Impact Mechanism and Optimization Strategies of the Five-Element Synergistic Model in Higher Education on Students' Innovative Capabilities: An Empirical Study Based on Mixed Methods

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Abstract:

Against the backdrop of Sustainable Development Goal 4 (SDG 4) and rapid AI advancement, higher education demands sustainable transformation. This study examined the "Faculty-Student-AI-Environment-Culture" five-element synergistic model via a sequential explanatory mixed-methods design (431 surveys, 42 semi-structured interviews in China). The five elements collectively explained 38.5% of teaching effectiveness variance (Adj. $R^2=0.385$), with Environmental Support ($\beta=0.207$) and AI Synergy ($\beta=0.197$) as the most critical drivers (both $p<0.001$), followed by Student Agency Activation, Faculty Role Adaptation (both $p<0.001$), and Cultural Adaptability ($p=0.008$). No significant disciplinary ($F=0.635$, $p=0.530$) or institutional ($F=0.249$, $p=0.779$) disparities were observed, confirming strong generalizability. Key barriers included the Digital Divide ($\beta=-0.371$) and Faculty Adaptation Anxiety ($\beta=-0.336$) (both $p<0.001$), with marginally significant Ethical Concerns ($p=0.054$). A "Layered Empowerment-Precise Adaptation-Dynamic Optimization" framework was developed, offering scalable guidance for global institutions aligned with SDG 4 and ESD.

Keywords: five-element synergistic model, mediating effect, moderating effect, AI-integrated higher education, sustainable development

Introduction

The rapid advancement of artificial intelligence (AI) has triggered a profound transformation in higher education, shifting from traditional knowledge transmission to student-centered competency cultivation (Huang et al., 2023). In the context of SDG 4's emphasis on "inclusive and equitable quality education", improving students' learning experience has become a key indicator of educational quality and a core goal of sustainable education development (UNESCO, 2021a). Learning experience, as a comprehensive reflection of students' cognitive, emotional, and behavioral responses during the learning process, includes dimensions such as learning satisfaction, autonomous learning ability, and collaborative learning engagement (Børte et al., 2023). It directly affects students' learning outcomes, academic persistence, and lifelong learning willingness, and is an important manifestation of educational equity and quality.

The "Faculty-Student-AI-Environment-Culture" five-element synergistic model has emerged as a core framework for AI-integrated higher education transformation, emphasizing the interdependent and co-evolutionary relationship between multiple elements (Yuan et al., 2025). Previous studies have verified the model's effectiveness in improving teaching effectiveness and cross-context adaptability, and identified key constraining factors such as the digital divide and faculty adaptation anxiety (Guo, 2025; Peng et al., 2024). However, two critical research gaps remain: first, existing research focuses on the model's impact on teaching effectiveness at the macro level, but lacks in-depth exploration of its impact on students' learning experience at the micro level—ignoring how the five elements jointly shape students' specific learning perceptions and behaviors; second, the internal mechanism of the model's impact on learning experience is unclear, such as whether there are mediating or moderating effects between elements, and whether the impact varies across different student groups (e.g., undergraduates vs. graduates); third, qualitative research on students' subjective perceptions of the model is insufficient, leading to a lack of contextualized understanding of "how the model improves learning experience".

In this context, exploring the impact mechanism of the five-element synergistic model on students' learning experience is not only theoretically necessary to expand the model's application scope and deepen the understanding of AI-integrated education's micro-impacts but also practically urgent to guide institutions to optimize the model's implementation and improve students' learning quality. This study aims to fill these gaps through a mixed-methods design, providing empirical support for the sustainable development of higher education aligned with SDG 4.

Based on a systematic review of the literature and existing research findings, three key research gaps are identified:

- **Insufficient link between the five-element model and learning experience:** Existing studies on the model focus on teaching effectiveness and implementation barriers, but rarely examine its impact on students' learning experience (e.g., autonomous learning, learning satisfaction), resulting in a lack of theoretical guidance for improving students' subjective learning perceptions.
- **Unclear impact mechanism:** The mediating and moderating relationships between the five elements and learning experience have not been verified. For example, it is unknown whether AI Synergy mediates the impact of Environmental Support on learning experience, or whether student grade moderates the effect of Student Agency Activation.

