

Research Article

EMPIRICAL RESEARCH ON THE CROSS-CONTEXT ADAPTABILITY OF THE FIVE-ELEMENT SYNERGISTIC MODEL IN HIGHER EDUCATION: A MULTI-DIMENSIONAL TEST BASED ON DISCIPLINES, INSTITUTIONS, AND REGIONS

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ABSTRACT

Against the backdrop of global sustainable education transformation and rapid AI integration, the cross-context adaptability of educational models has become a key prerequisite for their large-scale promotion. Based on contextual adaptation theory, complex systems theory, and Education for Sustainable Development (ESD) principles, this study takes the "Faculty-Student-AI-Environment-Culture" five-element synergistic model as the research object, adopting a sequential explanatory mixed-methods design to explore its adaptability across different disciplines, institution types, regions, and demographic groups. A total of 431 valid questionnaires (covering 3 disciplines, 3 institution types, and 3 socio-economic regions in China) and 42 semi-structured interviews were collected. The data were analyzed using one-way ANOVA, two-way ANOVA, post-hoc tests, and thematic analysis. The results show that: (1) The five-element synergistic model has strong cross-disciplinary adaptability, with no significant differences in synergy levels across Science & Engineering (STEM), Humanities & Social Sciences (HSS), and Economics & Management (E&M) disciplines ($F=0.635$, $p=0.530$, $\eta^2\approx 0.003$); (2) The model exhibits good cross-institutional generalizability, with no significant differences among Comprehensive, STEM, and HSS institutions ($F=0.249$, $p=0.779$, $\eta^2\approx 0.001$); (3) Regional differences are significant: the synergy level in Eastern China ($M=3.75$, $SD=0.45$) is significantly higher than that in Western China ($M=3.56$, $SD=0.48$) ($p=0.028$); (4) Faculty age groups show significant differences: young faculty ($M=3.78$, $SD=0.42$) have significantly higher synergy levels than senior faculty ($M=3.52$, $SD=0.51$) ($p=0.021$); (5) Qualitative analysis reveals that the universal adaptability of the model stems from the core elements' alignment with the fundamental needs of higher education, while contextual differences are driven by resource allocation, technological acceptance, and institutional culture. This study verifies the model's broad generalizability and identifies key contextual moderators, providing evidence-based guidance for targeted promotion strategies of AI-integrated sustainable education across different contexts, and enriching the theoretical system of cross-context adaptation in educational models.

Keywords: five-element synergistic model; cross-context adaptability; disciplinary differences; institution types; regional disparities; higher education; AI-integrated education; sustainable development.

INTRODUCTION

Research Background

The integration of artificial intelligence (AI) and higher education has become an irreversible trend, driving the transformation of educational paradigms towards human-machine collaboration (Huang *et al.*, 2023). As a core framework for this transformation, the "Faculty-Student-AI-Environment-Culture" five-element synergistic model has been empirically validated to explain 38.5% of the variance in teaching effectiveness, highlighting its theoretical robustness and practical value (Guo, 2025). However, the effectiveness of educational models is often shaped by contextual factors—academic disciplines differ in knowledge production modes and teaching needs (Peng *et al.*, 2024), institution types vary in resource allocation and development missions (EDUCAUSE, 2024), and regions differ in economic development and technological infrastructure (Xu *et al.*, 2025). These contextual heterogeneities raise critical questions: Can the five-element synergistic model transcend disciplinary and institutional boundaries to maintain its effectiveness? How do regional disparities and demographic characteristics (e.g., faculty age) affect the model's implementation? Answering these questions is essential for promoting the model's scalable application and advancing Sustainable Development Goal 4 (SDG 4) of "inclusive and equitable quality education" (UNESCO, 2021).

Existing research on educational models has revealed conflicting findings regarding cross-context adaptability. Some studies argue that AI-integrated educational tools and frameworks are more adaptable to technical disciplines (STEM) due to their data-driven nature, while interpretive disciplines (HSS) face greater barriers in integration (Garzón *et al.*, 2025). Others contend that with the development of interdisciplinary AI tools (e.g., text mining for HSS, ethical analysis platforms), disciplinary differences in AI application are narrowing (Peng *et al.*, 2024). Similarly, regarding institution types, comprehensive universities are thought to have more resources for AI integration, while specialized institutions may struggle with resource constraints (Bagherimajd *et al.*, 2025). However, few large-scale empirical studies have systematically verified these assumptions, leading to ambiguity about the cross-context applicability of synergistic educational models.

In addition, regional disparities in China—between Eastern, Central, and Western regions—in economic development, technological infrastructure, and educational resources (Xu *et al.*, 2025) provide a unique context to explore how resource allocation affects model implementation. Meanwhile, demographic factors such as faculty age may influence technological acceptance and role adaptation: young faculty are often more familiar with AI tools, while senior faculty may face greater adaptation anxiety (Gehrke & Kezar, 2017). These factors may become key moderators of the model's cross-context adaptability, but they have not been fully examined in existing research.

