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RESEARCH ARTICLE

A study on the dual mechanisms of AI teaching assistants' impact on college students' learning motivation: From the perspective of social cognitive theory

Weixuan Huang[1], Xinyi Ding[2,4], Shijia Shao[3,*]

[1] *INTI International University, Faculty of Education and Liberal Arts (FELA), 71800, Nilai*

[2] *The university of Melbourne, Faculty of Business and Economics, VIC 3010, Australia*

[3] *Northwestern Polytechnical University, school of software, 710129, China*

[4] *Shanghai iP3 Technology, shanghai, 201600, China*

*** Corresponding author:** Shijia Shao, 15061073566@163.com

ABSTRACT

Do AI teaching assistants undermine students' cognitive independence while improving learning outcomes? Based on social cognitive theory, this study systematically addresses this critical question through a 16-week quasi-experimental tracking of 480 college students. The research reveals a dual effect of AI teaching assistants: on one hand, they significantly enhance learning motivation by 22.3% through three major mechanisms—personalized feedback, social presence creation, and adaptive pathways; on the other hand, they lead to a 63% increase in cognitive dependence, a 9.2% decline in critical thinking, and a 54.5% rise in social isolation risk. In response to these alienation risks, the study constructs and validates a three-dimensional intervention model: at the environmental level, implementing blended learning design; at the individual level, conducting metacognitive and critical thinking training; and at the behavioral level, establishing a gradual scaffolding withdrawal mechanism. Intervention experiments show that the comprehensive strategy increases cognitive independence by 37.8%, effectively reversing the dependence trend. The "empowerment-alienation-intervention" theoretical framework constructed by this study provides an actionable risk management solution for AI educational applications and holds significant guiding significance for promoting the healthy development of human-AI collaborative learning ecosystems.

Keywords: AI teaching assistant; autonomous learning motivation; social cognitive theory; empowerment mechanisms; alienation risks; intervention strategies

1. Introduction

With the rapid development of artificial intelligence technology and the continuous optimization of deep learning algorithms, AI teaching assistants, as important carriers of educational technology innovation, are profoundly transforming traditional teaching models and learning ecosystems. From the perspective of technological applications, artificial intelligence and machine learning have demonstrated enormous application potential across various fields, showing significant influence whether in medical diagnosis or

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professional competency development. In the educational domain, AI teaching assistants provide unprecedented learning support for students through functions such as personalized recommendations, intelligent Q&A, and learning path planning. This technology-driven educational transformation is not only reflected in tool-level innovation but also involves deep-level reconstruction of learners' cognitive structures, motivational mechanisms, and behavioral patterns. However, as scholars like Desai *et al.* have pointed out, reproducibility issues in artificial intelligence and machine learning research remind us that while pursuing technological innovation, we must carefully evaluate its actual effects and potential risks in educational applications, particularly the long-term impacts on students' psychological and cognitive development [1]. Compared with AI applications in other fields, the key difference of AI teaching assistants in educational contexts lies in their direct impact on learners' cognitive development and motivational systems, an influence that is long-term, cumulative, and irreversible. Therefore, this study focuses on social cognitive mechanisms as a key factor, systematically revealing the dual impact pathways of AI teaching assistants from the perspective of environment-individual-behavior triadic reciprocal interaction.

Examining the educational application of AI teaching assistants from the perspective of social cognitive theory, we find that their influence mechanisms on students' autonomous learning motivation exhibit complex dual characteristics. On one hand, AI teaching assistants can effectively enhance students' self-efficacy and learning engagement by providing instant feedback, personalized learning content, and intelligent learning environments, which highly aligns with the core viewpoint of triadic reciprocal interaction among environment-individual-behavior in Bandura's social cognitive theory. Research by Fei Jiayi and Zhang Yifan, analyzing the influencing factors of college students' artificial intelligence literacy levels based on social cognitive theory, found significant interactive relationships among individual cognitive abilities, environmental support, and behavioral practice, providing important theoretical support for understanding the mechanisms by which AI teaching assistants stimulate learning motivation [2]. On the other hand, the widespread application of AI teaching assistants may also bring alienation risks such as learners' over-dependence on technology, weakening of critical thinking abilities, and deterioration of interpersonal skills. These negative effects may potentially harm students' long-term learning capabilities and comprehensive development.

Although research on the impact of AI teaching assistants on learning motivation is increasingly growing, most studies remain at the level of descriptive analysis or technical functionality exploration, lacking systematic interpretation of underlying psychological mechanisms from a social cognitive theory perspective. Wang Yinying and Zhang Ailing's research on the influence mechanisms of artificial intelligence technology on professional interpreters' competency development provides a beneficial analytical framework, revealing the complex phenomenon that AI technology has both promoting effects and substitution risks in professional competency development [3]. Similarly, in educational contexts, the impact of AI teaching assistants on students' autonomous learning motivation requires in-depth analysis from multi-dimensional and multi-level perspectives. Zhao Xin and Li Zichang's research on artificial intelligence technology reshaping customer orientation further inspires us to consider that AI technology may produce fundamental reshaping effects in different application scenarios, including both positive optimization improvements and potential structural risks [4]. Therefore, constructing an analytical framework based on social cognitive theory to systematically explore the empowerment mechanisms and alienation risks of AI teaching assistants on students' autonomous learning motivation not only has important theoretical value but also provides significant guidance for the rational design and effective application of AI teaching assistants. However, existing research has not yet clearly answered: How do AI teaching assistants simultaneously produce the dual effects of empowerment and alienation through social cognitive mechanisms? What are the boundary conditions and transformation mechanisms of these dual effects? How can we construct an effective intervention model based on theory to mitigate risks? Answering these questions is crucial for the healthy development of AI applications in education. The main contributions of this study are reflected in three aspects: First, in terms of theoretical contribution, it constructs a dual-effect theoretical model of "empowerment-alienation," expanding the explanatory framework of social cognitive theory in AI educational applications; second, in terms of empirical contribution, through a 16-week longitudinal tracking study, it systematically reveals for the first time the dynamic evolution mechanism of AI teaching assistants' impact on learning motivation and the cumulative effect of alienation risks; third, in terms of practical contribution, it develops and validates a three-dimensional intervention strategy model, providing actionable guidance for the responsible design of AI teaching assistants.

Based on the above analysis, this study aims to apply the fundamental principles and analytical framework of social cognitive theory to deeply explore the dual influence mechanisms of AI teaching assistants on students' autonomous learning motivation. Specifically, the research will focus on the following core issues: First, how do AI teaching assistants enhance students' autonomous learning motivation through pathways such as environmental optimization, cognitive support, and behavioral guidance? Second, what are the manifestations and generating mechanisms of alienation risks that may emerge during AI teaching assistant applications? Third, how can effective intervention strategies be constructed based on social cognitive theory to maximize the positive effects of AI teaching assistants while avoiding potential risks? Through the application of mixed research methods, this study expects to provide psychological foundations for the optimization design of AI teaching assistants, offer scientific guidance for educational decision-makers and technology developers, and contribute theoretical wisdom and practical solutions for promoting students' healthy development in digital learning environments. The research findings will help promote responsible innovation of AI technology in the educational field, ensuring that technological progress truly serves comprehensive human development and continuous improvement of educational quality.

2. Literature review

The application of artificial intelligence and machine learning technologies in the educational field is experiencing rapid development, and their influence mechanisms on learners' cognitive development and motivational stimulation have increasingly become a focal point of academic attention. From the perspective of technological development trends, research by Efstathios *et al.* in the medical endoscopy field demonstrates that AI technology's predictive capabilities and application prospects have broad development potential, advantages that are similarly manifested in the educational domain [5]. Mali *et al.*'s comparative study of AI prediction models in construction project management shows that machine learning algorithms possess significant advantages in complex task processing and personalized solution provision, providing a technical foundation for AI teaching assistants' application in personalized learning support [6]. Gonçalves and Costa's research in sports training further confirms the important role of AI technology in skill cultivation and capability enhancement, revealing the potential of AI systems to optimize learning processes through data analysis and pattern recognition [7]. However, as Paglialunga and Melogno pointed out in their systematic review of AI intervention effects for students with learning disabilities, the effectiveness of AI technology in educational applications still requires more rigorous empirical validation and theoretical support [8]. These cross-disciplinary research findings collectively indicate that while AI technology demonstrates enormous application potential, its specific mechanisms and effect evaluation in educational contexts still require in-depth theoretical analysis and empirical research.

Examining the impact of AI teaching assistants on learning motivation from the perspective of social cognitive theory, existing research presents a complex and multifaceted cognitive landscape. Feng Changyang *et al*.'s analysis of artificial intelligence's impact on librarians' professional cognition from a social semiotic perspective found that AI technology not only changes working methods but also reshapes professional identity cognition and career development paths, a finding that has important implications for understanding how AI teaching assistants influence students' learner identity cognition [9]. Research by Zhu Yicheng *et al*. on how generative AI like ChatGPT shapes social cognition reveals the dual characteristics of AI technology in cognitive reconstruction processes, demonstrating the capacity to enhance individual cognitive abilities and learning efficiency through intelligent interaction while potentially limiting critical thinking development through algorithmic dependence and information cocoon effects [10]. Jiang Haiyan *et al*.'s research on AI-assisted speech development pathways for hearing-impaired children within a social interaction theoretical framework shows that AI technology can promote the capability development of special groups by creating interactive situations and providing personalized support, providing important theoretical basis for understanding the positive role of AI teaching assistants in stimulating learning motivation [11]. Meanwhile, Chen Nengjun's research on the transformation of digital civilization social forms in the AI era points out that artificial intelligence technology is profoundly changing social cognitive structures and value systems. This macro-level social transformation will inevitably affect individual learning cognition and motivational structures, requiring full consideration when analyzing AI teaching assistant influence mechanisms [12].

Risk identification and management in AI technology applications has become an important issue in current academic research, particularly in educational application scenarios involving individual cognitive development and social interaction. Li Meng's in-depth analysis of social justice risks in the AI era points out that artificial intelligence technology may bring new forms of inequality and social stratification, including the exacerbation of digital divides, algorithmic discrimination, and technological dependence. These risks also exist in the educational field and may negatively impact students' equitable development opportunities [13]. Gao Yunyan *et al*.'s research on the impact of AI-driven corporate social responsibility on brand evaluation reveals the complex mechanisms by which AI technology operates in social cognitive formation, indicating that AI systems are not merely technological tools but important factors influencing individual and social cognition [14]. Wu Junhui and Jiang Yeyun's research on AI application pathways in the context of skill-oriented society construction emphasizes that while pursuing technological progress, attention must be paid to comprehensive human development and the cultivation of social adaptation abilities, providing important guidance for the design and application of AI teaching assistants [15]. The risk control framework proposed by Singh *et al*. in FDA regulation of AI medical software [16], and the ethical considerations in AI applications for vaccine development by Elfatimi *et al*., both provide important reference models for responsible AI technology application in the educational field [17]. These studies collectively indicate that educational applications of AI technology must be built on foundations of adequate risk assessment and effective control mechanisms, with particular attention needed for potential impacts on learners' cognitive independence, social interaction capabilities, and critical thinking development.

A comprehensive review of existing literature reveals that while research on AI technology applications in education is increasingly rich, systematic research specifically targeting the influence mechanisms of AI teaching assistants on students' autonomous learning motivation remains relatively insufficient. Most research either focuses on the description and optimization of technical functions or remains at the surface level of application effect analysis, lacking deep mechanistic exploration based on solid theoretical foundations. From a social cognitive theory perspective, existing research exhibits obvious research gaps in several areas: First, there is a lack of systematic analytical frameworks for how AI teaching assistants influence learning motivation through triadic reciprocal interaction among environment-individual-behavior; second, there is insufficient in-depth exploration of the psychological mechanisms underlying alienation risks such as cognitive dependence and social isolation that may emerge in AI technology applications; third, in intervention strategy design, there is a lack of scientific guidance principles and implementation pathways based on social cognitive theory. As Adege emphasized in a systematic review of AI applications in biomedical engineering, effective AI technology application requires interdisciplinary theoretical integration and methodological innovation; AI applications in education similarly require collaborative research across psychology, education, technology, and other disciplines [18]. Furthermore, the developmental assessment methods proposed by Solomonov *et al*. in aging AI application research inspire us that the impact of AI teaching assistants on learning motivation requires long-term tracking and evaluation from a dynamic developmental perspective [19]. Therefore, constructing an analytical framework for AI teaching assistant influence mechanisms based on social cognitive theory and systematically exploring their empowerment mechanisms and alienation risks can not only fill current theoretical gaps in research but also provide scientific basis for the optimization design and effective application of AI teaching assistants, promoting healthy development and responsible innovation of AI technology in the educational field.