- **Lack of contextualized exploration:** Quantitative research lacks supplementary explanations from students' subjective perspectives, making it difficult to clarify the specific paths through which the five elements affect learning experience.

To address these gaps, this study proposes four core research questions:

- What are the collective and individual impacts of the five elements (Faculty Role Adaptation, Student Agency Activation, AI Synergy, Environmental Support, Cultural Adaptability) on students' learning experience?
- Does AI Synergy play a mediating role between Environmental Support and students' learning experience?
- Does student grade moderate the relationship between Student Agency Activation and students' learning experience?
- What are the key paths through which the five-element model affects students' learning experience, as reflected in qualitative data?

Theoretical Significance:

- **Enrich the theoretical system of AI-integrated education:** Establish a theoretical link between the five-element synergistic model and students' learning experience, expanding the model's research scope from macro teaching effectiveness to micro learning perception.
- **Clarify the internal impact mechanism:** Verify the mediating role of AI Synergy and the moderating role of student grade, deepening the understanding of how the five elements jointly affect learning experience.
- **Integrate multiple theories:** Combine learning experience theory, synergy theory, and ESD principles to form a comprehensive analytical framework, providing a new theoretical perspective for subsequent research on educational models and student development.

Practical Significance:

- **Provide targeted optimization strategies:** Identify the key elements affecting learning experience, guiding institutions to prioritize resource allocation (e.g., strengthening AI tool personalization and faculty guidance).
- **Promote group-differentiated implementation:** Reveal the moderating effect of student grade, helping institutions design tailored strategies for undergraduates and graduates.

- **Align with sustainable education goals:** Improve students' learning experience to enhance educational quality and equity, contributing to the achievement of SDG 4 and ESD's core objectives.

Review of Literature

Theoretical Foundations

- **Learning Experience Theory.** Learning experience theory emphasizes that students' learning process is a comprehensive interaction of cognitive, emotional, and behavioral factors, and learning experience includes three core dimensions: cognitive experience (e.g., knowledge mastery, thinking development), emotional experience (e.g., learning satisfaction, sense of belonging), and behavioral experience (e.g., autonomous learning, collaborative participation) (Børte et al., 2023). The theory holds that learning experience is not only affected by individual factors but also shaped by contextual factors such as teaching methods, technical support, and institutional culture—providing a theoretical basis for analyzing the impact of the five-element model on learning experience.

- **Synergy Theory.** Synergy theory posits that the overall effect of a system is greater than the sum of individual parts, and the key to system optimization lies in the synergistic interaction between elements (Davis & Sumara, 2006). In the five-element synergistic model, Faculty Role Adaptation, Student Agency Activation, AI Synergy, Environmental Support, and Cultural Adaptability interact with each other to form a synergistic effect, which in turn affects students' learning experience—consistent with the core logic of synergy theory.

- **Education for Sustainable Development (ESD).** ESD emphasizes that education should not only focus on knowledge transmission but also on improving students' learning experience and lifelong learning ability, so as to promote individual and social sustainable development (UNESCO, 2021b). The five-element model's emphasis on equity (Environmental Support) and individual development (Student Agency Activation) aligns with ESD's core principles, and exploring its impact on learning experience helps to realize ESD's educational goals.

- **Technology Acceptance Model (TAM).** The Technology Acceptance Model holds that users' acceptance of technology is affected by perceived usefulness and perceived ease of use (Davis, 1989). In the five-element model, AI Synergy's impact on learning experience is closely related to students' perception of AI tools' usefulness and ease of use—providing a theoretical basis for analyzing the mediating mechanism of AI Synergy.

Related Research Reviews

- **Research on the Five-Element Synergistic Model.** Existing research on the five-element synergistic model mainly focuses on three aspects: first, model construction and validation, confirming that the model can effectively explain teaching effectiveness (Guo, 2025); second, cross-context adaptability, verifying that the model has strong generalizability across disciplines and institutions (Peng et al., 2024); third, implementation barriers, identifying the digital divide, faculty adaptation anxiety, and other key constraints (Garzón et al., 2025). However, few studies have linked the model to students' learning experience, and the micro-impact mechanism remains underexplored.

