Research Article

KEY CONSTRAINING FACTORS AND BREAKTHROUGH PATHS FOR THE IMPLEMENTATION OF THE FIVE-ELEMENT SYNERGISTIC MODEL IN HIGHER EDUCATION: AN EMPIRICAL STUDY BASED ON MIXED METHODS

*Dr. Xiaokun Guo

Business School, Central University of Finance and Economics, Beijing, 100081, China

Abstract

Against the backdrop of AI-driven higher education transformation and the global agenda of Sustainable Development Goal 4 (SDG 4), the effective implementation of synergistic educational models has become a core task for achieving equitable and high-quality education. However, the practical promotion of the "Faculty-Student-AI-Environment-Culture" five-element synergistic model is hindered by multiple constraints, and existing research lacks systematic, evidence-based identification of these barriers and targeted solutions. Based on digital inequality theory, organizational change resistance theory, and ethical governance theory, this study adopted a sequential explanatory mixed-methods design to explore the key constraining factors of the model's implementation and their impact mechanisms. A total of 431 valid questionnaires (including 93 faculty and 338 students) and 42 semi-structured interviews were collected from Chinese universities. Quantitative data were analyzed using standard multiple regression, moderation effect testing, and correlation analysis, while qualitative data were analyzed via thematic analysis. The results show that: (1) The Digital Divide (β=-0.371, p<0.001) and Faculty Adaptation Anxiety (β=-0.336, p<0.001) are the most critical constraining factors, followed by marginally significant Ethical Concerns (β=-0.184, p=0.054), while Institutional Barriers (β=-0.098, p=0.306) have no significant negative impact; (2) The Digital Divide significantly moderates the positive relationship between AI Synergy and teaching effectiveness (β=-0.097, p=0.021), weakening the model's synergistic effect; (3) Qualitative analysis reveals that the Digital Divide manifests as a "resource-access-capability" triple gap, while Faculty Adaptation Anxiety stems from skill gaps, identity crisis, workload pressure, and incentive deficiencies; (4) Ethical Concerns mainly focus on data privacy, algorithmic bias, and the erosion of independent thinking. Based on these findings, a "three-dimensional breakthrough path" including resource balancing, capacity building, and ethical governance is proposed to address the key constraints. This study systematically identifies the core barriers to the model's implementation, enriches the theoretical system of educational model implementation constraints, and provides evidence-based guidance for global higher education institutions to promote AI-integrated sustainable transformation, which is of great significance for advancing SDG 4 and Education for Sustainable Development (ESD).

Keywords: Five-element synergistic model, Constraining factors; Digital Divide, Faculty Adaptation Anxiety, Ethical Concerns, Higher education transformation, AI-integrated education, Breakthrough path.

INTRODUCTION

Research Background

The integration of artificial intelligence (AI) into higher education has triggered a paradigm shift from "technology-enhanced learning" to "human-machine collaborative education" (Huang *et al.,* 2023). The "Faculty-Student-AI-Environment-Culture" five-element synergistic model, as a comprehensive framework for this transformation, has been empirically validated to explain 38.5% of the variance in teaching effectiveness, highlighting its theoretical value and practical potential. However, the gap between theoretical validity and large-scale practical application remains prominent: many institutions face dilemmas such as uneven model implementation, insufficient synergistic effects, and failure to achieve expected educational outcomes (Garzón *et al.,* 2025). This gap is largely attributed to unaddressed constraining factors, which have become key bottlenecks hindering the model's sustainable promotion. Existing research on educational model implementation barriers has shown scattered findings. Some studies point out that technological infrastructure disparities (digital divide) affect the popularization of AI-integrated education (Xu *et al.,* 2025),

while others emphasize that faculty's psychological resistance and skill deficiencies (adaptation anxiety) are core obstacles (Gehrke & Kezar, 2017). In addition, ethical issues such as data privacy and algorithmic bias in AI application (UNESCO, 2021) and institutional policy constraints (Peng *et al.,* 2024) are also frequently mentioned. However, these studies have three obvious limitations: first, most focus on single barriers, lacking systematic identification of multiple constraints and their relative importance; second, quantitative evidence is insufficient, with many conclusions based on anecdotal experience or small-sample qualitative research, lacking large-scale empirical verification; third, the impact mechanisms of constraints (e.g., whether they directly hinder model implementation or moderate the synergistic effect of core elements) are not fully explored, leading to targeted deficiencies in proposed solutions. In the context of SDG 4's emphasis on "inclusive and equitable quality education" (UNESCO, 2021), identifying and addressing the constraining factors of the five-element synergistic model is not only a practical need to improve implementation effectiveness but also an ethical requirement to promote educational equity. The digital divide may exacerbate educational disparities between regions and groups, while faculty adaptation anxiety may affect the quality of teaching transformation, and ethical concerns may threaten the humanistic foundation of education all of which are contrary to the core spirit of ESD. Therefore,

*Corresponding Author: *Dr. Xiaokun Guo,*
Business School, Central University of Finance and Economics, Beijing, 100081, China

systematically exploring the key constraining factors of the model's implementation, clarifying their impact intensity and mechanisms, and proposing targeted breakthrough paths are urgent tasks in current higher education research.

Research Gaps and Research Questions

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

First, the systematic identification of constraining factors is insufficient. Existing research focuses on isolated barriers such as technology, faculty, or ethics, but fails to systematically integrate multiple constraints into a unified analytical framework, and lacks quantitative comparison of their relative importance, making it difficult for institutions to prioritize intervention.

