Assessment of dependence on artificial intelligence and associated factors among medical students

Tıp öğrencilerinde yapay zekaya bağımlılık ve ilişkili faktörlerin değerlendirilmesi

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doi.org/10.35232/estudamhsd.1915530

ESTUDAM Public Health Journal. 2026;11(2):131-140

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***Geliş Tarihi / Received:** 26.03.2026*

***Kabul Tarihi / Accepted:** 20.04.2026*

Abstract

This study aimed to assess the level of dependence on artificial intelligence (AI) among medical students and to identify its associated factors. The study population of this cross-sectional study consisted of 236 medical students in years 1–4 at a university in November 2025. Data were collected using a questionnaire that included sociodemographic characteristics, AI usage characteristics, the Scale for Dependence on AI (DAI), the Academic Self-Efficacy Scale (ASES), and the Multidimensional Scale of Perceived Social Support (MSPSS). The mean age of the participants was 20.02±1.65 years, and 49.2% were male. DAI scores ranged from 5 to 25, with a mean of 11.04±4.08. Higher mean DAI scores were observed among students who used AI for more than 30 minutes daily, checked AI without intending to use it, and used it for academic and social chatting/emotional sharing purposes ($p<0.05$). DAI scores showed a weak negative correlation with ASES scores ($r=-0.235$) and a moderate negative correlation with MSPSS scores ($r=-0.376$; $p<0.001$). In hierarchical regression analysis, dependence on AI was associated with daily AI use duration, checking AI without intention, using AI for academic and social chatting/emotional sharing purposes, academic self-efficacy, and perceived social support. In line with these findings, raising awareness, promoting balanced use, and strengthening academic self-efficacy and social support may be beneficial in reducing the risk of AI dependence.

Keywords: Artificial Intelligence, dependence, medical students, academic self-efficacy, perceived social support

Özet

Çalışmada tıp öğrencilerinin yapay zekaya (YZ) bağımlılık düzeyleri ve ilişkili faktörlerin değerlendirilmesi amaçlandı. Kesitsel tasarımdaki çalışmanın araştırma grubunu, Kasım 2025'te bir üniversitede öğrenim gören 1–4. sınıf tıp öğrencisi 236 kişi oluşturmuştur. Veriler sosyodemografik özellikler, yapay zeka kullanım özellikleri ile Yapay Zekaya Bağımlılık Ölçeği (YZBÖ), Akademik Özyeterlik Ölçeği (AÖÖ) ve Çok Boyutlu Algılanan Sosyal Destek Ölçeği (ÇBASDÖ)'nün yer aldığı anket formu ile toplandı. Katılımcıların yaş ortalaması 20,02±1,65 olup, %49,2'si erkekti. YZBÖ puanları 5–25 arasında değişmekte olup ortalaması 11,04±4,08 idi. Yapay zekayı günlük 30 dakikadan fazla kullananlarda, kullanma niyeti olmadığı halde kontrol edenlerde ve akademik ile sosyal sohbet/duygusal paylaşım amaçlı kullananlarda YZBÖ puan ortalaması daha yüksekti ($p<0,05$). YZBÖ ile AÖÖ arasında zayıf ($r=-0,235$), ÇBASDÖ ile orta düzeyde negatif ilişki saptandı ($r=-0,376$; $p<0,001$). Hiyerarşik doğrusal regresyon analizinde, yapay zekaya bağımlılığın; günlük yapay zekâ kullanım süresi, kullanma niyeti olmadan yapay zekayı kontrol etme, yapay zekayı akademik ve sosyal sohbet/duygusal paylaşım amacıyla kullanma, akademik öz-yeterlik ve algılanan sosyal destek ile ilişkili olduğu bulundu. Bu bulgular doğrultusunda, farkındalığın artırılması, dengeli kullanımın teşvik edilmesi ve akademik öz-yeterlik ile sosyal desteğin güçlendirilmesi, yapay zekâ bağımlılığı riskini azaltmada yararlı olabilir.

