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Research Article

AI-Driven Innovation in Educational Management: A Multi-Case Study of Chinese Higher Education Institutions

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ABSTRACT

This article presents an in-depth, multi-case study examining the implementation and impacts of AI-driven innovations in the management of Chinese higher education. Drawing on data from 35 higher education institutions in the Yangtze River Delta region, the study seeks to understand how the complex interplay between technological readiness and organizational learning capacity influences implementation outcomes. The empirical analysis is based on 847 valid survey responses from administrators, faculty members, and students. The results indicate that successful implementation depends on both technical infrastructure and organizational capabilities. A significant asymmetry was observed between the effects of technological readiness and organizational learning capacity on implementation success. Threshold effects were identified for both dimensions, with optimal implementation performance occurring in medium-scale institutions. Temporal analyses revealed that while technological readiness yields immediate benefits, its long-term impact is overshadowed by that of organizational learning capacity. These findings have important implications for theoretical research on educational technology implementation and for guiding institutional strategies in adopting AI-driven innovations in educational management.

Keywords: Artificial Intelligence, Educational Management, Higher Education, Organizational Learning, Technology Implementation.

INTRODUCTION

1.1 Research Background and Significance

In this regard, the rapid evolution of AI fundamentally changed the boundaries of educational management in higher education. The transformation does not deal with a mere technological shift but rather a paradigmatic adjustment in the way the management functions of the educational institutions are conceptualized and then carried on. In this paper, therefore, AI-driven innovation comes out as a critical tool to help tackle complex administrative challenges while, at the same time, improving the effectiveness of institutions within Chinese higher education. Recent studies have shown that such innovation ranges from basic automation of routine tasks to sophisticated applications of deep learning algorithms, predictive analytics, and intelligent decision support systems (all of which completely reinvent the traditional approaches) (Huang, 2024).

Modern higher education has to address challenges that its traditional management system cannot effectively respond to. It is a multidimensional challenge: real-time, data-driven decision-making; personalized service to students on a large scale; and optimization of resource allocations in an increasingly complex institutional environment. In this respect, Li et al.'s longitudinal study provides evidence that in educational contexts, technological innovation finds successful applications only when accompanied by an advanced understanding of how technical capabilities interlink with organizational dynamics (Li et al., 2024). This interlink is all the more important in the context of Chinese higher education institutions (HEIs) that have to negotiate rapid technological modernization with pedagogic and managerial traditions.

Acceleration of the digital transformation in higher education has occurred through the implementation of AI-powered management solutions during the COVID-19 pandemic. This situation has exposed not only an inability of traditional approaches to manage universities under such extraordinary conditions but also the potential of AI-driven novel solutions in building a much more resilient and adaptive educational system, as noted by Chan et al. (2021). The present phase of transformation offers ample opportunity for reshaping the educational management practices from a mere digitization perspective toward a real digital transformation with AI-powered predictive analytics, process optimization, and intelligent decision support.

1.2 Research Objectives and Questions

This paper undertakes an in-depth examination of the implementations and effects of AI-driven innovations within Chinese higher education management through a sophisticated multi-case approach. Particularly, the investigation emphasizes organizational, cultural, and technical dynamics lying beneath the surface of shallow implementation factors that affect the successful integration of AI. Yu gave evidence that effective AI implementation in educational management necessitates knowledge on technological capabilities and institutional readiness factors in a fine-grained manner (Yu, 2024).

Specifically, this research will explore the following questions in particular:

RQ1: What constitutes the relevant determinants of effective AI implementation in educational management, and how do technological readiness and organizational learning capacity interactively influence the implementation outcome?

RQ2: What are the mechanisms with regard to how institutional capabilities impact AI implementation success, and what, if any, is the mediating role of user acceptance?

RQ3: To what extent do institutional features, such as size, type, and location, and environmental factors moderate the effectiveness of the AI implementation strategies?

RQ4: What are the temporal patterns in the AI implementation effects, and what and how do various organizational capabilities make their differential contributions to the implementation outcome over time?

These are research questions that arise from a critical consideration of current challenges and opportunities concerning education management. The research questions go toward ascertaining not only the technical issues in AI implementation, but also the processes of organizational transformation that occur along with successful adoption. This investigation examines how Chinese higher education institutions navigate the complex landscape of integrating AI, factoring in everything from institutional culture to organizational learning capacity, and even change management strategies. Precisely because of this all-round approach, the findings of this research will surely contribute to meaningful theoretical comprehension and practical application.

