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The Impact of Computer-Assisted Instruction Features on Medical Students' Learning Motivation: An Exploration of the Mediating Role of Cognitive Load

Acknowledgements：SFBT Intervention on Learning Engagement in College Students

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Abstract

Objective: To explore the impact of computer-assisted instruction (CAI) features on medical students' learning motivation and examine the mediating role of cognitive load in this relationship. Methods: A quasi-experimental pretest-midtest-posttest design was adopted, with 102 medical students randomly divided into an experimental group (CAI, n=51) and a control group (traditional teaching, n=51). The study lasted for 8 weeks, and data were collected using the CAI Feature Evaluation Scale, Cognitive Load Scale, and Learning Motivation Scale. Repeated measures analysis of variance (ANOVA), correlation analysis, and structural equation modeling (tested by Bootstrap method) were used for data analysis. Results: Repeated measures ANOVA showed that the experimental group had significantly lower cognitive load and significantly higher learning motivation than the control group in the midtest and posttest (significant time × group interaction, $P<0.05$). Posttest correlation analysis indicated that perceived CAI features were significantly positively correlated with learning motivation ($r=0.47$) and significantly negatively correlated with cognitive load ($r=-0.41$); cognitive load was significantly negatively correlated with learning motivation (r=-0.38). Structural equation modeling revealed that CAI features had a direct positive predictive effect on learning motivation (β=0.38) and an indirect effect by negatively predicting cognitive load (β=-0.42), which in turn negatively influenced learning motivation (β=-0.31). The mediating effect of cognitive load was significant, with an effect value of 0.13, accounting for 25.49% of the total effect. Conclusion: CAI can effectively reduce medical students' cognitive load and enhance their learning motivation. Cognitive load plays a partial mediating role between teaching features and learning motivation. Optimizing CAI design to manage cognitive load is an important psychological mechanism for realizing technology-enabled learning and stimulating students' intrinsic motivation.

Keywords: Computer-Assisted Instruction; Learning Motivation; Cognitive Load; Mediating Role; Medical Education

With the rapid development of information technology, computer-assisted instruction has become a key force driving the modern transformation of education. Medical education is characterized by intensive knowledge and strong practicality, where the application of CAI is of great significance for improving teaching effectiveness[1]. However, the application of technology itself does not automatically translate into positive learning outcomes. Studies have shown inconsistent effects of CAI on learning outcomes[2], indicating that there may be under-revealed mediating psychological mechanisms between the technical features of CAI and learning effectiveness. Learning motivation is the core internal drive that promotes learning behavior and predicts academic achievement, which is crucial for medical students to cope with heavy academic burdens[3]. Although some studies suggest that digital and AI-assisted teaching can enhance learning motivation by improving interactivity and personalization[4-5], technical intervention may also lead to cognitive overload due to improper design, thereby undermining learning interest[6]. Therefore, clarifying the specific pathways through which CAI affects learning motivation is the core issue for realizing technology empowerment rather than technology burden. Cognitive load theory holds that individuals have limited working memory capacity, and teaching design and information presentation methods directly affect the allocation of cognitive resources[7-8]. In the CAI environment, if the arrangement of multimedia elements, interaction logic, and information organization do not follow cognitive rules, it is likely to lead to excessive extraneous cognitive load, occupying cognitive resources for in-depth understanding, thereby causing learning frustration and decreased motivation[9]. Previous studies have pointed out that teaching methods can be associated with learning motivation by influencing cognitive processes[10], and improving teaching models can affect learning motivation[11]. Although the application value of cognitive load in medical education has received attention, the internal mechanism by which specific technical features of CAI affect medical students' learning motivation through cognitive load as a mediating variable has not been fully revealed and verified at the empirical level. In view of this, this study adopted a longitudinal quasi-experimental design to focus on constructing and testing a mediation model centered on cognitive load, aiming to reveal the internal mechanism of CAI affecting learning motivation from the perspective of cognitive psychology.

1 Objects and Methods

1.1 Research Objects

A quasi-experimental design was used. From September 2023 to January 2024, students from two parallel natural classes taking the course “Pathophysiology” in the same semester at our university were selected as research objects. The two classes were consistent in class hours, teachers, and teaching syllabi. Inclusion criteria: ① Full-time medical students enrolled in the course; ② Voluntarily participating in the entire research process and signing the informed consent form; ③ Authorizing the research team to collect their learning platform behavior data. Exclusion criteria: ① Non-registered students such as exchange students and advanced students; ② Interrupting learning for more than two weeks during the research period; ③ Experience sampling response rate lower than 70% or major data missing. Through cluster random sampling, the two classes were randomly divided into two groups: the experimental group (n=53) adopted the CAI model; the control group (n=52) adopted traditional teaching. Calculated using G Power 3.1 software (effect size f=0.25, α=0.05, power=0.80), considering a follow-up loss rate and incomplete data of approximately 5%, the final valid sample included in the analysis was 102 (51 in the experimental group and 51 in the control group).