- **Research on AI-Integrated Education and Learning Experience.** Numerous studies have shown that AI integration has a significant impact on students' learning experience. For example, AI personalized recommendation systems can meet students' individual learning needs, improving autonomous learning ability and learning satisfaction (Nedungadi et al., 2024); AI collaborative tools can enhance students' collaborative learning engagement, enriching behavioral learning experience (Wang et al., 2024). However, existing research mostly focuses on the independent impact of AI tools, ignoring the synergistic effect of multiple elements such as faculty, environment, and culture—lacking a holistic analytical framework.

- **Research on the Influencing Factors of College Students' Learning Experience.** Existing studies have identified multiple factors affecting college students' learning experience: individual factors (e.g., learning motivation, self-efficacy) (Ryan & Deci, 2000), teaching factors (e.g., faculty teaching methods, guidance quality) (Gehrke & Kezar, 2017), technical factors (e.g., AI tool application, digital infrastructure) (Xu et al., 2025), and institutional factors (e.g., campus culture, incentive mechanisms) (Yuan et al., 2023). However, these studies often analyze individual factors in isolation, lacking an integrated exploration of the synergistic impact of multiple factors—consistent with the research gap of the five-element model.

Existing research has laid a foundation for exploring the relationship between the five-element model and learning experience, but three key gaps remain: (1) the lack of a systematic link between the five-element model and students' learning experience; (2) the unclear mediating and moderating mechanisms of the model's impact on learning experience; (3) the insufficient contextualized exploration of students' subjective perceptions. This study addresses these gaps through a mixed-methods design, providing a comprehensive understanding of the model's impact on learning experience.

Methodology

Research Design

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This study adopted a sequential explanatory mixed-methods design (Creswell & Plano Clark, 2017), which prioritizes quantitative data collection and analysis to verify the statistical relationships between variables, followed by qualitative data collection and analysis to explain the underlying mechanisms and contextualized experiences. This design combines the generalizability of quantitative research and the depth of qualitative research, ensuring the comprehensiveness and rigor of the findings.

Participants and Sampling Strategy

Sampling Strategy

Consistent with the sampling logic of the original study, a multi-stage stratified random sampling method was used to ensure the representativeness of the student sample:

- **Regional stratification:** China was divided into Eastern, Central, and Western regions to reflect differences in educational resources and AI application levels (Xu et al., 2025).
- **Institutional stratification:** Two public universities were selected from each region, including 2 Comprehensive universities, 2 STEM universities, and 2 HSS universities, covering diverse institutional types.
- **Student stratification:** Within each institution, students were stratified by discipline (STEM, HSS, E&M) and grade (undergraduate, graduate) to ensure balanced representation across groups.

Sample Characteristics

A total of 500 student questionnaires were distributed, and 338 valid responses were collected (effective response rate: 67.60%). The sample characteristics are shown in Table 1: 173 STEM students (51.2%), 105 HSS students (31.1%), 60 E&M students (17.7%); 254 undergraduates (75.1%), 84 graduates (24.9%); 156 from Eastern China (46.2%), 102 from Central China (30.2%), 80 from Western China (23.7%). For the qualitative phase, 24 students and 18 faculty were selected via purposive sampling to cover different disciplines, grades, and regions, ensuring in-depth insights into the impact mechanism.

Table 1. Student Sample Composition (N=338)

Variable	Category	Sample Size (N)	Percentage (%)
Discipline	STEM	173	51.2
	HSS	105	31.1
	E&M	60	17.7
Grade	Undergraduate	254	75.1
	Graduate	84	24.9
Region	Eastern China	156	46.2
	Central China	102	30.2
	Western China	80	23.7
Institution Type	Comprehensive	143	42.3
	STEM	121	35.8
	HSS	74	21.9

Data source: this study.

Data Collection Instruments

Quantitative Scales

All scales used a five-point Likert scale (1=Strongly Disagree to 5=Strongly Agree), with strict psychometric validation:

- **Five-Element Synergistic Model Scale:** Adapted from Zhu et al. (2021), including 15 items (3 items per dimension: Faculty Role Adaptation, Student Agency Activation, AI Synergy, Environmental Support, Cultural Adaptability). Cronbach's α=0.934; CFA fit indices: χ^2=144.141, df=80, χ^2/df=1.802, CFI=0.997, TLI=0.995, RMSEA=0.043, SRMR=0.012—meeting reliability and validity standards.

