Jordan Journal of Nursing Research,
DOI: https://doi.org/10.14525/JJNR.183

Jordan Journal of Nursing Research

https://jjnr.just.edu.jo/jjnr

Psychometric Evaluation of the Dependence on Artificial Intelligence Scale in Nursing Students: A Turkish Adaptation and Assessment of Validity and Reliability

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ARTICLE INFO

Article History:
Received: April 14, 2026
Accepted: September 13, 2026

ABSTRACT

Background: The increasing integration of artificial intelligence (AI) into nursing education has created a need for valid and reliable instruments to assess dependence on AI technologies. However, no validated instrument has been available to evaluate AI dependence among Turkish nursing students. ***Purpose:*** This study aimed to adapt the Dependence on AI Scale, originally developed by Morales-García et al. (2024), into Turkish and to examine its validity and reliability among nursing students. ***Methods:*** This methodological study was conducted with nursing students from two universities. A total of 486 students participated, of whom 422 were included in the main psychometric analyses. To evaluate construct validity, exploratory factor analysis (EFA; n = 211) and confirmatory factor analysis (CFA; n = 211) were performed. ***Results:*** The scale demonstrated a single-factor structure, explaining 43.536% of the total variance. Factor loadings ranged between 0.466 and 0.802. CFA results indicated an excellent model fit ($\chi^2/df = 0.623$; RMSEA = 0.000; CFI = 0.993; TLI = 0.991). The internal consistency of the scale was found to be acceptable (Cronbach's $\alpha = 0.777$; CR = 0.786). The average variance extracted (AVE = 0.435) was slightly below the conventional threshold of 0.50, but remained acceptable when interpreted together with the satisfactory composite reliability (CR = 0.786). Test-retest analysis revealed high reliability (r = 0.84). ***Conclusion:*** The Turkish version of the Dependence on AI Scale is a valid and reliable instrument for assessing AI dependence among nursing students and may support future research, nursing education, and responsible AI integration into clinical training. ***Implications for Nursing:*** The scale provides nursing educators and researchers with a valid tool to identify AI dependence, evaluate AI literacy initiatives, and support educational strategies that promote critical thinking, independent clinical reasoning, and the responsible use of AI in nursing education.

Keywords: Nursing students, Artificial intelligence dependence, Scale adaptation, Validity, Reliability, Psychometrics.

What does this paper add?

1. It provides the first psychometric evaluation of the Turkish Dependence on AI Scale among nursing students.
2. It demonstrates that the Turkish DAIS is a valid and reliable instrument for assessing AI dependence in nursing education.
3. It supports AI literacy initiatives and responsible AI integration into nursing curricula.

Introduction

The rapid advancement of artificial intelligence (AI)

technologies is transforming learning, decision-making, and knowledge production processes across educational and professional settings (Beard & Wolf, 2001; Feuerriegel et al., 2024; Huang & Rust, 2018). In higher education, AI-based systems facilitate rapid access to information, personalized learning, and decision support; however, their widespread use also raises concerns regarding excessive reliance on technological systems and potential changes in cognitive processes (Beard & Wolf, 2001; Feuerriegel et al., 2024; Huang & Rust, 2018).

Behavioral addiction research suggests that excessive use of digital technologies may negatively affect psychological well-being, academic performance, and social functioning (Chen et al., 2026; van Rooij et al., 2011), Within this context, dependence on AI refers to excessive reliance on AI systems for task completion, decision-making, and performance maintenance, often accompanied by reduced autonomy and functional dependence (Glauberman et al., 2023; Huang et al., 2024). Previous studies have linked overdependence on AI with cognitive offloading, reduced critical thinking, and lower self-efficacy (Glauberman et al., 2023; Morales-García et al., 2024).

The increasing integration of AI into healthcare education is particularly important for nursing students, whose training emphasizes clinical reasoning, patient safety, and ethical responsibility (Glauberman et al., 2023). Excessive reliance on AI may reduce the use of independent clinical judgment and increase dependence on external decision-support systems, potentially affecting both learning outcomes and future professional practice (Chen et al., 2026; Glauberman et al., 2023). Although AI dependence shares certain characteristics with behavioral addictions, it represents a distinct construct characterized primarily by excessive reliance on AI systems rather than compulsive use or loss of behavioral control.