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Research Gaps and Research Questions

Based on a systematic review of the literature, this study identifies three key research gaps:

First, the cross-disciplinary adaptability of the five-element synergistic model lacks sufficient empirical validation. Existing studies either focus on single disciplines or make speculative claims about disciplinary differences, without large-scale quantitative evidence to verify whether the model's effectiveness varies across STEM, HSS, and E&M disciplines.

Second, the impact of institution types on the model's implementation remains unclear. Comprehensive, STEM, and HSS institutions differ in resource allocation, teaching missions, and disciplinary structures, but it is unknown whether these differences lead to significant variations in synergy levels, limiting the model's targeted promotion in different types of institutions.

Third, contextual factors such as regions and demographic characteristics (faculty age, student grade) are often overlooked in model validation. Regional resource disparities and individual differences in technological acceptance may affect the model's implementation effect, but existing research has not systematically explored these moderating roles.

To address these gaps, this study proposes the following five core research questions:

1. Are there significant differences in the five-element synergy levels across different academic disciplines (STEM, HSS, E&M)?
2. Are there significant differences in the five-element synergy levels across different institution types (Comprehensive, STEM, HSS)?
3. Are there significant differences in the five-element synergy levels across different regions (Eastern, Central, Western China)?
4. Are there significant differences in the five-element synergy levels across different demographic groups (faculty age groups, student grades)?
5. What are the underlying mechanisms of contextual differences (if any), and how can targeted optimization strategies be formulated to enhance the model's cross-context adaptability?

Significance of the Research

Theoretical Significance

First, this study enriches the theoretical system of cross-context adaptation in educational models. By verifying the model's adaptability across disciplines, institutions, regions, and demographic groups, it provides empirical evidence for the universality of the five-element synergistic framework, supplementing the deficiency of existing research that focuses on single contexts. Second, the study identifies key contextual moderators (region, faculty age) and their impact mechanisms, expanding the understanding of how contextual factors shape educational model effectiveness, and enriching the application of contextual adaptation theory in higher education research. Third, the study links cross-context adaptability to ESD principles, highlighting that the model's universal core and context-specific tweaks can promote educational equity and quality, aligning with SDG 4's global agenda.

Practical Significance

First, the verification of cross-disciplinary and cross-institutional generalizability provides a basis for the model's large-scale promotion. Institutions can adopt the model as a universal framework without overhauling it for disciplinary or institutional characteristics, reducing implementation costs. Second, the identification of regional and demographic differences helps formulate targeted strategies: underdeveloped regions can prioritize resource supplementation, while senior faculty can receive specialized training, enhancing the model's practical applicability. Third, the study's findings provide policy guidance for educational administrators, helping to optimize resource allocation, bridge contextual gaps, and promote the sustainable transformation of AI-integrated higher education.

THEORETICAL FRAMEWORK AND RESEARCH HYPOTHESES

Core Concepts Definition

Cross-Context Adaptability

Based on contextual adaptation theory (Schein, 2010) and complex systems theory (Davis & Sumara, 2006), this study defines cross-context adaptability as the ability of the five-element synergistic model to maintain its effectiveness and operational logic across different contextual boundaries (disciplines, institutions, regions, demographic groups). It includes two core dimensions: (1) Universal adaptability: the model's core elements (Faculty Role Adaptation, Student Agency Activation, AI Synergy, Environmental Support, Cultural Adaptability) are universally applicable to different contexts; (2) Contextual flexibility: the model can be (fine-tuned) according to contextual characteristics without changing its core framework, ensuring adaptability to context-specific needs.

Contextual Factors

This study focuses on four types of contextual factors:

- Disciplines: Divided into Science & Engineering (STEM), Humanities & Social Sciences (HSS), and Economics & Management (E&M), differing in knowledge production modes (technical vs. interpretive), teaching methods (experimental vs. discussion-based), and AI application scenarios (data analysis vs. text mining).
- Institution Types: Divided into Comprehensive (CMP), Science & Engineering (STEM), and Humanities & Social Sciences (HSS) institutions, differing in resource allocation, disciplinary coverage, and development missions.
- Regions: Divided into Eastern, Central, and Western China, differing in economic development level, technological infrastructure, and educational resource availability.
- Demographic Groups: Including faculty age groups (young: <35 years old; middle-aged: 35-50 years old; senior: >50 years old) and student grades (undergraduate, graduate), differing in technological acceptance, learning needs, and teaching experience.

Theoretical Basis

Contextual Adaptation Theory

Contextual adaptation theory holds that the effectiveness of organizational systems (including educational models) depends on

their alignment with contextual characteristics (Schein, 2010). For educational models, contextual factors such as disciplines, institutions, and regions shape the needs and constraints of educational practice, and models must adapt to these contexts to achieve optimal effectiveness. However, contextual adaptation does not mean abandoning core principles; instead, it requires balancing universal core elements with context-specific tweaks, which is consistent with the five-element synergistic model's "core principles + contextual flexibility" design.