Anahtar Kelimeler: Yapay zeka, bağımlılık, tıp öğrencileri, akademik özyeterlik, algılanan sosyal destek

Introduction

Artificial intelligence (AI) is a field that focuses on developing machines, software, and applications capable of performing tasks typically associated with human cognition, including natural language understanding, pattern recognition in data, and decision-making based on available information, and the development of these systems (1, 2). In recent years, AI technologies have been widely adopted across various domains, shaping how individuals learn, communicate, and carry out tasks (3, 4). Due to their advanced interaction capabilities and ability to generate high-quality responses, AI technologies attract attention from various user groups (3, 5). Indeed, as of 2025, approximately 32.7% of individuals aged 16–74 in the European Union reported using generative AI tools, with usage primarily for personal purposes, followed by work-related and formal education use (6).

The rapid and widespread adoption of AI has also brought certain risks to the forefront. In particular, individuals' frequent and uncontrolled reliance on AI tools has raised the concept of AI dependency (3, 7). Dependence on AI may emerge as a form of behavioral tendency characterized by excessive reliance on automated systems for decision-making, task execution, or validation; while these technologies enhance efficiency, they may simultaneously contribute to feelings of insecurity and fear of falling behind (8). Dependent use of AI has been shown to be associated with several adverse outcomes, including reduced critical thinking and problem-solving skills, decreased academic productivity, increased laziness, inert thinking, diminished creativity, and weakened critical and independent thinking (3, 9, 10).

Medical education is a demanding process in which students face a wide range of stressors, including heavy academic workload, difficulties in time management, peer relationships, financial challenges, uncertainties regarding career planning, performance anxiety, and a competitive learning environment, as well as limited extracurricular activities and increasing concerns about their future profession (11, 12). The tendency of individuals to turn to external digital systems in order to cope with uncertainty and cognitive load suggests that the use of AI may extend beyond functional purposes and evolve into dependent use driven by the need for digital reassurance, instant access to information, and continuous connectivity. In this context, the inherently information-intensive nature of medical education, which requires rapid and efficient access to knowledge, may render medical students more susceptible to the development of dependence on AI (13).

Given this potential vulnerability, academic self-efficacy and perceived social support may also be associated with AI dependency among medical students. Lower academic self-efficacy has been shown to be associated with AI dependency among students, with this relationship being mediated by academic stress and performance expectations (10). In addition, the conversational and advisory functions of generative AI tools may help individuals cope with feelings of loneliness and address their social interaction needs (14, 15). Accordingly, individuals with lower perceived social support may be more likely to view AI as an alternative social environment and tend to use these tools more frequently, potentially increasing the risk of dependent use.

Overall, dependence on AI may become more pronounced among medical students who are under high academic workload and performance expectations. Accordingly, the present study aimed to assess the factors associated with

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Nasıl Atıf Yaparım / How to Cite:
Akbulut Zencirci S. Assessment of dependence on artificial intelligence and associated factors among medical students. ESTUDAM Public Health Journal. 2026;11(2):131-140

dependence on AI among medical students.

Material and Method

Research Design and Participants

This cross-sectional study was conducted in November 2025 among 1st–4th grade students of the Faculty of Medicine at Bilecik Şeyh Edebali University. The study aimed to reach all students and no sampling method was applied. After informing the students about the aim and content of the study, a link to the questionnaire, which had been transferred to a digital platform, was shared via student WhatsApp groups. Participation was voluntary; therefore, 236 students (77.6%) who agreed to participate and completed the questionnaire were included.

Data Collection Instruments

A questionnaire was prepared in accordance with the aim of the study. The questionnaire included items on participants' sociodemographic characteristics, AI use features, the Scale for Dependence on Artificial Intelligence (DAI), the Academic Self-efficacy Scale (ASES), and the revised form of Multidimensional Scale of Perceived Social Support (MSPSS).