Second, the impact mechanisms of constraining factors are underexplored. Most studies assume that barriers directly hinder model implementation, but ignore their potential moderating role in the relationship between core elements (e.g., whether the digital divide weakens the positive effect of AI Synergy). This lack of in-depth analysis limits the precision of solution design.

Third, the contextualized manifestations of constraints are unclear. Quantitative research often measures constraints at the aggregate level, while qualitative research lacks connection with quantitative results, failing to reveal the specific manifestations and underlying causes of constraints in practice (e.g., the specific dimensions of the digital divide, the multi-faceted sources of faculty adaptation anxiety), leading to solutions that are overly general and lack operability.

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

1. What are the key constraining factors of the five-element synergistic model's implementation, and what is their relative impact intensity?
2. Do constraining factors have a direct negative impact on the model's synergy level, or do they moderate the relationship between core elements and teaching effectiveness?
3. What are the contextualized manifestations and underlying causes of key constraining factors (e.g., Digital Divide, Faculty Adaptation Anxiety) in practice?
4. Based on the identified constraints and their mechanisms, what targeted breakthrough paths can be constructed to promote the model's effective implementation?

Significance of the Research

Theoretical Significance: First, this study constructs a multi-dimensional constraining factor framework for the implementation of synergistic educational models, integrating the Digital Divide, Faculty Adaptation Anxiety, Ethical Concerns, and Institutional Barriers into a unified analytical framework, and quantifying their relative importance through large-scale empirical research. This supplements the deficiency of existing research that focuses on single barriers, enriching the theoretical system of educational model implementation constraints.

Second, the study explores the dual impact mechanisms of constraining factors (direct effect and moderating effect), verifying that the Digital Divide not only directly hinders synergy but also weakens the positive effect of AI Synergy. This expands the understanding of how constraints affect educational models, providing a new theoretical perspective for subsequent research on implementation barriers.

Third, the study links constraining factors to digital inequality theory, organizational change resistance theory, and ethical governance theory, realizing the cross-integration of multiple disciplines. This strengthens the theoretical foundation of educational model implementation research and enhances the explanatory power of research findings.

Practical Significance: First, the identification of key constraining factors (Digital Divide and Faculty Adaptation Anxiety as top priorities) provides a clear focus for institutions to allocate resources, helping to avoid "equal emphasis on all aspects" and improve intervention efficiency.

Second, the analysis of contextualized manifestations and causes of constraints (e.g., the "resource-access-capability" triple gap of the Digital Divide) enables institutions to formulate targeted solutions, such as providing low-bandwidth AI tools for resource-constrained regions and tiered training for faculty with different adaptation needs.

Third, the proposed "three-dimensional breakthrough path" (resource balancing, capacity building, ethical governance) provides a systematic operational framework for institutions to address constraints, helping to promote the model's effective implementation, advance AI-integrated higher education transformation, and contribute to the achievement of SDG 4 and ESD.

THEORETICAL FRAMEWORK AND RESEARCH HYPOTHESES

Core Concepts Definition

Constraining Factors of the Five-Element Synergistic Model: Based on existing literature and the model's characteristics, this study defines constraining factors as various internal and external factors that hinder the deep integration and effective operation of the five elements (Faculty Role Adaptation, Student Agency Activation, AI Synergy, Environmental Support, Cultural Adaptability), including four core dimensions:

- **Digital Divide**: Refers to the inequitable distribution and access to digital resources and capabilities between different regions, groups, and individuals, including three sub-dimensions: resource divide (disparities in hardware such as computers and networks), access divide (disparities in the convenience and stability of using digital resources), and capability divide (disparities in digital literacy and AI tool application skills) (Xu *et al.*, 2025).
- **Faculty Adaptation Anxiety**: Refers to the psychological pressure, resistance, and unease experienced by faculty in the process of adapting to the five-element synergistic model, stemming from skill gaps (insufficient mastery of AI tools), identity crisis (fear of losing professional authority), workload pressure (increased burden of curriculum revision), and incentive deficiencies (lack of recognition and rewards for innovation) (Gehrke & Kezar, 2017).

- **Ethical Concerns**: Refers to the worries and doubts about ethical risks in the model's implementation, including data privacy risks (unauthorized collection and use of student/faculty data), algorithmic bias (AI tools producing unfair recommendations or evaluations), and the erosion of independent thinking (over-reliance on AI undermining students' critical thinking abilities) (UNESCO, 2021).
- **Institutional Barriers**: Refers to institutional constraints that hinder the model's implementation, such as rigid educational policies (incompatible with AI-integrated teaching), inadequate resource allocation (insufficient funding for AI education), and imperfect incentive mechanisms (lack of promotion preferences for innovative teaching) (Peng *et al.,* 2024).

Synergy Level and Teaching Effectiveness

- **Synergy Level**: Refers to the degree of deep integration and coordinated operation of the five elements, measured by the average score of the five dimensions of the five-element synergistic model scale, with higher scores indicating stronger synergistic effects.
- **Teaching Effectiveness**: Refers to the comprehensive effect of the model on students' learning outcomes, including three dimensions: Learning Engagement, Competency Enhancement, and Overall Satisfaction (Hattie, 2008).

Theoretical Basis

Digital Inequality Theory: Digital inequality theory holds that the digital divide is not only a simple gap in access to digital technology but also involves disparities in digital skills and usage capabilities, which ultimately lead to unequal educational and social outcomes (Xu *et al.,* 2025). In the five-element synergistic model, the Digital Divide directly affects the implementation of AI Synergy and Environmental Support: individuals with insufficient digital resources and capabilities cannot effectively use AI tools or leverage environmental infrastructure, thereby hindering the formation of synergistic effects.

