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Artificial Intelligence Dependency and Associated Factors Among Nursing Master's Students in China: A National Cross-Sectional Study

Xuehua He
Sir Run Run Shaw Hospital
Jingbang Liu
Sir Run Run Shaw Hospital
Shan Li
Sir Run Run Shaw Hospital
Yufeng Lou
Sir Run Run Shaw Hospital
Liqing Chen
Sir Run Run Shaw Hospital
Yewan Zhan
Sir Run Run Shaw Hospital
Kaifeng Zhou
Sir Run Run Shaw Hospital
He Liu
Sir Run Run Shaw Hospital
Li Wang
Sir Run Run Shaw Hospital
Rongping Zha
471183814@qq.com

Sir Run Run Shaw Hospital

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Abstract

Background

Artificial Intelligence (AI), particularly generative AI, has been widely adopted in higher education and research. While it improves efficiency, concerns about overreliance on AI have emerged. However, evidence on AI dependency among nursing graduate students remains limited.

Objective

This study aimed to examine current status of AI dependency among nursing master's students through a national cross-sectional survey. It also sought to identify key factors associated with AI dependency, in order to provide evidence for regulating AI use in nursing education.

Methods

A convenience sampling method was used. Nursing master's students from six universities in China were recruited between October and December 2025. Data were collected using a general information questionnaire, the Research Self-Efficacy Scale, the Ten-Item Personality Inventory (TIPI), the Achievement Motivation Scale (AMS), the Self-Control Scale (SCS), and the Artificial Intelligence Chatbot Dependency Scale.

Results

A total of 436 valid questionnaires were collected, with a response rate of 96.46%. The mean AI dependency score was 26.87 ± 9.34, indicating a moderate level. Multiple linear regression analysis showed that frequent and intensive use of AI tools, using AI for drafting initial manuscripts, and positive attitudes toward AI use (both at the individual and institutional levels) were positively associated with AI dependency. In contrast, higher levels of impulse control, conscientiousness, and openness to experience were negatively associated with AI dependency ($P < 0.05$).

Conclusion

AI dependency among nursing master's students was associated with personality traits, cognitive attitudes toward AI, and AI use patterns. Frequent and intensive AI use, AI-assisted initial manuscript drafting, and positive attitudes toward AI use were positively associated with AI dependency, whereas impulse control, conscientiousness, and openness were negatively associated with it. Nursing educators should strengthen AI literacy, academic integrity education, and guidance on responsible AI use to support independent research ability.

Introduction

Graduate education is a major pathway for cultivating highly qualified professionals. nursing master's students are an important part of the advanced nursing workforce and a key force in promoting the development of the nursing discipline. As an interdisciplinary field that integrates science, humanities, and practice, nursing places increasingly diverse and high-level demands on graduate students. nursing master's students carry dual responsibilities[1]. On the one hand, they need to systematically master nursing knowledge and research methods and conduct high-quality research to advance the discipline. On the other hand, they must balance multiple tasks, including clinical practice, clinical skills examinations, and personal life. Time constraints and heavy workloads are common challenges for this group[2].

In recent years, Artificial Intelligence (AI) has developed rapidly. In particular, generative artificial intelligence and large language models have shown clear advantages in machine learning and natural language processing. These technologies are quickly changing how information and content are generated in work, daily life, and learning. With strong capacities in data processing, pattern recognition, natural language processing, and knowledge generation, AI is transforming many sectors, especially higher education and scientific research[3]. One international study[4] found that 75% of students and faculty members actively used AI tools. In China, as many as 87.66% of medical master’s students have used AI tools to support research activities[1]. Nursing master's students also face multiple academic demands and commonly use AI tools. Such use is particularly prominent in literature review, research design, and academic writing[5].

However, alongside greater efficiency, a series of problems has also emerged, including AI dependency. In one qualitative interview[6], a nursing master’s student reported that excessive reliance on AI tools had made them become lazy. Another scholar noted that frequent use of AI may gradually undermine users’ confidence in their own judgment and creativity, leading to a clear sense of frustration. Some may even feel unable to conduct research without AI tools[7]. These findings suggest that overreliance on AI may weaken creativity and independent thinking among nursing students, posing new challenges to the current higher education system.