Several instruments have been developed to evaluate technology-related behaviors, such as internet addiction, smartphone addiction, digital technology use, and attitudes toward artificial intelligence. Recent studies have also investigated AI-related attitudes and dependency among university students using different measurement approaches (Arce et al., 2025; Uyar et al., 2026). However, these instruments primarily assess problematic technology use, technology acceptance, or general perceptions of AI rather than dependence on AI itself. The Dependence on Artificial Intelligence Scale (DAIS), developed by Morales-García et al. (2024), is one of the few instruments specifically designed to assess excessive reliance on AI systems for task completion, decision-making, and performance maintenance (Morales-García et al., 2024). Accordingly, it was considered the most appropriate instrument for cross-cultural adaptation and psychometric validation among Turkish nursing students. The original DAIS was developed and validated in a sample of 528 Peruvian medical students, although the original article refers more broadly to "university students" in its title (Morales-García et al., 2024). In contrast, the only Turkish adaptation to date was conducted among university students in sports sciences by Savaş (2024). Although that study demonstrated acceptable validity and reliability, psychometric properties cannot be assumed to remain equivalent across different educational populations (Savaş, 2024). Compared with sports sciences students, nursing students are conceptually and professionally more comparable to medical students, because both nursing and medical education emphasize clinical decision-making, patient safety, evidence-based practice, and the increasing use of AI-supported healthcare technologies. Therefore, further psychometric evaluation of the Turkish DAIS among nursing students was considered necessary to determine whether its validity, reliability, and factor structure could be confirmed within this healthcare education context. Based on this rationale, this study aimed to adapt the Dependence on Artificial Intelligence Scale into Turkish and evaluate its validity and reliability among nursing students.

Materials and Methods

Research Design

This study was designed as a methodological study to adapt the scale into Turkish. The adaptation process, including validity and reliability analyses, was carried out in line with the recommendations of Hambleton and Patsula (1999) and Seçer (2015), following the steps of translation, exploratory and confirmatory factor analyses, item validity, and reliability assessment (Hambleton & Patsula, 1999; Seçer, 2015). This methodological study was reported in accordance with the EQUATOR Network-listed guideline "Recommendations for reporting the results of studies of instrument and scale development and testing" (Streiner & Kottner, 2014).

Participants

The population consisted of 780 nursing students enrolled at two public universities in Türkiye. Data was collected from 486 students. Of these, 20 participants were included in the pilot study, 24 participated in the test-retest assessment, and 20 were excluded due to incomplete questionnaires. Therefore, the final sample used for the main psychometric analyses consisted of 422 participants. To evaluate construct validity, the sample was randomly divided into two independent groups: one for exploratory factor analysis (EFA; n = 211) and the other for confirmatory factor analysis (CFA; n = 211). The use of separate samples for EFA and CFA is recommended to strengthen evidence for construct validity (Brown, 2015; Kline, 2023). Given the five-item structure of the scale, the sample size exceeded commonly recommended criteria for factor analysis (Comrey & Lee, 1992; Hair et al., 2010). The EFA and CFA groups showed similar demographic characteristics, with the majority of participants being female, aged 18-23 years, single, and reporting AI use of less than 30 minutes per day.

Scale Adaptation Process

The scale adaptation process included language validity, content validity, pilot testing, construct validity, and reliability analyses and was conducted in accordance with established recommendations for cross-cultural translation and adaptation of measurement instruments (Hambleton & Patsula, 1999; Sousa & Rojjanasrirat, 2011). The original scale was translated into Turkish by two language experts and synthesized by two nursing academics experienced in artificial intelligence research. Subsequently, two independent bilingual academics performed back-translation, and the final Turkish version was established after comparison with the original scale. Content validity was evaluated by five nursing faculty members, and necessary revisions were made based on expert feedback. The revised scale was pilot-tested with 20 participants to assess clarity and comprehensibility. Temporal stability was examined using the test-retest method with 24 nursing students at a two-week interval (r = 0.84). Construct validity was assessed through Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) following KMO and Bartlett's Test evaluations. Reliability was determined using Cronbach's alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) values.

Data Collection Instruments

Personal Information Form

A 12-item questionnaire developed by the researchers was used to collect data on participants' gender, age, marital status, academic year, income level, perceived health status, presence of chronic illness, duration and purpose of AI use, perceived impact of AI on productivity, and difficulty in completing tasks without AI.