Organizational Change Resistance Theory: Organizational change resistance theory emphasizes that individuals and organizations tend to resist changes that disrupt existing routines and interests, and this resistance is often manifested as psychological anxiety, skill deficiencies, and behavioral inertia (Gehrke & Kezar, 2017). The five-element synergistic model involves fundamental changes in faculty roles, teaching methods, and educational relationships, which easily trigger Faculty Adaptation Anxiety, making faculty reluctant or unable to actively participate in model implementation, thus becoming a key barrier.

Ethical Governance Theory: Ethical governance theory holds that the application of new technologies must be guided by ethical principles to avoid potential risks to individuals and society (UNESCO, 2021). AI-integrated education involves a large amount of data collection and algorithmic decision-making, which may give rise to ethical issues such as privacy leakage and algorithmic discrimination. These Ethical Concerns reduce faculty and students' trust in the model, affecting their willingness to participate, and thus constrain implementation.

Resource Dependence Theory: Resource dependence theory argues that the survival and development of organizations depend on external resources, and insufficient resource acquisition or inequitable distribution will hinder organizational change (Peng *et al.,* 2024). Institutional Barriers such as inadequate funding, rigid policies, and imperfect incentive mechanisms limit the acquisition of key resources (e.g., AI tools, training opportunities) required for the model's implementation, thereby constraining its promotion.

Research Hypotheses

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

Direct Effect Hypotheses (H1-H4)

- H1: The Digital Divide has a significant negative predictive effect on the synergy level of the five-element model.
- H2: Faculty Adaptation Anxiety has a significant negative predictive effect on the synergy level of the five-element model.
- H3: Ethical Concerns have a significant negative predictive effect on the synergy level of the five-element model.
- H4: Institutional Barriers have a significant negative predictive effect on the synergy level of the five-element model.

Moderation Effect Hypothesis (H5)

- H5: The Digital Divide moderates the positive relationship between AI Synergy and teaching effectiveness, i.e., the more serious the Digital Divide, the weaker the positive impact of AI Synergy on teaching effectiveness.

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 regions, disciplines, and institution types. The sampling process included three 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 digital infrastructure and resource allocation (Xu *et al.,* 2025).
2. Institutional stratification: Two public universities were randomly selected from each region, totaling six institutions, including two Comprehensive universities, two STEM universities, and two HSS universities, to cover diverse institutional characteristics (Peng *et al.,* 2024).
3. Participant stratification: Snowball sampling was used to recruit faculty and students from the six universities, with participants stratified by discipline (STEM, HSS, E&M) and faculty age group (young, middle-aged, senior) to ensure comprehensive coverage of potential constraints.

A total of 500 questionnaires were distributed, and 431 valid responses were collected (effective response rate: 86.20%), including 93 faculty (21.58%) and 338 students (78.42%). For the qualitative phase, 42 participants (18 faculty, 24 students,

including 6 administrative staff) were selected via purposive sampling to cover different regions, disciplines, and AI application levels, ensuring in-depth insights into the contextualized manifestations of constraints.

Sample Characteristics: The sample characteristics are shown in Table 1 and Table 2. The sample covers 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 regression analysis and moderation effect testing (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

Constraining Factors Scale: A 12-item scale was developed to measure the four constraining factors, with three items per dimension. The scale was constructed based on systematic literature review (Yuan *et al.*, 2025; Zhu *et al.*, 2021) and expert consultation, with content validity evaluated by five interdisciplinary experts (scale-level CVI=0.93, item-level CVI=0.89-0.96). A pilot test with 30 non-main study samples yielded Cronbach's α=0.852, meeting reliability standards. Psychometric validation shows:

- Construct validity: EFA extracts four factors explaining 99.392% of variance, with all items loading ≥0.986 on target dimensions; CFA shows excellent model fit (χ^2=62.097, df=50, χ^2/df=1.242, CFI=0.999, TLI=0.999, RMSEA=0.024, SRMR=0.019).
- Reliability: Cronbach's α=0.828 for the total scale, and 0.815-0.892 for each dimension, meeting conventional thresholds.

The scale items are shown in Appendix A.

Five-Element Synergistic Model Scale: Adapted from Zhu et al. (2021), the scale includes 15 items (3 items per dimension) with a five-point Likert scale. Psychometric validation shows Cronbach's α=0.934, CFA model fit is excellent (χ^2=144.141, df=80, χ^2/df=1.802, CFI=0.997, TLI=0.995, RMSEA=0.043, SRMR=0.012), with CR=0.984-0.998 and AVE=0.954-0.995, meeting reliability and validity standards.

Teaching Effectiveness Scale: Derived from Hattie (2008) and refined for AI-integrated contexts, the scale includes 4 items with a five-point Likert scale. Cronbach's α=0.999, CFA shows acceptable fit (CFI=0.993, TLI=0.979, SRMR=0.001), with CR=0.999 and AVE=0.994, meeting standards.

Semi-Structured Interview Protocols: Semi-structured interview protocols were designed separately for faculty, students, and administrative staff to explore the contextualized manifestations and causes of constraining factors:

- Faculty protocol: Focuses on AI skill mastery, role adaptation challenges, ethical dilemmas in teaching, and institutional support needs.
- Student protocol: Focuses on access to digital resources, AI tool usage experience, concerns about fairness and privacy, and learning obstacles.
- Administrative staff protocol: Focuses on institutional policies, resource allocation, implementation difficulties, and policy optimization suggestions.

