BMC Medical Education

RESEARCH Open Access

Untold stories of digital transformation in medical education: AI overdependence and nomophobia among medical students

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Abstract

Background This study aims to investigate the relationship between AI dependence and nomophobia among medical students based on various demographic characteristics.

Methods This study adopts a quantitative correlational research design. Dependence on Artificial Intelligence Scale (DAI) and the Nomophobia Questionnaire (NMP-Q) were used to collect data. Data were collected online via Google Forms. Medical students from four public and two private universities in Turkey participated in the study. Data were analyzed using Pearson correlation analysis, Two-Way ANOVA, and Multiple Regression Analysis.

Results The results revealed a significant positive correlation between AI dependence and nomophobia among medical students. Students who reported higher levels of AI dependence were also more likely to exhibit signs of smartphone addiction and internet access dependency. Demographic factors, such as gender, age and year of study, were found to have significant effects on the relationship.

Conclusions The study highlights a significant relationship between AI dependence and nomophobia among medical students, suggesting that overreliance on AI technologies may contribute to several negative consequences.

Keywords Artificial intelligence, Nomophobia, Medical education, Medical student, Faculty of medicine

Background

Digital transformation has broadly reshaped many aspects of our daily life and has become an integral part of our routines. With continuous advancements in digital innovation and emerging technologies, education, in particular, has been significantly influenced by these developments. The widespread use of smart devices such as smartphones and tablets has made learning more flexible, allowing students to access educational resources anytime and anywhere [1–3]. Moreover, the explosive and rapid growth of artificial intelligence has introduced new innovations and these technologies have fundamentally transformed medical education [4–6]. Furthermore, the integration of these technologies with AI has led to a new paradigm in medical education.

While the origins of AI date back to the 1950s, the widespread public access to advanced large language models like ChatGPT marks a major milestone in AI's history [7, 8]. AI has undeniably revolutionized medical education and clinical practice, providing valuable support for both students and educators. It plays a transformative role in healthcare, offering numerous benefits through AI-powered tools like medical imaging analysis,

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diagnostic support systems, and personalized learning platforms that enhance students' access to information and accelerate learning [9]. It also assists healthcare professionals in administrative workflows, clinical documentation, and patient engagement while providing specialized support in areas such as image analysis, medical device automation, and patient monitoring [10]. Additionally, AI contributes significantly to health sciences education by supporting health monitoring, patient data management, medication evaluation, surgery, telemedicine, health statistics, individualized care, and the visualization of medical investigations [11].

However, alongside its benefits, AI-driven advancements have posed significant risks, including overdependency and cognitive complacency, raising pedagogical, psychological, and ethical concerns [12]. AI overdependence is a condition in which individuals become excessively reliant on AI systems for medical decision-making, leading to a decline in their critical thinking abilities [13, 14]. Due to the rapid and convenient solutions AI tools provide, medical students may fail to develop their clinical reasoning and judgment skills [15], and negatively affect their professional competence by weakening their ability to make independent decisions, result in reduced awareness of errors and cognitive laziness in the learning process [16, 17] and can lead to a decline in their higher-order cognitive skills such as creativity, critical reasoning, decision making and problem-solving [18, 19]. Therefore, it is crucial to integrate AI into medical education in a way that promotes balanced use, ensuring that students develop essential cognitive and decision-making skills while leveraging AI's capabilities as a supportive tool rather than a substitute for critical thinking.

Another growing concern in education is nomophobia, which refers to the anxiety individuals experience when they cannot use their mobile phones due to a lack of signal or a low battery [20] or fear of being without a mobile device [21–23]. Various research suggest that nomophobia is a digital disease of the 21 st century [24–26]. Today, medical students heavily rely on smartphones and tablets for accessing educational materials, medical information, note-taking, etc. Of course, using these tools will help students in various ways during learning but the constant need for connectivity can lead to distractions, disrupt deep learning processes, and negatively affect academic performance [27–29].

As digital transformation continues to evolve, medical education faces the dual challenge of leveraging AI's benefits while mitigating the risks of overdependence and nomophobia. Theoretically, both AI dependence and nomophobia share underlying mechanisms related to digital reassurance-seeking, information immediacy, and connectivity needs. These mechanisms may heighten students' reliance on external digital systems to manage uncertainty or cognitive load, making medical students particularly vulnerable due to the high-stakes and information-intensive nature of medical education. Understanding the relationship between these two factors is critical for ensuring that medical students develop strong cognitive and professional competencies. This study aims to investigate the relationship between AI dependence and nomophobia among medical students from various medical schools in Turkey. In line with this general objective, the research questions are as follows:

1. What are the levels of AI dependence and nomophobia among medical students?
2. Is there a significant relationship between medical students' levels of AI dependence and their levels of nomophobia?
3. Are there significant differences in medical students' AI dependence and nomophobia levels based on demographic characteristics?