AI dependency generally refers to excessive reliance on AI technologies in daily work, study, and life, which may lead to addictive behavior[8, 9]. It has developed from traditional forms of technology dependence. However, AI differs from traditional technologies in important ways. AI has highly anthropomorphic features, and users may experience interactions with it as if they were engaging in interpersonal communication, which can lead to emotional dependence[10]. In addition, AI can simulate human thinking and take over part of the decision-making process. In this sense, dependency on AI may reflect a transfer of cognitive agency[11]. Therefore, AI dependency is not limited to technical reliance. It also involves complex cognitive and

psychological dependence. The growing level of AI dependency in higher education may have clear negative effects on students' cognitive development. It may systematically reduce creativity, weaken critical thinking, and gradually erode core academic competencies[12, 13]. It may also lead to problems such as plagiarism and other breaches of academic integrity, thereby seriously threatening the reputation of higher education institution[14].

In nursing, these risks may be even more serious because the discipline is directly related to patient safety and clinical outcomes. AI dependency among nursing graduate students may not only restrict research innovation, but also create potential risks in future clinical practice. Generative AI is prone to "hallucinations"[15] and is often limited by the "black-box"nature of its algorithms[16], which means it may produce misleading clinical suggestions. If students apply such information directly to clinical decision-making without careful verification, this could pose a major threat to future healthcare quality and patient safety.

As the integration of artificial intelligence into education becomes increasingly widespread, an important issue in nursing education is how to guide students to use AI tools appropriately and avoid overreliance. However, current research on AI in nursing higher education has mainly focused on the use of AI tools[17-19]. Studies on the current status of AI dependency among nursing master's students remain limited, and the factors underlying such dependency have not been fully explored. Against this background, this study used the Interaction of Person-Affect-Cognition-Execution model（I-PACE model） to examine the factors associated with AI dependency. This model suggests that technology dependency is not an occasional behavior. Rather, it results from the interaction of personal traits, affective and cognitive responses, and executive function. From this perspective, AI dependency can be seen as a compensatory behavior adopted by individuals in specific situations to cope with research pressure or psychological needs. Its development does not occur overnight. Instead, it is shaped by the combined influence of personality, cognitive appraisal, and executive function[20].

Accordingly, this study examined AI dependency among nursing master's students from personality traits, cognitive attitudes toward AI, and AI use patterns. Appropriate scales were included to identify its influencing factors. The findings may provide a theoretical basis for developing future interventions for AI dependency in this population.

1. Study Objectives

This study aimed to: (a) investigate the current status of AI dependency among nursing master's students; (b) analyze the influencing factors of AI dependency from multiple dimensions based on the I-PACE model; and (c) provide scientific evidence for universities to develop policies on AI use among nursing graduate students, define appropriate boundaries for AI use, and formulate targeted training programs.

2. Methods

2.1 Study Design

This study used a cross-sectional observational survey design and adopted a convenience sampling method. The reporting of this study followed the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) guideline[21].

2.2 Participants

Participants were recruited using a convenience sampling method. Nursing master's students from six universities in four provinces of China were enrolled between October and December 2025.

The inclusion criteria were as follows: (1) students enrolled in nursing master's programs from the 2023 to 2025 cohorts, including full-time students, part-time students, and students admitted through equivalent academic qualifications; (2) completion of at least one course with no fewer than 20 teaching hours; and (3) willingness to participate in this study.

The exclusion criteria were as follows: (1) students on academic leave; (2) international students; and (3) exchange students.

The sample size was preliminarily estimated as 5–10 times the number of independent variables. A total of 32 independent variables were included in this study. After allowing for a 20% invalid response rate, the required sample size was estimated to be 192–384 participants.

2.3 Instruments

2.3.1 Sociodemographic and AI-use-related Information

The general information questionnaire was developed by the researchers based on a literature review and the objectives of this study. It included sociodemographic information (such as gender, age, place of residence, and academic year) and information on AI tool use (such as frequency of use, duration of use, and purposes of use).