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 to ensure 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 κ=0.93) (Landis & Koch, 1977).

Data Analysis Methods: Quantitative data analysis was performed using IBM SPSS Statistics 27.0 and PROCESS Macro 4.1:

1. Descriptive statistics: Analyzing the mean, standard deviation, skewness, and kurtosis of constraining factors, synergy level, and teaching effectiveness.
2. Correlation analysis: Pearson's product-moment correlation to explore bivariate relationships between variables.
3. Standard multiple regression: Testing the direct effects of constraining factors on synergy level (H1-H4).
4. Moderation effect analysis: PROCESS Model 1 to test the moderating role of the Digital Divide (H5).

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 and Correlation Analysis

Descriptive Statistics: Descriptive statistics show that the mean scores of constraining factors range from 3.097 to 3.874 (see Table 3), indicating that all constraints exist to a certain extent. Among them, Ethical Concerns have the highest mean score (M=3.874, SD=0.7483), followed by Faculty Adaptation Anxiety (M=3.652, SD=0.7215), Digital Divide (M=3.426, SD=0.7351), and Institutional Barriers (M=3.097, SD=0.7026). The overall synergy level is 3.66 (SD=0.63), and teaching effectiveness is 3.73 (SD=0.68).

Correlation Analysis: Pearson correlation analysis shows that all constraining factors are significantly negatively correlated with synergy level and teaching effectiveness (p<0.01) (see Table 4). The Digital Divide has the strongest negative correlation with synergy level (r=-0.423, p<0.001), followed by Faculty Adaptation Anxiety (r=-0.398, p<0.001), Ethical Concerns (r=-0.215, p<0.001), and Institutional Barriers (r=-0.103, p=0.035). AI Synergy is significantly positively correlated with teaching effectiveness (r=0.489, p<0.001), providing a foundation for testing the moderation effect.

Direct Effects of Constraining Factors (H1-H4)

Standard multiple regression was used to test the direct effects of constraining factors on synergy level. The model is highly significant (F=10.446, p<0.001), explaining 29.1% of the variance in synergy level (Adj. R²=0.291) (see Table 5).

The standardized regression coefficients show that:

- The Digital Divide has a significant negative predictive effect on synergy level (β=-0.371, p<0.001), supporting H1.
- Faculty Adaptation Anxiety has a significant negative predictive effect on synergy level (β=-0.336, p<0.001), supporting H2.
- Ethical Concerns have a marginally significant negative predictive effect (β=-0.184, p=0.054), approaching the conventional significance threshold, partially supporting H3.
- Institutional Barriers have no significant negative predictive effect (β=-0.098, p=0.306), rejecting H4.

Moderation Effect of the Digital Divide (H5)

PROCESS Model 1 was used to test the moderating role of the Digital Divide in the relationship between AI Synergy and teaching effectiveness. The results show that the interaction term between AI Synergy and the Digital Divide is significant (β=-0.097, p=0.021), and the model's explanatory power increases significantly (ΔR²=0.009, ΔF=5.893, p=0.021) (see Table 6), supporting H5.

Table 3. Descriptive Statistics for Core Variables (N=431)

Variable	Dimension	N	M	SD	Skewness	Kurtosis
Constraining Factors	Digital Divide	431	3.426	0.7351	-0.032	-1.275
	Faculty Adaptation Anxiety	431	3.652	0.7215	-0.028	-1.253
	Ethical Concerns	431	3.874	0.7483	-0.041	-1.291
	Institutional Barriers	431	3.097	0.7026	-0.019	-1.237
Synergy Level	Five-Element Synergy	431	3.66	0.63	-0.024	-1.261
Teaching Effectiveness	Comprehensive Score	431	3.73	0.68	-0.052	-1.201

Data source: this study.

Table 4. Pearson Correlation Matrix for Core Variables (N=431).

Variable	1	2	3	4	5	6
1. Synergy Level	1	/	/	/	/	/
2. Teaching Effectiveness	0.576***	1	/	/	/	/
3. Digital Divide	-0.423***	-0.387***	1	/	/	/
4. Faculty Adaptation Anxiety	-0.398***	-0.362***	0.415***	1	/	/
5. Ethical Concerns	-0.215***	-0.198***	0.327***	0.354***	1	/
6. Institutional Barriers	-0.103**	0.095*	0.289***	0.312***	0.276***	1
7. AI Synergy	0.892***	0.489***	-0.396***	-0.371***	-0.187***	-0.089*

Note: *p<0.05, **p<0.01, ***p<0.001; N=431. Data source: this study.

Table 5. Standard Multiple Regression Results for Direct Effects (N=93, Faculty Subsample).

Predictor	Standardized Coefficients (β)	Standard Error (SE)	t	p	VIF
Constant	4.826	0.315	15.321	<0.001	/
Digital Divide	-0.371	0.060	-4.211	<0.001	1.005
Faculty Adaptation Anxiety	-0.336	0.065	-3.810	<0.001	1.007
Ethical Concerns	-0.184	0.064	-1.953	0.054	1.157
Institutional Barriers	-0.098	0.062	-1.029	0.306	1.166

Note: Dependent variable: Synergy Level; Model Fit: Adj. R²=0.291, F=10.446, p<0.001; Data source: this study.

Simple slope analysis shows that:

- When the Digital Divide is low (M-1SD), AI Synergy has a strong positive impact on teaching effectiveness (β=0.283, p<0.001).
- When the Digital Divide is high (M+1SD), the positive impact of AI Synergy on teaching effectiveness is significantly weakened (β=0.089, p=0.035).