Methods

This study, which adopted a quantitative correlational research design, aims to investigate the relationship between AI dependence and nomophobia among medical students in Turkey. Correlational comparative design aims to determine whether there is a relationship between two or more variables and the degree of the relationship [30].

Participants

The participants consisted of medical students from six different universities (four public and two foundation universities) in Turkey. Of the 958 participating students, 546 (57%) are female and 412 (43%) are male. 455 participants (47.5%) were Year 1 students, 275 (28.7%) were Year 2 students, 36 (3.8%) were Year 3 students, 67 (7%) were Year 4 students, 47 (4.9%) were Year 5 students, and 78 (8.1%) were Year 6 students. 742 (77.5%) of the students are public university students and 216 (22.5%) are foundation university students. Participation in the study was voluntary, and all students who would like to participate in the study signed informed consent forms. The inclusion criteria were being a student enrolled in a medical school in Turkey and willing to participate in this study voluntarily.

Data collection tools

To collect data about medical students' dependence on artificial intelligence (AI) and nomophobia, two validated measurement tools were used [Please see Supplementary file 1 and Supplementary file 2] to measure AI dependence and nomophobia. Some demographic variables have been added to the beginning of the scale by the researchers. These variables include "year of study,

gender, total daily technology usage time (computer, phone, tablet, etc.), student's grade point average (GPA) or academic achievement, level of knowledge about artificial intelligence use (beginner, intermediate, advanced), student's daily study time, purposes for using artificial intelligence tools, which artificial intelligence tools they use, and the preferred study method" to examine whether there are differences in medical students' levels of AI dependence and nomophobia based on these demographic variables.

Dependence on artificial intelligence scale (DAI)

This five-item Likert scale was developed by Morales-García et al. [31] and adapted into Turkish by Savaş [32] to measure AI dependence of the students who study at higher education institutions. Theoretically, while the scale measures general AI dependence rather than medical-specific AI reliance, its validated structure and relevance to medical students' use justify its application in this context. In the original study [31], the Cronbach's alpha (α) value was reported as 0.87. The original scale consists of five items and is a five-point Likert scale, ranging from 1 = Strongly Disagree to 5 = Strongly Agree. The lowest possible score on the scale is 5 (Not dependent at all), and the highest is 25 (Highly dependent). There are no reverse-scored items in the scale.

Based on the data obtained in this study, Cronbach's Alpha and McDonald's Omega reliability coefficients for the DAI were calculated, and a Confirmatory Factor Analysis (CFA) was conducted. Cronbach's Alpha was found to be 0.817 and McDonald's Omega was 0.806. The CFA fit indices were calculated as CFI = 0.961, TLI = 0.950, RMSEA = 0.069, and χ^2=148.549 (df = 43, p <.05). These values fall within acceptable ranges according to the scale development literature [33–35].

Nomophobia questionnaire (NMP-Q)

Nomophobia questionnaire was developed by Yıldırım and Correia [23] and adapted into Turkish by Yıldırım et al. [36]. The Nomophobia Questionnaire (NMP-Q) consists of 20 items that assess four dimensions of nomophobia: (1) Not Being Able to Access Information, (2) Losing Connectedness, (3) Not Being Able to Communicate, and (4) giving up convenience. All items are rated on a 7-point Likert scale, ranging from 1 (Strongly Disagree) to 7 (Strongly Agree). To validate the underlying structure of the items, a Confirmatory Factor Analysis (CFA) was conducted using AMOS 22 statistical software. The threshold values for acceptable model fit are as follows: normalized $\chi^2 \leq 3$, CFI ≥ 0.90, and RMSEA ≤ 0.08. The CFA results confirmed the validity of the relationships between factors and items ($\chi^2(164)$ = 469.90, normalized χ^2=2.86, CFI = 0.92, RMSEA = 0.08). The pretest of the scale indicated that the reliability of the NMP-Q was quite high (Cronbach's alpha = 0.92). Additionally, Cronbach's alpha values for these four factors were 0.90, 0.74, 0.94, and 0.91, respectively, demonstrating a sufficiently high level of reliability.

Similarly, based on the data obtained in this study, Cronbach's Alpha and McDonald's Omega reliability coefficients for the NMP-Q were calculated, and a Confirmatory Factor Analysis (CFA) was conducted. Cronbach's Alpha was found to be 0.932 and McDonald's Omega was 0.923. The CFA fit indices were calculated as CFI = 0.936, TLI = 0.923, RMSEA = 0.075, and χ^2=432.813 (df = 125, p <.05). These values fall within acceptable ranges according to the scale development literature.

Data collection process

Data were collected online via Google Forms. Medical educators from various medical schools were contacted by the researchers, and the students representatives from those medical schools assisted in disseminating the Google Forms link to ensure broad participation. Participation was voluntary, and responses remained anonymous to protect confidentiality. A consent form was included at the beginning of the online form, explaining the study's purpose, benefits, and contact information of the researchers.

