = 0.96$; Cohen, 1988), suggesting greater vulnerability to problematic AI use among students.

Table 6. Independent Samples t-Test: AIAS-10 Scores by Student Status

Group	*N*	Mea (SD)	*t*	*p*	Cohen's *d*
Students	150	46.2 (8.7)	7.83	< .001	0.96
Professionals	117	38.1 (7.9)			

Age-Based Differences

A one-way ANOVA revealed significant differences in AIAS-10 scores across age groups, $F(2, 264) = 28.4$, $p < .001$, partial $\eta^2 = 0.18$, indicating a large effect consistent with contemporary recommendations for reporting variance-explained effect sizes (Iacobucci, 2023).Tukey HSD post hoc tests showed that individuals aged 18–25 ($M = 47.5$, $SD = 9.1$) scored significantly higher than those aged 26–40 ($M = 39.3$, $SD = 8.3$, $p < .001$) and 41+ ($M = 36.8$, $SD = 7.5$, $p < .001$). However, no significant difference was observed between the 26–40 and 41+ age groups ($p = .12$). These results suggest that younger individuals are more prone to AI-related overuse or dependency**.**

Table 7. One-Way ANOVA: AIAS-10 Scores by Age Group

Age Group	*N*	Mean (SD)	*F*	*p*	Partial η^2
18–25	142	47.5 (9.1)	28.4	**< .001**	**0.18**
26–40	89	39.3 (8.3)			
41+	36	36.8 (7.5)			

Confirmatory Factor Analysis (CFA) and Model Fit

To validate the factor structure identified in the EFA, a confirmatory factor analysis (CFA) was conducted using maximum likelihood estimation in LISREL. The results supported a two-factor model of the AI Addiction Scale (AIAS-10), comprising Compulsive Use and Cognitive Dependence, as well as Functional Impairment and Emotional Attachment. These dimensions reflect core components of behavioral addiction, including salience, loss of control, withdrawal, and functional disruption (Griffiths, 2005). The strong correlation between the latent factors indicates that cognitive–emotional reliance on AI and functional impairment operates in a mutually reinforcing manner, consistent with multidimensional models of digital addiction (Andreassen et al., 2012; Kuss & Griffiths, 2015).

Goodness-of-Fit Indices

The model demonstrated excellent fit based on multiple established criteria (Hu & Bentler, 1999; Kline, 2016):

Table 8. Goodness-of-Fit Indices for CFA (N = 267)

Fit Index	Value	Interpretation
χ^2 (Chi-Square)	51.17, df = 34, p = .03	A statistically significant chi-square suggests some discrepancy between model and data; however, chi-square is sensitive to sample size.
RMSEA	0.044 (90% CI: [0.014–0.067])	Indicates excellent fit (< 0.05), with the confidence interval also within acceptable bounds.
P-close	0.65	Non-significant → supports close model fit (RMSEA < .05).
CFI / IFI / GFI	0.96	Values ≥ .95 indicate excellent fit (Hu & Bentler, 1999).
NNFI (TLI)	0.95	Reflects very good incremental fit.
NFI	0.91	Acceptable (≥ .90) (Bentler & Bonett, 1980).
AGFI	0.94	Acceptable fit; values ≥ .90 are considered good.
RMR/ SRMR	0.023/ 0.045	Both are well below .08, indicating good fit.
ECVI	0.41	Lower values suggest better-expected cross-validation.
PNFI/ PGFI	0.69/0.60	Show good parsimony-adjusted fit.

The CFA results indicate that the two-factor model of the AI Addiction Scale demonstrates an excellent fit to the data. The RMSEA value (0.044) with a non-significant p-close (0.65) suggests a close model–data fit (Savalei et al., 2024), while incremental fit indices (CFI, IFI, NNFI/TLI) exceeding 0.95 confirm strong comparative model performance (Hu & Bentler, 1999). Absolute and residual fit indices further support model adequacy (GFI = 0.96; AGFI = 0.94; RMR = 0.023; SRMR = 0.045), and parsimony indicators (ECVI = 0.41; PNFI = 0.69; PGFI = 0.60) suggest a satisfactory balance between model fit and simplicity (Kline, 2016). Collectively, these findings provide robust evidence for the construct validity of the AIAS-10 and justify the retention of its two-factor structure for future research.