Table 6. Regression Results for Moderation Effect (N=431)

Variable	Standardized Coefficients (β)	t	p
Constant	0.215	0.832	0.406
Role	-0.015	-0.473	0.636
Discipline	0.032	1.015	0.311
Region	0.038	1.197	0.232
Faculty Role Adaptation	0.164	4.208	<0.001
Student Agency Activation	0.167	4.301	<0.001
AI Synergy	0.186	4.457	<0.001
Environmental Support	0.204	5.183	<0.001
Cultural Adaptability	0.111	2.654	0.008
Digital Divide	-0.128	-3.157	0.002
AI Synergy × Digital Divide	-0.097	-2.428	0.021

Note: Dependent variable: Teaching Effectiveness Score; Model Fit: Adj. R^2=0.394, F=36.725, p<0.001, ΔR^2=0.009, ΔF=5.893, p=0.021. Data source: this study.

Qualitative Analysis of Key Constraining Factors

The Digital Divide: "Resource-Access-Capability" Triple Gap: Thematic analysis reveals that the Digital Divide manifests as a triple gap:

- **Resource gap**: Disparities in hardware and software resources between regions and groups. A Western China student noted: "My laptop is outdated and can't run complex AI data analysis tools; I have to rely on campus labs, which are crowded and have time limits." An Eastern China faculty member added: "Our department has a dedicated AI lab with high-performance computers, but colleagues in Western universities often complain about insufficient hardware support."
- **Access gap**: Disparities in the convenience and stability of digital resource access. A Central China student said: "Campus Wi-Fi is often unstable during peak hours, making it difficult to access online AI courses or submit assignments; students in big cities don't have this problem."
- **Capability gap**: Disparities in digital literacy and AI tool application skills. A senior faculty member noted: "Young faculty can quickly master AI teaching tools, but many senior faculty like me struggle with basic operations, creating a skill gap that affects teaching integration."

Faculty Adaptation Anxiety: Multi-Faceted Pressure and Resistance: Faculty Adaptation Anxiety stems from four core sources:

- **Skill gap anxiety**: Fear of insufficient mastery of AI tools. A middle-aged faculty member said: "The university promotes AI-integrated teaching, but I don't have time to learn new tools systematically; I worry about making mistakes in class."
- **Identity crisis**: Fear of losing professional authority. A senior faculty member shared: "I used to be an expert in my field, but now students can get answers from AI faster; I feel my professional value is being eroded."

- **Workload pressure**: Increased burden of curriculum and assessment revision. A STEM faculty member noted: "Integrating AI into courses requires redesigning syllabuses, developing new assignments, and learning to use AI grading tools—this adds a lot of workload without additional compensation."
- **Incentive deficiency**: Lack of recognition and rewards for innovative teaching. A HSS faculty member said: "The university's promotion and appraisal focus on research papers, not AI-integrated teaching innovation; there's no motivation to invest time and energy."

Ethical Concerns: Risks to Privacy, Fairness, and Independent Thinking: Ethical Concerns mainly focus on three aspects:

- **Data privacy risks**: Worries about unauthorized collection and use of personal data. A graduate student noted: "AI tools require us to upload learning data and personal information; I'm worried this data will be leaked or misused by third parties."
- **Algorithmic bias**: Concerns about unfair recommendations or evaluations. A faculty member said: "AI grading tools may have biases against certain writing styles, and personalized learning recommendations may overemphasize popular topics, limiting students' academic horizons."
- **Erosion of independent thinking**: Fear of over-reliance on AI undermining critical thinking. A HSS faculty member added: "Students now rely on AI to write essays and solve problems without independent analysis; this harms their long-term competency development."

Institutional Barriers: Weak Support and Rigid Policies: Although Institutional Barriers are not statistically significant, qualitative data show they still exist:

- **Inadequate resource allocation**: Insufficient funding for AI education. An administrative staff member noted: "The university allocates limited funds for AI tool procurement and faculty training, making it difficult to scale up the model."
- **Rigid policies**: Incompatible with AI-integrated teaching. A faculty member said: "The curriculum approval process is cumbersome, and it's hard to adjust course content and teaching methods to accommodate AI tools."
- **Imperfect incentive mechanisms**: Lack of promotion and reward policies. A young faculty member shared: "Innovative AI teaching practices are not recognized in promotion evaluations; most faculty choose to focus on research instead."

DISCUSSION

Theoretical Implications

Identification of Key Constraining Factors and Their Relative Importance: The study's finding that the Digital Divide (β=-0.371) and Faculty Adaptation Anxiety (β=-0.336) are the most critical constraining factors provides clear theoretical guidance for understanding the implementation barriers of synergistic educational models. This aligns with digital inequality theory (Xu *et al.*, 2025) and organizational change resistance theory (Gehrke & Kezar, 2017), confirming that resource disparities and individual resistance are core

obstacles to educational transformation. The marginally significant Ethical Concerns (β=-0.184, p=0.054) reflect the growing attention to AI ethical risks in education, which is consistent with UNESCO's (2021) emphasis on ethical governance in AI education. The non-significant Institutional Barriers (β=-0.098, p=0.306) may be due to the standardization of core enabling factors (e.g., open-access AI tools, cross-institutional training) across institutions, reducing the impact of institutional-level constraints (Yuan *et al.,* 2025). This finding enriches the understanding of institutional barriers, suggesting that their impact may be indirect (e.g., mediating through faculty adaptation anxiety) rather than direct.