Data analysis

Parametric tests were conducted without examining the normal distribution status of the artificial intelligence (AI) dependence and nomophobia scale scores obtained by the participants. Tests that assess normality are highly sensitive [37]. Additionally, in many studies (especially in social sciences), measurements related to dependent variables do not exhibit a normal distribution [38]. The Central Limit Theorem suggests that if the sample size is sufficiently large (n = 30+), the sampling distribution of the means will be normally distributed regardless of the distribution of the variables, and a violation of normality will not cause a significant problem [37–40]. In addition, in large samples, skewness does not significantly deviate from normality. When the sample size exceeds 100, positive kurtosis begins to diminish, and when it exceeds 200, negative kurtosis starts to disappear [37]. Based on this information, it was decided by the researchers to conduct the analyses using parametric statistical techniques.

Despite the explanations provided in the literature, kurtosis, skewness, normality, and homogeneity tests were conducted on the dataset. The analyses indicated that kurtosis and skewness values were within ±0.5. In the normality tests (Kolmogorov–Smirnov and Shapiro–Wilk), the DAI data were found to be normally distributed (p >.05), while two subfactors of the NMP-Q did not show normal distribution (p <.05); however, the other two subfactors and the total score demonstrated normal

Table 1 Demographic characteristics (descriptive statistics)

	Variable	Frequency (Percentage)
Gender	Female	546(57)
	Male	412(43)
Year	Year 1	455(47.5)
	Year 2	275(28.2)
	Year 3	36(3.8)
	Year 4	67(7)
	Year 5	47(4.9)
	Year 6	78(8.1)
University Type	Public University	742(77.5)
	Foundation University	216(22.5)
How much time do you spend using technology (computer, phone, tablet, etc.) in total each day?	0–2 h	40(4.2)
	3–5 h	283(29.5)
	6–8 h	506(52.8)
	9 h and Above	129(13.5)
How do you evaluate your academic success (grade point average)?	2.00 and Below	33(3.4)
	2.01–2.99	371(38.7)
	3.00–3.49.00.49	316(33)
	3.50 and Above	238(24.8)
How would you rate your level of knowledge regarding the use of artificial intelligence?	Low	303(31.6)
	Middle	555(57.9)
	High	100(10.4)
How much study time do you have per day?	0–2 h	440(45.9)
	3–5 h	443(46.2)
	6–8 h	75(7.8)
For what purposes do you use artificial intelligence tools?	Studying or doing projects, Doing research, Producing creative content, Making daily life easier	162(16.9)
	Studying or doing projects, Doing research, Making daily life easier	158(16.5)
	Studying or doing projects, Producing creative content, Making daily life easier	61(6.4)
	Conducting research, Making daily life easier	99(10.3)
	Studying or doing projects, Making daily life easier	85(8.9)
	Studying or doing projects, doing research	155(16.2)
	Making daily life easier	85(8.9)
	Studying or doing projects	153(16)
What AI tools do you use?	ChatGPT, Google GeminiFlash, Deep Seek	58(6.1)
	ChatGPT, Google GeminiFlash	123(12.8)
	ChatGPT, Copilot	31(3.2)
	ChatGPT	708(73.9)
	Google GeminiFlash	38(4)
What method do you usually prefer to study?	Individual Study	867(90.5)
	Group Work	91(9.5)
Total		958(100)

distribution ($p > .05$). According to the results of Levene's homogeneity test, the total scores of the scales and their subfactors were homogeneous ($p > .05$). Based on these findings, it was concluded that the use of parametric test techniques was appropriate.

Pearson correlation analysis, Two-Way ANOVA, and Multiple Regression Analysis were used in the study. The categorical variables included in the analysis (gender, academic year, university, academic achievement, reason for using artificial intelligence, and study style through artificial intelligence) were converted into dummy variables, with one category from each categorical variable being used as the reference group. Including categorical variables in regression models as dummy variables is appropriate [41, 42]. When determining dummy variables, (k-1) new dummy variables were generated for each variable, where k represents the number of categories within that variable. The category of interest was coded as 1, while the other categories were coded as 0. The purpose of this approach was to include only one category of a variable in the analysis at a time while excluding the effects of the other categories. In this way, the effect of the category included is interpreted in relation to the omitted reference category [42].

Multicollinearity among predictors was examined in the regression analyses. The obtained Variance Inflation Factor (VIF) values were very close to 1. Therefore, it was concluded that there was no multicollinearity among the predictors [43, 44].

Ethics committee approval

This study was conducted with the approval of the İstanbul Medeniyet University Scientific Research Ethics Committee (Date of Approval: 22.01.2025/No: 2025/02–04).

Results

Distribution of participants' responses by demographic characteristics

In the data collection tool, participants were asked several demographic questions in addition to replying to the Nomophobia and AI Dependence scale items. The distribution of participants across these variables is presented in Table 1.