1.2 Research Methods

This study adopted a longitudinal quasi-experimental pretest-midtest-posttest design with a research cycle of 8 weeks.

(1) Research Tools

General Information Questionnaire: Including demographic information (age, gender) and average scores of previous professional courses.

CAI Feature Evaluation Scale: A self-constructed scale including 4 dimensions (20 items) such as intelligent interactivity and content adaptability. The final scale was formed after content validity evaluation by educational technology experts and reliability test in the pre-survey (Cronbach's α=0.923). A 5-point Likert scale was used, and the scale was administered after the completion of all teaching interventions (Week 8) to assess students' overall perception of the core features of the teaching system used.

Cognitive Load Scale[12]: The scale covers 3 dimensions: intrinsic, extraneous, and germane cognitive load, with a Cronbach's α coefficient of 0.896, using a 9-point scoring system. The scale was administered at pretest (Week 1), midtest (Week 4), and posttest (Week 8) respectively.

Learning Motivation Scale: The MSLQ motivation subscale[13] (22 items) was adopted, covering 4 dimensions such as intrinsic goals and self-efficacy, with a Cronbach's α coefficient of 0.931, using a 7-point Likert scale. The scale was administered at pretest (Week 1), midtest (Week 4), and posttest (Week 8) respectively.

(2) Research Process and Data Collection

The research process was divided into three phases:

Pretest Phase (Week 1): Obtaining informed consent and platform data authorization, administering the General Information Questionnaire and Learning Motivation Scale (pretest), and collecting previous academic scores as covariates.

Intervention Phase and Process Data Collection (Weeks 2-7): Students in the two groups completed the learning of the same core modules through the CAI model and traditional teaching model respectively.

Midtest and Posttest Phases: At Week 4 (midtest) and the end of the course at Week 8 (posttest), the Learning Motivation Scale and Cognitive Load Scale were administered to students in both groups collectively. In the posttest phase, the CAI Feature Evaluation Scale was additionally administered.

1.3 Statistical Methods

SPSS 26.0 and AMOS 24.0 software were used for statistical analysis. Measurement data were expressed as mean ± standard deviation, and count data were expressed as frequency (%). Independent samples t-test was used for inter-group comparison of measurement data, and repeated measures ANOVA was used for intra-group comparison to analyze the main effect of time, main effect of group, and time × group interaction effect. Chi-square test was used for inter-group comparison of count data. Pearson product-moment correlation analysis was performed on the total scores of CAI feature evaluation, cognitive load, and learning motivation of all students. A structural equation model was constructed based on posttest data to test the mediating role of cognitive load between CAI features and learning motivation. Maximum likelihood estimation was used for parameter estimation. The model fit criteria were: $\chi^2/df < 3$, RMSEA < 0.08, CFI > 0.90, TLI > 0.90, SRMR < 0.08. The Bootstrap method (5000 repeated samplings) was used to test the significance of the mediating effect. A P value < 0.05 was considered statistically significant.

2 Results

2.1 Homogeneity Test of Baseline Data

A total of 102 valid research objects were included, with 51 in both the experimental group and the control group. There were no statistically significant differences in baseline data such as age, gender, pretest total score of learning motivation scale, and average score of previous professional courses between the two groups ($P > 0.05$).

Table 1 Comparison of Baseline Data between the Two Groups

Items	Experimental Group（n=51）	Control Group （n=51）	t/ χ2 Value	P Value
Age (years)	20.12 ± 0.89	20.24 ± 0.91	-0.67	0.51
Gender (Male, %)	22 (43.14)	24 (47.06)	0.16	0.69
Pretest Total Score of Learning Motivation (points)	112.36 ± 14.28	110.94 ± 13.75	0.51	0.61
Average Score of Previous Professional Courses (points)	82.45 ± 6.33	81.87 ± 5.96	0.48	0.63

2.2 Longitudinal Changes in Cognitive Load and Learning Motivation Scores: Repeated Measures ANOVA

Repeated measures ANOVA on subjective cognitive load and learning motivation showed that the interaction between time and group was significant ($P<0.05$). Simple effect analysis indicated that at the midtest and posttest time points, the cognitive load of the experimental group was significantly lower than that of the control group ($P<0.05$), while the learning motivation was significantly higher than that of the control group ($P<0.05$).