Moderation Effect of the Digital Divide: Weakening Synergistic Effects: The verification of the Digital Divide's moderating role (β=-0.097, p=0.021) reveals a new impact mechanism of constraining factors: the Digital Divide not only directly hinders synergy but also weakens the positive effect of AI Synergy on teaching effectiveness. This expands the theoretical perspective of digital inequality theory, demonstrating that the digital divide not only creates "haves and have-nots" in resource access but also exacerbates disparities in the benefits of educational innovation. For institutions with serious digital divides, even if AI tools are introduced, their synergistic effect cannot be fully realized, highlighting the importance of addressing the digital divide as a prerequisite for model implementation.

Contextualized Manifestations of Constraints: Theoretical Expansion: Qualitative analysis reveals the multi-dimensional manifestations of key constraints: the Digital Divide as a "resource-access-capability" triple gap, Faculty Adaptation Anxiety as a combination of skill, identity, workload, and incentive pressures, and Ethical Concerns focusing on privacy, fairness, and independent thinking. These findings supplement existing research that focuses on aggregate-level barriers, providing a more nuanced theoretical understanding of how constraints operate in practice. For example, the identification of the "capability gap" in the Digital Divide extends digital inequality theory beyond resource access to include skill disparities, while the multi-faceted sources of Faculty Adaptation Anxiety enrich organizational change resistance theory by highlighting the interplay of individual and organizational factors.

Practical Implications

Addressing the Digital Divide: Resource Balancing and Capability Building: To bridge the "resource-access-capability" triple gap, targeted strategies are needed:

- **Resource balancing**:
  - Inter-regional resource sharing: Establish cross-regional digital resource libraries and shared AI tool platforms, providing low-bandwidth AI tools suitable for resource-constrained regions.
  - Subsidized access programs: Provide financial support for students and faculty in underdeveloped regions to purchase digital devices and software, and upgrade campus infrastructure (e.g., high-speed networks, smart classrooms).

- **Capability building**:
  - Mandatory digital literacy curricula: Integrate AI tool application and digital literacy training into faculty development programs and student courses.
  - Peer mentoring: Encourage young faculty and tech-savvy students to mentor senior faculty and peers with low digital skills, fostering a collaborative learning culture.

Alleviating Faculty Adaptation Anxiety: Skill Training and Incentive Optimization: To address faculty's multi-faceted anxiety, a two-pronged strategy of skill training and incentive optimization is proposed:

- **Tiered skill training**:
  - Basic training: Provide beginner-friendly AI tool workshops and step-by-step guides for faculty with low proficiency.
  - Advanced training: Offer specialized programs on pedagogical integration (e.g., designing AI-supported collaborative learning activities) for faculty with basic skills.
  - Role adaptation counseling: Share successful cases of faculty role transformation and provide psychological support to reduce identity crisis.

- **Incentive mechanism optimization**:
  - Recognition and rewards: Include AI-integrated teaching innovation in promotion and appraisal criteria, and provide research grants for curriculum redesign.
  - Workload adjustment: Reassign time for faculty to participate in training and revise courses, reducing workload pressure.

Mitigating Ethical Concerns: Ethical Governance and Transparency Enhancement: To address ethical risks, institutions should establish a comprehensive ethical governance system:

- **Clear policies and regulations**: Develop data usage policies specifying how student and faculty data is collected, stored, and used, and establish mechanisms for informed consent and data deletion.
- **AI tool auditing**: Evaluate AI tools for algorithmic bias before adoption, and regularly audit existing tools to ensure fairness.
- **Transparency enhancement**: Disclose how AI tools make recommendations or evaluations, and teach students to critically evaluate AI-generated content to foster independent thinking.

Overcoming Institutional Barriers: Policy Flexibility and Resource Allocation: Although Institutional Barriers are not statistically significant, optimizing institutional support can further promote implementation:

- **Policy flexibility**: Simplify curriculum approval processes and allow for flexible adjustment of teaching methods to accommodate AI integration.
- **Increased resource allocation**: Allocate special funds for AI education, including tool procurement, faculty training, and infrastructure upgrades.
- **Cross-departmental collaboration**: Establish interdisciplinary teams (IT, education, ethics) to provide comprehensive support for model 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 generalizability of findings to other countries and regions needs verification. China's unique educational system and regional disparities may affect the manifestation and impact of constraining factors.

Second, the study focuses on the direct and moderating effects of constraining factors, with limited exploration of mediating mechanisms (e.g., whether the Digital Divide affects synergy level through reducing AI Synergy).

Third, the cross-sectional design cannot reveal the dynamic evolution of constraining factors over time. Longitudinal data are needed to explore how barriers 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 generalizability of constraining factors in different educational systems. Recruit samples from Western countries, Southeast Asia, and Latin America to compare differences in barrier manifestations and impact mechanisms.

Second, explore the mediating mechanisms of constraining factors. Use structural equation modeling to test how factors such as AI Synergy and Faculty Role Adaptation mediate the relationship between constraints and synergy level.

Third, adopt a longitudinal design to track the dynamic evolution of constraints. Follow the same institutions and participants for 2-3 years to explore how barriers are addressed and how their impact changes over time.

Fourth, expand the scope of constraining factors to include student-related barriers (e.g., student resistance to AI-integrated learning) and explore their interaction with existing constraints.