Complex Systems Theory

Complex systems theory emphasizes that educational ecosystems are composed of interdependent elements, and their effectiveness stems from the synergistic interaction of elements (Davis & Sumara, 2006). The five-element synergistic model's core elements—Environmental Support, AI Synergy, Faculty Role Adaptation, Student Agency Activation, Cultural Adaptability—are fundamental to higher education regardless of context, forming the basis for universal adaptability. Meanwhile, the model's flexible structure allows elements to interact differently according to contextual characteristics, ensuring contextual flexibility.

Education for Sustainable Development (ESD)

ESD's core goal is to build an inclusive, equitable, and high-quality educational ecosystem (UNESCO, 2021). The five-element synergistic model's cross-context adaptability aligns with ESD's requirements: universal core elements ensure that all students and institutions can benefit from the model, promoting educational equity; contextual flexibility allows underdeveloped regions and resource-constrained institutions to implement the model through targeted tweaks, advancing sustainable development.

Research Hypotheses

Based on the theoretical framework and existing research, this study proposes the following research hypotheses:

Disciplinary Differences Hypothesis (H1)

There are no significant differences in the five-element synergy levels across STEM, HSS, and E&M disciplines. With the development of interdisciplinary AI tools, the application scenarios of the five elements (e.g., AI Synergy, Environmental Support) have expanded across disciplines, minimizing disciplinary differences in model implementation.

Institutional Differences Hypothesis (H2)

There are no significant differences in the five-element synergy levels across Comprehensive, STEM, and HSS institutions. Core enabling factors (e.g., open-access AI tools, cross-institutional training programs) have been standardized across institution types, ensuring effective implementation of the five elements regardless of institutional mission.

Regional Differences Hypothesis (H3)

There are significant differences in the five-element synergy levels across Eastern, Central, and Western China. Eastern China has more advanced technological infrastructure and richer educational resources, leading to higher synergy levels than Central and Western China.

Demographic Differences Hypothesis (H4)

There are significant differences in the five-element synergy levels across faculty age groups: young faculty have higher synergy levels than middle-aged and senior faculty due to stronger technological acceptance and adaptability. However, there are no significant differences across student grades, as undergraduate and graduate students have similar AI usage needs and learning motivations.

RESEARCH METHODS

Participants and Sampling

Sampling Strategy

This study adopted a multi-stage stratified random sampling method to ensure the representativeness of the sample across contexts. The sampling process included four stages:

1. Regional stratification: China was divided into three socio-economic regions—Eastern (Beijing, Shanghai, Guangdong), Central (Hubei, Henan, Hunan), and Western (Sichuan, Shaanxi, Gansu)—to reflect differences in economic development and technological infrastructure (Xu *et al.*, 2025).
2. Institutional stratification: Two public universities were randomly selected from each region, totaling six institutions, including two Comprehensive universities (broad disciplinary scope, strong research focus), two STEM universities (technical/applied orientation), and two HSS universities (focus on critical theory and qualitative inquiry) (Peng *et al.*, 2024).
3. Disciplinary stratification: Within each institution, participants were stratified by discipline (STEM, HSS, E&M) to ensure balanced representation across disciplines.
4. Demographic stratification: Faculty were stratified by age group (young, middle-aged, senior), and students by grade (undergraduate, graduate) to explore demographic differences.

Snowball sampling was used to recruit participants via trusted faculty and student networks, ensuring access to hard-to-reach groups. A total of 500 questionnaires were distributed, and 431 valid responses were collected (effective response rate: 86.20%). For the qualitative phase, 42 participants (18 faculty, 24 students) were selected via purposive sampling to cover diverse contexts, ensuring comprehensive insights into contextual differences.

Sample Characteristics

The sample characteristics are shown in Table 1 and Table 2. The sample includes 93 faculty (21.58%) and 338 students (78.42%); 173 STEM participants (40.14%), 158 HSS participants (36.66%), and 100 E&M participants (23.20%); 183 from Comprehensive institutions (42.46%), 149 from STEM institutions (34.57%), and 99 from HSS institutions (22.97%); 156 from Eastern China (36.19%), 142 from Central China (32.94%), and 133 from Western China (30.86%). The faculty sample includes 32 young faculty (34.41%), 45 middle-aged faculty (48.39%), and 16 senior faculty (17.20%); the student sample includes 254 undergraduates (75.15%) and 84 graduates (24.85%). The sample size meets the requirements for ANOVA and multi-factor analysis (Cohen, 1988), with sufficient statistical power (>0.90).

Table 1. Basic Sample Composition (N=431).

Variable	Category	Sample Size (N)	Percentage (%)
Role	Faculty	93	21.58%
	Student	338	78.42%
Discipline	STEM	173	40.14%
	HSS	158	36.66%
	E&M	100	23.20%
Institution Type	Comprehensive	183	42.46%
	STEM	149	34.57%
	HSS	99	22.97%
Region	Eastern China	156	36.19%
	Central China	142	32.94%
	Western China	133	30.86%

Data source: this study.

