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# Influencing Factors of Medical Students' Acceptance of Generative Artificial Intelligence Based on the Extended Technology Acceptance Model: A Cross-Sectional Study

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*Article*

# Influencing Factors of Medical Students' Acceptance of Generative Artificial Intelligence Based on the Extended Technology Acceptance Model: A Cross-Sectional Study

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**Abstract**

Background: The popularization of generative artificial intelligence (GenAI) has brought both opportunities and challenges to medical education. Objective: To investigate medical students' usage status, usage intention of GenAI and its possible influencing factors. Methods: A questionnaire survey was conducted among 199 students from a medical university, and statistical analysis was performed using SPSSAU. Results: Tools such as DeepSeek and ChatGPT are widely used in medical students' learning and scientific research. High-frequency users (≥4 days per week) scored significantly higher than low-frequency users (<4 days per week) in 9 dimensions; gender showed significant differences in dimensions such as perceived ease of use ($P<0.05$), while major background differed only in some dimensions, and age showed no significant difference. Regression analysis revealed that external variables ($P<0.001$), perceived usefulness ($P=0.001$) and individual factors ($P=0.009$) had significant positive effects on behavioral intention, whereas effort expectancy ($P=0.049$) had a significant negative effect. Conclusion: GenAI has been deeply integrated into medical students' autonomous learning. External support, technical practicality and individual adaptability are key driving factors for usage intention, while effort expectancy constitutes a barrier. This study provides empirical evidence for the standardized application of GenAI in medical education.

**Keywords:** generative AI; medical students; questionnaire survey; usage intention; extended technology acceptance model

## 1. Introduction

The rapid development of generative artificial intelligence (GenAI) is profoundly transforming the landscape of medical education and practice. Its potential in improving learning efficiency, assisting clinical decision-making, and driving scientific research and innovation has become increasingly prominent. Against this backdrop, medical students, as the core force of the future healthcare system, their acceptance and actual usage of GenAI are not only relevant to the promotion and application of the technology itself, but also exert a far-reaching impact on the training model of medical talents and the form of future medical services. Therefore, exploring the current usage status, influencing factors, and cognitive attitudes toward GenAI among medical students has become an important topic in current research on medical education and technology acceptance.

Existing studies show that there are significant regional differences in the popularity and application patterns of GenAI among medical students. For instance, in a multicenter survey conducted in Ontario, Canada, more than 78.9% of medical students had used GenAI, among whom 53.0% were frequent users employing it at least once a week [1]. A survey conducted at a medical school in a certain city in the United States also shows that nearly 70 percent of its students have used AI chatbots, and more than half of them have employed them for academic purposes [2]. However, a Japanese study pointed out that only 41.9% of second-year medical students had used ChatGPT, reflecting that the penetration of GenAI remains in the initial stage in certain educational environments [3]. This difference suggests that cultural backgrounds, educational policies, and technological access conditions may jointly influence medical students' exposure to and use of GenAI.

Despite variations in usage rates, most medical students hold a positive attitude toward GenAI and recognize its auxiliary value in medical learning and future clinical practice. Studies show that more than 68% of students regard AI chatbots as useful educational resources and are willing to learn relevant skills to integrate them into their future work [1,2]. Meanwhile, medical students also generally pay attention to the limitations of GenAI, especially the accuracy, reliability and potential bias of its generated content. As many as 91.6% of students are aware of the risk of inaccurate information and generally adopt methods such as cross-validation to use the output results prudently [1,2]. This "proactive yet prudent" attitude highlights the characteristic of openness and critical thinking among medical students in the process of technology adoption.

However, existing research still has certain limitations. On the one hand, although relevant surveys on the use of GenAI by Chinese medical students have achieved some progress in recent years [4,5], most research still focuses on developed regions such as North America and Japan, lacking broader data support, and the universality of the conclusions needs further verification. On the other hand, GenAI technology is iterating rapidly, and medical students' usage behavior and attitudes may also change dynamically. Survey results based on a specific time point can hardly fully reflect its development trend. Therefore, it is necessary to conduct investigations and research among different groups to systematically grasp the current status, motivations and concerns of medical students in using GenAI.