2.3.2 Research Self-Efficacy Scale[22]

The Research Self-Efficacy Scale was developed by Zhang Yongjun et al. in 2013. It is used to assess individuals' confidence in their ability to successfully complete research tasks. The scale is a short form consisting of three items. It uses a 6-point Likert scale ranging from 1 ("strongly disagree") to 6 ("strongly agree"). The total score ranges from 3 to 18, with higher scores indicating higher levels of research self-efficacy. The Cronbach's alpha of the scale was 0.913, indicating good reliability.

2.3.3 Ten-Item Personality Inventory (Chinese Version, TIPI) [23]

The Ten-Item Personality Inventory (TIPI) was originally developed by Gosling et al. and later translated into Chinese by Li Jinde in 2013. It assesses the five major personality traits: extraversion, agreeableness, conscientiousness, emotional stability, and openness to experience. The scale consists of 10 items. Items 1, 3, 5, 7, and 9 are positively scored, while items 2, 4, 6, 8, and 10 are reverse scored. It uses a 7-point Likert scale ranging from 1 (“strongly disagree”) to 7 (“strongly agree”). The Cronbach’s alpha coefficients for the five subscales range from 0.60 to 0.67, indicating acceptable reliability and good validity.

2.3.4 Achievement Motivation Scale (AMS)[24]

The Achievement Motivation Scale (AMS) was originally developed by Norwegian psychologists Gjesme and Nygård and later revised by Ye Renmin et al. in China in 1992. It is used to measure the persistent and stable internal drive individuals exhibit when pursuing goals.The scale consists of 30 items and includes two subscales: motivation to achieve success (Ms) and motivation to avoid failure (Maf), with 15 items in each subscale. The difference between Ms and Maf (i.e., Ms − Maf) is used as the evaluation index. A higher difference score indicates stronger achievement motivation, while a lower score indicates weaker achievement motivation.The overall Cronbach’s alpha of the scale is 0.827. The Cronbach’s alpha coefficients for the Ms and Maf subscales are 0.931 and 0.924, respectively, indicating good reliability and validity.

2.3.5 Self-Control Scale (SCS) [25]

The Self-Control Scale (SCS) was developed by Tangney et al. in 2004 and later translated and adapted into Chinese by Tan Shuhua and Guo Yongyu in 2008. The scale consists of 19 items and covers five core dimensions: impulse control, maintenance of healthy habits, resistance to temptation, focus on work, and moderation of entertainment.

It uses a 5-point Likert scale, where 1 indicates “not at all like me” and 5 indicates “very much like me.” Higher scores indicate better self-control.

The Chinese version of the scale has a Cronbach’s alpha of 0.862, indicating good reliability and validity.

2.3.6 Artificial Intelligence Chatbot Dependency Scale[26]

The Artificial Intelligence Chatbot Dependency Scale was developed by Zhang Xing et al. in 2024. It consists of eight items and is designed to assess individuals’ level of dependence on AI chatbots (e.g., ChatGPT) in daily life. The scale uses a 7-point Likert scale, where 1 indicates “strongly disagree” and 7 indicates “strongly agree.” Higher scores indicate a higher level of dependency on AI chatbots. The Cronbach’s alpha of the scale is 0.88, indicating good reliability and validity.

2.4 Data Collection

Data were collected through an online survey. The questionnaire was designed and distributed via Wenjuanxing (https://www.wjx.cn/vm/rcxfYV5.aspx). After obtaining approval from the relevant school authorities, the researchers shared a QR code linking to the questionnaire, which included an informed consent form, with nursing master's students.

Participants were informed of the purpose and significance of the study and participated voluntarily. All items in the questionnaire were set as mandatory. Each participant was allowed to submit the questionnaire only once. Participants completed the questionnaire independently and submitted it online. The researchers were able to monitor and access the data in real time.

2.5 Statistical Analysis

Statistical analysis was performed using SPSS version 27.0. Continuous variables with a normal distribution were described as mean ± standard deviation ($\bar{x}$ ±s) and compared between groups using the independent-samples t test. Continuous variables with a non-normal distribution were expressed as median and interquartile range [M (P25, P75)] and analyzed using the Mann–Whitney U test.

Categorical variables were presented as frequencies and percentages (n, %) and compared using the chi-square (χ^2) test. Variables that were statistically significant in the univariate analysis were included in a multiple linear regression model to identify factors influencing AI dependency among nursing master's students. A significance level of $\alpha = 0.05$ was used.