Dependence on AI Scale (DAIS)

The Dependence on Artificial Intelligence Scale (DAIS), originally developed by Morales-García et al. (2024), was translated into Turkish to assess participants' dependence on artificial intelligence. The scale was developed by adapting dependency-related concepts derived from compulsive behaviors described in the *Diagnostic and Statistical Manual of Mental Disorders (DSM-5)* together with evidence from the behavioral addiction literature. It conceptualizes AI dependence as excessive reliance on AI systems for task completion, decision-making, and performance maintenance rather than simple technology use. The instrument evaluates five conceptual domains underlying AI dependence: (1) feelings of vulnerability when AI is unavailable, (2) concerns about maintaining academic or professional performance without AI support, (3) the need to remain up to date with AI technologies, (4) reliance on AI for external validation during decision-making, and (5) fear of personal obsolescence resulting from AI replacing one's existing skills or abilities. The original scale consists of five items rated on a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"), with higher scores indicating greater dependence on artificial intelligence. The original validation study demonstrated a unidimensional factor structure with excellent internal consistency (Cronbach's $\alpha = 0.87$) (Morales-García et al., 2024). The Turkish version retained the original five-item structure and does not include reverse-coded items.

Data Collection Procedure

Data was collected using a Google Forms-based online questionnaire during the spring semester of the 2025-2026 academic year. The survey link was distributed to nursing students enrolled in the Faculties of Health Sciences at Muş Alparslan University and Van

Yüzüncü Yıl University through their academic advisors via WhatsApp student groups and institutional e-mail. Before accessing the questionnaire, participants were first asked whether they agreed to participate in the study, and only those who provided informed consent were allowed to proceed. At the beginning of the questionnaire, participants were informed about the purpose and significance of the study, the voluntary nature of participation, the anonymity and confidentiality of their responses, and their right to withdraw from the study at any time without penalty. They were also informed that there were no right or wrong answers and were encouraged to respond honestly based on their own experiences after carefully reading each item. Participants were additionally asked whether they had regular access to AI platforms (e.g., ChatGPT, Copilot, and Gemini). The questionnaire required approximately 5-7 minutes to complete.

Data Analysis

Data was analyzed using SPSS and AMOS. After screening for missing data, outliers, and normality, descriptive statistics were calculated. The sample (n = 422) was randomly divided into two equal groups (n = 211 each). EFA was conducted on the first group using Principal Axis Factoring with Oblimin rotation, and factors were retained based on eigenvalues >1 and factor loadings ≥0.40. The resulting factor structure was then tested in the second group using CFA. In the CFA model, the residual errors of items A3 and A4 were allowed to covary based on the modification indices and the conceptual relatedness of these items. Model fit was evaluated using χ^2/df, RMSEA, RMR, GFI, AGFI, CFI, TLI, IFI, and NFI indices, while AIC and ECVI values were used for model comparison. Convergent validity was assessed using AVE and CR values, and reliability was evaluated using Cronbach's alpha coefficient.

Results

The findings obtained within the scope of the study are presented in this section.

As shown in Table 1, the majority of the 422 nursing students participating in the study were female (74.2%). Regarding age distribution, most participants were between 18 and 23 years old (84.6%). In terms of academic year, students were predominantly in the second year (38.9%).

Table 1. Demographic characteristics of participants (n = 422)

Variable	Category	n	%
Gender	Female	313	74.2
	Male	109	25.8
Age	18-23	357	84.6
	24-29	52	12.3
	30 and above	13	3.1
Academic Year	1st year	29	6.9
	2nd year	164	38.9
	3rd year	133	31.5
	4th year	96	22.7
Income Level	Less than expenses	148	35.1
	Equal to expenses	235	55.7
	More than expenses	39	9.2
Health Perception	Low	25	5.9
	Moderate	315	74.6
	High	82	19.4
Chronic Disease	Yes	46	10.9
	No	376	89.1
Marital Status	Single	407	96.4
	Married	15	3.6
Access to AI Platforms	Yes	364	86.3
	No	58	13.7
Daily Usage Duration	Less than 30 minutes	267	63.3

	30-60 minutes	105	24.9
	1-2 hours	31	7.3
	More than 2 hours	19	4.5
Perceived Effect on Productivity	Yes	223	52.8
	No	24	5.7
	Partially	175	41.5
Difficulty without Artificial Intelligence	Yes	83	19.7
	No	180	42.7
	Partially	159	37.7
Purpose of Use	Entertainment	19	4.5
	Facilitating daily life	118	28.0
	Work/project-related	14	3.3
	Academic/learning	271	64.2

With respect to income level, more than a half of the students reported that their income was equal to their expenses (55.7%), while only a small proportion indicated that their income exceeded their expenses (9.2%). Perceived health status was generally at a moderate level (74.6%), with 19.4% reporting high health perception. The prevalence of chronic illness was low, with only 10.9% of students reporting a chronic condition. Most participants were single (96.4%).

