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The relationship between instructional feedback and academic performance: the role of artificial intelligence perception

Min Jiao[1], Chenglin Liu[2], Hongmin Li[1*] and Dongxu Li[1*]

Abstract

Background Instructional feedback can effectively improve academic performance of students. This research aims to explore the impact of instructional feedback on academic performance and to assess the indirect association of AI perception in this relationship.

Methods A cross-sectional study design was employed, conducted at Jining Medical University. The independent variable was instructional feedback, the dependent variable was the academic performance, and the mediating variable was the AI perception level. First, univariate and multiple regression analysis were conducted. Then, the bootstrap method was used to test the significance of the mediating effect. Finally, a restricted cubic spline (RCS) model was used to explore potential non-linear associations between AI perception and instructional feedback.

Results A total of 470 medical undergraduate students were included in the analysis. Among the participants, 349(74.255%) respondents indicated that lecturers used AI to provide timely instructional feedback. Multivariate regression analysis revealed that academic performance was higher among female students ($P=0.017$), urban students ($P<0.001$), and those reporting instructional feedback ($P=0.002$). Mediation analysis showed that instructional feedback was associated with AI perception ($\beta=0.465$, $P=0.041$), but AI perception was not significantly associated with academic performance after adjustment ($\beta=0.227$, $P=0.110$). RCS analysis suggested an overall association between AI perception and instructional feedback with no evidence of non-linearity (P-overall = 0.044; P-non-linear = 0.648).

Conclusion Instructional feedback was associated with academic performance among medical undergraduates, and it was also associated with AI perception. However, mediation analysis did not support a statistically significant indirect association via AI perception. RCS analysis suggested an overall association between AI perception and the odds of reporting receipt of instructional feedback, with no evidence of non-linearity. These findings suggest that integrating AI-enabled instructional feedback into course delivery may be a useful approach to support learning, while the role of AI perception as an explanatory pathway warrants further investigation.

Keywords Instructional feedback, AI perception, Academic performance, Mediating effect

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Background

In recent years, the emergence and development of artificial intelligence (AI) has greatly changed some aspects of education, especially medical education [1]. With the close integration of AI technology and educational platforms, intelligent teaching platforms such as Chaoxing [2] have added functions similar to ChatGPT and intelligent tutoring systems [3]. Recent studies indicate that these platforms can build knowledge graphs [4], process large amounts of medical learning data, and provide targeted feedback and guidance, potentially improving learning efficiency.

Timely and effective feedback helps students identify gaps in learning and supports improvement [5]. In medical education, instructional feedback can be provided through traditional classroom-based approaches as well as through AI-enabled functions on the Chaoxing platform. For example, teachers may use AI tutoring [6] for assignment feedback and AI scoring [7] to record and highlight frequently missed questions. Such AI-based feedback may support monitoring of learning progress and promote student engagement.

A growing body of research suggests that AI perception may shape how they evaluate and respond to AI-enabled learning support [8–9]. Studies have found that when students perceive AI functions as useful and usable, they may be more likely to engage with feedback, adjust learning strategies, and use platform resources (e.g., knowledge graphs and learning videos) to address weak areas [10–11]. TAM provides a useful conceptual background by highlighting how perceptions of usefulness and ease of use may relate to subsequent learning behaviors and outcomes [12–13]. However, in the context of AI-enabled instructional feedback, empirical evidence remains limited regarding how teacher-provided AI feedback relates to students' academic performance and whether AI perception statistically accounts for this association.

Therefore, this study aimed to examine the relationships among instructional feedback, medical students' AI perception, and academic performance in the Social Medicine course. The study was guided by the following hypotheses:

> H1: Students who receive instructional feedback will have higher academic performance.
> H2: Students who receive instructional feedback will report higher AI perception.
> H3: AI perception will show a statistically significant indirect association between instructional feedback and academic performance.