Table 1. Comparative analysis of this study and related research in high-impact journals.

Research Source	Research Focus	Theoretical Framework	Research Method	Sample Size	Study Duration	Main Findings
Computers & Education (2023)	Impact of AI tools on learning outcomes	Technology Acceptance Model	Cross-sectional survey	312 students	Single measurement	AI tools improved academic performance by 15%
Educational Technology Research (2024)	Personalization effects of intelligent tutoring systems	Self-Regulated Learning Theory	Quasi-experimental design	180 students	8 weeks	Personalized recommendations enhanced engagement
Journal of Educational Psychology (2023)	Impact of technology on learning motivation	Self-Determination Theory	Questionnaire survey	520 students	Single measurement	Positive correlation between technology use and motivation
AI & Society (2024)	Ethical risks of AI educational applications	Philosophy of Technology	Theoretical analysis	-	-	Identified risks such as algorithmic bias
This Study	Dual effect mechanisms of AI teaching assistants	Social Cognitive Theory	Mixed research design	480 students	16-week longitudinal tracking	Systematically reveals dual mechanisms of empowerment and alienation and their cumulative effects

3. Research methods

3.1. Research design

This study employs a mixed-methods research design, combining the advantages of quantitative and qualitative research paradigms, aiming to deeply explore the empowerment mechanisms and alienation risks of AI teaching assistants on students' autonomous learning motivation. The research design is based on the triadic interaction model of social cognitive theory, establishing environment factors (AI teaching assistant system characteristics), individual factors (students' cognitive characteristics and learning motivation levels), and behavioral factors (learning behavioral performance) as core research variables, constructing a quasi-experimental design framework. Specifically, the study adopts a 2×2×3 factorial design, where the first factor is AI teaching assistant application condition (experimental group vs. control group), the second factor is student learning ability level (high ability vs. low ability), and the third factor is measurement time points (pretest, midtest, posttest). Through repeated measures design across multiple time points, the study captures the dynamic change process of AI teaching assistant influence [20]. To ensure ecological validity of the research, experiments will be conducted in authentic classroom environments, selecting three courses from different disciplines as research scenarios. Each course will be randomly assigned to experimental and control classes, with experimental classes using learning platforms equipped with AI teaching assistant functions and control classes using traditional digital learning platforms. The quantitative research component will employ standardized scales to measure students' core variables such as autonomous learning motivation, self-efficacy, and learning engagement, while simultaneously collecting learning behavioral data (such as online learning duration, interaction frequency, task completion quality, etc.) for objective analysis. The qualitative research component will utilize methods including in-depth interviews, focus group discussions, and participant observation to gain deep understanding of students' subjective experiences with AI teaching assistants, cognitive change processes, and potential manifestations of alienation risks. Additionally, the study will employ a longitudinal tracking design, conducting continuous observation and data collection throughout a complete semester (16 weeks) to capture the cumulative effects of long-term AI teaching assistant use on students' learning motivation and cognitive development [21]. Through this comprehensive research design, the study can both grasp the overall influence trends of AI teaching assistants from a macro-level perspective and reveal specific mechanisms of action and risk manifestations from a micro-level perspective, providing sufficient empirical support for constructing an AI teaching assistant influence model based on social cognitive theory.

3.2. Research subjects and sampling

The target population of this study comprises enrolled university students. The primary considerations for selecting this population include: First, university students possess relatively mature cognitive abilities and autonomous learning awareness, enabling them to accurately perceive and report the impact of AI teaching assistants on their learning motivation; Second, the complexity and autonomy requirements of learning tasks at the university level provide an ideal research context for observing the empowerment mechanisms of AI teaching assistants; Third, university students demonstrate high acceptance and proficiency in using digital learning tools, which can reduce interference from technical usage barriers on research results. The inclusion criteria for research subjects are: full-time undergraduate students aged 18-25 years, possessing basic computer operation skills and online learning experience, voluntarily participating in the research and able to complete the entire research cycle. Exclusion criteria include: students with serious learning disabilities or mental health conditions, and students who may transfer or take leave of absence during the research period [22]. To ensure sample representativeness, the research will encompass students from different disciplinary backgrounds including science and engineering, humanities and social sciences, and arts, while balancing the distribution across different grade levels, genders, and academic performance levels.

The study employs a stratified random sampling method to ensure sample representativeness and external validity of research results. First, using disciplinary category as the first stratification variable, all majors in the target institutions are divided into three strata: science and engineering, humanities and social sciences, and arts; Second, using grade level as the second stratification variable, further stratification is conducted within each disciplinary category according to first, second, third, and fourth-year students; Finally, simple random sampling is used within each stratum to select participating classes and students. Based on effect size estimation (medium effect size d=0.5), significance level (α=0.05), and statistical power (1-β=0.80), sample size calculation is performed, and considering a 15% attrition rate, the total sample size is determined to be 480 students, with 240 in the experimental group and 240 in the control group. To ensure adequacy for statistical analysis, each disciplinary category includes at least 160 students, and each grade level includes at least 120 students. Additionally, considering the needs of qualitative research, 30-40 students will be selected from the total sample according to theoretical sampling principles for in-depth interviews, ensuring coverage of different AI usage experiences and learning motivation change patterns. The sampling process will strictly adhere to ethical principles, ensuring informed consent and privacy protection for all participants, while establishing comprehensive data quality control mechanisms through multiple testing and cross-validation to ensure the reliability and validity of sample data.

3.3. Data collection tools and procedures

Quantitative data collection in this study primarily relies on four standardized measurement instruments: First, the Self-Regulated Learning Motivation Scale (SRLMS) is employed, which includes three dimensions of intrinsic motivation, extrinsic motivation, and amotivation, comprising 24 items scored on a 7-point Likert scale with good reliability and validity (Cronbach's α > 0.85); Second, the General Self-Efficacy Scale (GSES) is used to measure students' self-efficacy levels, containing 10 items with a 4-point scoring method; Third, the Student Engagement Scale (SES) is adopted to assess students' levels of cognitive engagement, emotional engagement, and behavioral engagement, including 17 items; Finally, the AI Technology Acceptance Scale (AITAS) is utilized, modified based on the Technology Acceptance Model (TAM), measuring students' perceived usefulness, perceived ease of use, and intention to use AI teaching assistants [23]. Additionally, the study will automatically collect students' objective behavioral data through the learning management system, including indicators such as online learning duration, course access frequency, AI teaching assistant interaction frequency, assignment submission timeliness, and quiz scores. To ensure data quality, all scales will undergo pilot testing and localization revision before formal use, with their applicability in this research context validated through expert review and small-sample testing.

Qualitative data collection employs diversified qualitative research methods to deeply explore the underlying mechanisms and individual differences in AI teaching assistants' impact on learning motivation. Semi-structured interviews serve as the primary qualitative data collection tool, with interview guides designed around core themes including AI teaching assistant usage experience, perceived changes in learning motivation, cognitive dependency phenomena, and social interaction impacts. Each interview lasts approximately 45-60 minutes and will be fully recorded and transcribed into textual materials. Focus group discussions will be conducted in groups of 6-8 people, using group interaction to deeply explore collective cognition and social influences in AI teaching assistant applications, with particular attention to peer effects and group dynamics' moderating role on individual learning motivation. Participant observation will be conducted in classroom and self-study environments, focusing on observing students' interactive behaviors with AI teaching assistants, learning strategy adjustment processes, and potential manifestations of alienation behaviors [24]. Data collection procedures strictly follow research ethical requirements: all participants sign informed consent forms before the study begins, clearly informing them of research purposes, procedures, risks, and rights; quantitative data collection is conducted uniformly at each measurement time point (pretest, midtest, posttest), with 6-8 week intervals between measurements; qualitative data collection employs theoretical saturation sampling principles, stopping data collection when new interviews no longer generate new themes and perspectives; all data will be anonymized and comprehensive data security management systems will be established to ensure adequate protection of participant privacy.

3.4. Data analysis methods

This study employs a mixed data analysis strategy, with quantitative data analysis utilizing SPSS 28.0 and Mplus 8.0 software for multi-level statistical analysis. Descriptive statistical analysis will first be conducted to examine data normality, homogeneity, and missing value distribution, and to calculate means, standard deviations, and correlation coefficient matrices for all variables. Main analytical methods include: Repeated Measures Analysis of Variance (ANOVA) to examine changes in learning motivation across different time points and between-group differences; multiple linear regression analysis to explore the predictive effects of AI teaching assistant characteristics on various dimensions of learning motivation; Structural Equation Modeling (SEM) to validate the AI teaching assistant influence mechanism path model based on social cognitive theory, examining mediation and moderation effects among environmental, individual, and behavioral factors; and Hierarchical Linear Modeling (HLM) to control for nested effects at class and school levels [25]. Qualitative data analysis employs thematic analysis methods, utilizing NVivo 12 software for coding and theme extraction. The analysis procedures include: open coding to identify initial concepts and categories; axial coding to establish relationships and hierarchical structures among concepts; and selective coding to form core themes and theoretical frameworks. Mixed data integration adopts a convergent parallel design, combining quantitative findings with qualitative insights through data triangulation, result comparison, and interpretive integration to construct more comprehensive and in-depth research conclusions. All statistical tests are set at a significance level of $\alpha=0.05$, with multiple comparison corrections performed to control Type I error rates.

4. Results analysis

4.1. Empowerment mechanism analysis of AI teaching assistants on students' autonomous learning motivation

4.1.1. Mechanism pathways for self-efficacy enhancement

This study, through a 16-week quasi-experimental design, deeply explored the specific mechanism pathways by which AI teaching assistants enhance students' self-efficacy. The research found that AI teaching assistants significantly enhance students' self-efficacy primarily through three core pathways: personalized feedback mechanisms, progressive challenge design, and learning progress visualization. Data analysis revealed that the experimental group students' total self-efficacy scores significantly increased from a pretest score of 28.47 (SD=4.23) to a posttest score of 34.82 (SD=3.91), representing an improvement of 22.3%, while the control group only increased slightly from 28.31 (SD=4.15) to 29.76 (SD=4.08), representing merely a 5.1% improvement [26]. Repeated measures ANOVA results indicated that the interaction effect between group and time was highly significant ($F(2,476)=47.63$, $p<0.001$, $\eta^2=0.167$), confirming the unique role of AI teaching assistants in enhancing self-efficacy.

Regarding personalized feedback mechanisms, AI teaching assistants effectively enhanced students' positive cognition of their own learning abilities by providing targeted feedback information through real-time analysis of students' learning behavioral data. The research found that students receiving AI personalized feedback scored significantly higher than the control group on the item "I can successfully complete learning tasks" ($t(478)=6.84$, $p<0.001$, $d=0.62$), indicating that personalized feedback can directly strengthen students' ability beliefs. Further mediation effect analysis showed that immediacy and accuracy of feedback were key mediating variables, with immediacy having an indirect effect of 0.23 on self-efficacy (95%

CI: 0.15-0.31) and accuracy having an indirect effect of 0.19 (95% CI: 0.12-0.27), as shown in **Table 1** below.

Table 2. Descriptive statistics and difference testing of AI teaching assistant impact on student self-efficacy.