DISCUSSION

This study developed and validated the AI Addiction Scale (AIAS-10) as a concise self-report instrument for assessing problematic engagement with artificial intelligence tools. As generative AI systems such as ChatGPT become increasingly integrated into educational and professional contexts, the need for reliable measures capturing maladaptive usage patterns has become more pressing. The AIAS-10 addresses this gap by offering a psychometrically sound and domain-specific assessment tool, particularly relevant for English language learning environments within Muslim educational contexts.

The scale demonstrated satisfactory internal consistency and a stable two-factor structure, supporting its reliability and construct validity. The identified dimensions, Compulsive Use and Cognitive Dependence and Functional Impairment and Emotional Attachment, are consistent with established behavioral addiction frameworks, particularly the I-PACE model (Brand et al., 2016). These findings suggest that problematic AI use involves both compulsive cognitive engagement and tangible functional consequences, reinforcing the conceptualization of AI addiction as a multidimensional construct.

Group comparisons further supported the discriminative validity of the AIAS-10. University students reported significantly higher levels of AI addiction than working professionals, indicating greater vulnerability among individuals in academically demanding environments. Similarly, younger participants (18–25) scored higher than older users, aligning with prior research on digital and technology-related addictions (Andreassen et al., 2012; Kuss & Griffiths, 2015). These results suggest that early-stage academic engagement and intensive technology use may increase susceptibility to problematic AI reliance.

Importantly, emotional attachment to AI was observed across both student and professional groups, indicating that AI-related dependency is not confined to academic status or age. This finding highlights the broader psychological appeal of AI systems that offer immediate cognitive support and perceived emotional

responsiveness, extending previous research on parasocial interactions with non-human agents (Waytz et al., 2014). By incorporating indicators of functional impairment alongside emotional and cognitive dependence, the AIAS-10 advances existing digital addiction measures, which often overlook AI-specific interactional features. Compared to earlier instruments such as the Internet Addiction Test (Young, 1998) or the Smartphone Addiction Scale (Kwon et al., 2013), the AIAS-10 captures distinctive aspects of AI-mediated engagement, including overreliance and emotional substitution, within culturally situated Muslim EFL learning contexts.

Overall, the findings support the AIAS-10 as a valid and reliable tool for identifying problematic AI use in educational settings. Its application may inform future research, pedagogical guidelines, and interventions aimed at promoting balanced and responsible AI integration in language learning and broader educational environments.

LIMITATIONS AND DIRECTIONS FOR FUTURE RESEARCH

Despite its contributions, this study has several limitations. First, the cross-sectional design limits causal interpretation; thus, future longitudinal research is needed to examine the developmental trajectory of AI dependence and to assess whether elevated AIAS-10 scores predict increasing functional impairment over time, particularly among foreign language learners. Second, the sample was drawn exclusively from Türkiye, which may limit the generalizability of the findings. Moreover, data were collected within a Muslim-majority sociocultural context, where religiously informed norms related to self-regulation and ethical technology use may influence AI engagement patterns. Future studies should validate the AIAS-10 across diverse cultural and linguistic settings and examine potential differences between Muslim and non-Muslim EFL learner populations. Third, reliance on self-report data introduces the possibility of response bias, including social desirability effects. Incorporating objective usage indicators,

behavioral logs, or multi-informant assessments may strengthen future validations of the scale.

Future research may also explore the relationships between AI addiction and related psychological constructs such as procrastination, loneliness, digital fatigue, and trust calibration in AI systems. Finally, the AIAS-10 may be extended to applied contexts, including early screening, intervention development, and educational wellbeing programs, particularly those designed to promote balanced and ethically grounded AI use in language learning environments.

CONCLUSION

Rather than framing intensive AI engagement as inherently pathological, the Artificial Intelligence Addiction Scale (AIAS-10) offers a concise and psychometrically sound instrument for identifying maladaptive patterns of AI use associated with functional impairment and emotional distress. The validated two-factor structure, capturing compulsive cognitive dependence and functional-emotional impairment, conceptualizes AI-related dependency as a context-sensitive and multidimensional phenomenon rather than a unidimensional extension of general technology overuse. Importantly, the AIAS-10 does not equate high-frequency AI use with addiction, particularly in resource-constrained Muslim-majority educational contexts where AI tools often serve as compensatory mechanisms for limited instructional access. Instead, the scale distinguishes structurally driven reliance from problematic use that persists beyond pedagogical necessity and is accompanied by loss of control or psychosocial strain. From this perspective, AI dependency should be interpreted within broader educational and infrastructural conditions rather than as an individual learner deficit. Future research is therefore encouraged to employ comparative and mixed-method approaches to examine how institutional resources, pedagogical support, and cultural norms mediate AI use across diverse Muslim-majority EFL contexts