Methods

Research setting and participants

From June 1st to June 30th, 2025, a total of 483 full-time third-year undergraduates majoring in Preventive Medicine and Clinical Medicine at Jining Medical University were invited to participate in an anonymous online questionnaire survey conducted via the Chaoxing platform. Of these, 470 students completed the survey, resulting in a response rate of 97.31%. The distribution, completion, and collection of the questionnaires were all managed on the platform, ensuring the anonymity of the information and the security of the data.

Inclusion criteria included: ① Voluntarily participating in the survey and having signed a written informed consent form; ② Possessing basic reading and questionnaire-filling abilities, no perception or language communication disorders, and being proficient in operating Superstar Learning Platform to complete the online questionnaire; ③ No major physical or mental illnesses (e.g., severe physical diseases, acute episodes of mental illness) within the recent period (1 month before the survey) and being able to complete the questionnaire independently.

Exclusion criteria included: ① Students on suspension or grade repetition, or those who had been absent from school for a long time (cumulative ≥ 2 weeks) due to internships, leave, or other reasons during the survey period, making it difficult to ensure the completeness of the questionnaire; ② Students with definite perception impairment, a history of mental illness, or those in the acute phase of physical illness at the time of the survey, who were unable to accurately understand the questionnaire content and operation prompts of Chaoxing Platform.

Ethical considerations

This study was approved by the Medical Ethics Committee of Jining Medical University (Approval No.: JNMC-2022-YX-013) and strictly followed the ethical guidelines of the Declaration of Helsinki of the World Medical Association [14] throughout the entire process. Before the study was initiated, the research explanation was pushed to all subjects through the professional class groups on Chaoxing Platform, fully informing them of the research purpose, their right to freely participate in or withdraw from the study, and the data confidentiality clauses. After being informed, the subjects of the investigation signed a written informed consent form.

Survey instruments

Demographic information questionnaire

The Demographic Information Questionnaire covered the following basic information items: basic demographic characteristics (gender, age, residence), family education background (maternal educational level, paternal

educational level), economic status (monthly living expenses), and subjective attitude (satisfaction with AI). Specifically, "Strongly Dissatisfied" "Dissatisfied" and "Neutral" were defined as unsatisfactory, while "Satisfied" and "Strongly Satisfied" were defined as satisfactory.

AI perception scale

A perception assessment scale for AI among undergraduate medical students was designed. The items of scale were generated based on relevant literature and the functional characteristics of the Chaoxing platform's AI features, and the wording and content were refined through thematic group discussions. The final item set was aligned with two conceptual dimensions, perceived usefulness and perceived usability. The scale was divided into 2 parts: perceived usefulness and usability of AI functions, used to assess the AI perception level of the research subjects (Supplementary File 1).

The scale included 10 items, each of which was scored using a Likert 5-point scale. The scoring criteria were assigned as follows: A = 0 point, B = 0.2 point, C = 0.5 point, D = 0.8 point, and E = 1 point. Thus, the total score range was 0 to 10 points. A score of 1 (E) represented strong agreement with positive perceptions of AI function, while a score of 0 (A) indicated strong disagreement. This scoring method was chosen based on expert consensus and allows for a more nuanced interpretation of student perceptions compared to a traditional Likert scale.

A preliminary survey was conducted with 100 randomly selected medical students to assess the clarity and relevance of the questionnaire items. Based on feedback, the wording of the items was slightly adjusted to ensure they were easier to understand and appropriately worded. Small-sample reliability and validity tests were also performed on the questionnaire.

(1) Reliability Analysis

Table 1 Exploratory factor analysis results of the AI perception questionnaire

Items	Element		Cumulative variance contribution rate
	1	2	
A1	-0.006	0.758	**37.765**
A2	0.111	0.737	
A3	0.078	0.819	
A4	0.073	0.905	
A5	0.032	0.794	
B1	0.764	0.186	**65.985**
B2	0.788	-0.080	
B3	0.796	0.029	
B4	0.819	0.099	
B5	0.878	0.071	

The Cronbach's α coefficient [15] of the scale was 0.814.