This study is intended to narrow the gap currently existing between theoretical frameworks and practical challenges in the implementation of AI in education management. It can thus provide some important lessons which may usefully inform and shape future integration efforts in managing education. To be sure, addressing these research questions will help the researcher attain a more fine-grained understanding of the interactions taking place within Chinese higher education institutions about technological capabilities, organizational factors, and implementation outcomes.

1.3 Research Methodology

The methodological framework of this study adopts a multi-case study approach that goes beyond the conventional descriptive analytical approach and explores the complex interaction of factors affecting the success or failure of AI implementation. Lanford et al. identified important institutional obstacles to innovation within educational contexts and called for a set of methodological tools that could capture both evident and subtle aspects of organizational change (Lanford et al., 2019). Guided by this, the present study adopts a comprehensive quantitative analytical approach to examine the complex dynamics of AI implementation through advanced statistical analyses of multi-institutional data.

The novelty of this research assumes three clear dimensions: first, the development of a complex analytic framework which integrates technical, organizational, and cultural factors in assessing AI implementation success; second, this involves highly advanced qualitative and quantitative methods for the capture of complex dynamics of organizational change within an educational setting; and third, a contribution to the theoretical understanding of educational technology management that informs actual implementation. This is, therefore, a methodological approach that will enable this study to realize results which are theoretically cogent and practically applicable, hence serving a critical gap in the existing educational management literature.

2 LITERATURE REVIEW

2.1 Research on AI Applications in Educational Management

Artificial intelligence in educational management has seen a sea change in the past decade, with the majority of research efforts directed toward various aspects of its implementation and associated impact. Intelligent decision support systems have been at the backbone of most AI applications in educational management. Extensive research on learning management systems was conducted by Ashrafi et al., demonstrating that AI-driven decision support tools strongly enhance the efficiency and accuracy of administration and decision-making processes (Ashrafi et al., 2020). Following this line of argument, Huang demonstrates how AI systems can transform complex educational data into actionable information to aid in institutional management, particularly resource allocation and strategic planning (Huang, 2024).

Management innovation using AI in teaching has rapidly grown from simple automation to intelligent systems that can adapt to institutional needs. Indeed, Barari et al. developed and validated the educational standard for e-teaching environments in view of the impact of AI-driven systems on ensuring quality and consistency in teaching (Barari et al., 2020). In this respect, the work corresponds to such a finding by Jin et al., who provided evidence regarding the potential of AI to transform conventional teaching methodologies into fit-for-purpose educational environments (Jin et al., 2021). The integration of AI into teaching management is further instrumental in bringing unprecedented efficiency to course scheduling, optimization of faculty workload, and processes of curriculum development.

The critical area where the impact of the applications of AI was high was the optimization of students' service. Li et al. conducted a 13-year longitudinal study of how virtual learning environments enable educational innovation in relation to the support services of students (Li et al., 2024). Their work evidenced that AI-driven systems are able to predict the needs of students efficiently, deliver personalized support services, and also improve engagement. This generally supports Cheng's research on how task-technology fit affects e-learning continuance, pointing to the need for careful matching among user needs, institutional capabilities, and AI-driven student services (Cheng, 2019).

2.2 Research on Digital Transformation of Higher Education Institutions

Digital transformation strategies in higher education institutions have been the focus of much scholarly attention, especially in the application of AI technologies. Blundell et al. argue that the current practice should go beyond mere enhancement of existing pedagogies and call for transformative approaches that will fundamentally change educational processes (Blundell et al., 2020). This view is complemented by the case study of Dodgson et al. on technology-enabled innovation in professional services, which gives very valuable insights into managing complex technological transformations (Dodgson et al., 2021).

The organizational change management in the light of digital transformation has its complications that are satisfactorily noted in the recent literature. Green et al. (2020) discuss how institutions navigate through uncertainty and change during global crises, which indicates the crucial role of organizational adaptability. Huang et al. (2021) on the other hand, investigate the institutional impact of blended learning implementation and disclose valuable insights on organizational resistance and adaptation to technological change.