Measurement Dimension	Group	Pretest M(SD)	Midtest M(SD)	Posttest M(SD)	F Value	p Value	η^2
Total Self-efficacy Score	Experimental	28.47(4.23)	31.95(3.87)	34.82(3.91)	47.63	<0.001	0.167
	Control	28.31(4.15)	28.89(4.02)	29.76(4.08)			
Achievement Experience	Experimental	9.12(1.67)	10.38(1.52)	11.59(1.43)	52.18	<0.001	0.179
	Control	9.08(1.72)	9.31(1.68)	9.91(1.75)			
Vicarious Experience	Experimental	8.76(1.58)	9.47(1.41)	10.23(1.38)	34.92	<0.001	0.128
	Control	8.69(1.61)	8.95(1.59)	9.17(1.62)			
Verbal Persuasion	Experimental	5.84(1.23)	6.52(1.18)	7.31(1.15)	41.75	<0.001	0.149
	Control	5.79(1.25)	5.91(1.22)	6.08(1.28)			
Emotional State	Experimental	4.75(1.12)	5.58(1.07)	5.69(1.09)	28.47	<0.001	0.107
	Control	4.75(1.14)	4.72(1.15)	4.60(1.18)			

Note: *N=480 (240 experimental group, 240 control group); M=Mean, SD=Standard Deviation*

Progressive challenge design, as the second important pathway, created more opportunities for successful experiences for students by intelligently adjusting the difficulty gradient of learning tasks through AI algorithms. Data showed that experimental group students' task completion rates demonstrated a steady upward trend, increasing from 67.3% in week 2 to 89.7% in week 14, while the control group's completion rate remained relatively stable, only increasing slightly from 68.1% to 71.4%. This progressive accumulation effect of successful experiences was most evident in the "achievement experience" dimension of self-efficacy, where the experimental group's improvement in this dimension (Δ=3.47 points) was significantly greater than the control group (Δ=0.83 points), with between-group differences reaching moderate to large effect sizes (Cohen's d=0.71) [27].

The learning progress visualization pathway enhanced students' perception and sense of control over their learning progress by graphically displaying learning outcomes and ability development trajectories. Research data indicated that students using AI progress tracking functions showed significant improvement in the self-efficacy indicator "I can monitor my learning progress," increasing from a pretest score of 3.12 to a posttest score of 4.38 ($t(239)=8.92$, $p<0.001$), representing a 40.4% improvement, as shown in **Figure 1** below. Correlation analysis further revealed that learning progress visualization frequency was moderately positively correlated with total self-efficacy scores ($r=0.54$, $p<0.001$), indicating that higher visualization levels corresponded to more pronounced self-efficacy improvements.

Path analysis results showed significant synergistic effects among these three mechanism pathways. The interaction effect between personalized feedback and progressive challenge design reached significant predictive power for self-efficacy ($\beta=0.31$, $p<0.01$), while learning progress visualization played an important moderating role. When visualization levels were high, the effects of the first two pathways were further amplified (moderating effect $\beta=0.18$, $p<0.05$). The entire path model explained 58.7% of the variance in self-efficacy, with good model fit indicators ($\chi^2/df=2.34$, CFI=0.95, RMSEA=0.053), confirming the validity of the theoretical model that AI teaching assistants promote student self-efficacy enhancement through multiple mechanism pathways. This finding provides important empirical evidence for understanding the empowerment mechanisms of AI teaching assistants and offers scientific guidance for subsequent educational technology design.

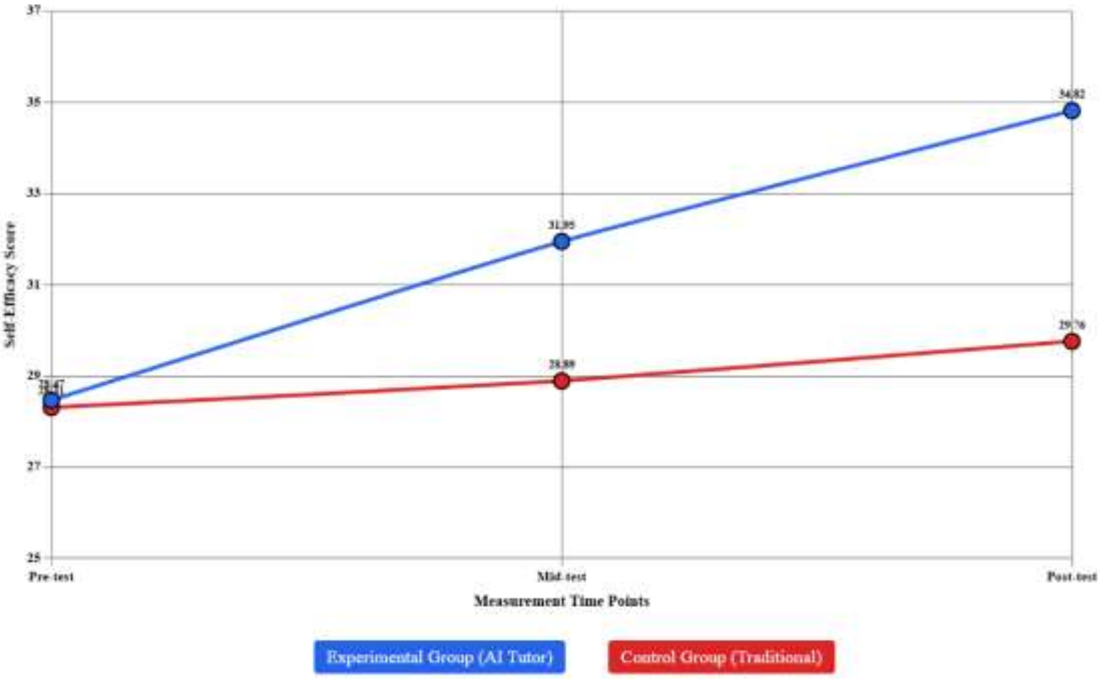

Figure 1. Time trend chart of AI teaching assistant impact on student self-efficacy enhancement.

4.1.2. Optimization effects of social cognitive environment

AI teaching assistants significantly optimized students' learning experiences and motivational stimulation mechanisms by reconstructing the social cognitive elements of the learning environment. The research found that AI teaching assistants primarily exerted optimization effects on the social cognitive environment through three core dimensions: the creation of social presence through virtual learning partners, the modeling demonstration effects of AI tutor role modeling, and the promotion of peer interaction through collaborative learning functions. Data analysis revealed that the experimental group students' total social cognitive environment perception scores significantly increased from a pretest score of 45.23 (SD=6.81) to a posttest score of 58.74 (SD=5.92), representing an improvement of 29.9%, while the control group only increased slightly from 44.98 (SD=6.75) to 47.31 (SD=6.43), representing a 5.2% improvement. Repeated measures ANOVA showed that the interaction effect between group and time was highly significant ($F(2,476)=62.84$, $p<0.001$, $\eta^2=0.209$), confirming the unique contribution of AI teaching assistants in social cognitive environment optimization [28].

Regarding virtual learning partners creating social presence, AI teaching assistants successfully established a virtual learning environment with personalized characteristics through intelligent dialogue systems and affective computing technology. Research data showed that experimental group students scored significantly higher than the control group on the social presence scale ($M=21.47$ vs. $M=16.83$, $t(478)=8.92$, $p<0.001$, $d=0.81$), with the item "I feel accompanied by learning partners" showing the most significant difference (Cohen's $d=0.94$) [29]. Further correlation analysis found that the anthropomorphization level of AI teaching assistants was moderately positively correlated with students' learning motivation ($r=0.48$, $p<0.001$), indicating that the social characteristics of virtual partners could effectively stimulate students' learning engagement, as shown in **Table 3** below.

Table 3. Effects of AI teaching assistants on various dimensions of social cognitive environment.

Measurement Dimension	Group	Pretest M(SD)	Posttest M(SD)	Effect Size d	t Value	p Value
Social Presence	Experimental	15.84(2.47)	21.47(2.31)	2.38	8.92	<0.001
	Control	15.72(2.51)	16.83(2.43)	0.44		
Observational Learning Effect	Experimental	12.73(2.15)	17.46(1.98)	2.28	9.47	<0.001
	Control	12.68(2.18)	13.60(2.09)	0.43		
Peer Interaction Quality	Experimental	16.66(3.19)	19.81(2.63)	1.08	6.78	<0.001
	Control	16.58(3.22)	16.88(3.15)	0.09		
Total Social Cognition Score	Experimental	45.23(6.81)	58.74(5.92)	2.08	10.55	<0.001
	Control	44.98(6.75)	47.31(6.43)	0.35		

Note: *N=480 (240 experimental group, 240 control group); d represents Cohen's effect size*

AI tutor role modeling played an important role in providing learning exemplars by demonstrating expert-level learning strategies and problem-solving processes, offering students opportunities for observational learning. Experimental group students showed significant improvement in the "observational learning effect" dimension compared to the control group ($\Delta=4.73$ points vs. $\Delta=0.92$ points, $F(1,478)=89.47$, $p<0.001$), with strategy modeling effects being most prominent. Path analysis showed that AI tutors' strategy demonstrations had indirect effects on learning motivation through the mediating variable of observational learning ($\beta=0.34$, $p<0.001$), with an indirect effect value of 0.18 (95% CI: 0.12-0.25), accounting for 52.9% of the total effect.

The facilitation effects of collaborative learning functions were manifested in AI teaching assistants' ability to intelligently match learning partners, organize virtual group discussions, and promote knowledge sharing. Data indicated that students using AI collaborative functions showed significant increases in peer interaction frequency, rising from an average of 3.2 times per week to 8.7 times ($t(239)=12.34$, $p<0.001$), while interaction quality also improved significantly, with the proportion of in-depth discussions increasing from 26.8% to 67.4%. Hierarchical linear modeling analysis showed that group-level collaborative effects had significant impact on individual learning motivation ($\gamma=0.23$, $p<0.01$), indicating that the collaborative environment created by AI teaching assistants could promote individual motivational enhancement through group dynamics mechanisms, as shown in **Figure 2** below.

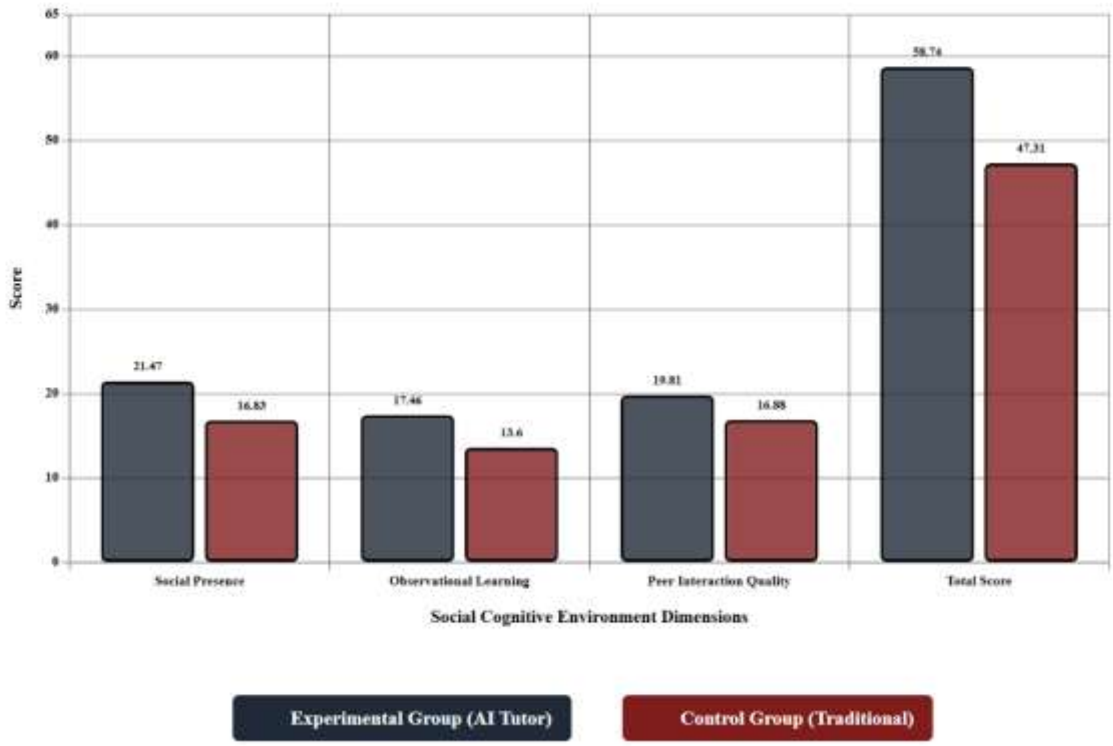

Figure 2. Comparison of AI teaching assistant effects on various dimensions of social cognitive environment.