(2) Exploratory Factor Analysis

The KMO of the AI perception questionnaire was 0.839, Bartlett's test χ^2=472.974, df = 45, and P < 0.001, indicating that the questionnaire was suitable for factor analysis. The results showed that two common factors were extracted, with a cumulative variance contribution rate of 65.985%. The factor loadings of A1-A5 and B1-B5 were both > 0.7, indicating that the AI perception questionnaire had good structural validity. Table 1 provides more detailed information.

Outcome variable

In this analysis, the independent variable was defined as the implementation of instructional feedback by lecturers of the Social Medicine course [16] using AI tools via the Chaoxing Platform. It was measured through the question: During the learning process of the "Social Medicine" course this semester, the lecturer provided you with timely instructional feedback through the AI functions of the Chaoxing platform (such as intelligent teaching assistant [6], real-time Q&A robot [14], homework correction [17], etc.)? This variable had two options and adopted a numerical coding format: the number "0" represented "No", and the number "1" represented "Yes" (Supplementary File 1).

The outcome variable was the respondents' final academic performance in Social Medicine during the second semester of the 2024–2025 academic year. It was mainly extracted from the course management system of the Social Medicine course on the Chaoxing Platform, and intuitively reflected the respondents' course learning outcomes through specific score values.

Data analysis

For descriptive statistics, categorical variables were expressed as frequencies and percentages and continuous variables as mean (SD). Academic performance was analyzed as a continuous outcome using OLS linear regression, with key covariates entered into adjusted models. Mediation analysis was conducted with 5000 bootstrap resamples to estimate the indirect effect. Restricted cubic spline (RCS) models were used to examine potential nonlinear associations between AI perception and instructional feedback. Statistical analysis was performed using R 4.3.1and SPSS software. The significance level for the hypothesis test was set at 0.05.

Results

Sample characteristics and univariate analysis results

A total of 470 medical undergraduate students were included in the analysis. 248(52.766%) were female, 209

(44.468%) were over 20 years old, and 285(60.638%) lived in rural areas. 262(55.745%) had monthly living expenses of less than 1,500 yuan, and more than half of fathers (58.511%) had an education level of high school or below. In terms of subjective attitudes and instructional feedback, 169(35.957%) expressed dissatisfaction with artificial intelligence, 349(74.255%) reported that lecturers had used AI to provide timely instructional feedback during the semester.

One-way analyses were conducted to examine differences in academic performance across participant characteristics. Preliminary analyses showed that academic performance differed by gender, residence, satisfaction level, and exposure to instructional feedback. Female students achieved higher academic performance than male students ($t_{362.719}$=-3.623, P<0.001). Urban students also had higher academic performance than rural students ($t_{467.757}$=-3.762, P<0.001). Students who reported being satisfied with AI applications had higher academic performance than those who were unsatisfied ($t_{321.886}$=-2.155, P=0.012). In addition, students who reported receiving AI-based instructional feedback from lecturers had higher academic performance than those who did not ($t_{165.712}$=-3.115, P=0.003). More detailed information on the sample statistical description is provided in Table 2.

Table 2 Participant characteristics related to the academic performance

Variables	Values, *n* (%)	Academic performance		*P* value
		Mean (SD)	t test (df)	
Gender			-3.623 (362.719)	< 0.001
Male	222(47.234)	89.721 (7.870)		
Female	248(52.766)	91.944 (4.915)		
Age			-0.102 (468)	0.447
≤ 20 years	261(55.532)	90.866(6.693)		
>20 years	209(44.468)	90.928(6.425)		
Residence			-3.762 (467.757)	< 0.001
Rural	285(60.638)	90.065(7.426)		
Urban	185(39.362)	92.170(4.705)		
Monthly living expenses			-0.009 (468)	0.959
≤ 1500 yuan	262(55.745)	90.891(7.076)		
>1500 yuan	208(44.255)	90.897(5.883)		
Education level of father			0.623 (468)	0.341
Below high school level	275(58.511)	90.735(6.005)		
High school and above	195(41.489)	91.118(7.299)		
Education level of mother			-0.107 (468)	0.197
Below high school level	241(51.277)	90.925(6.022)		
High school and above	229(48.723)	90.860(7.111)		
Satisfaction level			-2.155(321.886)	0.012
Unsatisfactory	169(35.957)	89.994(6.939)		
Satisfactory	301(64.043)	91.387(6.313)		
Instructional feedback			-3.115 (165.712)	0.003
No	121(25.745)	89.050 (8.066)		
Yes	349(74.255)	91.533(5.841)		