The majority of nursing students reported having access to AI platforms (86.3%). In terms of daily usage, most participants used AI for less than 30 minutes per day (63.3%). More than a half of the students (52.8%) indicated that AI increased their productivity, while 41.5% reported a partial effect. Regarding difficulty without AI, 19.7% stated that they experienced difficulty, and 37.7% reported partial difficulty. In terms of purpose of use, the majority of students (64.2%) used AI for academic and learning purposes. Other uses included facilitating daily life (28.0%), entertainment (4.5%), and work/project-related purposes (3.3%).

Exploratory factor analysis (EFA) was conducted to examine the construct validity of the dependence on AI Scale. The analysis was performed on a sample of 211 nursing students.

Table 2. Exploratory factor analysis (EFA)

Factor	Item	Factor Loading	Eigenvalue	Variance Explained (%)
Factor 1	A2	0.802	2.679	43.536
	A4	0.786		
	A1	0.678		
	A3	0.489		
	A5	0.466		
Total Variance Explained: 43.536%				
KMO: 0.767				
Bartlett's Test: $\chi^2(10) = 299.900$, $p < 0.001$.				

Note: Principal Axis Factoring was used as the extraction method. A single-factor structure was obtained. Factor loadings ≥ 0.40 are reported. The analysis converged after seven iterations.

As presented in Table 2, exploratory factor analysis (EFA) was conducted to examine the construct validity of the Dependence on AI Scale. Prior to factor extraction, the suitability of the dataset was evaluated using the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's Test of Sphericity. A KMO value above 0.60 is considered acceptable, while values above 0.80 indicate good sampling adequacy (Field, 2018). In this study, the KMO value was 0.767, indicating that the sample was adequate for factor analysis.

Bartlett's Test of Sphericity was statistically significant ($\chi^2(10) = 299.900$, $p < 0.001$), demonstrating that the correlations among variables were sufficient for factor analysis (Tabachnick & Fidell, 2013). These results confirmed that the dataset was appropriate for factor analysis.

Principal Axis Factoring was employed as the

extraction method. Based on eigenvalues greater than 1, a single-factor structure was identified (Kaiser, 1974). The extracted factor had an eigenvalue of 2.679 and explained 43.536% of the total variance. In health sciences, a total explained variance of 40% or higher is generally considered acceptable (Hair et al., 2018). Accordingly, this result indicates adequate construct validity.

Factor loadings ranged from 0.466 to 0.802. In the literature, loadings above 0.40 are regarded as acceptable (Stevens, 2002). Since all items exceeded this threshold, no items were removed from the analysis. The solution converged after seven iterations.

Overall, the EFA findings indicate that the Dependence on AI Scale has a unidimensional, statistically adequate, and theoretically meaningful structure.

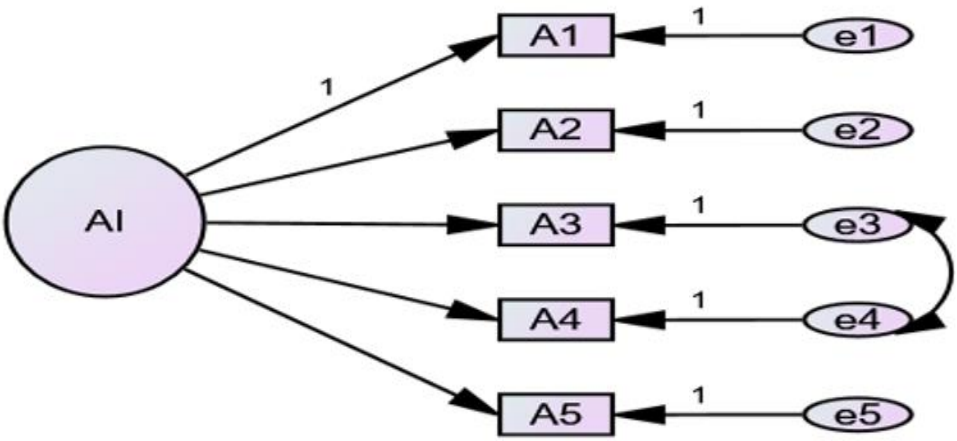


Figure 1. Path diagram of the confirmatory factor analysis

Dependence on artificial intelligence scale (original items)