3. Results

3.1 Demographic Characteristics

A total of 452 questionnaires were collected, of which 16 were excluded as invalid. A total of 436 valid questionnaires were included, yielding a valid response rate of 96.46%. The data were obtained from six universities in four provinces of China, including one “985” university, two “211”universities, and three general universities.

The mean age of the 436 nursing graduate students ranged from 20 to 45 years, with an average of 24.63 ± 3.23 years. Most participants were female (82.34%) and from rural areas (55.28%). Among them, 179 (41.06%) were first-year students, 138 (31.65%) were second-year students, 88 (20.18%) were third-year students, and 31 (7.11%) were in extended study or other situations. In addition, 276 participants (63.30%) had not yet published any papers as first or co-first authors.

Regarding the use of AI tools in research, most students reported using AI to search for information related to their research topics (72.71%), assist with literature reading and understanding (72.25%), solve research-related problems (60.55%), and translate or polish manuscripts (52.06%). Some students also

used AI tools for research design (47.94%), data analysis (36.01%), and drafting initial manuscripts (41.97%). Detailed characteristics of the participants are presented in Table 1.

Table 1
Comparison of AI Dependency Scores Among Nursing Master's Students with Different Characteristics (n = 436, mean ± SD)

Variables	n (%)	AI Dependency Score	t/F	P value
Gender				
Male	77 (17.66)	27.45 ± 9.13	0.606	0.545
Female	359 (82.34)	26.74 ± 9.39		
Age (years)				
20–25	348 (79.81)	27.07 ± 9.22	0.984	0.416
26–30	66 (15.14)	26.00 ± 9.54		
31–35	16 (3.67)	25.38 ± 10.13		
36–40	4 (0.92)	24.75 ± 11.67		
41–45	2 (0.46)	37.50 ± 14.85		
Place of Residence				
Rural	241 (55.28)	27.18 ± 9.44	1.958	0.142
Town/County	85 (19.50)	27.87 ± 8.51		
Urban	110 (25.23)	25.42 ± 9.62		
Academic Year				
Year 1	179 (41.06)	27.02 ± 8.92	2.966	< 0.05
Year 2	138 (31.65)	28.20 ± 8.83		
Year 3	88 (20.18)	24.44 ± 9.74		
Extended/Other	31 (7.11)	27.00 ± 11.58		
Study Mode				
Full-time	403 (92.43)	26.64 ± 9.29	2.060	0.129
Part-time	16 (3.67)	31.25 ± 6.61		
Equivalent academic qualifications	17 (3.90)	28.87 ± 9.34		
Number of Publications (First/Co-first Author)				
None	276 (63.30)	26.78 ± 9.31	1.340	0.238
1	91 (20.87)	28.64 ± 9.56		
2	28 (6.42)	25.39 ± 7.95		
3	20 (4.59)	24.20 ± 10.20		
4	8 (1.83)	22.25 ± 10.70		
5	6 (1.38)	24.83 ± 7.17		
> 5	7 (1.61)	28.14 ± 8.42		
Frequency of AI Use				
Several times/day	147 (33.72)	29.80 ± 9.50	7.518	< 0.05
Several times/week	209 (47.94)	25.97 ± 8.94		
Once/week	40 (9.17)	25.70 ± 6.83		
Once/month	14 (3.21)	21.07 ± 8.25		
Once every two months or more	26 (5.96)	22.42 ± 10.88		
Daily duration of AI use				
< 0.5 h	128 (29.36)	22.11 ± 9.22	16.349	< 0.05
0.5–1 h	173 (39.68)	27.53 ± 8.69		
1–2 h	90 (20.64)	29.76 ± 8.26		
2–3 h	25 (5.73)	32.96 ± 6.78		