Multivariate regression

After adjusting for covariates, female students had academic performance higher by 1.473 points than male students (P=0.017), and urban students had academic performance higher by 2.452 points than rural students (P<0.001). Students who reported receiving instructional feedback had academic performance higher by 2.115 points than those who did not (P=0.002). In contrast, age group, monthly living expenses, father's education, mother's education, and satisfaction level were not significantly associated with academic performance in the adjusted model. Collectively, these findings indicate that gender, residence, and instructional feedback were the primary correlates of academic performance in this sample. More details are presented in Table 3.

Mediation effect analysis

Firstly, we examined the association between instructional feedback and academic performance. The results showed that instructional feedback was positively associated with academic performance (total effect, c: β=2.115, P=0.002). We then tested the association between instructional feedback and AI perception and found that instructional feedback was also significantly positively associated with AI perception (path a: β=0.465, P=0.041). Furthermore, we examined the association between AI perception and academic performance after adjusting for instructional feedback and covariates. AI perception was not significantly associated with academic performance (path b: β=0.227, P=0.110). Finally, after controlling for AI perception, instructional feedback remained significantly positively associated with academic performance (direct effect, c': β=2.010, P=0.004). The indirect effect (a×b) was 0.1053, and the 95% bootstrap confidence interval included zero (-0.0251 to 0.2850), indicating that the indirect association via AI perception was not statistically significant. More details are given in Tables 4 and 5; Fig. 1.

Table 3 Multivariate associations between participant characteristics and academic performance

	Coefficient (SE)	β	95%CI	*P*
Gender				
Male	Ref	Ref	Ref	Ref
Female	1.473 (0.616)	0.112	(0.262, 2.683)	0.017
Age				
≤ 20 years	Ref	Ref	Ref	Ref
>20 years	-0.135 (0.599)	-0.010	(-1.311, 1.042)	0.822
Residence				
Rural	Ref	Ref	Ref	Ref
Urban	2.452 (0.702)	0.183	(1.073, 3.831)	< 0.001
Monthly living expenses				
≤ 1500 yuan	Ref	Ref	Ref	Ref
>1500 yuan	0.272 (0.630)	0.021	(-0.966, 1.511)	0.666
Education level of father				
Below high school level	Ref	Ref	Ref	Ref
High school and above	-0.041 (0.747)	-0.003	(-1.508, 1.427)	0.957
Education level of mother				
Below high school level	Ref	Ref	Ref	Ref
High school and above	0.936 (0.737)	0.071	(-0.511, 2.384)	0.204
Satisfaction level				
Unsatisfactory	Ref	Ref	Ref	Ref
Satisfactory	0.676 (0.633)	0.049	(-0.567, 1.919)	0.286
Instructional feedback				
No	Ref	Ref	Ref	Ref
Yes	2.115 (0.691)	0.141	(0.758, 3.473)	0.002

Non-linear association between AI perception and instructional feedback

To further explore whether the association between AI perception and instructional feedback deviated from linearity, we fitted a logistic regression model incorporating restricted cubic splines (RCS) for AI perception. Instructional feedback was treated as the outcome, and AI perception was modeled as the spline-transformed predictor, adjusting for age, gender, residence, parental education, and satisfaction level. Knots were placed at the 10th, 50th, and 90th percentiles of AI perception (three-knot specification). The RCS analysis indicated evidence of an overall association (*P*-overall = 0.044), with no evidence of non-linearity (*P*-non-linear = 0.648), suggesting that a linear term for AI perception may be adequate. More details are provided in Fig. 2.