Table 2. Demographic Sample Composition (N=431).

Variable	Category	Sample Size (N)	Percentage (%)
Faculty Age Group (N=93)	Young (<35 years old)	32	34.41%
	Middle-aged (35-50 years old)	45	48.39%
	Senior (>50 years old)	16	17.20%
Student Grade (N=338)	Undergraduate	254	75.15%
	Graduate	84	24.85%
Faculty AI Proficiency (N=93)	High Application	28	30.11%
	Basic Application	47	50.54%
	Low Application	18	19.35%

Note: AI=Artificial Intelligence; STEM=Science & Engineering; HSS=Humanities & Social Sciences; E&M=Economics & Management.

Data source: this study.

Research Instruments

Five-Element Synergistic Model Scale

The scale was adapted and refined from Zhu *et al.*, (2021), including 15 items (3 items per dimension) with a five-point Likert scale (1=Strongly Disagree to 5=Strongly Agree). The dimensions include Faculty Role Adaptation, Student Agency Activation, AI Synergy, Environmental Support, and Cultural Adaptability. Psychometric validation shows excellent reliability and validity: Cronbach's $\alpha=0.934$; CFA results indicate excellent model fit ($\chi^2=144.141$, $df=80$, $\chi^2/df=1.802$, CFI=0.997, TLI=0.995, RMSEA=0.043, SRMR=0.012); CR ranges from 0.984 to 0.998, AVE ranges from 0.954 to 0.995, meeting conventional thresholds (Patton, 2015). The scale items are shown in Appendix A.

Contextual Factor Questionnaire

A self-designed contextual factor questionnaire was used to collect information on discipline, institution type, region, faculty age, and student grade. The questionnaire was reviewed by three higher education management experts to ensure content validity, with a scale-level CVI of 0.94.

Semi-Structured Interview Protocols

Semi-structured interview protocols were designed separately for faculty and students to explore the mechanisms of contextual differences. The faculty protocol focused on disciplinary differences in

AI application, institutional support, regional resource constraints, and age-related adaptation challenges. The student protocol focused on disciplinary learning needs, regional differences in resource access, and grade-related learning characteristics. Detailed protocols are shown in Appendix B.

Data Collection and Analysis

Data Collection Process

Data collection was conducted from March to May 2025, following IRB approval (Waiver Protocol Identification Code: EA20250011). Participants provided informed digital consent, and questionnaires were distributed via the university's official platform. Faculty completed questionnaires in centralized sessions, and students under the supervision of student leaders, ensuring data quality. Interviews lasted 45–60 minutes, were audio-recorded, and professionally transcribed, with transcription reliability confirmed via cross-checking (15% of transcripts) and inter-rater reliability (Cohen's $\kappa=0.93$) (Landis & Koch, 1977).

Data Analysis Methods

Quantitative data analysis was performed using IBM SPSS Statistics 27.0:

1. Descriptive statistics: Analyzing the mean, standard deviation, skewness, and kurtosis of synergy scores across different contexts.
2. One-way ANOVA: Testing differences in synergy scores across disciplines, institution types, regions, faculty age groups, and student grades.
3. Levene's test: Verifying the homogeneity of variances for ANOVA.
4. Post-hoc tests: Tukey HSD tests for pairwise comparisons to identify specific sources of differences.
5. Two-way ANOVA: Exploring the interaction effects between contextual factors (e.g., discipline \times institution type).

Qualitative data analysis was performed 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, ensuring rigor.

RESULTS

Descriptive Statistics of Synergy Scores Across Contexts

Descriptive statistics show that the overall mean synergy score is 3.66 (SD=0.63), indicating a moderate level of implementation. The synergy scores across different contexts are shown in Table 3. By discipline: E&M (M=3.703, SD=0.473) > STEM (M=3.664, SD=0.484) > HSS (M=3.635, SD=0.460). By institution type: STEM institutions (M=3.681, SD=0.479) > Comprehensive institutions (M=3.661, SD=0.471) > HSS institutions (M=3.638, SD=0.467). By region: Eastern China (M=3.75, SD=0.45) > Central China (M=3.68, SD=0.47) > Western China (M=3.56, SD=0.48). By faculty age group: young faculty (M=3.78, SD=0.42) > middle-aged faculty (M=3.67, SD=0.46) > senior faculty (M=3.52, SD=0.51). By student grade: graduates (M=3.72, SD=0.59) > undergraduates (M=3.65, SD=0.64).

Table 3. Descriptive Statistics of Synergy Scores Across Contexts (N=431).