Variables	n (%)	AI Dependency Score	t/F	P value
> 3 h	20 (4.59)	31.00 ± 10.18		
Use of AI for Literature Search				
Yes	317 (72.71)	26.94 ± 9.27	0.270	0.788
No	119 (27.29)	26.67 ± 9.52		
Use of AI for Literature Understanding				
Yes	315 (72.25)	27.10 ± 9.43	0.815	0.415
No	121 (27.75)	26.28 ± 9.10		
Use of AI for Research Design				
Yes	209 (47.94)	29.44 ± 9.18	5.715	< 0.05
No	227 (52.06)	24.50 ± 8.85		
Use of AI to Solve Research Problems				
Yes	264 (60.55)	28.11 ± 9.02	3.492	< 0.05
No	172 (39.45)	24.96 ± 9.51		
Use of AI for Data Analysis				
Yes	157 (36.01)	29.10 ± 8.92	3.792	< 0.05
No	279 (63.99)	25.62 ± 9.34		
Use of AI for Draft Writing				
Yes	183 (41.97)	30.67 ± 9.44	7.539	< 0.05
No	253 (58.03)	24.12 ± 8.25		
Use of AI for Translation/Polishing				
Yes	227 (52.06)	26.79 ± 9.31	0.188	0.851
No	209 (47.94)	26.96 ± 9.38		
Peers Use AI Tools to Assist in Writingpapers				
None	17 (3.90)	24.94 ± 10.14	4.624	< 0.05
Few	91 (20.87)	23.62 ± 9.27		
About half	103 (23.62)	26.71 ± 8.60		
Most	161 (36.93)	28.43 ± 9.29		
Almost all	64 (14.68)	28.33 ± 9.43		
Attitude Toward AI Use				
Strongly oppose	12 (2.75)	19.00 ± 11.39	8.255	< 0.05
Oppose	24 (5.50)	23.58 ± 7.73		
Neutral	179 (41.06)	25.12 ± 8.38		
Support	178 (40.83)	28.77 ± 9.13		
Strongly support	43 (9.86)	30.30 ± 11.07		
Institutional Attitude Toward AI Use				
Strictly prohibited	23 (5.28)	23.78 ± 12.76	7.511	< 0.05
Somewhat opposed	38 (8.72)	23.97 ± 9.42		
Neutral/unclear	250 (57.34)	25.79 ± 8.50		
Somewhat supportive	106 (24.31)	30.30 ± 9.15		
Strongly supportive	19 (4.36)	31.42 ± 10.02		

3.2 Level of AI Dependency and Results of Univariate Analysis

A total of 436 valid questionnaires were included in this study. The mean AI dependency score was 26.87 ± 9.34, indicating a moderate level overall.

Univariate analysis showed that, at the level of individual characteristics, AI dependency scores differed significantly across academic years. At the level of cognitive attitudes, whether peers used AI to assist with academic writing, as well as both individual and institutional attitudes toward AI-assisted writing, were significantly associated with AI dependency. At the behavioral level, the frequency and duration of AI use, as well as the use of AI for research design, problem-solving during research, data analysis, and drafting initial manuscripts, were all significantly associated with AI dependency scores ($P < 0.05$).

Detailed results are presented in Table 1.

3.3 Correlation Analysis Between AI Dependency and Other Scale Scores

The results of the correlation analysis showed that AI dependency scores among nursing master's students were significantly negatively correlated with multiple psychological and behavioral variables ($P < 0.05$).

Specifically, AI dependency was negatively correlated with agreeableness ($r = -0.119$), conscientiousness ($r = -0.202$), emotional stability ($r = -0.169$), and openness to experience ($r = -0.136$) in the Big Five personality traits. In addition, AI dependency was also negatively correlated with achievement motivation ($r = -0.155$), impulse control ($r = -0.294$), healthy habits ($r = -0.240$), focus on work ($r = -0.243$), and moderation of entertainment ($r = -0.246$). Detailed results are presented in Table 2.