Dependence on AI was measured using the DAI. DAI was developed by Morales-García et al. and the Turkish validity and reliability study of the scale was conducted by Savaş in 2024 (8, 16). The scale consists of five items rated on a five-point Likert scale. The total score ranges from 5 to 25, with higher scores indicating a higher levels of dependence on AI. The Cronbach's alpha value of the scale was reported as 0.82 (16).

Academic self-efficacy was measured using the ASES. It was developed by Jerusalem and Schwarzer, and its Turkish validity and reliability study was conducted by Yılmaz et al. (17, 18). The scale consists of seven items rated on a four-point Likert scale, with higher scores indicating a higher levels of academic self-efficacy. The Cronbach's alpha value of the scale was reported as 0.79 (18).

Perceived social support was measured using the MSPSS, a scale developed by Zimet et al. and adapted into Turkish by Eker et al. (19, 20). The scale comprises three subdimensions—family, friends, and significant other—each represented by four items. It is a seven-point Likert-type scale, producing scores ranging from 12 to 84, with higher scores indicating higher levels of perceived social support. The Cronbach's alpha coefficient was reported as 0.89 for the total scale, with values ranging from 0.85 to 0.92 for the subdimensions (20).

Ethical Approval

Ethical approval was obtained from the Non-Interventional Clinical Research Ethics Committee of Bilecik Şeyh Edebali University (Approval No: 10; Date: 30 October 2025), and the necessary administrative permissions were also secured.

Statistical Analysis

Data were analyzed using SPSS version 15. Descriptive statistics were presented as mean and standard deviation for continuous variables, and as frequencies and percentages for categorical variables. The normality of the data was assessed using skewness and kurtosis values, as well as histogram and Q–Q plots. Independent samples t-test, one-way analysis of variance (ANOVA), and Pearson correlation analysis were used for comparisons.

Hierarchical multiple linear regression analysis was performed to identify the predictors of DAI scores. Variables were entered into the model in three sequential blocks. Demographic variables were included as control variables in the first block, followed by AI use features in the second block, and academic self-efficacy and perceived social support in the third block. Assumptions of the regression analysis were examined and found to be satisfied. Multicollinearity was assessed using Variance Inflation Factor (VIF) values, and all VIF values were below 2. Statistical significance was set at $p \leq 0.05$.

Results

Of the 236 students included in the study, 49.2% were male and 50.8% were female. Their ages ranged from 18 to 28 years, with a mean age of 20.02±1.65 years. A total of 66.1% of the students reported using AI for less than 30 minutes per day, and 86.4% reported using it for academic purposes (Table 1).

A total of 95.8% of the students reported using ChatGPT, 55.5% Gemini, and 10.6% Canva AI/ Notion AI (Figure 1).

Table 1: Distribution of students according to sociodemographic characteristics and AI usage features

Sociodemographic characteristics and AI usage features	n (%)
Age	
<20	102 (43.2)
≥20	134 (56.8)
Gender	
Male	116 (49.2)
Female	120 (50.8)
Place of residence	
Home – with family/friends	48 (20.3)
Home – alone	70 (29.7)
Dormitory	118 (50.0)
Daily AI use duration	
<30 minutes	156 (66.1)
≥30 minutes	80 (33.9)
Checking AI without intending to use it	
Yes	137 (58.1)
No	99 (41.9)
Using AI for academic purposes	
Yes	204 (86.4)
No	32 (13.6)
Using AI for social chat/emotional sharing	
Yes	73 (30.9)
No	163 (69.1)
Using AI for daily information seeking	
Yes	126 (53.4)
No	110 (46.6)
Using AI for entertainment/curiosity	
Yes	94 (39.8)
No	142 (60.2)