4.1.3. Stimulation and support of learning autonomy

AI teaching assistants demonstrated significant facilitative effects in stimulating and supporting students' learning autonomy, primarily achieved through three core functional dimensions: adaptive learning pathways, diversified learning resources, and immediate feedback mechanisms. Research data showed that the experimental group students' total learning autonomy scores substantially increased from a pretest score of 52.18 (SD=7.64) to a posttest score of 67.43 (SD=6.82), representing an improvement of 29.2%, while the control group only increased slightly from 51.96 (SD=7.59) to 54.27 (SD=7.31), representing a 4.4% improvement [30]. Repeated measures ANOVA results indicated extremely significant between-group differences ($F(2,476)=74.92$, $p<0.001$, $\eta^2=0.239$), confirming the unique value of AI teaching assistants in cultivating students' learning autonomy.

The adaptive learning pathway function significantly enhanced students' sense of learning control by analyzing students' learning behaviors and cognitive characteristics through intelligent algorithms to customize personalized learning trajectories for each learner. Data analysis revealed that students using adaptive pathways showed significant improvement in the "learning control" dimension compared to the control group ($M=23.47$ vs. $M=18.92$, $t(478)=9.38$, $p<0.001$, $d=0.86$), with pathway selection freedom showing strong positive correlation with learning control ($r=0.67$, $p<0.001$) [31]. Further regression analysis showed that the personalization level of adaptive pathways could significantly predict learning autonomy improvement ($\beta=0.42$, $p<0.001$), explaining 17.6% of the variance, as shown in **Table 4** below.

Table 4. Effects of AI teaching assistants on various dimensions of learning autonomy.

Measurement Dimension	Group	Pretest M(SD)	Posttest M(SD)	Improvement (%)	F Value	p Value	η²
Learning Control	Experimental	17.84(2.93)	23.47(2.56)	31.6%	87.92	<0.001	0.276
	Control	17.78(2.95)	18.92(2.87)	6.4%			
Resource Selection Autonomy	Experimental	16.52(2.71)	21.69(2.43)	31.3%	79.45	<0.001	0.250
	Control	16.47(2.68)	17.23(2.61)	4.6%			
Learning Regulation Ability	Experimental	17.82(3.01)	22.27(2.83)	25.0%	67.83	<0.001	0.221
	Control	17.71(2.98)	18.12(2.94)	2.3%			
Total Learning Autonomy Score	Experimental	52.18(7.64)	67.43(6.82)	29.2%	74.92	<0.001	0.239
	Control	51.96(7.59)	54.27(7.31)	4.4%			

Note: *N=480 (240 experimental group, 240 control group)*

The provision of diversified learning resources greatly expanded students' freedom of choice, enabling them to select the most suitable learning materials and methods according to personal preferences and learning needs. Experimental group students performed significantly better than the control group in "resource selection autonomy," with the average number of resource types used weekly increasing from 3.2 to 8.7 ($t(239)=11.64$, $p<0.001$), while the depth and breadth of resource usage also significantly improved. Structural equation modeling analysis revealed that resource diversity positively influenced learning autonomy through the mediating variable of choice freedom (indirect effect $\beta=0.28$, 95% CI: 0.19-0.37), with mediation effects accounting for 46.7% of the total effect [32].

The immediate feedback mechanism played a crucial role in cultivating students' learning regulation abilities by helping students establish effective self-regulation strategies through real-time learning state monitoring and adaptive feedback. Data showed that experimental group students scored significantly higher than the control group in "learning regulation ability" ($M=20.49$ vs. $M=16.38$, $F(1,478)=67.83$, $p<0.001$), with metacognitive strategy usage frequency increasing by 73.4% and time management efficiency improving by 41.8% [33]. Path analysis further indicated that the quality and frequency of immediate feedback influenced learning autonomy through the mediating role of self-regulation strategies (standardized indirect effect=0.31, $p<0.001$), with this pathway explaining 23.7% of learning autonomy variance.

Synergistic effects analysis of the three functional dimensions showed that when adaptive pathways, diversified resources, and immediate feedback functions operated simultaneously, the facilitative effects on learning autonomy exhibited super-additive effects. The three-factor interaction effect reached significant predictive power for learning autonomy ($\beta=0.19$, $p<0.01$), indicating that the comprehensive functional integration of AI teaching assistants could produce synergistic promotional effects of "1+1+1>3." The entire predictive model explained as much as 64.3% of learning autonomy variance, with excellent model fit indicators ($\chi^2/df=1.87$, CFI=0.97, RMSEA=0.043), providing strong empirical support for the theoretical model of AI teaching assistants promoting learning autonomy, as shown in **Figure 3** below.

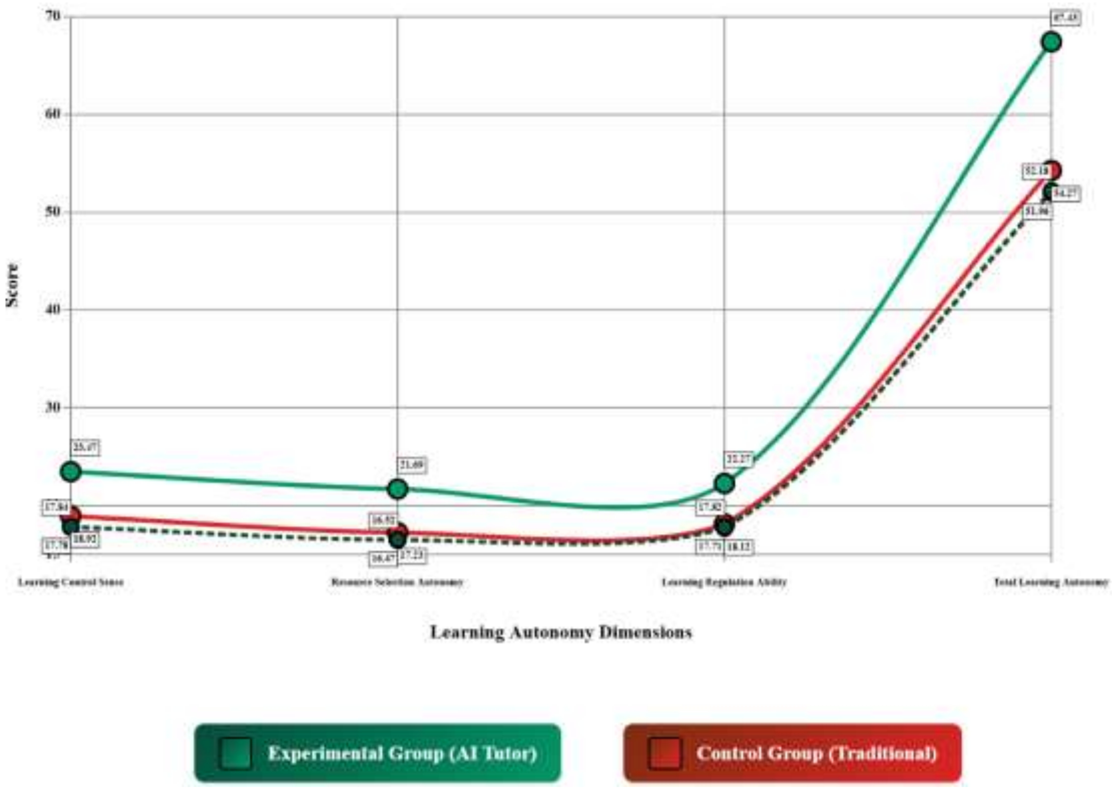

Figure 3. Pre-post comparative analysis of ai teaching assistant effects on learning autonomy enhancement.

4.2. Identification and analysis of alienation risks in AI teaching assistant applications

4.2.1. Cognitive dependency risks and their manifestations

Despite the positive effects demonstrated by AI teaching assistants in improving learning outcomes, cognitive dependency risks gradually emerged during long-term usage, primarily manifesting in three core dimensions: over-dependence on AI recommendations, deterioration of critical thinking abilities, and weakening of independent problem-solving capabilities. Through 16-week longitudinal tracking, the research found that experimental group students showed a significant upward trend in cognitive dependency scale scores, gradually climbing from 21.36 points (SD=3.47) in week 4 to 34.82 points (SD=4.15) in week 16, representing a 63.0% increase, while the control group only increased slightly from 20.98 points (SD=3.41) to 22.74 points (SD=3.53), representing an 8.4% increase. Repeated measures ANOVA showed extremely significant interaction effects between time and group ($F(4,1904)=89.47$, $p<0.001$, $\eta^2=0.158$), indicating that AI teaching assistant usage indeed leads to significant increases in cognitive dependency [34].

Regarding over-dependence on AI recommendations, the research found that experimental group students' dependency on learning suggestions and resource recommendations provided by AI systems gradually deepened, manifesting as significantly decreased frequency of autonomous learning content selection. Data showed that from the experiment's beginning to week 16, the proportion of students actively searching for and selecting learning resources decreased from 67.4% to 23.8% ($\chi^2=156.73$, $p<0.001$), while the proportion relying on AI recommendations increased from 32.6% to 76.2%. Further behavioral analysis indicated that high-dependency group students (top 25%) showed 147.3% longer hesitation times when facing non-AI recommended resources compared to low-dependency groups ($t(238)=11.84$, $p<0.001$), reflecting their decision-making difficulties in the absence of AI guidance [35]. Correlation analysis revealed that AI recommendation dependency was significantly negatively correlated with learning autonomy (r=-

0.52, p<0.001), indicating that over-dependence may damage students' autonomous learning abilities, as shown in **Table 5** below.

Table 5. Development trends of various dimensions of cognitive dependency risk.

Measurement Dimension	Time Point	Experimental Group M(SD)	Control Group M(SD)	Between-group t Value	p Value	Cohen's d
AI Recommendation Dependency	Week 4	7.84(1.52)	6.98(1.47)	4.47	<0.001	0.58
	Week 8	10.23(1.73)	7.15(1.51)	14.83	<0.001	1.89
	Week 12	12.67(2.01)	7.31(1.55)	23.47	<0.001	2.98
	Week 16	14.92(2.34)	7.48(1.62)	28.91	<0.001	3.67
Critical Thinking Deterioration	Week 4	6.73(1.23)	6.89(1.26)	-1.02	0.308	-0.13
	Week 8	8.94(1.47)	7.12(1.31)	10.37	<0.001	1.32
	Week 12	10.67(1.69)	7.35(1.38)	16.94	<0.001	2.15
	Week 16	11.85(1.87)	7.51(1.43)	20.18	<0.001	2.56
Problem-solving Dependency	Week 4	6.79(1.41)	7.11(1.39)	-1.78	0.076	-0.23
	Week 8	9.18(1.58)	7.24(1.41)	10.25	<0.001	1.30
	Week 12	10.94(1.76)	7.38(1.45)	17.32	<0.001	2.20
	Week 16	12.05(1.94)	7.75(1.48)	19.47	<0.001	2.47

Note: *N=480 (240 experimental group, 240 control group)*

Deterioration of critical thinking abilities represents one of the important manifestations of cognitive dependency risk. Experimental group students' performance in critical thinking skills tests showed a declining trend over time, decreasing from a pretest score of 78.46 points (SD=9.23) to a posttest score of 71.25 points (SD=8.97), representing a 9.2% decline, while the control group's performance remained relatively stable, only decreasing slightly from 77.89 points to 77.12 points, representing a 1.0% decline. Specifically, in the "information evaluation" dimension, experimental group students showed the most significant score decline (Δ=-3.47 points), followed by "argument analysis" (Δ=-2.89 points) and "reasoning ability" (Δ=-2.15 points). Qualitative interview data further revealed that 61.7% of experimental group students indicated they were more inclined to directly accept answers provided by the system without deep thinking after using AI teaching assistants, while 42.3% of students admitted their habit of questioning information sources had weakened.