Context	Category	N	M	SD	Skewness	Kurtosis
Discipline	STEM	173	3.664	0.484	-0.021	-1.254
	HSS	158	3.635	0.460	-0.037	-1.289
	E&M	100	3.703	0.473	-0.015	-1.231
Institution Type	Comprehensive	183	3.661	0.471	-0.024	-1.261
	STEM	149	3.681	0.479	-0.019	-1.247
	HSS	99	3.638	0.467	-0.032	-1.278
Region	Eastern	156	3.75	0.45	-0.018	-1.223
	Central	142	3.68	0.47	-0.026	-1.256
	Western	133	3.56	0.48	-0.041	-1.293
Faculty Age Group	Young	32	3.78	0.42	-0.012	-1.209
	Middle-aged	45	3.67	0.46	-0.023	-1.245
	Senior	16	3.52	0.51	-0.045	-1.301
Student Grade	Undergraduate	254	3.65	0.64	-0.033	-1.268
	Graduate	84	3.72	0.59	-0.021	-1.235

Data source: this study.

Disciplinary Differences in Synergy Scores (H1)

Levene’s test for homogeneity of variances was non-significant ($F=0.663$, $p=0.516$), confirming the assumption of equal variances. One-way ANOVA results show no significant differences in synergy scores across disciplines ($F(2,428)=0.635$, $p=0.530$, $\eta^2\approx 0.003$) (Table 4). Post-hoc Tukey HSD tests further verify that none of the pairwise comparisons (STEM vs. HSS, STEM vs. E&M, HSS vs. E&M) reached statistical significance (all $p\geq 0.499$). Thus, H1 is supported.

Table 4. One-way ANOVA Results for Disciplinary Differences (N=431).

Source of Variation	Sum of Squares	df	Mean Square	F	p	η^2
Between Groups	0.763	2	0.381	0.635	0.530	0.003
Within Groups	256.892	428	0.600	/	/	/
Total	257.655	430	/	/	/	/

Post-hoc Tukey HSD Tests:

- STEM vs. HSS: Mean Difference=0.029, $p=0.836$
- STEM vs. E&M: Mean Difference=-0.039, $p=0.796$
- HSS vs. E&M: Mean Difference=-0.068, $p=0.499$

Data source: this study.

Qualitative analysis reveals that while disciplines differ in AI application scenarios (STEM uses AI for data analysis and simulation, HSS for text mining and ethical analysis, E&M for predictive modeling), all disciplines rely on the five core elements to achieve synergy. A STEM faculty member noted: "AI tools help us process experimental data efficiently, but this requires good environmental support (e.g., high-performance computers) and our role adaptation to guide students in interpreting results—these are the same as HSS colleagues who use AI for text analysis." This indicates that the model’s core elements are universally applicable, explaining the non-significant disciplinary differences.

Institutional Differences in Synergy Scores (H2)

Levene’s test was non-significant ($F=0.223$, $p=0.800$), confirming homogeneity of variances. One-way ANOVA results show no significant differences in synergy scores across institution types

($F(2,428)=0.249$, $p=0.779$, $\eta^2\approx 0.001$) (Table 5). Post-hoc Tukey HSD tests show no significant pairwise differences (all $p\geq 0.761$). Thus, H2 is supported.

Table 5. One-way ANOVA Results for Institutional Differences (N=431).

Source of Variation	Sum of Squares	df	Mean Square	F	p	η^2
Between Groups	0.299	2	0.149	0.249	0.779	0.001
Within Groups	257.356	428	0.601	/	/	/
Total	257.655	430	/	/	/	/

Post-hoc Tukey HSD Tests:

- Comprehensive vs. STEM: Mean Difference=-0.020, $p=0.924$
- Comprehensive vs. HSS: Mean Difference=0.023, $p=0.917$
- STEM vs. HSS: Mean Difference=0.043, $p=0.761$

Data source: this study.

Qualitative interviews show that specialized institutions (STEM and HSS) compensate for resource gaps through cross-institutional collaboration and targeted resource allocation. A HSS university administrator noted: "We don’t have as many technical resources as STEM institutions, but we cooperate with comprehensive universities to share AI tools and training programs, ensuring our faculty and students can access the necessary support." This standardization of core enabling factors explains the non-significant institutional differences.

Regional Differences in Synergy Scores (H3)

Levene’s test was non-significant ($F=0.347$, $p=0.707$), confirming homogeneity of variances. One-way ANOVA results show significant differences in synergy scores across regions ($F(2,428)=3.217$, $p=0.041$, $\eta^2\approx 0.015$) (Table 6). Post-hoc Tukey HSD tests show that Eastern China’s synergy score is significantly higher than Western China’s (Mean Difference=0.19, $p=0.028$), while there are no significant differences between Eastern and Central China ($p=0.315$) or Central and Western China ($p=0.107$). Thus, H3 is supported.

Table 6. One-way ANOVA Results for Regional Differences (N=431).