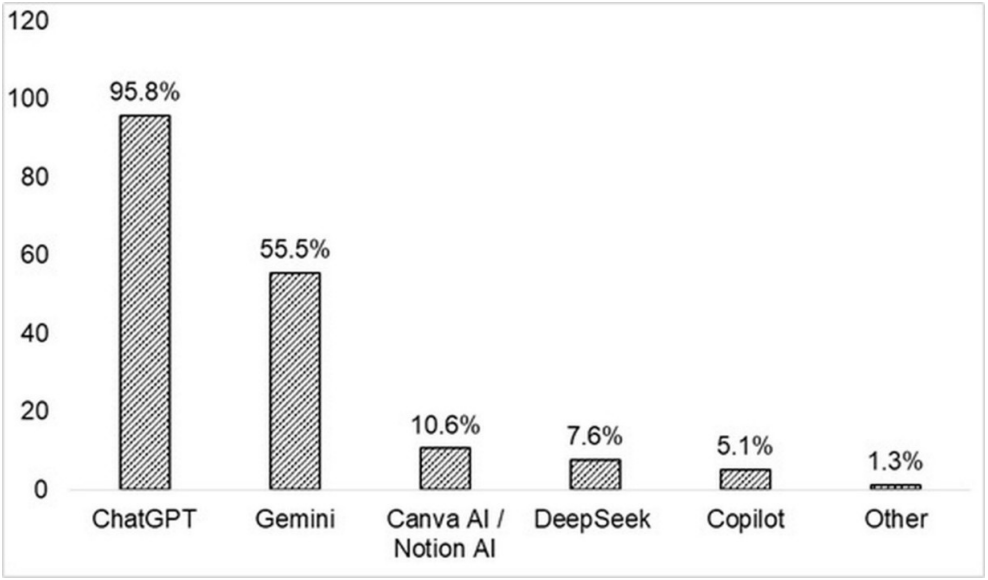


Figure 1: Distribution of AI tools used by students (frequencies based on participants)

In the study, DAI scores ranged from 5 to 25, with a mean of 11.04±4.08. Higher mean DAI scores were observed among students who reported using AI for more than 30 minutes per day, those who reported checking AI even when they did not intend to use it, and those who reported using AI for academic purposes and for social chat/emotional sharing (p<0.05) (Table 2).

Table 2: Comparison of DAI scores according to students' sociodemographic characteristics and AI usage features

Sociodemographic characteristics and AI usage features	DAI Mean ± SD	p
Age		
<20	10.76 ± 3.75	0.346*
≥20	11.26 ± 4.31	
Gender		
Male	10.84 ± 4.48	0.446*
Female	11.25 ± 3.65	
Place of residence		
Home – with family/friends	11.90 ± 4.06	0.106**
Home – alone	10.30 ± 4.25	
Dormitory	11.14 ± 3.93	
Daily AI use duration		
<30 minutes	9.93 ± 3.52	**<0.001***
≥30 minutes	13.21 ± 4.23	
Checking AI without intending to use it		
Yes	11.74 ± 4.31	**0.001***
No	10.08 ± 3.53	
Using AI for academic purposes		
Yes	11.28 ±4.13	**0.021***
No	9.50 ± 3.42	
Using AI for social chat/emotional sharing		
Yes	12.82 ± 4.73	**<0.001***
No	10.25 ± 3.48	
Using AI for daily information seeking		
Yes	11.43 ± 4.23	0.120*
No	10.60 ± 3.87	
Using AI for entertainment/curiosity		
Yes	10.46 ± 3.75	0.073*
No	11.43 ± 4.25	

**Independent samples t-test; **One-way ANOVA*

The students' mean ASES score was 18.39 ± 3.93, and their mean MSPSS score was 56.72±16.12. A weak negative correlation was found between DAI and ASES scores (r=-0.235, p<0.001), whereas a moderate negative correlation was found between DAI and MSPSS scores (r=-0.376, p<0.001).

In the hierarchical linear regression analysis, dependence on AI was significantly associated with daily AI use duration, checking AI without intending to use it, using AI for academic purposes, and using AI for social chat/emotional sharing purposes, as well as lower academic self-efficacy and lower perceived social support (Table 3).