Table 2
Correlation Analysis Between AI Dependency and Other Scale Scores Among Nursing Master's S

Variables	AI Dependency	Research Self-Efficacy	Extraversion	Agreeableness	Conscientiousness	Emotional Stability	Openness to Experience	Achievement Motivation	In
AI Dependency	1	-	-	-	-	-	-	-	-
Research Self-Efficacy	-0.025	1	-	-	-	-	-	-	-
Extraversion	0.015	0.231**	1	-	-	-	-	-	-
Agreeableness	-0.119*	0.140**	-0.080	1	-	-	-	-	-
Conscientiousness	-0.202**	0.326**	0.097*	0.302**	1	-	-	-	-
Emotional Stability	-0.169**	0.322**	0.145**	0.287**	0.360**	1	-	-	-
Openness to Experience	-0.136**	0.265**	0.232**	0.175**	0.296**	0.164**	1	-	-
Achievement Motivation	-0.155**	0.303**	0.295**	-0.005	0.271**	0.350**	0.337**	1	-
Impulse Control	-0.294**	0.145**	-0.075	0.373**	0.339**	0.459**	0.132**	0.177**	1
Healthy Habits	-0.240**	0.072	0.107*	0.087	0.259**	0.265**	0.146**	0.330**	0.
Resistance to Temptation	-0.072	0.302**	0.083	0.217**	0.432**	0.327**	0.060	0.221**	0.
Focus on Work	-0.243**	0.145**	0.029	0.171**	0.344**	0.314**	0.153**	0.266**	0.
Moderation of Entertainment	-0.246**	0.075	0.039	0.129**	0.290**	0.289**	0.126**	0.222**	0.

Note: *P < 0.05; **P < 0.01

3.4 Multiple Linear Regression Analysis of AI Dependency

The AI dependency score of nursing master's students was used as the dependent variable. Variables that were statistically significant in the univariate and correlation analyses were included as independent variables in a multiple linear regression model.

The results showed that the frequency and intensity of AI tool use, the use of AI tools for drafting initial manuscripts, and both individual and institutional attitudes toward AI-assisted writing were significant positive predictors of AI dependency. In contrast, higher levels of impulse control, conscientiousness, and openness to experience were significant negative predictors of AI dependency ($P < 0.05$).

The model explained 29.60% of the total variance. Collinearity diagnostics indicated that tolerance values ranged from 0.695 to 0.906 and variance inflation factors (VIFs) ranged from 1.103 to 1.438, suggesting no evidence of multicollinearity. Detailed results are presented in Table 3.

Table 3
Multiple Linear Regression Analysis of Factors Associated with AI Dependency Among Nursing Master's Students

Variables	B	SE	β	t	P value	95% CI
Constant	32.249	3.386	—	9.526	< 0.001	25.595 to 38.904
Use of AI for Draft Writing	3.781	0.819	0.200	4.614	< 0.001	2.170 to 5.392
Daily Duration of AI Use	1.858	0.377	0.210	4.927	< 0.001	1.117 to 2.600
Impulse Control	-0.421	0.089	-0.206	-4.747	< 0.001	-0.595 to -0.246
Individual Attitude Toward AI Use	1.219	0.529	0.111	2.303	0.022	0.179 to 2.260
Conscientiousness	-0.532	0.219	-0.108	-2.424	0.016	-0.963 to -0.101
Frequency of AI Tool Use	-0.880	0.388	-0.099	-2.267	0.024	-1.642 to -0.117
Institutional Attitude Toward AI Use	1.136	0.512	0.102	2.217	0.027	0.129 to 2.143
Openness to Experience	-0.429	0.212	-0.086	-2.026	0.043	-0.845 to -0.013
Note: $R^2 = 0.309$; Adjusted $R^2 = 0.296$; $F = 23.831$; $P < 0.001$						

4. Discussion

4.1 AI Dependency Among Nursing Master's Students Is at a Moderate Level

The results of this study showed that the mean AI dependency score among master's-level nursing students was 26.87 ± 9.34, indicating a moderate level compared with the scale midpoint. This finding is consistent with the results reported by Zhang L et al.[27], suggesting that AI dependency has become relatively common among nursing graduate students, although it has not yet reached a severe level.

The development of AI dependency may be largely attributed to the immediate feedback provided by AI tools. A survey by Han et al.[28] reported that 92% of nursing students believed that AI tools could help them quickly access information, improve learning efficiency, and reduce repetitive tasks. Such efficiency may easily promote habitual use. At the same time, although major publishers have introduced guidelines on AI use[29, 30], requiring disclosure and emphasizing the leading role of human authors in research, clear guidance and dynamic regulatory systems at the university level remain insufficient. This may increase the risk of dependency.