Table 2 Results of Repeated Measures ANOVA for Cognitive Load and Learning Motivation

Variables	Effects	F Value	PValue
Cognitive Load	Main effect of time	15.82	＜ 0.001
	Main effect of group	8.71	0.004
	Time × group interaction	20.33	＜ 0.001
Learning Motivation	Main effect of time	25.46	＜ 0.001
	Main effect of group	12.05	0.001
	Time × group interaction	18.94	＜ 0.001

Table 3 Comparison of Cognitive Load and Learning Motivation Scores between the Two Groups at Different Time Points

Variables	Groups	Pretest (Week 1)	Midtest (Week 4)	Posttest (Week 8)
Total Cognitive Load Score	Experimental Group	45.23 ± 8.12	38.56 ± 7.24	36.78 ± 6.85
	Control Group	44.87 ± 7.96	43.25 ± 8.03	42.91 ± 7.88
Total Learning Motivation Score	Experimental Group	112.36 ± 14.28	123.45 ± 13.67	128.72 ± 12.94
	Control Group	110.94 ± 13.75	113.28 ± 14.05	111.63 ± 13.52

2.3 Scores of CAI Features, Cognitive Load, and Learning Motivation and Their Correlation Analysis

The total scores of CAI feature evaluation, cognitive load, and learning motivation in the posttest phase (Week 8) were statistically analyzed, and the Pearson product-moment correlation coefficients between variables were calculated, as shown in Table 4. The score of CAI feature evaluation was significantly positively correlated with learning motivation ($r=0.47$, $P<0.01$) and significantly negatively correlated with cognitive load ($r=-0.41$, $P<0.01$). Meanwhile, cognitive load was significantly negatively correlated with learning motivation ($r=-0.38$, $P<0.01$). The absolute values of the correlation coefficients between all variables were less than 0.70, initially indicating no serious multicollinearity problem.

Table 4 Scores of CAI Features, Cognitive Load, and Learning Motivation and Their Correlation Analysis (n=102)

Variables	M ± SD	CAI Features	Cognitive Load	Learning Motivation
CAI Features	3.82 ± 0.65	1		
Cognitive Load	39.85 ± 8.02	-0.41	1	
Learning Motivation	120.18 ± 15.23	0.47	-0.38	1

2.4 Structural Equation Model Analysis of CAI Features, Cognitive Load, and Learning Motivation

To test the mediating role of cognitive load between teaching features and learning motivation, a structural equation model was constructed. The model fit well ($\chi^2/df=2.41$, RMSEA=0.07, CFI=0.93, TLI=0.91, SRMR=0.05). Path analysis showed that CAI features had a direct positive predictive effect on learning motivation ($\beta=0.38$, $P<0.001$) and an indirect effect through cognitive load. Teaching features significantly negatively predicted cognitive load ($\beta=-0.42$, $P<0.001$), while cognitive load had a significant negative predictive effect on learning motivation ($\beta=-0.31$, $P=0.002$). Bootstrap test indicated that the mediating effect value of cognitive load was 0.13, with a 95% CI [0.05, 0.22], accounting for 25.49% of the total effect (0.51), and the mediating effect was significant.

Table 5 Path Model Analysis of the Mediating Effect of Medical Students' Cognitive Load between CAI Features and Learning Motivation

Path Relationships	β	S.E.	ZValue	PValue	95% CI
CAI Features→Learning Motivation	0.38	0.07	5.43	< 0.001	0.25 - 0.51
CAI Features→Cognitive Load	-0.42	0.08	-5.25	< 0.001	-0.57 - -0.27
Cognitive Load→Learning Motivation	-0.31	0.10	-3.10	0.002	-0.50 - -0.12

Table 6 Mediating Effect Analysis of Medical Students' Cognitive Load between CAI Features and Learning Motivation

Effect Types	Effect Value	S.E.	95% CI	Effect Ratio (%)
Direct Effect	0.38	0.07	0.25 - 0.51	74.51
Indirect Effect	0.13	0.04	0.05 - 0.22	25.49
Total Effect	0.51	0.08	0.36 - 0.66	100

3 Discussion

With the deep integration of information technology and medical education, CAI has become a key force driving the innovation of teaching models. However, the effect of teaching models themselves on learning outcomes is often achieved by influencing learners' internal psychology. Cognitive load theory reveals the limited capacity of working memory in the learning process, which is divided into three types: intrinsic, extraneous, and germane. Effective teaching design needs to maximize germane load and minimize extraneous load to promote schema construction [7]. Learning motivation is the core driving force for learning behavior, covering a continuum from external goals to internal interests. Its intensity and direction directly affect the depth and persistence of learning investment [14]. The medical professional knowledge system is complex and abstract, and students face high academic pressure, often encountering problems of cognitive overload and motivation exhaustion, making it particularly urgent to explore how to optimize cognitive and motivational states through technology. Based on the above theoretical background, this study aims to deeply explore the mechanism between CAI features, cognitive load, and learning motivation, providing empirical evidence for intelligent medical education.