Table 3: Hierarchical multiple linear regression results for factors associated with students' DAI scores

Parameters	Model 1 B (95% CI)	Model 2 B (95% CI)	Model 3 B (95% CI)
Age	0.487 (-0.571; 1.545)	0.177 (-0.785; 1.138)	0.028 (-0.877; 0.934)
Gender	0.382 (-0.667; 1.430)	0.150 (-0.802; 1.102)	0.126 (-0.782; 1.033)
AI usage features			
Daily AI use duration		2.587 (1.514; 3.661)***	2.176 (1.150; 2.301)***
Checking AI without intending to use it		0.701 (-0.310; 1.713)	0.978 (0.022; 1.935)*
Using AI for academic purposes		1.664 (0.270; 3.059)*	1.597 (0.280; 2.913)*
Using AI for social chat/ emotional sharing		1.643 (0.570; 2.717)**	1.187 (0.152; 2.221)*
Academic self-efficacy			-0.145 (-0.267; -0.023)*
Perceived social support			-0.063 (-0.094; -0.032)***
R^2	0.006	0.210	0.308
F	0.703	10.148***	12.616***

**p≤0.05, **p ≤ 0.01, ***p≤0.001*

Discussion

In today's educational landscape, the rapid integration of AI technologies is transforming the ways in which students learn. In this context, AI has moved beyond being merely a tool that facilitates access to information and has begun to assume an active role in students' academic and cognitive processes (3, 4). Particularly within the context of medical education, which is characterized by a high academic workload and constant performance pressure, sustained interaction with AI may increase the likelihood of evolving into problematic usage patterns (10, 11, 13). Accordingly, the present study focuses on examining the factors associated with dependence on AI among medical students.

In this study, no significant relationship was found between gender and the level of dependence on AI. Although some studies have reported similar findings (21, 22), another study has indicated that dependence levels may be higher among women (13). In addition, there is evidence suggesting that attitudes toward AI are more positive among men (23, 24). Taken together, these findings suggest that dependence on AI may be a construct that emerges independently of gender; however, the inconsistencies across studies should be interpreted with caution, as they may stem from differences in sample characteristics, study contexts, and measurement tools. Furthermore, no significant relationship was identified between age and the level of dependence on AI in this study. This may be attributed to the relatively narrow and homogeneous age range of the study sample.

Within the framework of behavioral addictions, it is noted that the increasingly frequent and repetitive nature of use constitutes one of the core components of addiction (25). Similarly, in the present study, individuals with higher daily usage duration and

those who checked AI without intending to use it were found to have higher levels of dependence on AI. Studies on digital technologies likewise indicate that sustained intensive and repetitive use, as well as frequent checking behaviors, may be associated with problematic usage patterns (26-28). These findings suggest that, as in other forms of digital addiction, usage behaviors occupy a significant place among the factors associated with dependence on AI.

In this study, it was found that students who used AI for academic purposes had higher levels of dependence on AI compared to those who did not. ChatGPT, one of the widely used artificial intelligence tools, is described as a valuable tool that facilitates the understanding of complex topics, supports academic tasks, and offers personalized feedback along with interactive learning opportunities (29). Considering the demanding nature of medical education, it is reasonable that students may turn to AI tools that provide quick and practical support for academic tasks. Indeed, a study conducted with university students reports that AI is most commonly used for academic purposes (10). However, it is also suggested that such facilitating support provided by AI tools may, over time, encourage students to rely on these systems more frequently; excessive use, in turn, may lead to negative outcomes for critical thinking and problem solving skills (10). In this context, although the use of AI for academic purposes may initially represent a functional choice, it may gradually evolve into a more intensive usage pattern and become associated with higher levels of dependence on AI.