Table 1 shows that the participants in the study are evenly distributed in terms of gender. The majority of the participants are from Year 1 and Year 2, and the majority of them study at public universities. Most participants use technology for 6–8 h a day. The general distribution of participants' academic performance ranges between 2.01 and 3.49. The majority of participants perceive their knowledge of artificial intelligence at an intermediate level. In general, participants study between 0 and 5 h a day. Among the participants, the most common uses of

Table 2 Medical students' AI dependence levels (descriptive statistics)

	AI Dependence (Items)	*N*	Mean (S. Deviation)	Median (Min.-Max.)
1.	I feel unprotected when I do not have access to AI.	958	1.89(0.82)	2(1–5)
2.	I'm concerned about the idea of being left behind in my tasks or projects if I do not use AI.	958	3.93(1.03)	4(2–5)
3.	I do everything possible to stay updated with AI to impress or remain relevant in my field.	958	2.51(0.97)	3(1–5)
4.	I constantly need validation or feedback from AI systems to feel confident in my decisions.	958	4.11(1.02)	4(2–5)
5.	I fear that AI might replace my current skills or abilities.	958	2.59(1.28)	2(1–5)

artificial intelligence are: first, "*Studying or doing projects*, *Doing research*, *Producing creative content*, *Making daily life easier*"; second, "*Studying or doing projects*, *Doing research*, *Making daily life easier*"; third, "*Studying or doing projects*, *doing research*"; and fourth, "*Studying or doing projects*." The most commonly used artificial intelligence application is ChatGPT, and the participants mostly use AI for individual study.

Medical students' AI dependence levels

Medical students' AI dependence levels were analyzed for each item of the scale, considering the arithmetic mean, standard deviation, median, and the minimum and maximum scores obtained. The results are presented in Table 2.

Each item on the AI Dependence Scale can be scored between a minimum of one and a maximum of five points. It has been determined that medical students exhibit varying levels of agreement with the items. The items indicating the highest level of dependence are "*I'm concerned about the idea of being left behind in my tasks or projects if I do not use AI*" and "*I constantly need validation or feedback from AI systems to feel confident in my decisions*," while the items indicating the lowest level of dependence are "*I feel unprotected when I do not have access to AI*" and "*I fear that AI might replace my current skills or abilities.*"

Medical students' nomophobia levels

The nomophobia levels of the 958 medical students who participated in the study were analyzed for each item of the scale in terms of arithmetic mean, standard deviation, median, and the minimum and maximum scores obtained. The results are presented in Table 3.

Each item on the Nomophobia Scale can be scored from a minimum of one to a maximum of seven points. In this context, it can be said that medical students have

Table 3 Medical students' nomophobia levels (descriptive statistics)

	Nomophobia (Items)	*N*	Mean (S. Deviation)	Median (Min.-Max.)
1.	I would feel uncomfortable without constant access to information through my smartphone.	958	3.91(1.66)	4(1–7)
2.	I would be annoyed if I could not look information up on my smartphone when I wanted to do so.	958	4.18(1.78)	4(1–7)
3.	Being unable to get the news (e.g., happenings, weather, etc.) on my smartphone would make me nervous.	958	4.07(1.84)	4(1–7)
4.	I would be annoyed if I could not use my smartphone and/or its capabilities when I wanted to do so.	958	4.31(1.84)	5(1–7)
5.	Running out of battery in my smartphone would scare me.	958	4.45(1.91)	5(1–7)
6.	If I were to run out of credits or hit my monthly data limit, I would panic.	958	3.92(1.96)	4(1–7)
7.	If I did not have a data signal or could not connect to Wi-Fi, then I would constantly check to see if I had a signal or could find a Wi-Fi network.	958	4.28(1.89)	5(1–7)
8.	If I could not use my smartphone, I would be afraid of getting stranded somewhere.	958	3.41(1.97)	3(1–7)
9.	If I could not check my smartphone for a while, I would feel a desire to check it.	958	4.14(1.89)	4(1–7)
10.	I would feel anxious because I could not instantly communicate with my family and/or friends.	958	4.25(1.88)	4(1–7)
11.	I would be worried because my family and/or friends could not reach me.	958	4.57(1.94)	5(1–7)
12.	I would feel nervous because I would not be able to receive text messages and calls.	958	4.29(1.78)	4(1–7)
13.	I would be anxious because I could not keep in touch with my family and/or friends.	958	4.32(1.85)	4(1–7)
14.	I would be nervous because I could not know if someone had tried to get a hold of me.	958	4.53(1.75)	5(1–7)
15.	I would feel anxious because my constant connection to my family and friends would be broken.	958	4.20(1.73)	4(1–7)
16.	I would be nervous because I would be disconnected from my online identity.	958	2.55(1.59)	2(1–7)
17.	I would be uncomfortable because I could not stay up-to-date with social media and online networks.	958	2.72(1.59)	2(1–7)
18.	I would feel awkward because I could not check my notifications for updates from my connections and online networks.	958	2.96(1.71)	3(1–7)
19.	I would feel anxious because I could not check my email messages.	958	2.38(1.52)	2(1–7)
20.	I would feel weird because I would not know what to do.	958	3.02(1.64)	3(1–7)