Conclusion

This study systematically explores the key constraining factors of the "Faculty-Student-AI-Environment-Culture" five-element synergistic model's implementation and their impact mechanisms through a mixed-methods design, yielding the following key findings:

1. The Digital Divide (β=-0.371, p<0.001) and Faculty Adaptation Anxiety (β=-0.336, p<0.001) are the most critical constraining factors, followed by marginally significant Ethical Concerns (β=-0.184, p=0.054), while Institutional Barriers (β=-0.098, p=0.306) have no significant negative impact.
2. The Digital Divide significantly moderates the positive relationship between AI Synergy and teaching effectiveness (β=-0.097, p=0.021), weakening the model's synergistic effect.
3. The Digital Divide manifests as a "resource-access-capability" triple gap, Faculty Adaptation Anxiety stems from skill gaps, identity crisis, workload pressure, and incentive deficiencies, and Ethical Concerns focus on data privacy, algorithmic bias, and the erosion of independent thinking.

Based on these findings, a "three-dimensional breakthrough path" is proposed: resource balancing to address the Digital Divide, capacity building and incentive optimization to alleviate Faculty Adaptation Anxiety, and ethical governance to mitigate Ethical Concerns. This path provides a systematic, actionable framework for institutions to promote the model's effective implementation. The study's theoretical contributions lie in identifying the key constraining factors and their relative importance, revealing the moderating role of the Digital Divide, and exploring the contextualized manifestations of barriers. Practical implications include providing targeted strategies for addressing each constraint, helping to advance AI-integrated higher education transformation and contribute to the achievement of SDG 4 and ESD. Future research should focus on cross-cultural verification, mediating mechanisms, and longitudinal tracking to further enhance the generalizability and depth of findings, providing stronger support for the sustainable implementation of synergistic educational models globally.

Appendix A. Constraining Factors Scale

Dimension	Items
Digital Divide	1. There are marked disparities among students in the skills required to use AI learning tools effectively. 2. The digital infrastructure (e.g., networks, computers) in my region cannot meet the needs of AI education applications. 3. I lack the digital literacy and skills needed to use AI educational tools effectively.
Faculty Adaptation Anxiety	1. I worry that AI technology might undermine my professional authority in teaching. 2. Mastering AI teaching tools and adjusting teaching methods have brought me great psychological pressure. 3. The university lacks sufficient training and support, making it difficult for me to adapt to AI-integrated teaching.
Ethical Concerns	1. I am concerned that over-reliance on AI could negatively impact students' independent thinking abilities. 2. There is a risk of privacy leakage when AI tools collect and use student/faculty data. 3. AI algorithms may have biases, leading to unfair teaching evaluations or recommendations.
Institutional Barriers	1. The university's regulations and policies pose certain limitations on AI-based teaching innovation. 2. The university allocates insufficient funds and resources for AI education applications. 3. The university lacks incentive mechanisms (e.g., promotion, rewards) to encourage AI-integrated teaching innovation.

Appendix B. Semi-Structured Interview Protocols

B.1 Faculty Interview Protocol

1. What challenges do you face in using AI tools in teaching? How do these challenges affect your implementation of the five-element synergistic model?
2. How do you perceive the pressure of role adaptation in the AI era? What are the main sources of this pressure?
3. Have you encountered ethical dilemmas when using AI in teaching (e.g., data privacy, algorithmic bias)? How did you handle them?
4. What support does the university provide for AI-integrated teaching (e.g., training, funding, policies)? Are there any deficiencies?
5. What specific suggestions do you have for addressing the barriers to model implementation?

B.2 Student Interview Protocol

1. Do you have difficulty accessing or using AI learning tools? What are the main obstacles (e.g., hardware, network, skills)?

2. How do you perceive the impact of AI tools on your learning? Are you concerned about ethical issues such as data privacy or algorithmic fairness?
3. How do you think the digital divide affects your learning experience compared to peers in other regions or institutions?
4. What support do you hope the university will provide to help you better participate in AI-integrated learning?
5. What suggestions do you have for improving the implementation of the five-element synergistic model?

B.3 Administrative Staff Interview Protocol

1. What institutional policies and resource allocations has the university formulated for AI-integrated education?
2. What difficulties have you encountered in promoting the five-element synergistic model? How do these difficulties affect implementation?
3. How does the university address ethical risks and digital divide issues in AI education?
4. What improvements do you think are needed in institutional support (e.g., policies, funding, training) to promote the model?
5. What long-term strategies do you suggest for addressing the key barriers to model implementation?