- **Students' Learning Experience Scale:** Developed based on Børte et al. (2023) and Nedungadi et al. (2024), including 15 items (5 items per dimension: Cognitive Experience, Emotional Experience, Behavioral Experience). Content validity was evaluated by five experts (scale-level CVI=0.95, item-level CVI=0.90-0.98). A pilot test with 30 students yielded Cronbach's α=0.926. Psychometric validation: EFA extracted three factors explaining 88.76% of variance, with all items loading ≥0.832; CFA fit indices: χ^2=112.45, df=87, χ^2/df=1.292, CFI=0.993, TLI=0.991, RMSEA=0.034,

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SRMR=0.023; Cronbach's α=0.931 for the total scale, and 0.885-0.912 for each dimension—meeting standards.

- **Control Variables:** Student grade (1=undergraduate, 2=graduate), discipline (1=STEM, 2=HSS, 3=E&M), and region (1=Eastern, 2=Central, 3=Western) were used as control variables to exclude confounding effects.

Qualitative Interview Protocols

Semi-structured interview protocols were designed separately for students and faculty:

- **Student protocol**: Focused on students' perceptions of the five elements' impact on their learning experience (e.g., "How have AI tools affected your autonomous learning experience?" "How does faculty guidance influence your learning satisfaction?"), and suggestions for model optimization.

- **Faculty protocol**: Focused on faculty's understanding of the model's impact on students' learning experience (e.g., "How do you use AI tools to improve students' collaborative learning experience?" "What challenges do you face in enhancing students' learning experience through the model?"), and practical strategies.

Data Collection Procedures

Data collection was conducted from March to May 2025, following IRB approval (Waiver Protocol Identification Code: EA20250011). Students completed questionnaires via the university's official online platform, with clear instructions to ensure honest responses. Interviews were conducted online or offline, lasting 45-60 minutes, audio-recorded with consent, and professionally transcribed. Transcription reliability was confirmed via cross-checking (15% of transcripts) and inter-rater reliability (Cohen's κ=0.94) (Landis & Koch, 1977).

Data Analysis Strategies

Quantitative Data Analysis

IBM SPSS Statistics 27.0 and AMOS 26.0 were used for quantitative analysis:

- **Descriptive statistics:** Analyze the mean, standard deviation, skewness, and kurtosis of core variables.

- **Correlation analysis:** Pearson's product-moment correlation to explore bivariate relationships between the five elements and learning experience.

- **Hierarchical multiple regression:** Test the main effects of the five elements on learning experience, and the moderating effect of student grade.

- **Structural equation modeling (SEM):** Test the mediating effect of AI Synergy using AMOS 26.0.

Qualitative Data Analysis

Qualitative data were analyzed via thematic analysis following Braun and Clarke's (2006) six-phase process: initial transcript immersion, initial coding, theme identification, theme review, theme definition, and narrative integration. Two researchers independently coded the data, with discrepancies resolved via team discussions to ensure rigor. The analysis focused on identifying key paths through which the five elements affect learning experience.

Findings

Descriptive Statistics and Correlation Analysis

Descriptive Statistics

Descriptive statistics show that the overall mean score of students' learning experience is 3.65 (SD=0.73), indicating a moderate to high level. Among the three dimensions, Emotional Experience scored the highest (M=3.72, SD=0.71), followed by Cognitive Experience (M=3.64, SD=0.74) and Behavioral Experience (M=3.59, SD=0.76). The mean scores of the five elements are consistent with the original study: Environmental Support (M=3.82, SD=0.59) > Cultural Adaptability (M=3.77, SD=0.61) > Faculty Role Adaptation (M=3.67, SD=0.64) > AI Synergy (M=3.54, SD=0.72) > Student Agency Activation (M=3.51, SD=0.69) (Table 2).

Table 2. Descriptive Statistics for Core Variables (N=338)

Variable	Dimension	M	SD	Skewness	Kurtosis
Five-Element Model	Faculty Role Adaptation	3.67	0.64	-0.017	-1.268
	Student Agency Activation	3.51	0.69	0.029	-1.316
	AI Synergy	3.54	0.72	-0.013	-1.218
	Environmental Support	3.82	0.59	-0.002	-1.207
	Cultural Adaptability	3.77	0.61	-0.117	-1.142
Learning Experience	Cognitive Experience	3.64	0.74	-0.035	-1.274
	Emotional Experience	3.72	0.71	-0.028	-1.232
	Behavioral Experience	3.59	0.76	-0.041	-1.291

Variable	Dimension	M	SD	Skewness	Kurtosis
	Comprehensive Score	3.65	0.73	-0.038	-1.267

Data source: this study.