The Technology Acceptance Model (TAM) was proposed by Davis in 1989. It is a theoretical framework designed to explain and predict users' acceptance and usage behavior of new technologies [6,7]. Thanks to its simplicity and explanatory power, this model has been widely adopted across various industries to explore the relationship between user behavior and technology adoption. At the core of TAM are two key constructs: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). The model states that Perceived Ease of Use directly influences users' behavioral intentions, and also indirectly affects behavioral intentions by influencing Perceived Usefulness. Perceived Usefulness directly impacts users' attitudes toward technology use and behavioral intentions, ultimately driving actual technology adoption behavior. Since its introduction, TAM has become one of the most widely applied models in the field of technology adoption and has been validated across numerous technological applications, such as electronic health records [6], intelligent monitoring system [8] and metaverse technology [9]. However, the study also found that relying solely on the two variables of perceived usefulness and perceived ease of use has certain limitations in explaining and predicting user behavior, especially when facing new technologies that are complex, dynamic, or strongly socially embedded [10]. For example, in scenarios such as virtual reality/augmented reality (VR/AR) sports experiences, these two variables alone are often insufficient to fully explain users' willingness to participate [10]. To overcome these limitations, researchers have extensively extended the TAM by introducing external variables, forming the Extended Technology Acceptance Model (ETAM) [7]. These extensions are designed to enhance the model's interpretability and predictive power, making it more suitable for diverse technical application scenarios and enabling it to more effectively address the challenges posed by emerging technologies.

Against the above background, this study aims to use a questionnaire based on the extended Technology Acceptance Model, focusing on medical university students, to investigate the current usage status, acceptance level and influencing factors of generative artificial intelligence among them, explore the key elements affecting their usage intention, so as to provide empirical evidence and

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strategic references for the rational integration and standardized application of GenAI in medical education.

## 2. Subjects and Methods

### *2.1. Survey Subjects*

This study takes students enrolled in a medical university as the survey subjects. Inclusion criteria: (1) having basic knowledge of generative AI and practical experience in using it; (2) having used generative AI more than 10 times cumulatively in the past two years; (3) having good cognitive and judgmental abilities and being able to understand and complete the questionnaire. Exclusion criterion: individuals whose single use duration of generative AI is no more than 3 minutes (regarded as ineffective or occasional use, which cannot reflect real usage cognition and attitudes).

Sample size estimation: This study adopts a cross-sectional survey design. According to the sample size estimation method proposed by statisticians Krejcie & Morgan, when the population size is unknown but assumed to be large, to achieve a 95% confidence level ($\alpha$=0.05) and an acceptable sampling error (approximately ±7%), the required minimum sample size is about 196 people [11]. According to the general rule of thumb for sample size calculation in multivariate regression analysis, where the sample size is usually 5 to 10 times the number of independent variables, this study has a total of 11 independent variables, requiring a minimum sample size of 55 participants. In this study, 199 valid questionnaires were actually recovered and met the inclusion and exclusion criteria, which satisfies the sample size estimation requirement and provides sufficient power for subsequent statistical analysis.

### *2.2. Research Instruments*

This study adopted a self-designed questionnaire developed based on the extended Technology Acceptance Model integrated with the context of medical education for data collection. The questionnaire was designed on the basis of the classic TAM theory. To more comprehensively explore the acceptance mechanism of generative artificial intelligence among the specific group of medical students, in addition to the core constructs of TAM, multiple extended variables were integrated, including demographic characteristics, practical application status, and perceptions of potential risks. The specific contents of the questionnaire are as follows:

(1) Demographic characteristics: Basic information of the respondents, including gender, age, academic stage, affiliated school, and so on.

(2) GenAI application status: A survey on the types, frequency, main scenarios (such as learning, scientific research, and clinical assistance) and specific functions (such as literature reading, code generation, text polishing, etc.) of GenAI tool usage.