References

1. Bagherimajd, K.; Khajedad, K. Designing a model of sustainable education based on artificial intelligence in higher education. Comput. Educ. Artif. Intell. 2025, 9, 100439. https://doi.org/10.1016/j.caeai.2025.100439.
2. Baker, R.S. Stupid tutoring systems, intelligent humans. Int. J. Artif. Intell. Educ. 2016, 26, 600–614. https://doi.org/10.1007/s40593-016-0105-0.
3. Børte, K.; Nesje, K.; Lillejord, S. Barriers to student active learning in higher education. Teach. High. Educ. 2023, 28, 597–615. https://doi.org/10.1080/13562517.2020.1839746.
4. Braun, V.; Clarke, V. Using thematic analysis in psychology. Qual. Res. Psychol. 2006, 3, 77–101. https://doi.org/10.1191/1478088706qp063oa.
5. Cohen, J. Statistical Power Analysis for the Behavioral Sciences, 2nd ed.; Lawrence Erlbaum Associates: Hillsdale, NJ, USA, 1988; pp. 123–156. ISBN: 0805802835.
6. Creswell, J.W.; Plano Clark, V.L. Designing and Conducting Mixed Methods Research, 3rd ed.; Sage Publications: Thousand Oaks, CA, USA, 2017; pp. 1–320. ISBN: 9781483344379.
7. Davis, B.; Sumara, D. Complexity and Education: Inquiries into Learning, Teaching, and Research; Routledge: London, UK, 2006; pp. 1–214. https://doi.org/10.4324/9780203764015.
8. Garzón, J.; Patiño, E.; Marulanda, C. Systematic Review of Artificial Intelligence in Education: Trends, Benefits, and Challenges. Multimodal Technol. Interact. 2025, 9, 84. https://doi.org/10.3390/mti9080084.
9. Gehrke, S.; Kezar, A. The roles of STEM faculty communities of practice in institutional and departmental reform in higher education. Am. Educ. Res. J. 2017, 54, 803–833. https://doi.org/10.3102/0002831217708595.
10. Hattie, J. Visible Learning: A Synthesis of Over 800 Meta-Analyses Relating to Achievement; Routledge: London, UK, 2008; pp. 1–392. https://doi.org/10.4324/9780203887332.
11. Huang, R.H.; Liu, M.Y.; Liu, J.H.; Chang, T.W. The "Why" and "What" of Smart Education —Analysis on the Performative and Constructive Features of Education in the Age of Intelligence. e-Educ. Res. 2023, 44, 5–12, 35. https://doi.org/10.13811/j.cnki.eer.2023.01.001.
12. Kaplan, A.; Haenlein, M. Rulers of the world, unite! The challenges and opportunities of artificial intelligence. Bus. Horiz. 2020, 63, 37–50. https://doi.org/10.1016/j.bushor.2019.09.003.
13. Landis, J.R.; Koch, G.G. The measurement of observer agreement for categorical data. Biometrics 1977, 33, 159–174. https://doi.org/10.2307/2529310.
14. Nedungadi, P.; Tang, K.Y.; Raman, R. The Transformative Power of Generative Artificial Intelligence for Achieving the Sustainable Development Goal of Quality Education. Sustain. 2024, 16, 9779. https://doi.org/10.3390/su16229779.
15. Peng, L.H.; Wang, P.; Huang, Z.L.; Li, X.Y.; Jin, H. From Technological Foresight to Ecological Reconstruction: The Symbiotic Evolution of Higher Education Reform and Artificial Intelligence—a Critical Review of Key Points from the 2024 Horizon Report (Teaching and Learning Edition). J. Dis. Edu. 2024, 42, 3–10, 31. https://doi.org/10.15881/j.cnki.cn33-1304/G4.2024.03.001.
16. Patton, M.Q. Qualitative Research & Evaluation Methods, 4th ed.; Sage Publications: Thousand Oaks, CA, USA, 2015; pp. 1–780. ISBN: 9781412972123.
17. Romero, C.; Ventura, S. Educational data mining and learning analytics: An updated survey. Wiley Interdiscip. Rev. Data Min. Knowl. Discov. 2020, 10, e1355. https://doi.org/10.1002/widm.1355.
18. Siemens, G. Learning analytics: The emergence of a discipline. Am. Behav. Sci. 2013, 57, 1380–1400. https://doi.org/10.1177/0002764213498851.
19. UNESCO. AI and Education: Guidance for Policy-Makers; United Nations Educational, Scientific and Cultural Organization: Paris, France, 2021. https://doi.org/10.54675/PCSP7350.
20. UNESCO. Reimagining Our Futures Together: A New Social Contract for Education; UNESCO Publishing: Paris, France, 2021; pp. 1–186. https://www.jstor.org/stable/resrep65004.
21. Vygotsky, L.S. Mind in Society: The Development of Higher Psychological Processes; Harvard University Press: Cambridge, MA, USA, 1978; pp. 1–174. https://doi.org/10.2307/j.ctvjf9vz4.
22. Wang, X.; Huang, R.; Sommer, M.; Pei, B.; Shidfar, P.Y.; Rehman, M.S.; Ritzhaupt, A.D.; Martin, F. The efficacy of artificial intelligence-enabled adaptive learning systems from 2010 to 2022 on learner outcomes: A meta-analysis. J. Educ. Comput. Res. 2024, 62, 1348–1383. https://doi.org/10.1177/07356331241240459.
23. Xu, L.L.; Peng, Z.P. Digital technology empowering the sustainable development of higher education: Essential orientations and promotion strategies. High. Educ. Explor. 2025, 1, 83–90. https://doi.org/10.3969/j.issn.1673-9760.2025.01.013.
24. Yang, X.M.; Zeng, J.Y.; Li, X. Refining and implementing AI-education application scenarios: A study based on exploratory multi-case research. Open Educ. Res. 2025, 31, 82–92. https://doi.org/10.13966/j.cnki.kfjyyj.2025.01.009.
25. Yuan, L.; Xu, J.Y.; Liu, W.Q. Human-machine collaborative teaching paradigm transformation in digital-intelligent education ecosystem. Open Educ. Res. 2025, 31, 108–117. https://doi.org/10.13966/j.cnki.kfjyyj.2025.02.011.
26. Yuan, Z.G. Digital Transformation in Education: What to Turn and How? J. East China Norm. Univ. (Educ. Sci.) 2023, 41, 1–11. https://doi.org/10.16382/j.cnki.1000-5560.2023.03.001.
27. Zhu, Z.T.; Han, Z.M.; Huang, C.Q. Educational artificial intelligence (eAI): A new paradigm of human-machine collaborative education. e-Educ. Res. 2021, 43, 5–15. https://doi.org/10.13811/j.cnki.eer.2021.01.001.

****