Discussion

This research enrolled 470 medical undergraduates as research subjects and systematically explored the correlation mechanism between instructional feedback, AI perception of students, and final academic performance in the course "Social Medicine", based on the Chaoxing Platform. It also revealed the potential impacts of sociodemographic characteristics on learning outcomes. The results indicated that AI-based instructional feedback was associated with higher academic performance and higher AI perception, consistent with TAM-related perceptions of usefulness and ease of use.

AI empowers teaching innovation

Teachers provided timely feedback through the AI function of the Chaoxing platform, which had a positive impact on learning performance. This reflects that the technological advantages of the platform are well matched with the teaching needs of social medicine [18]. Social medicine is a discipline that combines medicine and social science [19]. The course content such as the prevention and control of chronic diseases [20] and health policy analysis [21] not only requires students to learn theoretical knowledge such as the social determinants of health [22], but also requires them to have practical skills. However, in traditional teaching, teachers usually only focus on whether the answer is correct or not [23].

Maya Usher affirmed the value of AI in education, pointing out that integrating AI feedback with traditional teaching methods could leverage their complementary advantages. Also noted that AI often provided higher-quality feedback, offering detailed insights and specific improvement guidance [24]. The AI functions of the Chaoxing Platform formed a complete feedback process ranging from collecting learning data and identifying knowledge gaps to pushing personalized learning content. Specifically, the AI-based learning situation analysis tracked learning behaviors of students in real time and generated personal knowledge gap. If a student lost points in the community health promotion program case analysis, the system would automatically mark issues such as feasibility of intervention measures and push relevant interpretation materials of the Outline of the "Healthy China 2030" Plan [25]. Additionally, the AI question generating function created targeted practice questions based on incorrect answers, while the AI feedback function completed grading and provided detailed explanations. Afnan Almegren et al. also confirmed the reliability of AI feedback. Using a dataset of 30 essays written by English, they compared the evaluation results of AI tools with those of human assessors [26]. Research has found that although the quality of essays varies, AI tools still provide with referenceable opinions, which is

Table 4 Analysis of the mediating effect of undergraduate students' AI perception on instructional feedback and academic performance

Variables	Academic performance		AI perception		Academic performance	
	β (95%CI)	*P* value	β (95%CI)	*P* value	β (95%CI)	*P* value
Instructional feedback	2.115	0.002	0.465	0.041	2.010	0.004
(Ref: NO)	(0.758, 3.473)		(0.018, 0.911)		(0.649, 3.371)	
AI perception	N/A	N/A	N/A	N/A	0.227	0.110
(Ref: NO)					(-0.051, 0.505)	
Gender	1.473	0.017	0.516	0.011	1.356	0.029
(Ref: Male)	(0.262, 2.683)		(0.118, 0.914)		(0.139, 2.573)	
Age	-0.135	0.822	0.273	0.167	-0.197	0.743
(Ref: ≤20)	(-1.311, 1.042)		(-0.114, 0.660)		(-1.374, 0.980)	
Residence	2.452	<0.001	0.193	0.403	2.408	< 0.001
(Ref: Rural)	(1.073, 3.831)		(-0.261, 0.647)		(1.031, 3.786)	
Monthly living expenses group(Ref: ≤1500 yuan)	0.272 (-0.966, 1.511)	0.666	0.064 (-0.344, 0.471)	0.759	0.258 (-0.979, 1.495)	0.682
Satisfaction level	0.676	0.286	0.534	0.011	0.555	0.383
(Ref: Dissatisfied)	(-0.567, 1.919)		(0.125, 0.943)		(-0.695, 1.805)	
Education of father	-0.041	0.957	0.139	0.571	-0.072	0.923
(Ref: Below high school)	(-1.508, 1.427)		(-0.344, 0.622)		(-1.538, 1.393)	
Education of mother	0.936	0.204	0.092	0.704	0.916	0.214
(Ref: Below high school)	(-0.511, 2.384)		(-0.384, 0.568)		(-0.530, 2.361)	

Table 5 Mediation effect summary

Effect	Estimate	95% Bootstrap CI	*P* value
Indirect effect (a×b)	0.1053	(-0.0251, 0.2850)	—
Total effect (c)	2.1150	(0.7580, 3.4730)	0.002
Direct effect (c')	2.0101	(0.6489, 3.3712)	0.0039

consistent with the actual role of the Chaoxing platform that we have seen in our research.