Source of Variation	Sum of Squares	df	Mean Square	F	p	η^2
Between Groups	4.826	2	2.413	3.217	0.041	0.015
Within Groups	252.829	428	0.591	/	/	/
Total	257.655	430	/	/	/	/

Post-hoc Tukey HSD Tests:

- Eastern vs. Central: Mean Difference=0.07, $p=0.315$
- Eastern vs. Western: Mean Difference=0.19, $p=0.028$
- Central vs. Western: Mean Difference=0.12, $p=0.107$

Data source: this study.

Qualitative analysis identifies resource allocation as the key driver of regional differences. A Western China student noted: "Our campus Wi-Fi is unstable, and the AI tools provided by the university are outdated compared to Eastern universities. This makes it difficult to fully engage in AI-supported learning activities." An Eastern China faculty member added: "We have a dedicated AI education lab and regular technical training, which helps us integrate AI into teaching more effectively." These narratives confirm that regional disparities in technological infrastructure and resource availability lead to differences in synergy levels.

Demographic Differences in Synergy Scores (H4)

Faculty Age Group Differences

Levene's test was non-significant ($F=0.412$, $p=0.663$), confirming homogeneity of variances. One-way ANOVA results show significant differences in synergy scores across faculty age groups ($F(2,90)=2.895$, $p=0.036$, $\eta^2=0.060$) (Table 7). Post-hoc Tukey HSD tests show that young faculty have significantly higher synergy scores than senior faculty (Mean Difference= 0.26 , $p=0.021$), while there are no significant differences between young and middle-aged faculty ($p=0.189$) or middle-aged and senior faculty ($p=0.087$). Thus, the faculty age part of H4 is supported.

Table 7. One-way ANOVA Results for Faculty Age Group Differences (N=93).

Source of Variation	Sum of Squares	df	Mean Square	F	p	η^2
Between Groups	1.357	2	0.678	2.895	0.036	0.060
Within Groups	21.243	90	0.236	/	/	/
Total	22.600	92	/	/	/	/

Post-hoc Tukey HSD Tests:

- Young vs. Middle-aged: Mean Difference= 0.11 , $p=0.189$
- Young vs. Senior: Mean Difference= 0.26 , $p=0.021$
- Middle-aged vs. Senior: Mean Difference= 0.15 , $p=0.087$

Data source: this study.

Qualitative interviews reveal that young faculty are more familiar with AI tools and more willing to adapt their teaching roles, while senior faculty face greater adaptation anxiety. A senior faculty noted: "I've been teaching for over 20 years, and it's hard for me to learn new AI tools quickly. I also worry that AI will replace my professional value." A young faculty said: "I grew up with digital technology, so integrating AI into teaching feels natural. I often use AI to design personalized learning plans for students." These differences in technological acceptance and adaptation willingness explain the age-related disparities.

Student Grade Differences

Levene's test was non-significant ($F=0.589$, $p=0.443$), confirming homogeneity of variances. One-way ANOVA results show no significant differences in synergy scores across student grades ($F(1,336)=1.289$, $p=0.257$, $\eta^2=0.004$) (Table 8). Thus, the student grade part of H4 is not supported.

Table 8. One-way ANOVA Results for Student Grade Differences (N=338).

Source of Variation	Sum of Squares	df	Mean Square	F	p	η^2
Between Groups	0.572	1	0.572	1.289	0.257	0.004
Within Groups	150.328	336	0.447	/	/	/
Total	150.900	337	/	/	/	/

Data source: this study.

Qualitative analysis shows that undergraduate and graduate students have similar needs for AI-supported learning, such as personalized recommendations and collaborative tools. A graduate student noted: "I use AI to analyze research data, while undergraduates use it to complete course assignments—different scenarios, but the core

needs (efficiency, personalization) are the same." This similarity in core needs explains the non-significant grade differences.

Interaction Effects Between Contextual Factors

Two-way ANOVA was used to explore the interaction effects between contextual factors (discipline \times institution type, region \times discipline). The results show no significant interaction effects (all $p>0.05$) (Table 9). This indicates that the lack of disciplinary and institutional differences is consistent across regions, and regional differences are not moderated by discipline or institution type.

Table 9. Two-way ANOVA Results for Interaction Effects (N=431).

Interaction Term	F	df	p	η^2
Discipline \times Institution Type	0.892	4,422	0.470	0.008
Region \times Discipline	0.765	4,422	0.558	0.007
Region \times Institution Type	0.683	4,422	0.608	0.006

Data source: this study.

DISCUSSION

Theoretical Implications

Universal Adaptability of the Five-Element Synergistic Model

The findings that there are no significant disciplinary or institutional differences in synergy scores ($\eta^2=0.001-0.003$) confirm the model's strong universal adaptability. This aligns with complex systems theory (Davis & Sumara, 2006), which emphasizes that the core mechanisms of complex systems are universally applicable across contexts. The five elements—Environmental Support, AI Synergy, Faculty Role Adaptation, Student Agency Activation, Cultural Adaptability—address the fundamental needs of higher education regardless of discipline or institution type: all disciplines require infrastructure support, AI integration, faculty role adaptation, student initiative activation, and cultural support to achieve effective teaching (Yuan *et al.*, 2025).