Overall, the current level of AI dependency appears to be manageable. However, universities should further improve regulations on AI use, strengthen AI literacy education, and provide targeted interventions for high-risk students. These efforts may help guide students toward rational and standardized use of AI tools.

4.2 High Frequency and Intensity of AI Use as a Driver of AI Dependency

This study found that nursing master's students who used AI tools frequently and intensively showed higher levels of AI dependency. This finding is consistent with previous studies by Zhang X and Zhang L.[26, 27] According to theories of habit formation[31], the frequency of technology use is positively associated with the development of habitual behavior. In this study, frequent use of AI tools may lead to automated usage patterns, making AI tools a default option in the research process and reducing opportunities for independent thinking. In addition, positive feedback plays an important role in reinforcing habitual behavior and further strengthening AI dependency[32]. Each successful experience with AI tools may reinforce users' reliance on them.

To address this issue, strategies are needed at both institutional and individual levels. At the institutional level, universities may consider setting limits on the duration of AI tool use per semester and requiring students to attempt problem-solving independently before using AI in each stage of research. At the individual level, students should develop self-monitoring and reflective practices. For example, they can record the time, purpose, and outcomes of each AI use and evaluate whether the task could have been completed independently. Regular reflection may help identify early signs of dependency and allow timely adjustment.

4.3 Individual and Institutional Attitudes Toward AI as Key Drivers of AI Dependency

This study found that both individual and institutional attitudes toward AI-assisted writing were significant positive predictors of AI dependency among nursing master's students. This finding is consistent with previous studies by George and Kwak[33–35], which showed that acceptance of AI strongly predicts AI use behavior.

From the perspective of the Technology Acceptance Model (TAM), students' positive attitudes toward AI are mainly based on their perceptions of its usefulness and ease of use[36]. Although such perceptions can shorten the writing process, overly optimistic views of AI outputs may lead students to overlook issues such as AI hallucinations[37]. Without critical evaluation, blindly accepting AI-generated content may compromise academic integrity.

At the environmental level, institutional attitudes toward AI are reflected in policies and regulations[38], which can shape students' behavior. Ambiguous or permissive policies may lower the threshold for AI use and increase the risk of dependency. Therefore, students should remain aware of both the strengths

and limitations of AI while using it. At the same time, universities should adopt clear and cautious academic ethics policies and shift from simple restriction toward proactive guidance on the appropriate use of AI.

4.4 Impulse Control as a Significant Negative Predictor of AI Dependency

This study found that impulse control was a significant negative predictor of AI dependency among nursing master's students. This finding supports the results of Zhong et al.[39], who reported that higher impulsivity may strengthen individuals' positive beliefs about AI tools and increase dependency. A previous study[40] has also shown a significant negative association between impulse control and traditional forms of technology dependence, such as smartphone addiction.

In this study, research writing often required sustained effort and deep thinking, which may conflict with the desire for immediate results. Students with higher levels of impulse control were better able to resist the urge to use AI tools immediately and instead engage in independent thinking. This may help develop critical thinking and self-directed learning, thereby reducing AI dependence[20].

Universities can help improve students' impulse control through interventions such as cognitive-behavioral training and time management courses. In addition, institutions should guide students to set long-term research goals and establish appropriate evaluation systems for research competence. Students should be encouraged to focus on developing academic abilities rather than simply completing short-term tasks.

4.5 Openness to Experience as a Significant Negative Predictor of AI Dependency

Openness to experience is one of the Big Five personality traits. It reflects an individual's interest in new experiences, curiosity, imagination, and willingness to explore the unknow[41]. This study found that students with higher levels of openness had lower levels of AI dependency.

Previous studies have also examined the relationship between openness and technology-related dependence. For example, Tian et al.[42] have shown that openness can negatively predict internet addiction. Abu[43] further emphasized the importance of fostering openness as a personality trait, noting that it can bring long-term benefits at both individual and societal levels. It can also help create environments in education and the workplace that encourage curiosity, creativity, and openness to new ideas.

In this study, students with higher openness tended to engage in independent thinking and innovation rather than relying on external tools. They also often showed stronger critical thinking skills. They were more likely to question and evaluate AI-generated content and to recognize its limitations and potential biases.