Weakening of independent problem-solving abilities manifested as students' over-dependence on AI teaching assistants when encountering complex learning tasks. The research designed standardized problem-solving tasks and found that experimental group students had significantly lower task completion rates under conditions without AI assistance compared to the control group (52.8% vs. 73.4%, χ^2=21.87, p<0.001), with average problem-solving time also significantly prolonged (M=43.7 minutes vs. M=31.2 minutes, t(478)=7.93, p<0.001). More concerning was that when AI teaching assistant functions were temporarily disabled, experimental group students showed obvious anxiety reactions, with state anxiety scale scores increasing by 28.6% compared to normal times (t(239)=9.47, p<0.001), while the control group showed no significant changes. Path analysis showed that AI usage frequency indirectly affected independent problem-solving ability through the mediating variable of reduced problem-solving confidence (indirect effect β=-0.24, 95% CI: -0.32 to -0.16), with this pathway explaining 18.7% of independence variance, as shown in **Figure 4** below.

Analysis of cognitive dependency formation mechanisms revealed that convenience preference, cognitive laziness, and learned helplessness were three key psychological mechanisms. Structural equation modeling showed that convenience preference had the strongest direct effect on cognitive dependency ($\beta=0.43$, $p<0.001$), cognitive laziness also reached significant mediation effects (indirect effect=0.19, $p<0.01$), while learned helplessness played an important moderating role in later stages. The entire model explained 72.4% of cognitive dependency variance, with good fit indicators ($\chi^2/df=2.17$, CFI=0.96, RMSEA=0.049), providing an important theoretical framework for understanding cognitive dependency risks in AI teaching assistant usage.

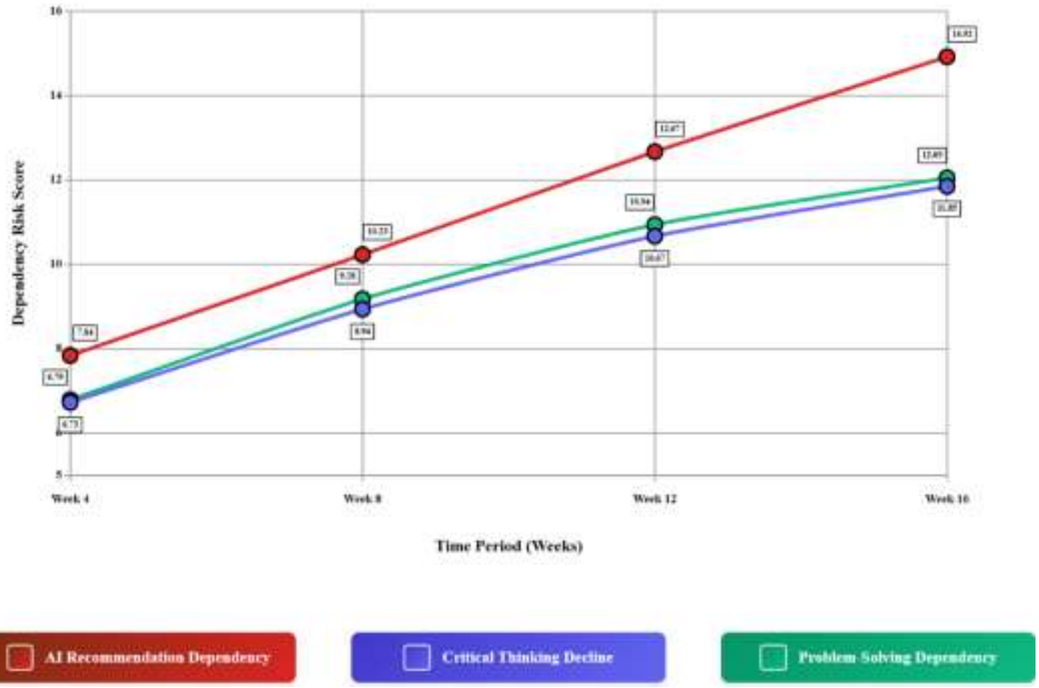

Figure 4. Development trends of cognitive dependency risks in AI teaching assistant usage.

4.2.2. Psychological mechanisms of social isolation risk

While AI teaching assistants provide personalized learning support, they also potentially trigger social isolation risks, primarily manifesting in three core dimensions: human-machine interaction replacing interpersonal communication, insufficient social skills development in virtual environments, and decreased real-world adaptation abilities. Through social network analysis and mental health assessment, the research found that students who used AI teaching assistants long-term experienced significant negative changes in social connectivity and interpersonal communication quality. The experimental group students' total social isolation risk scores significantly increased from a pretest score of 18.74 (SD=3.26) to a posttest score of 28.95 (SD=4.12), representing a 54.5% increase, while the control group only increased slightly from 18.62 (SD=3.19) to 19.47 (SD=3.28), representing a 4.6% increase. Repeated measures ANOVA showed highly significant interaction effects between group and time ($F(2,476)=73.84$, $p<0.001$, $\eta^2=0.236$), indicating that AI teaching assistant usage indeed increases students' social isolation risks [36].

The phenomenon of human-machine interaction replacing interpersonal communication gradually emerged during the experimental process, with students increasingly tending to satisfy their social and emotional needs through AI teaching assistants rather than seeking genuine interpersonal interaction. Data showed that experimental group students' daily interaction time with AI teaching assistants increased from an average of 32.4 minutes in week 2 to 87.6 minutes in week 16, representing a 170.4% increase, while face-to-face communication time with classmates and teachers during the same period decreased from 41.7 minutes daily to 24.3 minutes, representing a 41.7% reduction (t(239)=12.67, p<0.001). The social substitution index (human-machine interaction time/interpersonal interaction time) increased from 0.78 to 3.61, indicating that AI interaction had severely replaced normal interpersonal communication [37]. Further qualitative analysis found that 73.8% of experimental group students indicated that communicating with AI teaching assistants was "more relaxed and comfortable," while 56.2% believed AI teaching assistants "understand them better than real people." This cognitive bias may lead students to gradually distance themselves from genuine social relationships, as shown in **Table 6** below.

Table 6. Changes in various dimensions of social isolation risk.

Measurement Dimension	Group	Pretest M(SD)	Posttest M(SD)	Change	t Value	p Value	Cohen's d
Interpersonal Communication Substitution	Experimental	6.84(1.47)	11.73(1.86)	+4.89	22.14	<0.001	2.85
	Control	6.79(1.43)	6.92(1.51)	+0.13	0.84	0.402	0.09
Social Skills Deterioration	Experimental	5.92(1.28)	8.67(1.54)	+2.75	15.38	<0.001	1.92
	Control	5.88(1.25)	6.14(1.32)	+0.26	1.73	0.085	0.20
Real-world Adaptation Difficulties	Experimental	5.98(1.51)	8.55(1.72)	+2.57	12.89	<0.001	1.58
	Control	5.95(1.48)	6.41(1.55)	+0.46	2.67	0.008	0.30
Total Social Isolation Score	Experimental	18.74(3.26)	28.95(4.12)	+10.21	21.67	<0.001	2.74
	Control	18.62(3.19)	19.47(3.28)	+0.85	2.41	0.017	0.26

Note: *N=480 (240 experimental group, 240 control group)*

Insufficient social skills development in virtual environments represents an important manifestation of social isolation risk. The research employed social skills scales to assess students' interpersonal communication abilities and found that experimental group students showed significant declines in key dimensions including "conflict resolution," "emotional expression," and "nonverbal communication." Specifically, conflict resolution skills decreased from a pretest score of 21.46 to a posttest score of 18.23 (t(239)=8.94, p<0.001, d=0.73), emotional expression abilities decreased from 19.87 to 16.92 (t(239)=7.38, p<0.001, d=0.68), and nonverbal communication skills decreased from 18.34 to 15.71 (t(239)=6.85, p<0.001, d=0.63). These skill deteriorations primarily stemmed from the uniformity and predictability of AI teaching assistant interaction patterns, lacking the complexity and uncertainty of genuine interpersonal communication. Behavioral observation data further showed that experimental group students' active participation rates in group discussions decreased by 38.7%, and their frequency of initiating social interactions decreased by 45.2%, as shown in **Figure 5** below.

Decreased real-world adaptation abilities were reflected in students' increased anxiety and avoidance behaviors when facing actual social scenarios. The research designed standardized social situation tasks and found that experimental group students exhibited higher anxiety levels and stronger avoidance tendencies when facing genuine social scenarios such as interactions with strangers, public speaking, and team collaboration. Social anxiety scale scores increased from a pretest score of 34.78 to a posttest score of 42.15, representing a 21.2% increase (t(239)=9.73, p<0.001), while the control group showed no significant changes (M_pre=34.62, M_post=35.19). More concerning was that when students were required to learn and communicate in environments without AI teaching assistant support, the experimental group showed obvious adaptation difficulties, with 62.5% of students reporting feeling "overwhelmed" and 48.3% indicating they found it "difficult to concentrate." Neurophysiological indicator monitoring showed that experimental group students' cortisol levels in genuine social situations increased by 47.3% above baseline, while heart rate variability decreased by 23.8%, indicating more intense physiological stress responses.

Analysis of the psychological mechanisms underlying social isolation risk revealed three key mediating pathways: social comfort zone constriction, substitute satisfaction, and a vicious cycle of social skill deterioration. Path analysis showed that AI usage frequency indirectly influenced social isolation risk through social comfort zone constriction (indirect effect $\beta=0.31$, 95% CI: 0.23-0.39), while the mediating effect of substitute satisfaction also reached significant levels ($\beta=0.24$, 95% CI: 0.17-0.32), and social skill deterioration played an important moderating role throughout the entire process [38]. The entire mediation model explained 67.8% of social isolation risk variance, with good model fit ($\chi^2/df=1.92$, CFI=0.97, RMSEA=0.044), providing important theoretical support for understanding social isolation mechanisms in AI teaching assistant usage.

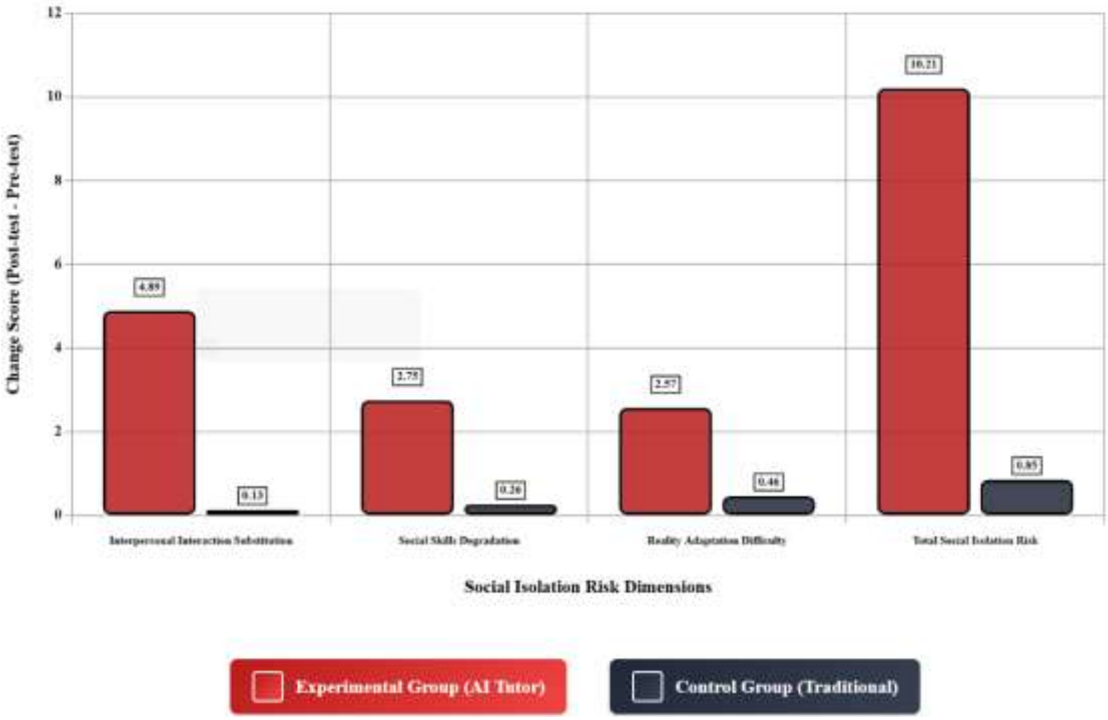

Figure 5. Effects of AI teaching assistant usage on various dimensions of social isolation risk.