Item No.	Item	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
1.	I feel unprotected when I do not have access to AI.	1	2	3	4	5
2.	I'm concerned about the idea of being left behind in my tasks or projects if I do not use AI.	1	2	3	4	5
3.	I do everything possible to stay updated with AI to impress or remain relevant in my field.	1	2	3	4	5
4.	I constantly need validation or feedback from AI systems to feel confident in my decisions.	1	2	3	4	5
5.	I fear that AI might replace my current skills or abilities.	1	2	3	4	5

Note: The scale is unidimensional and consists of five items rated on a 5-point Likert scale. The total score ranges from 5 to 25, with higher scores indicating greater dependence on artificial intelligence (5 = no dependence, 25 = very high dependence). There are no reverse-coded items in the scale.

Yapay Zekâya Bağımlılık Ölçeği

Madde No.	İfade	Kesinlikle katılmıyorum	Katılmıyorum	Ne Katılıyorum, Ne katılmıyorum	Katılıyorum	Tamamen katılıyorum
1.	Yapay zekâya erişimim olmadığında kendimi korunmasız hissediyorum.	1	2	3	4	5
2.	Yapay zekâ kullanmazsam görevlerimde veya projelerimde geride kalacağım fikrinden endişe duyuyorum.	1	2	3	4	5
3.	Alanımda etki yaratmak ya da ilgimi sürdürmek amacıyla yapay zekâ alanındaki gelişmeler konusunda güncel kalmaya çalışıyorum.	1	2	3	4	5
4.	Kararlarımdan emin olmak için sürekli olarak yapay zekâ sistemlerinden gelen doğrulamaya veya geri bildirime ihtiyacım var.	1	2	3	4	5
5.	Yapay zekânın mevcut becerilerimin veya yeteneklerimin yerini alabileceğinden korkuyorum.	1	2	3	4	5

NOT: Ölçek tek boyutlu ve 5'li likert tipindedir. Ölçekten alınabilecek en düşük puan 5 (Hiç bağımlı değil), en yüksek puan 25 (Son derece bağımlı)'dır. Ölçekte ters puanlanan madde bulunmamaktadır.

As shown in Figure 1 and Table 2, all items are significantly loaded on the single latent factor representing dependence on artificial intelligence ($p < 0.001$). Standardized factor loadings ranged from 0.401 to 0.890, with the highest loadings observed for items A1 (0.890) and A2 (0.795).

The final CFA model included a correlated residual between items A3 and A4. The CFA results demonstrated excellent model fit: $\chi^2(4) = 2.491$, $p = .646$, $\chi^2/df = 0.623$, RMR = 0.021, GFI = 0.995, AGFI = 0.982, and RMSEA = 0.000 (90% CI: 0.000-0.084; PCLOSE = 0.820). Incremental fit indices also indicated excellent fit (NFI = 0.993, RFI = 0.981, IFI = 0.989, TLI = 0.991, CFI = 0.993). In addition, AIC (24.491) and ECVI (0.117) values were substantially lower than those of the independence model, supporting the superiority of the proposed model. Hoelter indices (0.05 = 800; 0.01 = 1120) further confirmed sample adequacy (Browne & Cudeck, 1993; Hu & Bentler, 1999).

Overall, the findings support the single-factor structure of the Dependence on AI Scale and demonstrate excellent construct validity. Based on the standardized factor loadings, Average Variance Extracted (AVE) and Composite Reliability (CR) values were calculated and are presented in Table 3.

Table 3. AVE, CR, and Cronbach's alpha values for the factor

Variable	Number of Items	AVE	CR	Cronbach's Alpha
Artificial Intelligence Dependence	5	0.435	0.786	0.777

As shown in Table 3, the Dependence on AI Scale demonstrated acceptable reliability, with a Cronbach's alpha coefficient of 0.777 and a Composite Reliability (CR) value of 0.786. Although the Average Variance Extracted (AVE) value (0.435) was below the recommended threshold of 0.50, AVE values above 0.40 are considered acceptable when CR exceeds 0.70 (Fornell & Larcker, 1981). These findings indicate acceptable convergent validity and support the internal consistency and construct reliability of the scale.