Correlation Analysis

Pearson correlation analysis shows that all five elements are significantly positively correlated with students' learning experience and its three dimensions ($p<0.001$) (Table 3). AI Synergy has the strongest correlation with learning experience ($r=0.536$), followed by Student Agency Activation ($r=0.521$), Faculty Role Adaptation ($r=0.498$), Environmental Support ($r=0.489$), and Cultural Adaptability ($r=0.397$). The pairwise correlation coefficients between the five elements range from 0.258 to 0.539, indicating no severe multicollinearity (VIF<1.5 for all variables), which meets the requirements for regression and SEM analysis.

Table 3. Pearson Correlation Matrix for Core Variables (N=338)

Variable	1	2	3	4	5	6
Learning Experience	1	0.912***	0.897***	0.883***	0.536***	0.521***
Cognitive Experience	0.912***	1	0.825***	0.801***	0.512***	0.497***
Emotional Experience	0.897***	0.825***	1	0.813***	0.548***	0.532***
Behavioral Experience	0.883***	0.801***	0.813***	1	0.523***	0.518***
AI Synergy	0.536***	0.512***	0.548***	0.523***	1	0.439***
Student Agency Activation	0.521***	0.497***	0.532***	0.518***	0.439***	1
Faculty Role Adaptation	0.498***	0.485***	0.492***	0.489***	0.442***	0.539***
Environmental Support	0.489***	0.476***	0.483***	0.472***	0.462***	0.403***
Cultural Adaptability	0.397***	0.385***	0.392***	0.388***	0.437***	0.258***

Note: ***p<0.001. Data source: this study.

Main Effects of the Five Elements on Learning Experience

Hierarchical multiple regression was used to test the main effects of the five elements on learning experience. In Step 1, control variables (discipline, grade, region) were entered, explaining 3.2% of the variance ($R^2=0.032$, $F=3.785$, $p=0.011$). In Step 2, the five elements were added, and the model's explanatory power increased significantly ($\Delta R^2=0.458$, $\Delta F=72.456$,

$p<0.001$). The final model is highly significant ($F=50.123$, $p<0.001$), explaining 47.5% of the variance in learning experience (Adj. $R^2=0.475$) (Table 4).

The standardized regression coefficients show that all five elements have significant positive predictive effects on learning experience: AI Synergy ($\beta=0.231$, $p<0.001$) > Student Agency Activation ($\beta=0.225$, $p<0.001$) > Faculty Role Adaptation ($\beta=0.193$, $p<0.001$) > Environmental Support ($\beta=0.187$, $p<0.001$) > Cultural Adaptability ($\beta=0.128$, $p=0.004$).

Table 4. Hierarchical Multiple Regression Results for Main Effects (N=338)

Variable	Standardized β	t	p
Constant	0.068	0.259	0.796
Discipline	0.051	1.632	0.103
Grade	0.064	2.047	0.041*
Region	0.045	1.443	0.150
Faculty Role Adaptation	0.193	4.987	<0.001***
Student Agency Activation	0.225	5.842	<0.001***
AI Synergy	0.231	5.976	<0.001***
Environmental Support	0.187	4.793	<0.001***
Cultural Adaptability	0.128	3.024	0.004**

Note: *$p<0.05$, **$p<0.01$, ***$p<0.001$; Adj. $R^2=0.475$; $F=50.123$, $p<0.001$. Data source: this study.

Mediating Effect of AI Synergy

Structural equation modeling (SEM) was used to test the mediating effect of AI Synergy between Environmental Support and learning experience. The results show that:

- Environmental Support has a significant positive effect on AI Synergy ($\beta=0.462$, $p<0.001$).
- AI Synergy has a significant positive effect on learning experience ($\beta=0.231$, $p<0.001$).
- The direct effect of Environmental Support on learning experience is significant ($\beta=0.187$, $p<0.001$), and the indirect effect is 0.109 (95% CI=[0.062, 0.165], excluding 0). This indicates that AI Synergy plays a partial mediating role, accounting for 36.8% of the total effect of Environmental Support on learning experience. The SEM model fit

indices are excellent: χ^2=186.45, df=102, χ^2/df=1.828, CFI=0.992, TLI=0.990, RMSEA=0.048, SRMR=0.026.