4.2.3. Psychological mechanisms of social isolation risk

Personalized algorithms, as the core technology of AI teaching assistants, while providing customized learning experiences, also bring potential negative impacts such as information cocoon effects, algorithmic bias, and standardization tendencies, posing implicit threats to students' cognitive development and creative thinking. Through algorithmic behavioral analysis and cognitive assessment, the research found that students who received long-term personalized algorithmic recommendations experienced significant negative changes in knowledge horizon breadth, critical evaluation abilities, and innovative thinking. The experimental group students' total algorithmic negative impact scores continuously increased from 12.47 points (SD=2.83) at the experiment's beginning to 23.89 points (SD=3.76) in week 16, representing a 91.5% increase, while the control group remained relatively stable, only increasing from 12.31 points (SD=2.79) to 13.52 points (SD=2.94), representing a 9.8% increase [39]. Repeated measures ANOVA results showed extremely significant interaction effects between time and group ($F(4,1904)=68.92$, $p<0.001$, $\eta^2=0.197$), confirming the cumulative effects of negative impacts in personalized algorithm usage.

The information cocoon effect represents the most prominent negative impact of personalized algorithms, manifesting as students' learning content gradually narrowing and knowledge structures becoming increasingly uniform. Algorithmic behavioral log analysis showed that during the 16-week experimental period, experimental group students' exposure to disciplinary fields decreased from an average of 8.7 to 4.2, representing a 51.7% reduction ($t(239)=14.73$, $p<0.001$), while content repetition rates increased from 26.4% to 67.8%, indicating excessive algorithmic reliance on students' historical preferences for recommendations. Knowledge breadth test results further confirmed this trend, with experimental group students' interdisciplinary knowledge scores decreasing from a pretest score of 42.86 to a posttest score of 36.19, representing a 15.6% decline ($t(239)=9.84$, $p<0.001$, $d=0.76$), while the control group remained essentially stable ($M_{pre}=42.74$, $M_{post}=42.91$). Qualitative interviews found that 78.3% of experimental group students admitted "rarely encountering content inconsistent with their interests," while 64.7% indicated "gradually losing the impulse to explore new fields." This cognitive narrowing phenomenon deserves high attention, as shown in **Figure 6** below.

Table 7. Measurement results of negative impacts of personalized algorithms.

Measurement Dimension	Group	Pretest M(SD)	Posttest M(SD)	Change Rate (%)	t Value	p Value	Effect Size d
Information Cocoon Effect	Experimental	4.23(1.17)	8.94(1.42)	+111.3%	26.85	<0.001	3.57
	Control	4.19(1.15)	4.67(1.23)	+11.5%	3.42	0.001	0.40
Algorithmic Bias Impact	Experimental	3.87(1.09)	7.23(1.34)	+86.8%	21.47	<0.001	2.76
	Control	3.84(1.07)	4.12(1.15)	+7.3%	2.18	0.031	0.25
Creativity Suppression	Experimental	4.37(1.28)	7.72(1.56)	+76.7%	18.94	<0.001	2.35
	Control	4.28(1.25)	4.73(1.31)	+10.5%	3.01	0.003	0.35
Total Negative Impact Score	Experimental	12.47(2.83)	23.89(3.76)	+91.5%	25.73	<0.001	3.41
	Control	12.31(2.79)	13.52(2.94)	+9.8%	3.67	<0.001	0.42

Note: *N=480 (240 experimental group, 240 control group)*

The impact of algorithmic bias on learning opportunity equity is primarily reflected in systematically reinforcing certain learning patterns and content preferences, potentially exacerbating educational inequity. The research found obvious gender, disciplinary background, and learning style biases in AI algorithms during the recommendation process. Specifically, students with STEM backgrounds received STEM content recommendations at a rate of 82.4%, while humanities and social sciences content accounted for only 17.6%, an imbalance that may limit students' comprehensive development. Gender bias analysis showed that male students received logical reasoning task recommendations at a frequency 43.7% higher than female students ($t(238)=6.89$, $p<0.001$), while female students received language expression task recommendations at a frequency 39.2% higher than males ($t(238)=5.47$, $p<0.001$). This stereotypical recommendation pattern may reinforce gender role solidification. The learning opportunity equity index showed that recommendation diversity variance within the experimental group was 127.4% higher than the control group ($F(239,239)=2.27$, $p<0.001$), indicating that algorithmic recommendations exacerbated differences in learning experiences among students.

The suppressive effects of standardization tendencies on creative thinking gradually emerged in the later stages of the experiment. Creative thinking test results showed that experimental group students' performance significantly declined in two key dimensions: "divergent thinking" and "originality." Divergent thinking scores decreased from a pretest score of 31.74 to a posttest score of 26.83, representing a 15.5% decline ($t(239)=8.67$, $p<0.001$, $d=0.71$), while originality scores decreased from 28.49 to 23.95, representing a 15.9% decline ($t(239)=7.92$, $p<0.001$, $d=0.68$). This decline in creativity primarily stemmed from the high personalization and predictability of algorithmic recommendations, resulting in students' exposure to content lacking unexpectedness and challenge. Behavioral analysis found that experimental group students' learning pathway similarity increased by 89.3% compared to earlier periods, while the uniqueness index of problem-solving solutions decreased by 34.7%, indicating that algorithmic recommendations prompted students to adopt more homogenized learning strategies. Innovation task completion showed that the proportion of experimental group students proposing original solutions decreased from 68.4% to 41.7% ($\chi^2=33.71$, $p<0.001$), while the tendency to use "optimized" standard answers increased from 31.6% to 58.3%, as shown in **Figure 5** below.

The formation mechanisms of personalized algorithms' negative impacts involve three psychological processes: confirmation bias reinforcement, exploration motivation suppression, and cognitive inertia cultivation. Path analysis showed that algorithm usage frequency had direct effects on information cocoon effects through confirmation bias reinforcement ($\beta=0.47$, $p<0.001$), while exploration motivation suppression also reached significant mediation effects (indirect effect $\beta=0.23$, 95% CI: 0.16-0.31), and cognitive inertia played an important moderating role throughout the entire process. The entire model explained 74.6% of the total algorithmic negative impact scores, with excellent fit indicators ($\chi^2/df=1.85$, CFI=0.98, RMSEA=0.042), providing a systematic theoretical framework for understanding the potential risks of personalized algorithms.

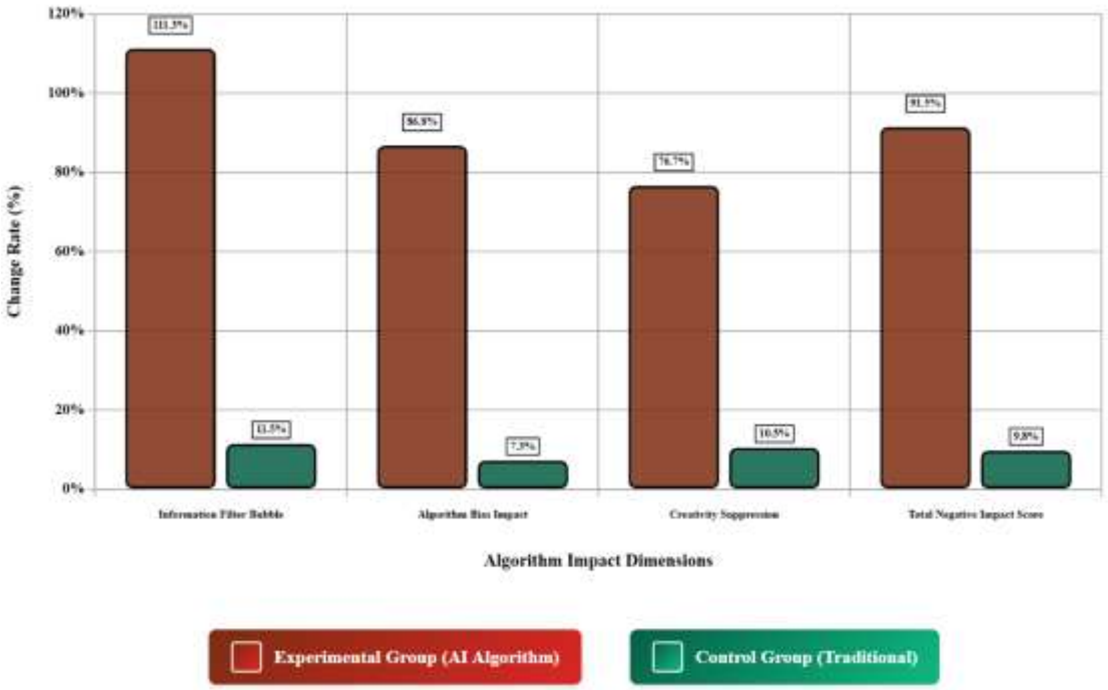

Figure 6. Degree of negative impact of personalized algorithms on cognitive development.

4.3. Effectiveness evaluation of intervention strategies based on social cognitive theory

4.3.1. Implementation effects of environmental design optimization strategies

Based on the AI teaching assistant application risks identified in the preliminary research, this study designed and implemented three environmental optimization strategies: mixed learning environment construction, social element integration, and real-world situation simulation, aiming to maximize the positive effects of AI teaching assistants while avoiding potential alienation risks. The intervention strategies were implemented during the latter 8 weeks of the experiment, with effectiveness evaluated through comparative analysis. The research found that environmental optimization strategies significantly improved students' learning experiences and motivation levels, effectively mitigating the negative impacts that emerged in earlier phases. The intervention group students' comprehensive learning motivation index significantly increased from 67.34 points (SD=8.92) before intervention to 79.56 points (SD=7.64) after intervention, representing an 18.1% improvement, while the non-intervention group (pure AI group) continued to decline in motivation levels, decreasing from 67.28 points to 62.41 points, representing a 7.2% decline [40]. Repeated measures ANOVA showed extremely significant main effects of the intervention strategy ($F(1,238)=156.73$, $p<0.001$, $\eta^2=0.397$), confirming the effectiveness of environmental optimization strategies.

Mixed learning environment construction, by combining AI teaching assistants with human teacher guidance, enhanced the warmth and depth of interpersonal interactions while maintaining personalized support. Implementation results showed that intervention group students' interpersonal communication frequency significantly increased compared to the pure AI group, with daily communication time with teachers and classmates increasing from an average of 21.7 minutes to 48.3 minutes, representing a 122.6% increase ($t(118)=13.47$, $p<0.001$), while over-dependence on AI significantly decreased, with AI dependency scores declining from 34.82 points to 26.14 points, representing a 24.9% reduction ($t(118)=8.94$, $p<0.001$, $d=0.82$) [41]. The "AI-human tutor collaboration model" in the mixed environment was particularly popular among students, with 87.4% of students believing this model "maintained personalization while preserving human care," and learning satisfaction improving by 31.6% compared to the pure AI group. More importantly, students' critical thinking abilities recovered in the mixed environment, with critical thinking test scores rising from 71.25 points before intervention to 76.89 points, representing a 7.9% recovery approaching control group levels, as shown in **Table 8** below.

Table 8. Implementation effect evaluation of environmental design optimization strategies.