3.1 The Impact of CAI on Cognitive Load and Learning Motivation

This study found that CAI has a systematic impact on cognitive load and learning motivation through its core features. The reduction of cognitive load in the experimental group is attributed to the effective management of extraneous cognitive load by CAI. In traditional medical classrooms, students need to simultaneously process multi-channel and sometimes sequentially conflicting information flows from teachers’ oral presentations, blackboard writing, textbook texts, and complex diagrams, which easily leads to distraction and working memory overload [8]. The application of the CAI model effectively integrates medical concepts originally scattered in multiple sources of information through structured knowledge graphs and visualization tools, reducing the extraneous cognitive load caused by disorganized information. This finding echoes Deng Tao’s practical results in medical imaging teaching, which confirmed that the use of computer-assisted 3D reconstruction and dynamic demonstration of images can effectively reduce students’ cognitive difficulty in understanding spatial structures and dynamic processes [1]. The systematic change of teaching models can help students form cognitive scaffolding at a deeper level, reduce blindness in learning, thereby reallocating the saved cognitive resources to the in-depth processing and integration of core concepts, and increasing germane cognitive load [7]. This reallocation of cognitive resources from high extraneous load to high germane load is crucial for promoting the long-term memory and transfer application of medical knowledge [9].

In addition, the improvement of learning motivation of students in the experimental group in this study is more driven by the joint effect of technology-enabled experience and cognitive state optimization. On the one hand, students’ direct perception of the intelligence, adaptability, and usefulness of the learning system constitutes the external conditions for motivation stimulation. When technical tools are perceived to effectively improve learning efficiency and autonomy, they will enhance students' self-efficacy and mastery expectations, thereby directly improving their learning willingness [4-5]. Studies have found that the rich resources and interactive support provided by CAI can positively shape learners' emotional attitudes and participation, which is consistent with the findings of this study. On the other hand, the reduction of cognitive load creates the necessary psychological space for the arousal of intrinsic motivation. According to self-determination theory, when the cognitive challenge brought by learning tasks matches an individual's ability, the individual is more likely to experience flow and competence, thereby stimulating intrinsic interest[15]. In medical learning, this positive experience brought by manageable cognitive challenges is of great significance for combating academic burnout and maintaining long-term learning investment.

3.2 The Mediating Role of Cognitive Load between CAI and Medical Students' Learning Motivation

Motivation arises partly from external stimuli and partly from the mediating transformation of internal cognitive and emotional states. Through structural equation modeling, this study clarified the mediating role of cognitive load in the process of CAI features affecting learning motivation. Path analysis showed that CAI features not only have a direct positive predictive effect on learning motivation but also indirectly improve learning motivation by significantly reducing cognitive load. This mediation model has important theoretical integration value: it connects the technology acceptance model, cognitive load theory, and motivation theory into a dynamic process model. This means that whether a technology can stimulate motivation depends not only on its surface usefulness and ease of use (direct path) but also on its ability to effectively manage users' cognitive resources and reduce psychological burden in actual interaction (indirect path) [16]. The value of excellent teaching models lies not only in the effective transmission of knowledge but also in optimizing the allocation of cognitive resources, reducing the extraneous cognitive load in the learning process, thereby releasing the limited working memory capacity and creating the necessary psychological conditions for stimulating and maintaining learning motivation. This finding is consistent with Lü Dandan's [9] study on the negative correlation between mathematical cognitive load and autonomous learning ability, which also reveals the negative effect of cognitive overload on intrinsic motivation. In medical education, if the teaching model only pursues complex functions or information accumulation while ignoring its cognitive friendliness, it may instead undermine students' learning confidence and interest by increasing extraneous load[6]. Therefore, for educational technology developers and instructional designers, evaluating and optimizing the cognitive load management ability of teaching models should become a key criterion. The following points should be noted when designing teaching plans: ①Information simplification and sequencing: Reducing extraneous load through clear interface design and logical organization, such as the explicit and structured processing of second language pragmatic teaching materials by Shen Zhiqi et al. [17]; ②Provision of timely cognitive scaffolding: Reducing the intrinsic load of dealing with complex medical problems through prompts, feedback, examples, etc., such as the adaptive support based on behavior analysis in the MOOC system by Wu Xingye[16]; ③ Personalized challenge adaptation: Dynamically adjusting the difficulty and presentation method of learning content to make the task difficulty close to the students' zone of proximal development, promoting the active investment of germane load.

4 Conclusion

Through a quasi-experimental design, this study found that compared with traditional teaching, CAI can significantly reduce medical students' cognitive load and enhance their learning motivation. Medical students' positive perception of the intelligent interaction, content adaptation, and other features of the teaching system not only directly enhances learning motivation but also indirectly promotes it by effectively reducing cognitive load. Cognitive load plays a key mediating role, accounting for 25.49% of the total effect. The study confirms that optimizing the design of CAI to manage cognitive load is an important psychological mechanism for realizing technology-enabled learning and stimulating students' intrinsic motivation.

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