Table 4. Descriptive statistics for the dependence on AI scale (n = 422)

Variable	Min.	Max.	Mean	SD	Skewness	Kurtosis
Artificial Intelligence Dependence	5.00	25.00	12.73	3.51	0.29	0.40

As presented in Table 4, the mean score of the dependence on AI was 12.73 (SD = 3.51). Considering the possible score range of 5 to 25, this average indicates that nursing students exhibit a low to moderate level of dependence on artificial intelligence tools.

The skewness value was 0.29 and the kurtosis value was 0.40, both of which fall within the ±1 range. This suggests that the data distribution approximates normality and is suitable for parametric statistical analyses (George & Mallery, 2010).

Discussion

The present study examined the validity and reliability of the Turkish version of the Dependence on AI Scale developed by Morales-García et al. (2024) among nursing students. The findings indicate that the scale is a valid and reliable instrument for assessing dependence on artificial intelligence within the Turkish cultural context. The translation, back-translation, expert review, and pilot testing procedures supported the linguistic and conceptual equivalence of the Turkish version, which is a fundamental requirement in cross-cultural scale adaptation studies (Beaton et al., 2000; Hambleton & Patsula, 1999).

The construct validity findings confirmed the original unidimensional structure proposed by Morales-García et al. (2024). The EFA results supported a single-factor solution, and the total variance explained (43.536%) was within acceptable limits for social science research (Hair et al., 2018). Furthermore, the CFA results demonstrated excellent model fit, with all fit indices meeting or exceeding recommended criteria (Brown, 2015; Hu & Bentler, 1999). These findings indicate that the Turkish version measures the same underlying construct as the original scale and provide evidence for the structural validity of the instrument (Morales-García et al., 2024). The preservation of the single-factor structure is also consistent with the Turkish adaptation conducted among sports science students, suggesting that the construct of AI dependence remains stable across different educational settings (Savaş, 2024).

The reliability analyses further supported the psychometric adequacy of the scale. The Cronbach's alpha coefficient (0.777) indicated acceptable internal consistency, although it was slightly lower than that reported by Morales-García et al. (2024) in the original study (α = 0.87) (Morales-García et al., 2024). Nevertheless, the value remained above the generally accepted threshold for reliability (Nunnally & Bernstein, 1994). Similarly, the Composite Reliability value (CR = 0.786) exceeded the recommended level of 0.70, confirming adequate construct reliability. Although the Average Variance Extracted (AVE) value (0.435) was slightly below the conventional threshold of 0.50, previous studies have suggested that AVE values above 0.40 may still indicate acceptable convergent validity when Composite Reliability exceeds 0.70. In the present study, the CR value (0.786) exceeded the recommended threshold, supporting adequate construct reliability. Consistent with the recommendation of Fornell and Larcker (1981), the convergent validity of the Turkish DAIS can therefore be considered satisfactory despite the relatively low AVE, particularly given the brevity of the instrument and its five-item unidimensional structure.

The test-retest correlation coefficient (r = 0.84) demonstrated strong temporal stability, indicating that the scale produces consistent measurements over time. This finding is particularly important, because dependence on AI is an emerging construct, and stable measurement is necessary for monitoring changes in AI-related behaviors and attitudes.

Another noteworthy finding is that nursing students reported generally low-to-moderate levels of dependence on artificial intelligence. Although AI technologies are increasingly integrated into educational and clinical learning environments, dependence levels do not yet appear to have reached problematic levels. Nevertheless, previous research has suggested that excessive reliance on AI may contribute to cognitive offloading, reduced critical thinking, and diminished self-efficacy (Glauberman et al., 2023; Huang et al., 2024). Given the importance of clinical reasoning,

professional judgment, and patient safety in nursing, monitoring AI dependence remains important.

Overall, the findings support the use of the Turkish version of the Dependence on AI Scale as a psychometrically sound instrument for nursing students. By extending the work of Morales-García et al. (2024) to a population with significant responsibilities related to clinical decision-making and patient care, this study contributes to the growing literature on AI dependence and provides a useful tool for future research in healthcare education. Recent research examining artificial intelligence literacy among midwifery students further reflects the growing scholarly attention to students' knowledge, competencies, and interactions with AI technologies in healthcare education (Jakalat et al., 2025).