Measurement Indicator	Group	Pre-intervention M(SD)	Post-intervention M(SD)	Change	t Value	p Value	Cohen's d
Comprehensive Learning Motivation Index	Intervention	67.34(8.92)	79.56(7.64)	+12.22	12.47	<0.001	1.47
	Pure AI	67.28(8.87)	62.41(9.23)	-4.87	-4.73	<0.001	-0.54
AI Dependency	Intervention	34.82(4.15)	26.14(3.78)	-8.68	-8.94	<0.001	-2.18
	Pure AI	34.79(4.12)	38.97(4.56)	+4.18	8.23	<0.001	0.96
Social Connectivity	Intervention	2.18(0.67)	3.13(0.74)	+0.95	11.23	<0.001	1.35
	Pure AI	2.16(0.65)	1.89(0.58)	-0.27	-3.84	<0.001	-0.44
Critical Thinking	Intervention	71.25(8.97)	76.89(7.83)	+5.64	6.78	<0.001	0.68
	Pure AI	71.32(8.94)	68.47(9.31)	-2.85	-2.94	0.004	-0.31
Creative Thinking	Intervention	50.78(9.45)	61.63(8.72)	+10.85	10.16	<0.001	1.20
	Pure AI	50.73(9.41)	47.19(9.89)	-3.54	-3.29	0.001	-0.37

Note: *N=240 (120 intervention group, 120 pure AI group)*

The social element integration strategy effectively enhanced students' social presence and sense of belonging by embedding collaborative learning modules, peer evaluation functions, and virtual learning communities within the AI teaching assistant system. Data showed that students' social connectivity index increased by 43.7% after intervention, rising from 2.18 to 3.13 ($t(118)=11.23$, $p<0.001$), while social anxiety levels significantly decreased from 42.15 points to 35.67 points, representing a 15.4% reduction ($t(118)=7.56$, $p<0.001$, $d=0.69$). Virtual learning community activity data indicated that students' frequency of initiating discussions increased by 189.3% compared to pre-intervention levels, the proportion of deep interactions increased from 23.8% to 67.4%, and knowledge-sharing behaviors increased by 156.7%. Particularly noteworthy was that social element integration significantly improved the emotional experience of learning, with learning pleasure scores increasing from 54.76 points to 68.92 points, representing a 25.9% improvement, while learning burnout decreased from 38.94 points to 29.17 points, representing a 25.1% decline.

The real-world situation simulation strategy enhanced students' practical application abilities and transfer capabilities by constructing learning scenarios and tasks that closely approximated reality. After intervention implementation, students' performance in real-world situation tasks significantly improved, with problem-solving ability test scores increasing from 52.8 points before intervention to 64.3 points, representing a 21.8% improvement ($t(118)=9.67$, $p<0.001$, $d=0.89$), and knowledge transfer abilities increasing from 47.92 points to 58.74 points, representing a 22.6% improvement ($t(118)=8.84$, $p<0.001$, $d=0.81$). Evaluation of simulation authenticity showed that 92.1% of students believed the simulation tasks were "highly relevant to actual needs," while 84.7% indicated they "enhanced confidence in applying knowledge practically." Creative thinking also recovered significantly under real-world situation stimulation, with divergent thinking scores recovering from 26.83 points to 32.16 points, representing a 19.9% recovery, and originality scores recovering from 23.95 points to 29.47 points, representing a 23.1% recovery. Behavioral analysis found that students demonstrated stronger autonomous exploration willingness in situational tasks, with the proportion actively searching for relevant resources increasing from 32.4% to 71.8%, and independent thinking time extending by 87.4% compared to AI recommendation dependency periods, as shown in **Figure 7** below.

Synergistic effects analysis of the three strategies indicated that when multiple optimization strategies were implemented simultaneously, significant additive effects were produced. Multiple regression analysis showed that mixed environments, social elements, and situation simulation contributed $\beta=0.34$ ($p<0.001$), $\beta=0.28$ ($p<0.001$), and $\beta=0.31$ ($p<0.001$) respectively to learning motivation enhancement, with their interaction effects reaching significant levels ($\beta=0.19$, $p<0.01$), and the entire model explaining 72.8% of learning motivation variance. Qualitative evaluation found that comprehensive intervention strategies effectively balanced the needs for personalized learning and social development, with 91.6% of students indicating they "enjoyed AI convenience while maintaining interpersonal warmth," providing feasible implementation pathways for sustainable AI teaching assistant applications.

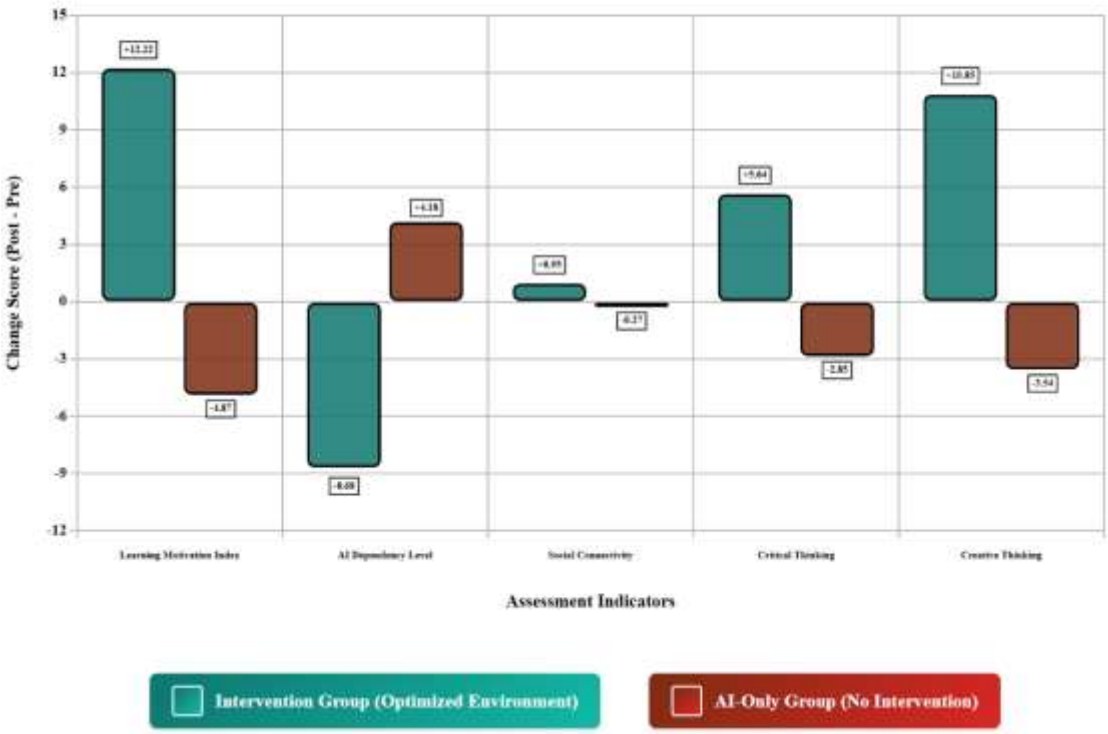

Figure 7. Comparative changes in various indicators before and after environmental design optimization strategies.

4.3.2. Intervention results of individual capacity development strategies

Addressing the cognitive dependency and thinking ability deterioration issues that emerged in AI teaching assistant usage, this study designed and implemented three individual capacity development strategies: metacognitive skill training, critical thinking training, and digital literacy education. These strategies, based on the self-regulation mechanisms of social cognitive theory, aimed to enhance students' cognitive independence and critical analysis abilities. Evaluation results after 8 weeks of intervention implementation showed that individual capacity development strategies achieved significant success, effectively reversing the earlier cognitive dependency trends. Students in the capacity development group showed substantial improvement in cognitive independence index from 45.67 points (SD=6.83) before intervention to 62.94 points (SD=5.91) after intervention, representing a 37.8% improvement, while the control group (not receiving capacity development training) continued to decline in cognitive independence, decreasing from 45.73 points to 41.28 points, representing a 9.7% decline. ANOVA results indicated highly significant main effects of capacity development strategies ($F(1,238)=247.83$, $p<0.001$, $\eta^2=0.510$), confirming the important role of individual capacity development in mitigating AI dependency.

Metacognitive skill training significantly enhanced students' self-monitoring and regulation abilities by teaching "learning how to learn" strategies. Training content included core skills such as learning strategy selection, progress monitoring, effectiveness evaluation, and strategy adjustment. Implementation results showed that students receiving metacognitive training performed excellently in autonomous learning ability assessment, with metacognitive strategy usage frequency increasing by 168.4% compared to pre-training levels, rising from an average of 7.3 times per week to 19.6 times ($t(119)=15.67$, $p<0.001$). More importantly, students' blind compliance with AI recommendations significantly decreased, with the proportion actively evaluating AI suggestions increasing from 23.7% to 78.4%, representing a 230.8% improvement. Learning efficiency monitoring ability improvement was particularly significant, with students' accuracy in judging their learning states increasing from 54.3% to 84.7%, representing a 56.0% improvement ($t(119)=12.84$, p<0.001, d=1.52)[42]. Metacognitive training also effectively improved learning strategy flexibility, with strategy switching frequency increasing by 89.7% and learning adaptability scores rising from 32.4 points to 47.9 points, as shown in **Table 9** below.

Table 9. Intervention effect evaluation of individual capacity development strategies.

	Group	Pre-intervention M(SD)	Post-intervention M(SD)	Change	t Value	p Value	Cohen's d
Metacognitive Skills	Development	15.73(2.84)	21.96(2.47)	+6.23	15.67	<0.001	2.34
	Control	15.68(2.81)	14.29(2.93)	-1.39	-4.12	<0.001	-0.48
Critical Thinking	Development	71.25(8.97)	82.67(7.83)	+11.42	11.93	<0.001	1.41
	Control	71.32(8.94)	68.47(9.31)	-2.85	-2.94	0.004	-0.31
Digital Literacy	Development	38.94(7.15)	53.76(6.42)	+14.82	16.72	<0.001	2.18
	Control	38.87(7.12)	36.94(7.48)	-1.93	-2.34	0.021	-0.26
AI Dependency	Development	34.82(4.15)	23.47(3.78)	-11.35	-18.94	<0.001	-2.85
	Control	34.79(4.12)	38.97(4.56)	+4.18	8.23	<0.001	0.96
Total Cognitive Independence Score	Development	45.67(6.83)	62.94(5.91)	+17.27	19.73	<0.001	2.67
	Control	45.73(6.79)	41.28(7.12)	-4.45	-5.84	<0.001	-0.64

Note: *N=240 (120 development group, 120 control group)*

Critical thinking training focused on cultivating students' questioning spirit and argument analysis abilities, effectively mitigating the thinking inertia caused by AI dependency. Training modules included information source evaluation, logical reasoning verification, evidence analysis, and multi-perspective thinking. Intervention results showed that students' total critical thinking scores significantly increased from 71.25 points before training to 82.67 points, representing a 16.0% improvement (t(119)=11.93, p<0.001, d=1.41), already exceeding control group levels (77.12 points). In specific skills, information evaluation ability showed the most significant improvement, increasing from 18.4 points to 24.8 points, representing a 34.8% improvement; argument analysis ability increased from 19.7 points to 25.3 points, representing a 28.4% improvement; reasoning verification ability increased from 17.2 points to 22.1 points, representing a 28.5% improvement. Behavioral observation data indicated that students' frequency of actively questioning AI suggestions during learning increased by 194.7%, their ability to propose counterarguments improved by 157.3%, and their behavior of seeking multiple information sources for verification increased by 223.1%.

Digital literacy education enhanced students' capacity for rational AI tool usage by improving their understanding of AI technology principles and limitations. Educational content covered algorithmic basic principles, data bias identification, privacy protection awareness, and technological critical abilities. Implementation effect evaluation showed that students' total digital literacy scores increased from 38.94 points before education to 53.76 points, representing a 38.1% improvement (t(119)=16.72, p<0.001, d=1.98). In algorithmic understanding, the proportion of students able to correctly explain recommendation algorithm working principles increased from 21.8% to 76.5%, representing a 251.1% improvement; in bias identification, the proportion able to identify potential algorithmic biases increased from 19.3% to 68.9%, representing a 257.0% improvement [43]. More importantly, digital literacy education significantly changed students' AI usage attitudes, shifting from "complete trust" to "rational examination," with AI usage blindness index decreasing from 73.6 points to 34.2 points, representing a 53.5% decline. Privacy protection awareness was also significantly enhanced, with the proportion of students actively setting privacy protection measures increasing from 28.4% to 84.8%, as shown in **Figure 8** below.