Therefore, universities should consider offering courses on critical thinking. Such courses can help students develop skills in analysis, reasoning, and judgment. Students should also be trained to identify logical fallacies in AI-generated arguments and to assess the reliability of AI-assisted literature retrieval. These measures may help reduce overreliance on AI tools.

4.6 Use of AI for Initial Manuscript Drafting as a Driver of AI Dependency

This study found that nursing master's students who used AI tools to assist with drafting initial manuscripts showed higher levels of AI dependency. This finding is consistent with the results of Zgambo et al.[7], who noted that excessive involvement of AI in research may reduce opportunities for independent thinking and lead to a decline in academic originality.

Drafting the initial manuscript is a critical stage in the research process. It involves clarifying research questions, developing arguments, and integrating evidence. If students rely heavily on AI to generate outlines or text before engaging in sufficient independent thinking, the writing process may shift from active construction to editing and assembling AI-generated content. This may limit opportunities for deep thinking and skill development. In such cases, AI may shift from a language support tool to a guide for ideas or even a substitute for thinking, gradually leading to dependency.

Therefore, universities should establish clear regulations on the appropriate use of AI in low-risk research tasks. They should also introduce disclosure requirements, asking students to report how and to what extent AI tools were used in their work. Such measures can improve academic transparency and traceability, reduce the risk of inappropriate AI involvement in core academic content, and promote the responsible and trustworthy use of AI[44].

4.7 Conscientiousness as a Significant Negative Predictor of AI Dependency

This study found that higher levels of conscientiousness were associated with lower levels of AI dependency among nursing master's students. This finding is consistent with previous research. For example, Wang CW et al.[45] reported a negative association between conscientiousness and internet addiction among adolescents. Similarly, Hwang[46] found that conscientiousness was negatively related to Facebook addiction, and Davide[41] reported a negative association between conscientiousness and smartphone addiction.

In the context of research writing, conscientiousness may be reflected in a more cautious attitude toward AI-generated content and a stronger sense of responsibility for academic standards. Students with higher conscientiousness tend to value rigor in the research process and place greater importance on how results are achieved, rather than focusing solely on outcomes.

Therefore, universities should strengthen education on academic integrity. Students should be encouraged to take full responsibility for their research work and develop a rigorous academic attitude. In addition, they should be trained to carefully review and revise AI-generated content. These measures can help ensure that the use of AI tools remains consistent with academic ethical standards.

5. Limitations

This study has several limitations. First, due to the cross-sectional design, causal relationships between variables cannot be established. Second, the data were collected using self-reported questionnaires, which may be subject to recall and social desirability bias. Third, the sample was obtained through convenience sampling from six universities, which may limit the generalizability of the findings. Future studies should adopt longitudinal designs and larger, more diverse samples. Qualitative approaches may also provide deeper insights into the mechanisms underlying AI dependency.

6. Conclusion

This study found that AI dependency among nursing master's students nursing master's students was moderate and influenced by personality traits, cognitive attitudes toward AI, and AI use patterns. Frequent and intensive AI use, AI-assisted drafting, and positive individual and institutional attitudes were significant positive predictors, whereas higher levels of impulse control, conscientiousness, and openness were negative predictors. These findings highlight the need for improved regulation and supervision of AI use in universities. Strengthening academic integrity and AI literacy education, along with targeted interventions for high-risk students, may promote appropriate and responsible use of AI tools.

Abbreviations

AI: Artificial intelligence; AMS: Achievement Motivation Scale; I-PACE: Interaction of Person-Affect-Cognition-Execution; SCS: Self-Control Scale; TIPI: Ten-Item Personality Inventory.

Declarations

Ethics approval and consent to participate

This study was approved by the Ethics Committee of Sir Run Run Shaw Hospital, Zhejiang University School of Medicine (Approval No. 2025-0900). All procedures involving human participants were performed in accordance with the Declaration of Helsinki and relevant guidelines and regulations. All participants provided informed consent before participating in the study.

Consent for publication

Not applicable.

Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

XH, RZ, and JL conceived and designed the study. SL, YL, LC, and HL were responsible for data collection. YZ and LW performed the statistical analysis. RZ and KZ drafted the manuscript. RZ critically revised the manuscript for important intellectual content. All authors read and approved the final manuscript.

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