(3) Perception of potential risks: An assessment of medical students' awareness and concern about the potential risks of GAI in terms of academic integrity, data security, content reliability, professional impact, and other aspects.

(4) Influencing Factor Scale Based on Extended TAM: This section serves as the core measurement instrument of this study. A 5-point Likert scale (1 = strongly disagree, 5 = strongly agree) is adopted to measure multiple variables mentioned in the aforementioned theoretical framework. The scale consists of the following dimensions and sample core measurement items: Perceived usefulness: measures the recognition of GenAI in improving learning and work efficiency (e.g., "It can improve my learning and work efficiency"); Perceived ease of use: measures the perception of the simplicity of using GenAI (e.g., "Learning to use... is easy for me"); Individual factors: cover digital literacy, personal interest and self-efficacy (e.g., "I am good at accepting and using new technologies"); Technical characteristics: evaluate the functional attributes of GenAI (such as accessibility, personalization, and multimodal interaction); Task-technology fit: measures the matching degree between GenAI functions and learning and research tasks (e.g., whether it is sufficient in information search and text generation); Social influence and external variables: examine

the impacts of external conditions such as the surrounding environment, public opinion, and technical support; Affective and risk perception: include hedonic motivation (pleasure during use), technological anxiety (e.g., concerns about impaired critical thinking), perceived risk (e.g., worries about plagiarism and security risks), and effort expectancy (perceived usage burden).

(5) Usage intention: directly measures the behavioral intention of continuous use in the future and recommending GenAI to others (e.g., "I will continue to use... in the future").

The overall structure of the questionnaire is as follows: demographic characteristics, actual application status, hidden danger cognition, influencing factor scale, and usage intention. The latter two parts are scored using a 5-point Likert scale, with responses to each item coded as "strongly disagree = 1", "disagree = 2", "neutral = 3", "agree = 4", and "strongly agree = 5".

The initial draft of the questionnaire was revised after a pretest. The Cronbach's $\alpha$ coefficient for each dimension of the questionnaire is greater than 0.75, indicating good internal consistency reliability.

### *2.3. Data Collection*

This study adopted the questionnaire survey method for data collection. The questionnaire was designed and distributed via the online survey platform "Wenjuanxing"(https://www.wjx.cn). First, a small-scale pre-survey (n=9) was conducted before the formal implementation of the study, and the questionnaire items were revised and optimized based on the feedback results to ensure the reliability and validity of the questionnaire. Subsequently, the questionnaires were distributed through multiple WeChat groups, and a total of 206 questionnaires were collected. The recovered questionnaires were screened according to the time spent filling in the questionnaires, whether the respondents had experience in using generative artificial intelligence, as well as the preset inclusion and exclusion criteria. After eliminating invalid questionnaires, 199 valid questionnaires were finally obtained for subsequent data analysis.

### *2.4. Data Analysis*

Data analysis for this study was conducted on the SPSSAU statistical platform, with specific procedures and analytical methods as follows: First, descriptive statistics were used for a preliminary analysis of the two sections: "Application status" and "Perception of potential risks". Second, for the scale section, based on the calculation of scores for each item, independent samples t-test or one-way analysis of variance (determined according to data distribution and homogeneity of variance) was adopted to explore differences in research variables across different genders, ages, professional backgrounds and usage frequencies. Finally, multiple linear regression analysis was performed to examine the correlations among variables, with individual factors, perceived ease of use, perceived usefulness, technological characteristics, task-technology fit, hedonic motivation, perceived risk, effort expectancy, technological anxiety, social influence and external variables as independent variables, and behavioral intention as the dependent variable. During the regression analysis, diagnostics were simultaneously conducted on the model's multicollinearity (VIF test) and residual autocorrelation (D-W test) to ensure the validity and robustness of the model.