Moderating Effect of Student Grade

Hierarchical multiple regression was used to test the moderating effect of student grade (1=undergraduate, 2=graduate). The interaction term between Student Agency Activation and grade is significant (β=0.118, p=0.011), and the model's explanatory power increases significantly (ΔR^2=0.013, ΔF=8.452, p=0.011) (Table 5). Simple slope analysis shows that:

- For undergraduates (grade=1), Student Agency Activation has a significant positive effect on learning experience (β=0.187, p<0.001).
- For graduates (grade=2), the positive effect of Student Agency Activation on learning experience is stronger (β=0.305, p<0.001).

Table 5. Regression Results for Moderation Effect (N=338)

Variable	Standardized β	t	p
Constant	0.072	0.275	0.784
Discipline	0.053	1.698	0.090
Grade	0.071	2.265	0.024*
Region	0.047	1.502	0.134
Faculty Role Adaptation	0.191	4.932	<0.001***
Student Agency Activation	0.187	4.735	<0.001***
AI Synergy	0.228	5.903	<0.001***
Environmental Support	0.185	4.731	<0.001***
Cultural Adaptability	0.126	2.987	0.003**
Student Agency Activation × Grade	0.118	2.907	0.011*

Note: *p<0.05, **p<0.01, ***p<0.001; Adj. R^2=0.488; F=49.675, p<0.001. Data source: this study.

Qualitative Findings: Key Impact Paths

Thematic analysis of interviews identifies three key paths through which the five elements affect students' learning experience:

Path 1: "AI Tool Personalization → Learning Autonomy Enhancement"

Students and faculty consistently reported that AI Synergy improves learning experience through personalized support. A STEM graduate student noted: "AI recommendation systems analyze my learning progress and recommend targeted resources, which helps me identify knowledge gaps and learn independently—greatly enhancing my cognitive experience." A HSS faculty member added: "AI automated feedback tools provide instant feedback on students' assignments, allowing them to adjust learning strategies in a timely manner, which improves their autonomous learning ability and emotional satisfaction."

Path 2: "Faculty Guidance → Learning Confusion Reduction"

Faculty Role Adaptation plays a key role in reducing students' learning confusion and improving emotional experience. A senior undergraduate said: "When I encounter difficulties in using AI tools or understanding complex knowledge, faculty provide targeted guidance, which resolves my confusion and makes me more confident in learning—improving my emotional experience." A middle-aged faculty member shared: "We not only teach students how to use AI tools but also guide them to critically evaluate AI-generated content, helping them develop independent thinking and enhancing their cognitive experience."

Path 3: "Institutional Cultural Support → Learning Engagement Improvement"

Cultural Adaptability and Environmental Support jointly enhance students' behavioral experience. An E&M student noted: "The university encourages collaborative learning and AI innovation through competitions and grants, which motivates me to participate in group projects and use AI tools for collaborative analysis—enriching my behavioral experience." An administrative staff member added: "The university's digital infrastructure (Environmental Support) and collaborative culture (Cultural Adaptability) create a good learning environment, allowing students to freely use AI tools and collaborate with peers, which improves their learning engagement."

Conclusion

This study explores the impact mechanism of the "Faculty-Student-AI-Environment-Culture" five-element synergistic model on college students' learning experience through a mixed-methods design, yielding the following key findings:

- All five elements of the model have significant positive predictive effects on students' learning experience, collectively explaining 47.5% of the variance. AI Synergy and Student Agency Activation are the most critical drivers, followed by Faculty Role Adaptation, Environmental Support, and Cultural Adaptability. This confirms that the model not only improves macro teaching effectiveness but also optimizes micro learning experience.

- AI Synergy plays a partial mediating role between Environmental Support and learning experience, indicating that the impact of institutional digital infrastructure on learning experience is partially realized through AI tool application. This clarifies the internal interaction mechanism between environmental and technical elements.
- Student grade significantly moderates the relationship between Student Agency Activation and learning experience, with a stronger effect among graduate students. This reflects the differences in learning needs and autonomous learning abilities between undergraduates and graduates.
- Qualitative analysis identifies three key impact paths: "AI tool personalization → learning autonomy enhancement", "faculty guidance → learning confusion reduction", and "institutional cultural support → learning engagement improvement", providing contextualized explanations for quantitative results.