The impacts of sociodemographic characteristics

This study found that socio-demographic characteristics such as gender and place of residence influence academic performance.

Potential mechanisms remain speculative because we did not directly measure feedback-seeking behaviors, learning engagement, or self-regulated learning. One study showed that males received more criticism from teachers and less instructional feedback. Instructional feedback was positively correlated with the proactive learning of students; the better the feedback was, the more proactive students were in their learning [27–28].

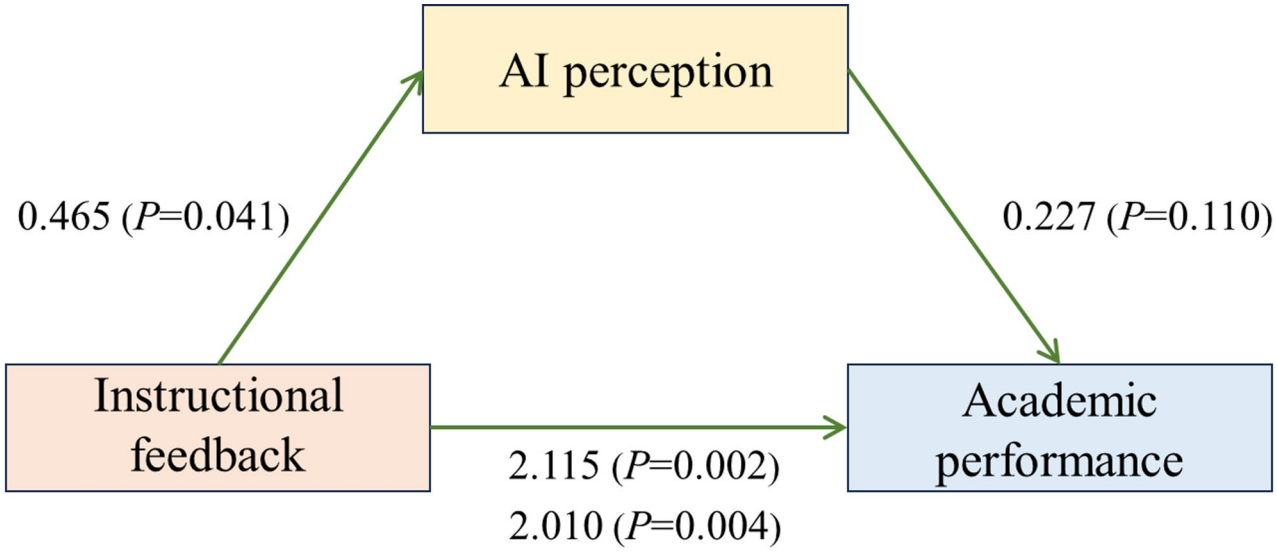

Fig. 1 The mediating effect of the AI perception on instructional feedback and the academic performance