### *2.5. Ethics Statement*

This study is a cross-sectional survey based on an online questionnaire. The design and implementation of the study strictly abide by the ethical principles of the Declaration of Helsinki. The informed consent statement is stated in the preamble of the questionnaire. Participants who voluntarily complete and submit the questionnaire anonymously after reading it shall be deemed to have given written informed consent. Throughout the survey process, no personally identifiable information of participants such as names, contact details and IP addresses was collected. All data were collected and analyzed in a fully anonymized manner, and researchers cannot trace the data back to specific individuals. In accordance with Article 32 of the Measures for the Ethical Review of

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Life Science and Medical Research Involving Human Subjects (National Health Science and Education Document No.〔2023〕4) of the People's Republic of China, which stipulates that "research using anonymized information and data may be exempted from ethical review", this study meets the conditions for exemption from ethical review, so no review application was submitted to the ethics committee prior to its commencement.

## 3. Results

### *3.1. Demographic Characteristics of the Sample*

A total of 199 valid questionnaires were collected in this study, and the basic demographic characteristics of the sample are shown in Table 1. As presented in Table 1, there were 117 female participants (58.79%). Participants aged 20 years (27.64%) and 19 years (27.14%) accounted for the highest proportions. In terms of academic stage, most participants were undergraduate students (183, 91.96%), while there were 10 master's students (5.03%) and 6 doctoral students (3.02%) respectively. Regarding the distribution of schools or hospitals, participants were mainly from the School of Basic Medical Sciences (38.19%) and the School of Nursing (32.16%), with the remainder distributed across the School of Pharmacy, directly affiliated hospitals, teaching hospitals, and other institutions.

**Table 1.** Demographic Characteristics of the Sample (n=199).

| | **Demographic Characteristics** | **Number of people** | **percentage (%)** |
|---|---|---|---|
| gender | female | 117 | 58.79 |
| | male | 82 | 41.21 |
| age | 18 | 25 | 12.56 |
| | 19 | 54 | 27.14 |
| | 20 | 55 | 27.64 |
| | 21 | 30 | 15.07 |
| | 22-30 | 35 | 17.59 |
| Academic stage | undergraduate | 183 | 91.96 |
| | Master's degree | 10 | 5.03 |
| | Doctor | 6 | 3.02 |
| College or Hospital Affiliated | School of Basic Medical Sciences | 76 | 38.19 |
| | School of Nursing | 64 | 32.16 |
| | Directly affiliated hospitals and teaching hospitals | 17 | 8.54 |
| | School of Pharmacy | 20 | 10.05 |
| | Others | 22 | 11.06 |
| **Total** | | **199** | **100.0** |

### *3.2. Application Status of Generative AI*

The main models reported by respondents to be used are DeepSeek (80.90%), ChatGPT (68.84%), and Kimi (63.32%). Doubao (59.30%) and Ernie Bot (49.75%) are also widely used. More than 55% (55.27%) of medical students use generative AI four days or more per week, among whom 20.60% use it daily. 35.68% of medical students use it 1–3 days per week.In specific tasks, the application proportions of programming and code generation (52.76%) and automated questionnaire design and data analysis (52.26%) are relatively high. The application proportions of virtual simulation and emulation (29.15%), medical image analysis (24.12%), and assisted patient management (10.05%) are relatively low.

In terms of knowledge learning, the commonly used functions include guided literature reading (74.87%), rapid cross-disciplinary learning (69.85%), and translation (67.84%). In research assistance, the application proportions of research design (59.30%), statistical analysis support (52.76%), and literature management (51.26%) are relatively high. In content creation, the applications of article abstract generation (74.37%), manuscript polishing (67.84%), report outline generation (59.30%), and creative writing assistance (50.75%) are relatively common.

*3.3. Medical Students' Perceptions of the Hidden Risks of Generative AI*

Medical students' perceptions of the potential risks of generative AI are shown in Table 2. In terms of academic integrity, 27.64% of respondents reported worrying about its negative impacts, and 42.21% expressed partial concern. Regarding the security of personal information and academic data, 37.69% of respondents clearly worried about the risk of leakage.

More than half of medical students (53.77%) believe that this technology may impact or replace traditional professional roles in the medical field.