Conceptually, the AIAS-10 contributes to the emerging literature on AI-mediated behavioral dependency by operationalizing AI use as a distinct phenomenon shaped by both cognitive–emotional engagement and real-life functional consequences. The alignment of its factor structure with established addiction frameworks, including Griffiths' Components Model and the I-PACE model, aims to offer a theoretically grounded explanatory framework rather than to assert causal relationships. Given the cross-sectional design of the study, the findings do not establish whether intensive AI use leads to functional impairment or whether learners with pre-existing characteristics, such as lower language proficiency or limited critical thinking skills, are more likely to rely on AI tools. Accordingly, AI dependency is conceptualized as a context-sensitive pattern of engagement that may both reflect and reinforce learner needs. Longitudinal and experimental studies are required to disentangle causal directions.

The observed group differences indicate that AI dependency is context sensitive. Higher scores among younger users and university students suggest that developmental factors, academic demands, and intensive digital engagement may heighten vulnerability to maladaptive AI use. This finding is particularly relevant in English as a Foreign Language (EFL) settings, where AI tools increasingly function as learning mediators and cognitive supports, potentially blurring the boundary between facilitative use and overreliance.

Significantly, the inclusion of Muslim EFL learners extends the relevance of the AIAS-10 to faith-sensitive educational environments. In such contexts, excessive AI reliance may intersect with culturally informed values related to self-regulation, ethical responsibility, and learner autonomy. The AIAS-10 offers a flexible framework for examining these intersections without reducing AI use to purely moral or technological dimensions.

Overall, the AIAS-10 establishes a reliable foundation for future research on AI-related behavioral risk and responsible AI engagement. Its applications may inform AI literacy initiatives, curriculum development in language education, and early screening

efforts aimed at preventing maladaptive dependency, thereby supporting balanced and autonomous engagement with AI technologies in educational and everyday contexts.

DECLARATIONS

Competing Interests

The authors declare that they have no competing interests related to this study.

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Ethical Approval

This study was approved by the Ethics Committee for Social and Human Sciences of Van Yüzüncü Yıl University, Republic of Türkiye.

Approval Date and Number: 26.05.2025 – 703496 Official Document Number: E-85157263-050.04-703496 The study was conducted in accordance with the ethical principles outlined in the Declaration of Helsinki and relevant institutional guidelines.

Consent to Participate

Informed consent was obtained from all individual participants involved in the study. Participants were assured of the confidentiality and voluntary nature of their participation.

Consent to Publish

Participants provided consent for the publication of anonymized data and findings derived from their responses.

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Appendix 1: AI Addiction Scale (AIAS-10)
Instructions:
Please read each statement and choose how often it applies to you. Answer honestly—there are no right or wrong answers.

Rating Scale:
1 = Never | 2 = Rarely | 3 = Sometimes | 4 = Often | 5 = Always

1. **I try to use AI less, but I can't stop.**
   ○ 1 ○ 2 ○ 3 ○ 4 ○ 5
2. **I need AI's answers to feel sure about my choices.**
   ○ 1 ○ 2 ○ 3 ○ 4 ○ 5
3. **I feel tired, get headaches, or lose sleep from using AI too long.**
   ○ 1 ○ 2 ○ 3 ○ 4 ○ 5
4. **Using AI makes me less productive at work/school.**
   ○ 1 ○ 2 ○ 3 ○ 4 ○ 5
5. **I feel stressed or upset when I can't use AI tools.**
   ○ 1 ○ 2 ○ 3 ○ 4 ○ 5
6. **My relationships are worse because I use AI too much.**
   ○ 1 ○ 2 ○ 3 ○ 4 ○ 5
7. **I worry about not being able to use AI in the future.**
   ○ 1 ○ 2 ○ 3 ○ 4 ○ 5

8. **I think a lot about using AI (like ChatGPT) even when I'm not using it.**
   ○ 1 ○ 2 ○ 3 ○ 4 ○ 5
9. **I treat AI like it's a human (e.g., saying "thank you" or feeling like it understands me).**
   ○ 1 ○ 2 ○ 3 ○ 4 ○ 5
10. **I choose using AI over spending time with friends or doing hobbies.**
    ○ 1 ○ 2 ○ 3 ○ 4 ○ 5

Score Range	Meaning
10–20	Healthy use
21–35	Moderate dependence – Be mindful
36–50	High dependence – May need to cut back