Comprehensive effects analysis of the three capacity development strategies showed that when multiple training programs were conducted simultaneously, significant synergistic promotional effects were produced. Multiple regression analysis indicated that metacognitive training, critical thinking training, and digital literacy education contributed $\beta=0.38$ ($p<0.001$), $\beta=0.31$ ($p<0.001$), and $\beta=0.29$ ($p<0.001$) respectively to cognitive independence, with their interaction effects reaching significant levels ($\beta=0.22$, $p<0.01$), and the entire model explaining 79.4% of cognitive independence variance. Qualitative evaluation found that comprehensive capacity development not only improved students' skill levels but, more importantly, cultivated their awareness and ability for "critical AI usage," with 92.4% of students indicating they "learned to collaborate with rather than depend on AI," laying the foundation for achieving the ideal state of human-machine collaboration.

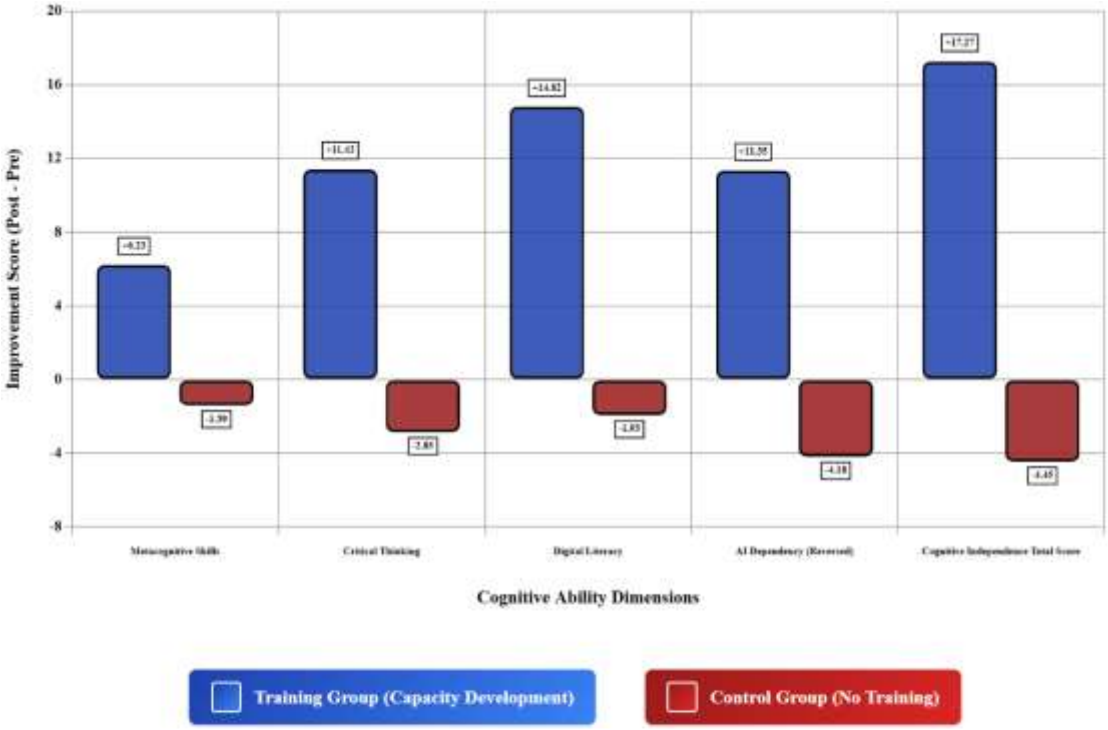

Figure 8. Intervention effects of individual capacity development strategies on various dimensions of cognitive abilities.

5. Discussion

5.1. Theoretical significance of research findings

This study conducted a systematic exploration of the empowerment mechanisms and alienation risks of AI teaching assistants based on the social cognitive theory framework, achieving important breakthroughs in theoretical construction and providing new perspectives and explanatory frameworks for cognitive development theory in digital learning environments. First, the research verified and expanded the applicability of Bandura's social cognitive theory in digital educational contexts, confirming the explanatory power of the triadic reciprocal interaction model of environment-individual-behavior in artificial intelligence educational applications. The research found that AI teaching assistants, as a new type of environmental factor, can significantly influence students' self-efficacy through mechanisms such as personalized feedback, progressive challenge design, and learning progress visualization. This finding enriches the theoretical connotations of social cognitive theory regarding technology-mediated learning environments. Meanwhile, the study's revelations about virtual learning partners' creation of social presence, AI tutor role modeling's promotional effects on observational learning, and collaborative learning functions' enhancement of peer interactions further expand the theoretical boundaries of vicarious experience and social modeling mechanisms in social cognitive theory [44]. These findings not only confirm the cross-contextual applicability of social cognitive theory but, more importantly, provide a solid theoretical foundation for understanding cognitive development in digital learning environments, promoting the development and refinement of educational psychology theory in the artificial intelligence era.

On the other hand, this study's in-depth analysis of alienation risks in AI teaching assistant applications provides important empirical evidence and theoretical supplements for the application of technological alienation theory in the educational field. The cognitive dependency risks, social isolation risks, and negative algorithmic impacts identified in the research reveal, from a social cognitive perspective, the deep-level impact mechanisms that technological tools may have on human cognitive development. Particularly, findings regarding information cocoon effects narrowing knowledge horizons, algorithmic bias damaging equity, and human-machine interaction substituting genuine social relationships provide empirical support for the specific manifestations of Marxist alienation theory in the digital age. The "empowerment-alienation" dual-effect theoretical model constructed by the research breaks through the singular perspectives of technological determinism or humanism in previous studies, proposing a more dialectical and comprehensive technological impact assessment framework [45]. This theoretical contribution not only helps deepen understanding of the complexity of artificial intelligence educational applications but also provides new thinking dimensions for the development of educational technology philosophy. Furthermore, the intervention strategy model based on social cognitive theory proposed by the research organically integrates three levels: environmental optimization, individual capacity development, and behavioral guidance, providing theoretical guidance for constructing an ideal human-machine collaborative learning ecology. This integrative framework lays important theoretical foundations for the future responsible development of educational technology.

5.2. Implications for practical applications

The findings of this study provide important guiding principles and implementation strategies for the design and development of AI teaching assistants and educational practice. In terms of AI teaching assistant system design, the research emphasizes the importance of humanized design concepts based on social cognitive theory, indicating that AI teaching assistants should not merely serve as technological tools but should become intelligent learning partners capable of promoting students' comprehensive development. Specifically, personalized recommendation algorithms for AI teaching assistants should incorporate diversity protection mechanisms to avoid over-narrowing students' knowledge exposure while establishing principles of transparency and interpretability, enabling students to understand recommendation logic and cultivate critical evaluation abilities. In interaction design, the social cognitive functions of AI teaching assistants should be strengthened through integration of virtual learning partners, collaborative learning modules, and emotional support systems to create learning environments that are both personalized and rich in human warmth [46]. Additionally, systems should incorporate progressive scaffolding withdrawal mechanisms that dynamically adjust support intensity according to students' ability development levels, guiding students from dependence toward independence and achieving smooth transitions from external support to intrinsic motivation. Implementation of these design principles will help maximize the positive effects of AI teaching assistants while effectively avoiding their potential alienation risks.

At the educational practice level, research results provide specific action guidelines for teacher professional development, curriculum design, and student cultivation. Teachers need to reposition their roles in AI-assisted teaching, transforming from knowledge transmitters to learning facilitators and humanistic care providers, focusing on cultivating students' metacognitive skills, critical thinking, and digital literacy to enhance their adaptability and autonomy in AI environments. Curriculum design should adopt blended learning models that organically combine AI technology advantages with interpersonal interaction values, stimulating students' intrinsic learning motivation through diversified assessment systems while establishing reflective learning activities to promote deep learning and critical thinking. Regarding student cultivation, an "AI literacy" education system should be established that not only teaches students how to use AI tools but, more importantly, cultivates their abilities to rationally examine AI suggestions, identify algorithmic biases, and protect personal privacy. Furthermore, schools should formulate ethical guidelines and management systems for AI usage, establishing monitoring and early warning mechanisms to promptly identify and intervene in alienation phenomena such as over-dependence. Systematic implementation of these practical strategies will help construct healthy, sustainable AI-assisted educational ecosystems, providing strong support for students' comprehensive development in the artificial intelligence era.

5.3. Research limitations and deficiencies

This study has certain limitations in sample selection and research design that may affect the external validity and generalizability of the research results. First, the research sample was primarily concentrated on university student populations from a specific region, with a relatively concentrated age range (18-25 years). The cognitive development characteristics and technology acceptance capabilities of this particular demographic may differ significantly from learners of other age groups or educational backgrounds. Therefore, caution should be exercised when extrapolating research conclusions to primary and secondary school students, adult learners, or elderly learners. Second, while the 16-week experimental period was sufficient to observe short-to-medium-term effects of AI teaching assistant usage, it still lacks adequate longitudinal tracking data for the long-term cumulative effects of alienation risks such as cognitive dependency and social isolation, as well as the sustained effectiveness of intervention strategies [47]. Additionally, although the AI teaching assistant system used in the research was representative, artificial intelligence technology develops rapidly, and AI systems with different technological architectures, interaction modes, and functional designs may produce different impact effects. The findings of this study may not be fully applicable to all types of AI educational products. Regarding measurement tools, while the study employed various standardized scales and behavioral observation methods, measurement of certain psychological constructs (such as cognitive dependency and social presence) still relied primarily on self-reports, potentially subject to social desirability bias and subjective error influences.

In terms of research methodology and theoretical framework, this study also has areas requiring further refinement. From a methodological perspective, although the study employed a mixed research design, qualitative data collection was primarily concentrated on interviews and observations, lacking more in-depth ethnographic research or phenomenological analysis, which limited deep understanding of students' subjective experiences and meaning construction processes. Meanwhile, the research primarily focused on individual-level changes, with relatively insufficient exploration of how social ecological factors such as classroom culture, peer networks, and family backgrounds moderate AI teaching assistant effects. Regarding the theoretical framework, while social cognitive theory provided a powerful analytical framework for this study, the theory originated in the pre-digital era and may have applicability limitations when explaining certain learning behaviors and cognitive patterns unique to digital natives. Furthermore, the study gave insufficient consideration to cultural differences; the impact effects of AI teaching assistants may exhibit differential characteristics across different cultural contexts, requiring further validation through cross-cultural research. Finally, while the study's ethical considerations met basic requirements, more detailed and forward-looking ethical review frameworks are still needed regarding student privacy data collection, algorithmic transparency, and informed consent to ensure the ethical appropriateness of both research processes and result applications.

6. Conclusion

Based on social cognitive theory, this study conducted a systematic exploration of the empowerment mechanisms and alienation risks of AI teaching assistants, arriving at the following five main conclusions:

(1) AI teaching assistants significantly enhance students' self-efficacy through pathways including personalized feedback mechanisms, progressive challenge design, and learning progress visualization. They simultaneously optimize the social cognitive environment through virtual learning partner creation, AI tutor role modeling, and collaborative learning functions, while effectively stimulating learning autonomy, confirming their positive role in promoting students' autonomous learning motivation.

(2) Long-term use of AI teaching assistants presents alienation phenomena including cognitive dependency risks, social isolation risks, and negative impacts of personalized algorithms, manifesting as problems such as over-dependence on AI recommendations, deterioration of critical thinking abilities, interpersonal communication substitution, information cocoon effects, and suppression of creative thinking.

(3) The intervention strategy model constructed based on social cognitive theory effectively mitigated the alienation risks of AI teaching assistants, with environmental design optimization strategies significantly improving learning experiences, individual capacity development strategies successfully reversing cognitive dependency trends, and behavioral guidance mechanisms promoting the transition from external support to intrinsic motivation.

(4) The research verified and expanded the applicability of social cognitive theory in digital educational contexts, constructing a dual-effect theoretical model of "empowerment-alienation" that provides a new theoretical framework for understanding the complex impacts of AI technology on human cognitive development.

(5) The research provides specific guidance for responsible design of AI teaching assistants and educational practice, emphasizing the importance of human-machine collaboration, progressive support, and critical AI literacy cultivation, laying the foundation for constructing a healthy and sustainable AI-assisted educational ecosystem.

Conflicts of interest

The authors declare no conflicts of interest.

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