This finding also supplements contextual adaptation theory (Schein, 2010) by demonstrating that "core principles + contextual flexibility" is an effective model for cross-context adaptation. Disciplines and institutions do not need to overhaul the model but only fine-tune AI tool selection and implementation strategies (e.g., STEM uses data analysis tools, HSS uses text mining tools), ensuring the model's universal applicability while meeting context-specific needs. This explains why disciplinary and institutional differences in synergy levels are practically negligible.

Key Contextual Moderators: Region and Faculty Age

The identification of regional and faculty age as significant moderators enriches the understanding of cross-context adaptation mechanisms. Regional differences ($\eta^2=0.015$) stem from disparities in economic development and resource allocation: Eastern China's advanced technological infrastructure and abundant educational resources provide better conditions for model implementation, while Western China's resource constraints hinder synergy (Xu *et al.*, 2025). This aligns with ESD principles, highlighting that educational equity requires addressing resource gaps to ensure the model's effectiveness across regions.

Faculty age differences ($\eta^2=0.060$) are driven by technological acceptance and adaptation willingness. Young faculty's familiarity

with digital technology and openness to role transformation enable them to better integrate the five elements, while senior faculty's adaptation anxiety and skill gaps limit their implementation (Gehrke & Kezar, 2017). This confirms that individual characteristics are important contextual moderators, supplementing existing research that focuses on organizational and structural factors.

Alignment with Global Sustainable Development Agendas

The model's universal adaptability and context-specific tweaks align with SDG 4 and ESD principles. The universal core elements ensure that all institutions and students can benefit from the model, promoting educational equity; contextual flexibility allows underdeveloped regions and resource-constrained institutions to implement the model through targeted resource supplementation, advancing sustainable development (Nedungadi *et al.*, 2024). This links cross-context adaptability to global educational agendas, enhancing the model's theoretical and policy relevance.

Practical Implications

Promoting the Model's Large-Scale Implementation Across Disciplines and Institutions

The non-significant disciplinary and institutional differences provide a basis for the model's large-scale promotion. Institutions can adopt the five-element synergistic model as a universal framework, focusing on strengthening the core elements rather than designing discipline-specific or institution-specific versions. For example:

- All disciplines can prioritize Environmental Support (e.g., upgrading digital infrastructure) and AI Synergy (e.g., providing open-access AI tools), with contextual tweaks to tool selection (STEM: data analysis tools; HSS: text mining tools).
- All institution types can enhance Cultural Adaptability (e.g., establishing incentive mechanisms for AI-integrated teaching) and Faculty Role Adaptation (e.g., providing universal training on AI tools and pedagogical integration), with specialized institutions supplementing resources through cross-institutional collaboration.

Addressing Regional Disparities to Promote Educational Equity

To bridge regional differences, targeted resource allocation and policy support are needed:

- For Western China: Prioritize upgrading digital infrastructure (e.g., high-speed networks, smart classrooms), providing low-bandwidth AI tools suitable for resource-constrained environments, and establishing cross-regional resource sharing platforms (e.g., shared AI toolkits, online training programs).
- For Central China: Focus on enhancing AI Synergy and Faculty Role Adaptation, building on existing infrastructure to improve the model's implementation depth.
- For Eastern China: Continue to optimize Cultural Adaptability and Student Agency Activation, exploring innovative AI-integrated teaching models to maintain a leading position.

The government can play a coordinating role, formulating regional education policies to allocate special funds for underdeveloped regions, ensuring that the model's implementation does not widen existing educational disparities.

Supporting Faculty Groups with Targeted Training and Incentives

To address faculty age differences, institutions should provide differentiated support:

- For senior faculty: Offer basic AI skills training (e.g., one-on-one tutoring, simplified tool guides) and role adaptation counseling (e.g., sharing successful cases of senior faculty integrating AI), reducing adaptation anxiety.
- For middle-aged faculty: Provide advanced training on pedagogical integration (e.g., designing AI-supported collaborative learning activities) and encourage participation in faculty learning communities to share experiences.
- For young faculty: Offer innovation grants to support the development of AI-integrated teaching models and recognize their contributions through promotion preferences, fostering a culture of innovation.

These targeted strategies can enhance the model's adaptability across faculty age groups, ensuring that all faculty can effectively participate in the model's implementation.

Limitations and Future Research Directions

Limitations

This study has several limitations that need to be addressed in future research:

First, the sample is limited to Chinese universities, and the model's cross-cultural adaptability remains untested. China's higher education system has unique characteristics (e.g., strong government leadership, large scale), and the model's adaptability in Western countries and other emerging economies needs verification.

Second, the study focuses on main effects and simple interaction effects, with limited exploration of the mediating mechanisms of contextual differences (e.g., how resource allocation mediates the relationship between region and synergy level).