**Table 2.** Distribution of Medical Students' Awareness of Potential Risks of Generative AI (n=199).

| | **Yes（n,%）** | **No（n,%）** | **Partially concerned/uncertain（n,%）** |
|---|---|---|---|
| undermine academic integrity | 55(27.64) | 60(30.15) | 84(42.21) |
| Disclosure of personal information or academic data | 75(37.69) | 52(26.13) | 72(36.18) |
| impact or replace traditional professional roles in the medical field | 107(53.77) | 36(18.09) | 56(28.14) |

*3.4. Descriptive Statistics and Intergroup Difference Analysis of GenAI Usage Intention*

The scores of each measurement item are shown in Table 3. After calculating the mean values for each latent variable, comparisons were made regarding differences across gender, age, professional background, and usage frequency, with the results presented in Table 4. Males scored significantly higher than females across six dimensions including perceived ease of use, perceived usefulness, and technical characteristics ($p < 0.05$); no significant differences were found among different age groups in all dimensions ($p > 0.05$); significant differences existed across different academic backgrounds in perceived ease of use, technical characteristics, and external variables ($p < 0.05$); high-frequency users (4 days or more per week) scored significantly higher than low-frequency users (fewer than 4 days per week) across nine dimensions including individual factors, perceived ease of use, perceived usefulness, and technical characteristics ($p < 0.05$).

**Table 3.** Scores of items on medical students' intention to use GenAI (n=199).

| variable | average value | standard deviation | median |
|---|---|---|---|
| individual factors | 3.894 | 0.642 | 4.000 |
| perceived ease of use | 3.978 | 0.727 | 4.000 |
| perceived usefulness | 4.041 | 0.643 | 4.000 |
| technical characteristics | 3.998 | 0.652 | 4.000 |
| task-technology fit | 3.697 | 0.696 | 3.667 |
| hedonic motivation | 3.670 | 0.850 | 4.000 |
| perceived risk | 3.688 | 0.774 | 3.667 |
| effort expectancy | 2.965 | 0.823 | 3.000 |
| technology anxiety | 3.487 | 0.988 | 4.000 |
| social influence | 3.873 | 0.765 | 4.000 |
| external variables | 3.897 | 0.568 | 3.917 |
| behavioral intention | 4.068 | 0.719 | 4.000 |

**Table 4.** Comparison of differences among various factors including gender, age group, professional background and usage frequency (mean ± standard deviation).