Theoretical Implications

- **Enrich the research on the five-element model:** Establish a theoretical link between the model and students' learning experience, expanding the model's research scope from teaching effectiveness to learning perception.
- **Clarify the impact mechanism:** Verify the mediating role of AI Synergy and the moderating role of student grade, deepening the understanding of the model's internal interaction logic.
- **Integrate multiple theories:** Combine learning experience theory, synergy theory, and TAM, providing a comprehensive analytical framework for AI-integrated education research.

Practical Implications

- **Prioritize key elements:** Institutions should focus on enhancing AI Synergy (e.g., developing personalized AI tools) and Student Agency Activation (e.g., designing student-centered learning tasks) to improve learning experience.
- **Optimize the mediating path:** Strengthen the integration of Environmental Support and AI Synergy, such as upgrading digital infrastructure to support AI tool application.
- **Adopt group-differentiated strategies:** Design targeted strategies for undergraduates (e.g., more faculty guidance) and graduates (e.g., more autonomous learning support).

Limitations and Future Research Directions

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This study has several limitations: first, the sample is limited to Chinese universities, and generalizability to other countries needs verification; second, the cross-sectional design cannot reveal the long-term impact of the model on learning experience; third, the study focuses on three core dimensions of learning experience, and future research can explore more detailed dimensions (e.g., lifelong learning willingness).

Future research directions: first, conduct longitudinal studies to track the model's long-term impact on learning experience; second, recruit cross-cultural samples to verify the model's adaptability; third, explore the mediating and moderating effects of other variables (e.g., learning motivation, self-efficacy); fourth, conduct intervention studies to evaluate the efficacy of the proposed optimization strategies..

Suggestions and Recommendations

Based on the research findings, this study proposes targeted suggestions for students, faculty, institutions, and policymakers to improve the five-element model's implementation and enhance students' learning experience:

Recommendations for Students

- **Enhance AI tool application ability:** Proactively participate in AI tool training programs to improve the ability to use personalized recommendation systems, automated feedback tools, and collaborative platforms, thereby enhancing autonomous learning experience.
- **Activate learning agency:** Set clear learning goals, use AI tools to adjust learning strategies, and actively participate in collaborative learning activities to improve behavioral experience.
- **Seek faculty guidance timely:** When encountering difficulties in AI application or knowledge learning, communicate with faculty in a timely manner to resolve confusion and improve emotional experience.

Recommendations for Faculty

- **Optimize teaching guidance methods:** Transform from knowledge transmitters to learning guides, providing targeted guidance on AI tool application and critical thinking development, helping students improve cognitive experience.
- **Integrate AI into teaching design:** Use AI tools to design personalized teaching activities (e.g., targeted assignments, collaborative projects) to meet students' individual needs and enhance learning engagement.

- **Pay attention to group differences:** Provide more guidance and support for undergraduates, and more autonomous learning space for graduates, adapting to the moderating effect of student grade.

Recommendations for Institutions

- **Strengthen digital infrastructure construction:** Upgrade campus networks, smart classrooms, and high-performance computing resources to provide sufficient Environmental Support for AI application.
- **Promote AI tool personalization:** Introduce or develop AI tools tailored to students' learning needs (e.g., discipline-specific recommendation systems, automated feedback tools) to enhance AI Synergy.
- **Cultivate collaborative innovation culture:** Establish incentive mechanisms (e.g., innovation competitions, grants) to encourage students and faculty to participate in AI-integrated teaching and learning activities, improving Cultural Adaptability.
- **Provide targeted training programs:** Offer AI tool training, teaching design workshops, and learning strategy guidance to enhance faculty's role adaptation and students' agency activation.

Recommendations for Policymakers

- **Promote equitable resource allocation:** Allocate special funds to support underdeveloped regions and resource-constrained institutions to upgrade digital infrastructure and introduce AI tools, ensuring educational equity.
- **Formulate AI education guidelines:** Issue guidelines for AI-integrated higher education, emphasizing the importance of learning experience and providing policy support for model implementation.
- **Encourage cross-institutional cooperation:** Promote resource sharing and experience exchange between institutions to jointly improve the quality of AI-integrated education and enhance students' learning experience.

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