From a nursing education perspective, the availability of a valid and reliable instrument to assess AI dependence may support educators in identifying students who rely excessively on AI technologies during learning and clinical preparation. Early identification of elevated AI dependence can help educators implement targeted educational strategies that promote critical thinking, independent clinical reasoning, and reflective decision-making. In addition, the scale may be useful for evaluating the effectiveness of educational interventions designed to promote safe, ethical, and evidence-based AI use throughout nursing education. The use of standardized and psychometrically evaluated assessment instruments is also important for the systematic evaluation of nursing students' educational outcomes (Khraisat et al., 2026). Furthermore, the scale may support curriculum planning and AI literacy initiatives by enabling nursing schools to monitor changes in students' AI dependence over time. As artificial intelligence becomes increasingly integrated into nursing education and healthcare practice, balancing the benefits of AI with the preservation of professional judgment and patient-centered care will become increasingly important.

Limitations

This study has several limitations. First, the sample consisted only of nursing students from two public universities in Türkiye, which may limit the generalizability of the findings to students from other disciplines or cultural settings. Second, the use of self-report measures may have introduced response bias and social desirability bias. Third, the cross-sectional design did not allow assessment of changes in AI dependence over time. In addition, although the present study demonstrated satisfactory evidence of structural validity and reliability, some psychometric properties, including discriminant validity and measurement invariance across demographic sub-groups (e.g., sex or academic year), were not evaluated. Future studies should also investigate criterion validity and predictive validity by examining the relationship between AI dependence and outcomes such as clinical reasoning, critical thinking, academic performance, and professional decision-making. In addition, further validation studies across different educational settings, healthcare disciplines, and cultural contexts are recommended to strengthen the generalizability of the findings. Finally, several foundational references older than five years were intentionally retained, because they represent seminal works that continue to underpin contemporary research on behavioral addiction, psychometric validation, and structural equation modeling.

Implications for Nursing

The Turkish version of the Dependence on AI Scale provides nursing educators and researchers with a valid and reliable instrument for assessing AI dependence among nursing students. The scale can be used to identify students who may rely excessively on AI technologies and to evaluate the effectiveness of educational interventions aimed at promoting responsible AI use. Furthermore, it may support curriculum development by encouraging educational strategies that strengthen critical thinking, independent clinical reasoning, and ethical decision-making while integrating AI into nursing education.

Conclusion

This study demonstrated that the Turkish version of the Dependence on AI Scale is a valid and reliable instrument for use among nursing students. The findings confirmed the single-factor structure, acceptable internal consistency, excellent model fit, and strong temporal stability.

As artificial intelligence becomes increasingly integrated into nursing education and clinical practice, the availability of a psychometrically sound instrument to assess AI dependence may help educators and researchers identify excessive reliance on AI

technologies while promoting responsible and ethical AI use. The scale may also support curriculum evaluation, AI literacy initiatives, and educational interventions aimed at strengthening critical thinking, independent clinical reasoning, and professional decision-making among future nurses. Future studies should evaluate the scale in larger and more diverse samples, investigate additional psychometric properties, and examine the relationship between AI dependence and educational as well as clinical outcomes. Ultimately, the availability of a culturally adapted and psychometrically sound measure of AI dependence may contribute to the responsible integration of artificial intelligence into nursing education and support the preparation of future nurses for AI-enhanced clinical practice.

Acknowledgements

The authors would like to thank all participants in this study.

Ethical Principles

Approval from Muş Alparslan University Scientific Research and Publication Ethics Committee for the research (Date and Approval No: 12.01.2026-228385) was obtained. Electronic informed consent was obtained from all participants.

Consent to Participate

Electronic informed consent was obtained from all participants.

Consent for Publication

Publication permission was obtained from the participants.

Conflict of Interests

The authors declare that they have no conflict of interests.

Funding or Sources of Financial Support

There was no funding for this study.

Author Contributions

Study Design: **MU**. Data Collection: **MFY**. Data Analysis: **MU, MFY.** Study Supervision: **MU**. Manuscript Writing: **MU, MFY**. Critical Revision for Important Intellectual Content: **MU, MFY**.

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