Table 4 The relationship between nomophobia and AI dependence (Pearson Correlation)

Variables	*N*	*r*	*p*
AI Dependence*Not being able to Access Information	958	0.172	< 0.001
AI Dependence* Giving Up Convenience	958	0.136	< 0.001
AI Dependence* Not Being Able to Communicate	958	0.009	0.776
AI Dependence* Losing Connectedness	958	0.153	< 0.001
AI Dependence*Nomophobia	958	0.127	< 0.001

low levels of nomophobia. The items with the highest scores are as follows:

- I would be annoyed if I could not use my smartphone and/or its capabilities when I wanted to do so.
- Running out of battery in my smartphone would scare me.
- If I did not have a data signal or could not connect to Wi-Fi, then I would constantly check to see if I had a signal or could find a Wi-Fi network.
- I would be worried because my family and/or friends could not reach me.
- I would be nervous because I would not be able to receive text messages and calls.

And the items with the lowest scores are:

- I would feel nervous because I would be disconnected from my online identity.
- I would feel uncomfortable because I could not stay up-to-date with social media and online networks.
- I would feel anxious because I could not check my email messages.

The relationship between nomophobia and AI dependence

The relationship between the scores on the Nomophobia Scale and its sub-factors and the AI Dependence Scale was examined. This relationship was analyzed using Pearson Correlation Analysis. The results are presented in Table 4.

There is a low-level, positive, and significant ($p < .05$) relationship between AI Dependence and the scores for Not being able to Access Information, Giving Up Convenience, Losing Connectedness, and the total score of the Nomophobia Scale. Based on this, it can be said that as the scores for Not being able to Access Information, Giving Up Convenience, Losing Connectedness, and nomophobia increase, AI dependence levels also increase. On the other hand, no significant relationship was found between AI Dependence and Not Being Able to Communicate ($p > .05$).

The authors who developed the Nomophobia Scale suggested cutoff points based on the scores obtained from the scale. According to the developers, individuals who score 20 points on the scale do not have nomophobia, those who score between 21 and 50.99 have a low level, those who score between 60 and 99.99 have a moderate level, and those who score between 100 and 140 points have a high level of nomophobia. Using these cutoff points, the nomophobia groups of the medical school students who participated in the study were determined. Then, differences in the level of AI Dependence according to nomophobia levels were examined. This analysis was conducted using a One-Way ANOVA Test. The results are presented in Table 5.

According to the analysis, the nomophobia level creates a significant difference in the level of AI Dependence ($p < .05$). Individuals with low levels of nomophobia have lower levels of AI Dependence compared to those with moderate and high levels of nomophobia.

Gender, academic year, and AI dependence

The differences in AI Dependence scores according to gender and academic year was examined using Factorial ANOVA (also known as Two-Way ANOVA). The results are presented in Table 6.

According to the analysis, one of the main effects, the academic year, creates a significant difference in the level of AI Dependence ($p < .05$). The resulting significant difference is at a medium effect size ($\eta^2 \geq 0.06$) [45]. Another main effect, gender, also creates a significant difference in the level of AI Dependence ($p < .05$), with a small effect size ($\eta^2 \geq 0.01$). The interaction between academic year and gender creates a significant difference in the level of AI Dependence ($p < .05$), with a small effect size ($\eta^2 \geq 0.01$) (Fig. 1).

To identify the significant differences based on academic year, Bonferroni multiple comparison test was conducted. According to this, the AI Dependence scores for Year 1 and Year 2 are higher than those for Year 4 and Year 5. Similarly, to identify the significant differences based on gender, Bonferroni multiple comparison test was conducted. According to this, female students have a higher level of AI Dependence than male students. In addition, to identify the significant differences based on

Table 5 AI dependence level according to nomophobia level (One-Way ANOVA)

Nomophobia Level	*N*	Mean (S. Deviation)	Median (Min.-Max.)	F	*p*	Significant Difference
Low	241	14.61(1.91)	15(9–20)	5.59	0.004	Light < Middle
Moderate	552	15.16(2.42)	15(8–22)			Light < High
High	165	15.22(2.28)	15(9–20)			

Table 6 AI dependence of medical students by gender and academic year (Two-Way ANOVA)

Year	Gender	*N*	Mean (S. Deviation)	ANOVA (F Test)		*p*	Partial Eta Squared Effect Size
Year 1	Female	281	15.02(2.27)	Year (Main Effect)	12.79	0.001	0.063
	Male	174	15.09(2.37)				
Year 2	Female	161	15.89(2.47)				
	Male	114	15.65(2.15)				
Year 3	Female	18	15.22(1.70)	Gender (Main Effect)	9.61	0.002	0.010
	Male	18	13.33(2.59)				
Year 4	Female	19	14.21(2.32)				
	Male	48	13.88(1.38)				
Year 5	Female	37	14.03(1.68)	Year*Gender (Interaction Effect)	2.35	0.039	0.012
	Male	10	13.50(0.53)				
Year 6	Female	30	14.97(1.16)				
	Male	48	13.65(1.88)				