| | individual factors | perceived ease of use | perceived usefulness | technical characteristics | task-technology fit | hedonic motivation | perceived risk | effort expectancy | technology anxiety | social influence | external variables | behavioral intention |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Gender | | | | | | | | | | | | |
| **Female(*n*=117)** | 3.82±0.59 | 3.82±0.68** | 3.93±0.61** | 3.91±0.62* | 3.58±0.67** | 3.58±0.80 | 3.75±0.62 | 3.00±0.75 | 3.57±0.87 | 3.79±0.75 | 3.77±0.48** | 3.97±0.65* |
| **Male(*n*=82)** | 4.00±0.70 | 4.20±0.74** | 4.20±0.66** | 4.13±0.67* | 3.86±0.70** | 3.79±0.91 | 3.59±0.95 | 2.92±0.92 | 3.37±1.13 | 3.99±0.78 | 4.07±0.63** | 4.21±0.79* |
| age | | | | | | | | | | | | |
| **18~20 (n=133)** | 3.88±0.67 | 3.95±0.72 | 4.01±0.64 | 4.02±0.65 | 3.74±0.72 | 3.69±0.87 | 3.69±0.77 | 2.70±1.01 | 3.50±1.00 | 3.92±0.77 | 3.92±0.62 | 4.04±0.70 |
| **21~30 (n=65)** | 3.92±0.60 | 4.04±0.75 | 4.09±0.65 | 3.97±0.66 | 3.63±0.63 | 3.62±0.80 | 3.66±0.78 | 2.75±0.96 | 3.45±0.96 | 3.79±0.74 | 3.89±0.60 | 4.14±0.75 |
| professional | | | | | | | | | | | | |
| **School of Basic Medical Sciences (n=76** | 3.83±0.63 | 3.81±0.75* | 4.06±0.61 | 4.14±0.57** | 3.79±0.59 | 3.68±0.82 | 3.51±0.77 | 2.61±0.94 | 3.32±0.99 | 3.85±0.83 | 3.93±0.62** | 4.07±0.78 |
| **School of Nursing (n=64)** | 3.99±0.71 | 4.15±0.71* | 4.11±0.68 | 4.07±0.68** | 3.65±0.82 | 3.70±0.91 | 3.80±0.79 | 2.67±1.13 | 3.53±1.07 | 3.90±0.79 | 4.05±0.64** | 4.17±0.72 |
| **Directly affiliated hospitals and teaching hospitals (n=17)** | 3.82±0.54 | 4.22±0.50* | 3.99±0.53 | 3.92±0.57** | 3.84±0.50 | 3.57±0.75 | 3.61±0.71 | 2.63±0.90 | 3.41±0.64 | 3.94±0.71 | 3.88±0.39** | 4.12±0.67 |
| **School of Pharmacy (n=20)** | 3.73±0.60 | 3.73±0.63* | 3.74±0.72 | 3.58±0.72** | 3.35±0.80 | 3.45±1.00 | 3.87±0.69 | 3.02±0.84 | 3.83±0.67 | 3.82±0.80 | 3.45±0.58** | 3.73±0.64 |
| **Others (n=22)** | 4.02±0.58 | 4.09±0.76* | 4.11±0.62 | 3.76±0.64** | 3.73±0.58 | 3.82±0.72 | 3.88±0.77 | 3.08±0.93 | 3.70±1.12 | 3.88±0.45 | 3.85±0.52** | 4.02±0.50 |
| usage frequency | | | | | | | | | | | | |
| **high frequency (n=110)** | 4.03±0.64** | 4.14±0.69** | 4.16±0.65** | 4.11±0.65** | 3.80±0.70* | 3.80±0.87* | 3.76±0.79 | 2.74±1.05 | 3.51±1.07 | 4.03±0.79** | 4.04±0.59** | 4.28±0.69** |
| **low frequency (n=89)** | 3.72±0.61** | 3.78±0.73** | 3.90±0.61** | 3.86±0.64** | 3.57±0.67* | 3.51±0.80* | 3.60±0.74 | 2.70±0.94 | 3.46±0.88 | 3.67±0.69** | 3.73±0.60** | 3.81±0.67** |

### *3.5. Multiple Linear Regression Analysis of Influencing Factors on Behavior Intention to Use GenAI*

Taking behavioral intention as the dependent variable, a multiple linear regression analysis was conducted with 11 latent variables as independent variables, and the results are shown in Table 5.

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The regression model was significant ($F(11, 187) = 25.001$, $p < 0.001$), with an adjusted $R^2$ of 0.571. Among them, external variables ($\beta = 0.317$, $p < 0.001$), perceived usefulness ($\beta = 0.238$, $p = 0.001$), and individual factors ($\beta = 0.161$, $p = 0.009$) had significant positive predictive effects on behavioral intention; effort expectancy ($\beta = -0.127$, $p = 0.049$) had a significant negative predictive effect on behavioral intention. The predictive effects of the remaining variables (perceived ease of use, technological characteristics, task-technology fit, hedonic motivation, perceived risk, technology anxiety, and social influence) did not reach the level of statistical significance ($p > 0.05$). The collinearity diagnosis of the model showed that all variance inflation factors (VIF) were less than 5, and the Durbin-Watson statistic was 1.888, indicating no problems of multicollinearity and serial autocorrelation.