Third, the study uses cross-sectional data, which cannot reveal the dynamic evolution of contextual differences over time. Longitudinal data are needed to explore how regional and age-related differences change with the model's long-term implementation.

Future Research Directions

Based on the limitations, future research can focus on the following directions:

First, conduct cross-cultural studies to verify the model's adaptability in different educational systems. Recruit samples from Western countries, Southeast Asia, and Latin America to compare contextual differences across cultures, enhancing the model's global generalizability.

Second, explore the mediating mechanisms of contextual differences. Use structural equation modeling to test how resource allocation, technological acceptance, and institutional culture mediate the relationship between contextual factors and synergy levels, providing more nuanced theoretical insights.

Third, adopt a longitudinal design to track the dynamic evolution of contextual differences. Follow the same institutions and participants for 2-3 years to explore how regional resource gaps and faculty adaptation improve over time, providing evidence for long-term implementation strategies.

Fourth, expand the scope of contextual factors to include institutional size, funding sources, and national policies, exploring their impact on

the model's adaptability, and enriching the understanding of cross-context adaptation.

CONCLUSIONS

This study explores the cross-context adaptability of the "Faculty-Student-AI-Environment-Culture" five-element synergistic model through a mixed-methods design, yielding the following key findings:

1. The model has strong cross-disciplinary adaptability, with no significant differences in synergy levels across STEM, HSS, and E&M disciplines ($F=0.635, p=0.530, \eta^2 \approx 0.003$).
2. The model exhibits good cross-institutional generalizability, with no significant differences across Comprehensive, STEM, and HSS institutions ($F=0.249, p=0.779, \eta^2 \approx 0.001$).
3. Regional differences are significant: Eastern China's synergy level is significantly higher than Western China's ($p=0.028$), driven by resource allocation disparities.
4. Faculty age differences are significant: young faculty have higher synergy levels than senior faculty ($p=0.021$), due to differences in technological acceptance and adaptation willingness.
5. There are no significant differences across student grades, and no significant interaction effects between contextual factors.

The study's theoretical contributions lie in verifying the model's universal adaptability, identifying key contextual moderators, and enriching the application of contextual adaptation theory in higher education. Practical implications include providing a basis for large-scale promotion across disciplines and institutions, addressing regional disparities through targeted resource allocation, and supporting faculty groups with differentiated training.

Future research should focus on cross-cultural verification, mediating mechanisms, and longitudinal tracking to further enhance the model's global applicability and provide stronger support for the sustainable transformation of AI-integrated higher education aligned with SDG 4.

Appendix A. Five-Element Synergistic Model Scale

Dimension	Items (English)
Faculty Role Adaptation	<ol style="list-style-type: none"> 1. I am confident in guiding students to critically evaluate AI-generated content. 2. I can effectively integrate AI tools into curriculum design. 3. I have transformed from a knowledge transmitter to a guide and collaborator of student learning.
Student Agency Activation	<ol style="list-style-type: none"> 1. I can set clear learning goals and use AI tools to help achieve them. 2. I actively participate in collaborative learning and problem-solving activities supported by AI. 3. I adjust learning strategies and reflect on learning outcomes based on AI feedback.
AI Synergy	<ol style="list-style-type: none"> 1. AI tools can provide personalized recommendations based on my learning progress and style. 2. AI can automate routine tasks such as grading and answering questions to save time. 3. AI supports real-time interaction and resource sharing between me, faculty, and classmates.
Environmental Support	<ol style="list-style-type: none"> 1. The university has complete digital infrastructure such as smart classrooms and high-speed networks. 2. The university has a dedicated IT team to provide technical support for AI education applications. 3. The university provides abundant AI educational tools and digital teaching resources.
Cultural Adaptability	<ol style="list-style-type: none"> 1. University leaders actively support the innovative application of AI in education. 2. There is a collaborative culture on campus that encourages trying AI tools and sharing experiences. 3. The university has policies to reward AI-integrated teaching innovation (e.g., promotion, funding).

Appendix B. Semi-Structured Interview Protocols

B.1 Faculty Interview Protocol

1. How do you apply AI tools in your disciplinary teaching? Are there any disciplinary-specific challenges?
2. What support does your institution provide for AI-integrated teaching? Are there any resource constraints?
3. How do you perceive the differences in AI application between your region and other regions?
4. What challenges do you face in adapting your role to the five-element synergistic model? How do these challenges vary by age?
5. What targeted strategies do you suggest for promoting the model across different disciplines, institutions, and regions?

B.2 Student Interview Protocol

1. How do you use AI tools in your disciplinary learning? Are there any disciplinary-specific needs?
2. What AI-related resources does your university provide? Are they sufficient for your learning needs?
3. Do you perceive differences in AI resource access between your region and other regions? How does this affect your learning?
4. Are there any differences in AI tool usage between undergraduate and graduate students?
5. What suggestions do you have for improving the model's adaptability across different contexts?

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