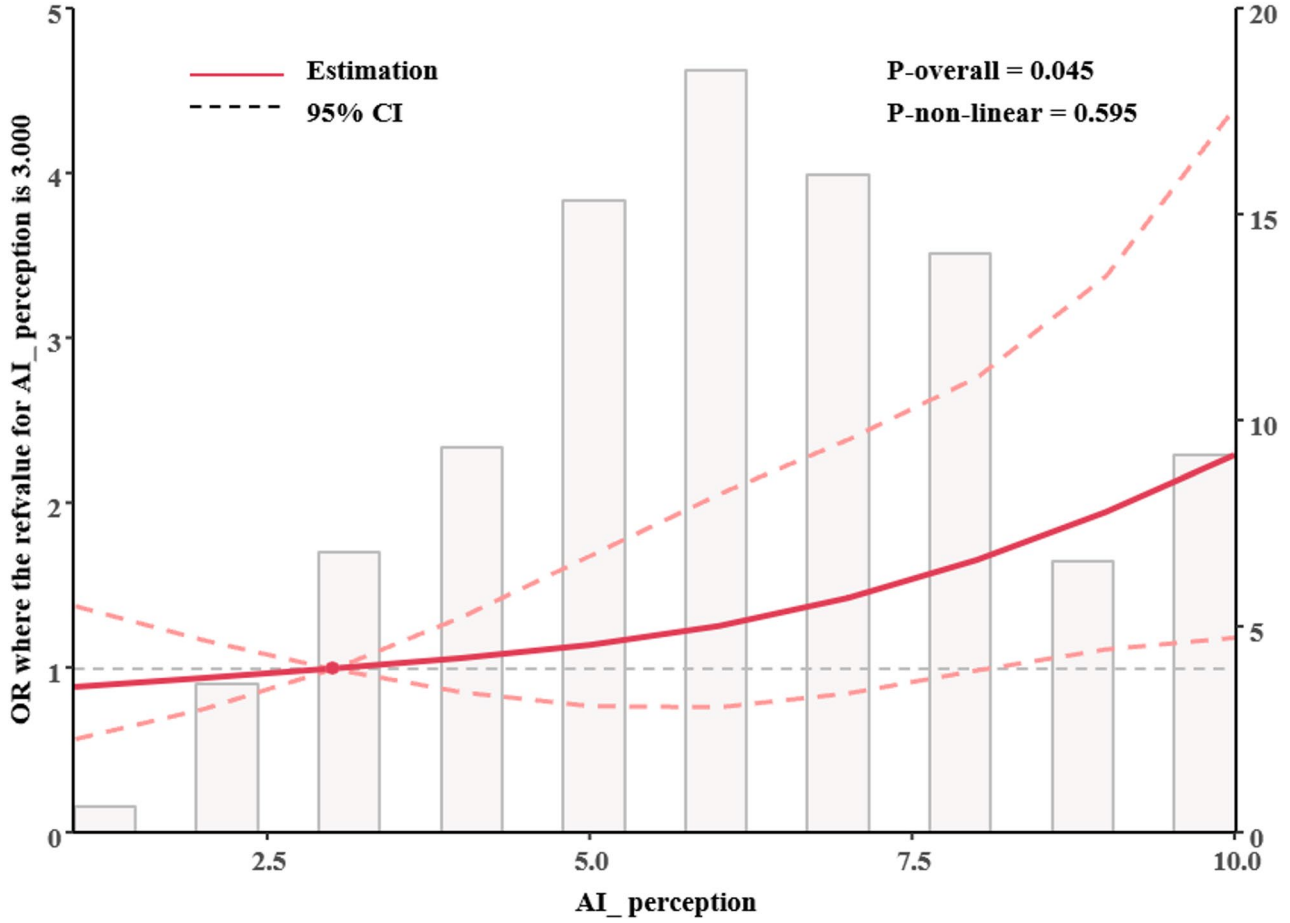

Fig. 2 RCS plot of the association between AI perception and the odds of reporting receipt of instructional feedback

Related studies also showed that instructional feedback had a positive impact on learning motivation [29–31]. Other research indicated that teachers gave females more instructional feedback, possibly because females were more willing to do more assignments to receive feedback [32]. Importantly, because we did not test interaction effects (e.g., gender × instructional feedback), we cannot conclude that the association between instructional feedback and academic performance differs by gender. Therefore, we report gender differences as observational associations and recommend future studies to formally test effect modification.