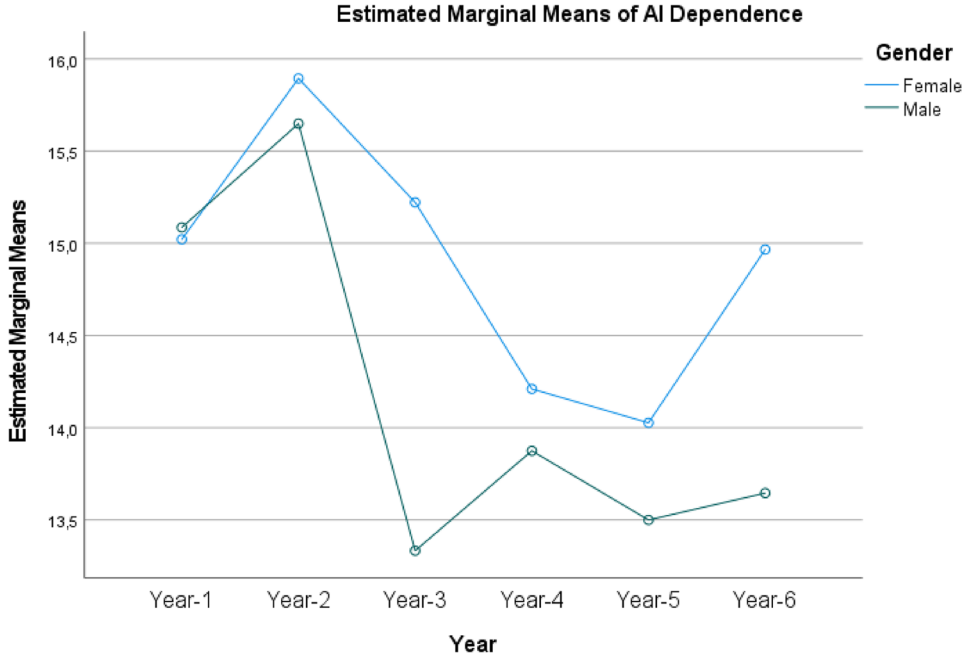


Fig. 1 Estimated marginal means of AI dependence

the interaction between academic year and gender, Bonferroni multiple comparison test was conducted. This test results revealed that:

- In Year 1, female students have higher AI Dependence scores than male students in Year 6.
- In Year 1, male students have higher AI Dependence scores than males in Year 6.
- In Year 2, female students have higher AI Dependence scores than male students in Year 6.
- In Year 2, male students have higher AI Dependence scores than males in Year 6.

Possible influencing variables on AI dependence

The effect of the variables such as the academic year, gender, type of university, academic performance, reasons for using Artificial Intelligence, preferred mode of working through Artificial Intelligence, and nomophobia on AI Dependence has been examined. This analysis was carried out using multiple regression analysis. In the analysis, categorical variables were included in the regression model as dummy variables. According to this:

- For the variable with six categories, "the academic year", Year 1 was used as the reference group, and the remaining five groups were included in the model.
- For "gender", the male group was taken as the reference group, and the female group was included in the model.
- For "type of university", foundation universities were taken as the reference group, and public universities were included in the model.

Table 7 Analysis of possible influencing variables on AI dependence (Multiple linear Regression)

Model	B	Std. Error	t	*p*	R^2	Model F Test (*p*)
Year 2	0.492	0.171	2.874	0.004	0.183	11.073 (0.001)
Year 3	−0.464	0.402	−1.152	0.249		
Year 4	−0.420	0.301	−1.397	0.163		
Year 5	−0.445	0.340	−1.309	0.191		
Year 6	−0.461	0.276	−1.670	0.095		
Female	0.491	0.156	3.141	0.002		
Public University	−0.433	0.178	−2.431	0.015		
2.00–2.99.00.99 Academic Success	−2.687	0.412	−6.521	< 0.0001		
3.00–3.49.00.49 Academic Success	−2.857	0.420	−6.803	< 0.0001		
3.50 and Above Academic Success	−2.577	0.419	−6.155	< 0.0001		
Studying or doing projects, Doing research, Making daily life easier	−0.991	0.250	−3.960	< 0.0001		
Studying or doing projects, Producing creative content, Making daily life easier	0.775	0.326	2.379	0.018		
Conducting research, Making daily life easier	−1.396	0.296	−4.712	< 0.0001		
Studying or doing projects, Making daily life easier	−0.087	0.295	−0.294	0.769		
Studying or doing projects, doing research	−0.579	0.250	−2.313	0.021		
Making daily life easier	−0.317	0.313	−1.013	0.311		
Studying or doing projects	−0.083	0.265	−0.312	0.755		
Individual Work	−0.514	0.274	−1.876	0.061		
Nomophobia	0.012	0.003	4.125	< 0.0001		

- For "academic performance", the group with a GPA (grade point average) below 2.00 was used as the reference group, and the remaining three groups were included in the model.
- For "reasons for using Artificial Intelligence", the category of using AI for "Studying or doing projects, Doing research, Producing creative content, Making daily life easier" was taken as the reference group, and the other seven groups were included in the model.
- For "preferred mode of working through Artificial Intelligence", the "working in groups" category was used as the reference group, and "individual work" was included in the model.
- The nomophobia, which is a continuous variable, was taken as it is in the model.