**Table 5.** Results of Multiple Linear Regression Analysis on Behavioral Intention (n=199).

| independent variable | B | Standard error | Beta | t | p | 95% CI | VIF |
|---|---|---|---|---|---|---|---|
| constant | -0.076 | 0.300 | - | -0.254 | 0.800 | -0.668 ~ 0.515 | - |
| **individual factors** | 0.180 | 0.068 | 0.161 | 2.658 | 0.009** | 0.046 ~ 0.313 | 1.687 |
| perceived ease of use | 0.099 | 0.067 | 0.100 | 1.471 | 0.143 | -0.034 ~ 0.232 | 2.136 |
| **perceived usefulness** | 0.266 | 0.082 | 0.238 | 3.234 | 0.001** | 0.104 ~ 0.428 | 2.499 |
| technical characteristics | 0.058 | 0.078 | 0.053 | 0.745 | 0.457 | -0.096 ~ 0.213 | 2.329 |
| task-technology fit | -0.021 | 0.063 | -0.020 | -0.333 | 0.740 | -0.146 ~ 0.104 | 1.731 |
| hedonic motivation | -0.078 | 0.050 | -0.092 | -1.559 | 0.121 | -0.177 ~ 0.021 | 1.615 |
| perceived risk | 0.103 | 0.055 | 0.111 | 1.867 | 0.063 | -0.031 ~ 0.182 | 1.638 |
| **effort expectancy** | -0.111 | 0.056 | -0.127 | -1.980 | 0.049* | -0.166 ~ -0.000 | 1.890 |
| technology anxiety | 0.028 | 0.047 | 0.039 | 0.605 | 0.546 | -0.064 ~ 0.120 | 1.902 |
| social influence | 0.101 | 0.064 | 0.108 | 1.591 | 0.113 | 0.098 ~ 0.305 | 2.117 |
| **external variables** | 0.401 | 0.109 | 0.317 | 3.682 | <0.0001** | 0.140 ~ 0.462 | 3.424 |

Model Summary $R^2 = 0.595$, Adjusted $R^2 = 0.571$, $F = 25.001$, $p < 0.001$, D-W value = 1.888. Note: The dependent variable is behavioral intention; *$p < 0.05$, **$p < 0.01$.

## 4. Discussion

This study investigated the current application status, risk perception, and influencing factors of generative AI use intention among medical students. The results show that generative AI has been deeply integrated into the self-directed learning of medical students, with their cognition and adoption behavior demonstrating significant scenario-based differentiation and complex influencing mechanisms, presenting new opportunities and challenges for medical education.

### *4.1. Generative AI has become a frequently used and scenario-differentiated auxiliary tool in medical students' autonomous learning*

Surveys show that GenAI has evolved into a crucial auxiliary tool for medical students in their studies and scientific research, with its applications characterized by high frequency, scenario-based usage, and strong functional practicality. It demonstrates particularly high practicality and acceptance in knowledge learning, literature processing, research design and other aspects, a result consistent with the findings of Salas et al. [12]. More than half of medical students use this technology for more than four days per week, indicating that it has evolved from an exploratory tool into a regular support resource. In terms of application scenarios, generative AI is mainly used for knowledge learning and research assistance, with the highest utilization rates particularly in guiding literature reading, cross-disciplinary learning, research design, and academic text processing. Kang and Ahn et al. have also reported on the application of GenAI in students' autonomous learning [13], which is highly consistent with the advantages of GenAI in information integration and efficiency improvement. In terms of tool selection, both mature mainstream models and localized models adapted to the medical context enjoy relatively high usage rates, reflecting medical students' dual considerations of tool reliability and domain applicability. However, the application proportion in

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teaching scenarios and clinical support links (such as patient management and imaging analysis) is significantly low, indicating that the current integration depth of technology is still concentrated on supporting individual learning and scientific research process optimization, with limited penetration in formal teaching systems and high-risk clinical decision-making.

While widely accepted, medical students also show a prudent awareness of the potential risks of generative artificial intelligence. More than half of the students are concerned about its possible impact on traditional professional roles, reflecting widespread attention to changes in occupational structure triggered by technological transformation [14]. In terms of academic integrity and data security, the existence of significantly divergent perceptions indicates that Duan et al. [15] also mentioned in their research medical students' concerns about privacy and ethical risks, suggesting that relevant ethical norms and risk education need to be further strengthened. These cognitive characteristics imply that while promoting the application of technology, it is necessary to simultaneously establish matching usage specifications, data governance frameworks, and guidance for professional competency development.