Residence was associated with academic performance in the adjusted model. This pattern may relate to contextual differences. Students in rural may be at a disadvantage in accessing AI, resulting in a lower utilization rate of AI instructional feedback. Existing research showed that rural education faces multiple challenges, including limited infrastructure [33] and lower AI technical proficiency of teachers and students. Poor internet connectivity and limited access to AI knowledge exacerbate the urban-rural education gap [34]. Meanwhile, previous studies have also pointed out that the use of AI technology can narrow the gap in educational resources between urban and rural [35]. AI can provide rural students with personalized learning methods [36–37] and better educational resources [38] to promote their academic performance. This suggested that medical education should focus on the difficulties faced by rural students and improve learning outcomes by providing AI equipment, technical training, and other methods.

Given that our data were collected from a single institution in China and within a specific course and platform context, these sociodemographic patterns may reflect local educational practices and sociocultural factors and may not generalize to other settings. Future multi-institution studies should incorporate contextual indicators (e.g., digital access, learning environment) and test interaction effects to better understand whether and how subgroup differences shape the observed associations.

The mediating role of AI perception

Based on the TAM theory and the views of Siemens, enhancing understanding of AI was extremely predominant in the learning process [39]. This study examined whether AI perception statistically accounted for the

association between instructional feedback and academic performance. Although instructional feedback was associated with AI perception, the bootstrapped indirect effect via AI perception was not statistically significant.

Previous studies have indicated that AI perception was an important factor influencing self-directed learning (SRL) [40]. Specifically, AI helped students develop targeted learning plans by providing instructional feedback [41–42]. The ability to complete assignments on time and achieve excellent academic results depended on the perception of AI: students will be more proactive in learning only when they perceive AI instructional feedback as readily available and valuable.

In our data, the indirect effect via AI perception was not statistically significant, suggesting that other factors (e.g., engagement, feedback utilization, or learning strategies) may play a more important role in explaining the association between instructional feedback and academic performance [43–45]. Future studies should incorporate longitudinal designs and additional process measures to clarify potential mechanisms.

Limitations

This study has several limitations. Firstly, this study employed a cross-sectional survey design. Therefore, temporal precedence could not be established and the mediation analysis cannot support causal inference. Second, participants were recruited from a single institution and one course context, which may limit generalizability to other settings. Additionally, the use of convenience sampling may introduce selection bias, as students who participated may differ systematically from those who did not. Third, instructional feedback was assessed using a single dichotomous item and did not capture frequency, quality, type, or intensity of exposure, limiting more nuanced interpretation. Fourth, AI perception and satisfaction were self-reported, raising the possibility of common method bias and social desirability bias, even though academic performance was obtained from the course management system. Fifth, endogeneity and reverse causality cannot be ruled out (e.g., higher-performing or more engaged students may be more likely to seek or receive feedback), which may confound observed associations. Finally, TAM was used as background framing only, the full TAM framework was not empirically tested, and behavioral intention was not measured.

Conclusion

Instructional feedback delivered through the platform's AI functions was associated with academic performance among medical undergraduates, and it was also associated with AI perception. However, mediation analysis did not support a statistically significant indirect association via AI perception. RCS analysis suggested an overall association between AI perception and the odds of reporting receipt of instructional feedback, with no evidence of non-linearity. These findings suggest that integrating AI-enabled instructional feedback into course delivery may be a useful approach to support learning, while the role of AI perception as an explanatory pathway warrants further investigation.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12909-026-09073-2.

Supplementary Material 1.

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Authors' contributions

Min Jiao conceived the research idea, designed the research plan and wrote the initial draft of the manuscript. Hongmin Li developed, distributed and collected the questionnaires. Dongxu Li was responsible for data collection. Chenglin Liu reviewed and made critical revisions to the manuscript. All authors have read and approved the final manuscript.

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Data availability

The dataset used in this study is available from the first author upon reasonable request.

Declarations

Ethics approval and consent to participate

This study was approved by the Medical Ethics Committee of Jining Medical University (Approval No.: JNMC-2022-YX-013). All participants provided informed written consent, and their anonymity and confidentiality were guaranteed. This study strictly adhered to the ethical guidelines of the Declaration of Helsinki.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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