The results are presented in Table 7.

The ANOVA model fit test of the constructed model is significant ($p < .05$). In this case, the model is considered to be a good fit and interpretable. It was determined that the variables included in the model explain 18% of the variance in AI Dependence ($R^2 = 0.183$). The effect of the variables on AI Dependence can be summarized as follows:

- Studying in Year 2 increases AI Dependence levels compared to studying in Year 1. This may be due to the fact that Year 2 students typically face a heavier academic workload, with more complex subjects such as pathology, pharmacology, and microbiology compared to the more foundational courses in Year 1. So, as the curriculum becomes more challenging, students may increasingly rely on AI tools for summarizing content, answering medical queries, or organizing study materials, etc. Additionally, second-year students may be more familiar with AI applications and their benefits for medical education.
- Being female increases AI Dependence compared to being male.
- Studying at a public university reduces AI dependence compared to studying at a foundation university.
- Academic performance levels of 2.00–2.99.00.99, 3.00–3.49.00.49, and above 3.50 reduce AI Dependence compared to academic performance scores below 2.00.
- Reasons for using artificial intelligence such as "Studying or doing projects, Doing research, Making daily life easier," "Conducting research, Making daily life easier," and "Studying or doing projects, Doing research" reduce AI Dependence compared to the reference category "Studying or doing projects, Doing research, Producing creative content, Making daily life easier."
- "Studying or doing projects, Producing creative content, Making daily life easier" increases AI Dependence compared to "Studying or doing projects, Doing research, Producing creative content, Making daily life easier."
- As nomophobia increases, AI Dependence also increases.

Discussion

The findings of this study provide significant insights into medical students' dependence on artificial intelligence (AI) and its relationship with nomophobia. The results indicate that while medical students do not exhibit extreme AI dependence levels, they express concerns about falling behind in their tasks without AI and often seek validation from AI systems for decision-making. This result is extremely important in that overreliance on these technologies may degrade higher-order thinking skills and essential clinical skills. Several research results are in line with this result in that if students may become overly dependent on AI tools, this could impair their development of their critical thinking and clinical reasoning skills in the future [15, 45, 46].

The positive correlation between AI dependence and the nomophobia subscales—specifically in terms of "not being able to access information, losing convenience, and losing connectedness" suggests that students who exhibit higher levels of nomophobia also tend to show higher levels of AI dependence. Although this association was statistically significant, the magnitude of the correlation was small. Therefore, the relationship should be interpreted as a weak but present association rather than a strong or causal connection, and future longitudinal studies are needed to explore the directionality of this link. This relationship indicates that both the inability to access information and the loss of connection, which are central to the experience of nomophobia, may trigger a greater reliance on AI systems. For example, in a study, conducted with 697 university students, it was found that there is a significant correlation between smart device addiction and artificial intelligence [20]. In addition, another study revealed that, as with nomophobia, not being able to reach AI can result also in fear and anxiety in educational environments [47].

The study also highlights the impact of several demographic variables on AI dependence. Academic year plays a significant role, with first- and second-year students showing higher AI dependence compared to fourth- and fifth-year students. This may be attributed to the greater exposure of senior students to clinical settings, where direct patient interaction and practical skills take precedence over AI-based assistance. Similarly, the first- and second-year students more reliance on AI can be explained by their upbringing in a digital era, where technology is deeply embedded in daily life, and as being more accustomed to various technological tools, including AI, they are more likely to incorporate them regularly as a resource in their academic work [48]. This correlates with the research that suggests younger university students have more reliance on AI, likely due to greater exposure to digital tools during previous years [49].

When gender was examined in terms of AI dependence, we found that female students exhibit higher AI dependence than male students, which could be linked to different learning strategies, risk perceptions, and technology adoption patterns that females and males have. This finding is interesting because in the beginning of the study, our hypothesis was that male students would be more dependent on AI as males are more interested in technological advancements than females, and, problematically, and therefore they would be more likely to have more reliance to them [50]. In several studies, AI dependence levels are similar between males and females, and the difference is not statistically significant, suggesting that there is no gender difference in AI dependence [31, 48, 51]. Similarly, there are some other studies that contrast with our finding in that males have higher AI dependence levels than females [52, 53].