*4.2. Medical students' intention to use generative artificial intelligence is mainly influenced by perceived usefulness, external conditions, individual factors, and difficulty of use.*

A multiple regression analysis examining the factors influencing usage intention reveals that external variables, perceived usefulness, and individual factors exert a significant positive predictive effect on medical students' behavioral intention to use GenAI. Among them, external variables ($p < 0.001$) and perceived usefulness ($p = 0.001$) indicate that the technical support and functions of GenAI itself are crucial to medical students' usage intention [5], while individual factors ($p = 0.009$) reflect the inherent characteristics of medical students, such as strong self-efficacy and innovativeness, which also play an important role in promoting their adoption of GenAI. These findings are partially consistent with the research results of Ittefaq et al. [16] and align with the basic logic of the Technology Acceptance Model, namely that positive perception and motivational factors promote actual usage behavior [17], while in turn strengthen these positive cognitions through practical experience [18,19], forming a virtuous cycle. Effort expectancy shows a significant negative predictive effect, possibly because the rigor of medicine itself leads medical students to skeptical the accuracy and reliability of such tools [5]. All these suggest that future efforts should be made in multiple aspects, such as technological development and legal support, to enhance trust in GenAI and address related ethical issues.

Among them, perceived risk has an insignificant correlation with technology anxiety, which may reflect the cognitive characteristics of current medical students toward GenAI. Medical students' anxiety about GenAI is fading; although they still have concerns about its risks, such concerns are not sufficient to prevent them from using GenAI, which also implies that current medical students hold a cautiously optimistic attitude toward GenAI [4]. Hedonic motivation shows an insignificant correlation, which aligns well with medical education and practical scenarios. This indicates that medical students use GenAI mainly for utilitarian purposes (assisting with learning and scientific research) rather than for entertainment. In addition, there is no significant correlation between task-technology fit and technical characteristics, reflecting that current GenAI is generally regarded by medical students as a general-purpose tool. This suggests that GenAI may be insufficient in personalized development and unable to complete certain specific tasks [5].

These results partially support the classic Technology Acceptance Model and highlight that at the current stage, the main driving forces for medical students to adopt this technology stem from their recognition of its practical utility, external support conditions, and personal adaptability. Especially in the context of professional education, the weight of "perceived usefulness" (i.e., the improvement in learning and research performance) far exceeds that of "perceived ease of use" [16]. It provides a theoretical foundation for the future development of GenAI in the medical field.

## 5. Conclusion

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This study conducted a questionnaire survey among medical students at a specific medical university to explore the application status of generative artificial intelligence (GenAI) in medical education, as well as risk perceptions and influencing factors of usage intention. The results indicate that generative artificial intelligence has been adopted at a relatively high frequency among medical students, mainly for assisting self-directed learning and scientific research, while its application in clinical practice and formal teaching remains limited. Medical students exhibit significant contradictions in their perceptions of the technology: while actively embracing its effectiveness, they maintain a prudent attitude rooted in professional culture toward data security, academic integrity, and professional ethics. The primary factors influencing students' usage intention include perceived usefulness of the technology, external support, and personal acceptance, whereas perceived difficulty of use reduces their willingness to adopt it. In addition, the significant gender differences identified in the study suggest that attention should be paid to potential issues related to equity, personalization, trust, and ethics during technology promotion. However, this study is limited by its cross-sectional design and sample from a single institution, requiring further validation for the generalizability and causal inference of the conclusions. Future research may expand sample representativeness, conduct longitudinal tracking, and adopt mixed-method designs to further explore the impact of long-term technology use on clinical thinking and professional identity, thereby providing more timely and practically valuable evidence for the systematic transformation of medical education in the era of artificial intelligence.

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