It has been shown that in interactions with AI, individuals may engage in emotional and personal disclosures, and that these systems provide a communicative environment that allows for self-expression (30, 31). Consistent with this, such emotional and social interactions established with social chatbots have been reported to be associated with compulsive usage behaviors and problematic usage patterns (32, 33). In the present study, students who used AI for social chat and emotional sharing were also found to have higher levels of dependence on AI. This finding suggests that this form of use may, over time, evolve into a more intensive and repetitive pattern, thereby becoming associated with higher levels of dependence on AI. In this study, it was found that as academic self-efficacy decreased, levels of dependence on AI increased. Similar findings have also been reported in a study conducted with university students (10). Individuals with low academic self-confidence may experience greater difficulty in their learning processes, and their participation in and motivation toward academic tasks may be limited (34, 35). This situation may lead individuals to seek external support in academic tasks. It has been reported that AI tools can be used by students to provide support in academic tasks and to facilitate learning processes (29). Accordingly, it is suggested that among individuals with low academic self-efficacy, the use of AI may, over time, develop into a more intensive pattern and become associated with higher levels of dependence.

It has been reported that individuals who experience deficiencies in social skills may tend to turn to online environments and engage in social interactions within these settings (36). Indeed, low perceived social support has been shown to be associated with internet addiction, and social media addiction (37, 38). Similarly, psychological states such as loneliness have been found to be related to individuals' tendencies to engage with AI-based systems (14, 15). In line with these findings, the present study also found that as perceived social support decreased, levels of dependence on AI increased. Therefore, as observed in other forms of technology-related addictions, individuals with lower levels of perceived social support may be more likely to turn to AI use, which in turn may contribute to higher levels of dependence.

According to the results of the hierarchical linear regression analysis, dependence on AI was found to be associated with daily AI usage duration, checking AI without intending to use it, the use of AI for academic purposes as well as for social chatting and emotional sharing, academic self-efficacy, and perceived social support. The Interaction of Person–Affect–Cognition–Execution (I-PACE) model proposes that addictive behaviors emerge from the interaction of individual characteristics, emotional and social processes,

cognitive evaluations, and executive mechanisms (39, 40). In line with this framework, the findings suggest that dependence on AI, as a relatively new construct, is a multidimensional phenomenon shaped not only by patterns of use but also by the interaction of individual and social factors, similar to the theoretical frameworks of other behavioral addictions.

This study has several limitations. First, due to the cross-sectional design, the relationships between variables cannot be interpreted causally. The fact that the study was conducted at a single university may limit the generalizability of the findings. Additionally, the use of self-report measures for data collection may introduce recall bias and may not fully reflect actual usage behaviors.

In addition to its limitations, this study also has several strengths. Evaluating psychosocial variables such as academic self-efficacy and perceived social support alongside AI usage features enabled a comprehensive examination of the topic. Addressing these variables together within a sample of medical students under intense academic stress adds originality to the study. Furthermore, the use of valid and reliable measurement instruments supports the robustness of the findings. In this respect, examining dependence on AI, which is a relatively new construct, in a multidimensional manner among medical students represents one of the key strengths of the study.

Conclusions

This study demonstrates that AI dependence among medical students is associated with usage features such as daily duration of use, checking AI without intending to use it, and the use of AI for academic purposes as well as for social chatting and emotional sharing, along with academic self-efficacy and perceived social support.

In line with these findings, raising awareness among medical students regarding AI usage duration and uncontrolled usage behaviors, as well as supporting balanced usage habits, may be beneficial. In addition, establishing supportive environments that strengthen students' academic self-efficacy and perceived social support, and promoting practices that enhance social interaction, may contribute to reducing the risk of dependence on AI.

Funding

This research received no financial or other support.

Author contributions

Conceptualization, methodology, analysis, investigation, data curation, writing—original draft preparation, review and editing, supervision: S.A.Z.

Ethics approval

Ethical approval was obtained from the Non-Interventional Clinical Research Ethics Committee of Bilecik Şeyh Edebali University (Approval No: 10; Date: 30 October 2025).

Conflict of interest statement

The author declares no conflicts of interest.

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