Another finding was that students with academic performance levels of 2.00–2.99.00.99, 3.00–3.49.00.49, and above 3.50 have lower AI Dependence compared to students with academic performance scores below 2.00. This could be attributed to the factor that higher-performing medical students likely have well-developed critical thinking skills and effective study habits and techniques, reducing their need for AI assistance. They may use AI tools selectively for efficiency rather than as a primary means of studying. Conversely, students with lower academic performance might rely on AI for explanations, content simplification, and assistance in organizing study materials, increasing their dependence on AI.

We also found that studying at a public university reduces AI dependence compared to studying at a foundation university. This may be because medical students at foundation universities might have greater exposure to technology-integrated learning environments, access to more advanced digital resources, or a curriculum that encourages the use of AI-based tools for studying. In contrast, public university students may rely more on traditional learning methods, such as textbooks, printed lecture notes, and in-person faculty guidance. In addition, differences in teaching styles and institutional expectations could also contribute to this variation. This finding contrasts with the research suggesting that students from private or foundational universities have a lower level of dependence on AI [54, 55].

Another finding of our study was that medical students with higher nomophobia levels are likely to have higher reliance on AI. Since AI-based applications are easily accessible via smartphones, students with nomophobia may frequently use AI for quick medical information

retrieval, diagnostic assistance, or even anxiety reduction. This could imply that this constant reliance on digital support may result in higher level of AI dependence. This finding is consistent with the research that suggests the students with a higher level of nomophobia or smartphones addiction have a high level of dependence or reliance on artificial intelligence [20].

Strengths and limitations

This study provides novel insights into the intersection of AI dependence and nomophobia among medical students, and to our knowledge, this is the first study to examine the relationship between nomophobia and artificial intelligence dependence specifically among medical students, making a significant contribution to the literature. Another strength is the wide number of participants from various medical schools in Turkey. However, while this study sheds light on the connection between medical students AI dependence and nomophobia levels, it does not explore the underlying psychological factors or the potential interventions to mitigate these issues in medical students.

Conclusion

This study examined the relationship between medical students' levels of dependence on artificial intelligence (AI) and their levels of nomophobia based on some demographic variables. The study highlights the potential risks of excessive dependence on AI in medical education, as it may contribute to an increased sense of digital dependency among students. While AI can enhance learning and decision-making, it is crucial for educational institutions to balance its use with efforts to promote healthy technology habits and reduce the potential for digital overdependence. Further research is needed to explore the long-term effects of AI dependence on medical students' academic performance, well-being, and professional development. Additionally, interventions aimed at fostering critical thinking, self-regulation, and resilience in the face of technological pressures may help mitigate the risks associated with AI dependence and nomophobia.

Recommendations

In the light of the results of this study, we would like to make some suggestions for medical educators, curriculum/policy makers, researchers and medical students.

Recommendations for medical educators

Medical educators should integrate digital literacy and responsible AI usage into the curriculum to raise awareness about technology dependence among students. Encouraging discussions on the benefits and risks of AI-based tools in medical education can help students develop a balanced approach to technology use. Additionally, educators should provide mentorship and guidance to ensure that students utilize AI tools effectively without becoming over-reliant on them.

For curriculum/policy makers

Curriculum and policy makers should develop regulations that promote the ethical and responsible use of AI in medical education, ensuring that students do not develop unhealthy dependencies. Curricula that focused on digital well-being should be implemented to equip students with strategies for managing their technology use. Furthermore, interdisciplinary collaboration between medical educators, psychologists, and technology experts is essential to address potential risks and create policies that support healthy technology habits.

For researchers

Future research should focus on longitudinal studies to explore the causal relationship between AI dependence and nomophobia among medical students. Investigating the psychological and academic effects of AI-assisted learning tools can provide valuable insights into their impact on medical students' cognitive and emotional well-being.

For medical students

Medical students should develop self-awareness regarding their AI usage and establish personal boundaries to prevent excessive dependence on AI and mobile technology. They should adopt an active approach to engage in discussions and academic activities that support critical thinking rather than passive reliance on AI tools.

Abbreviations

AI	Artificial Intelligence
GPA	Grade Point Average
VIF	Variance Inflation Factor

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12909-026-08675-0.

Supplementary Material 1.

Supplementary Material 2.

Acknowledgements

The authors would like to thank all medical students who voluntarily participated in the study.

Authors' contributions

G.K. planned the study. G.K. and Ç.T. collected and analyzed the data, and each author took equal responsibility for writing, revising and editing of the manuscript. Both authors read and approved the final version of the manuscript.

Funding
This study was not funded by any organizations or institutions.

Data availability
The data of this study are available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate
This study was conducted in accordance with the principles of the Declaration of Helsinki. Ethical approval was obtained from İstanbul Medeniyet University Scientific Research Ethics Committee (Date of Approval: 22.01.2025/No: 2025/02–04). Informed consent were obtained from all participants before participation in the study.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

Received: 26 March 2025 / Accepted: 21 January 2026
Published online: 27 January 2026

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