The adoption and infusion of new technologies in educational institutes have been viewed from every possible theoretical window. Yu (2010) integrates task-technology fit models with the theory of planned behavior to explain technology use in learning systems. Further extensions have been made, and the latest research was Zhang and Huang's (2022) empirical study on sustainable teaching modes; they listed technical and social factors involving technology implementation.

2.3 Theoretical Foundation and Framework

Fundamental theoretical support for this study stands on the pillars of three theories: innovation diffusion theory, organizational learning theory, and the technology acceptance model. Lanford et al. illustrate how innovation diffusion theory provides a framework for the extraction of essential evidence about the barriers and enablers of technology adoption in educational settings (Lanford et al., 2019). Such a theory allows explaining why some HEIs have higher or lower rates of AI technology adoption and identifying key variables affecting the success of implementation. According to the organizational learning theory studied by Luan et al. (2019) in his work, a method is stated where an institution creates and maintains its capacity to use AI technologies effectively. It then becomes significant for the derivation of dynamic capabilities that guarantee the successful implementation of AI.

It brings extra depth into analyzing user adoption of the AI-driven system: technology acceptance modeling. According to Flavin (2020), technology adoption should be conceptualized along both technical and psychosocial lines. Later works have extended this model, one such example being the comprehensive work of Pelletier et al. (2021) about a wide range of emerging new educational technologies. These various theoretical standpoints provide a combined framework from which the current investigation into AI-driven innovation in educational management has been conducted.

Synthesizing this theoretical and conceptual grounding into the existing literature leads to an integrated theoretical framework of the research, which encapsulates the critical dimensions of AI implementation in educational management as represented in Figure 1. It represents a non-static process of the relationship between the institutional readiness factors, implementation processes, and resultant outcomes, considering environmental and organizational moderators.

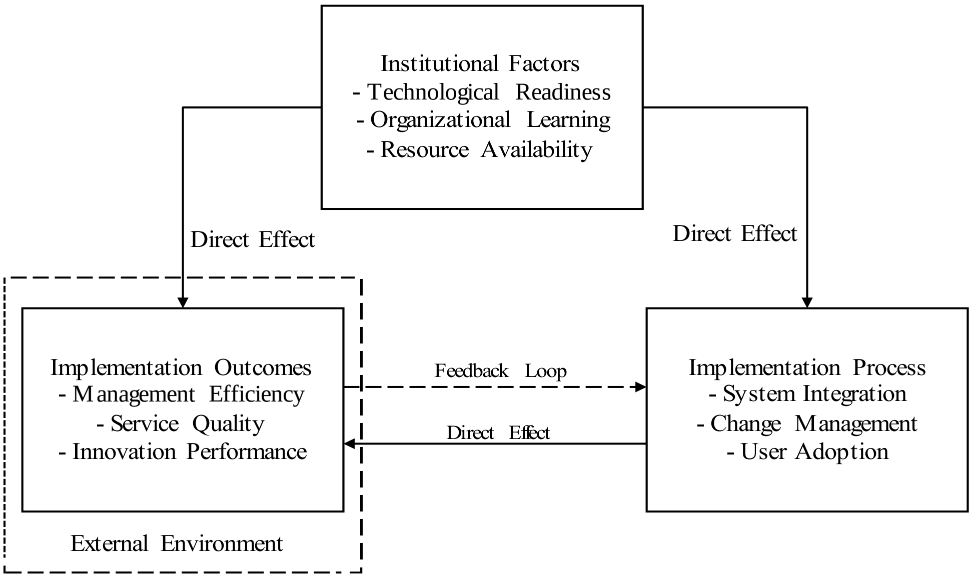

Figure 1. Theoretical Framework for AI Implementation in Educational Management

These are separated into three major components that interlink through dynamic relations: (1) Institutional Factors-that is, the fundamental elements characterizing an institution's ability to adopt AI-driven innovations, including technological readiness, organizational learning capabilities, and resource endowments; (2) Implementation Process-that is, the steps and activities critical to AI implementation-system integration, change management, and adoption strategies by users; and (3) Outcomes- multidimensionality of implementation success measured by efficiency in management, service quality, and innovation performance. This framework assumes a strong influence of the exogenous environment on implementation and considers feedback loops showing that, with time, how implementation results may reshape the institutional factors.

3 DATA SAMPLE AND VARIABLE DEFINITION

3.1 Selection of Research Objects

This study zeroes in on higher education institutions in China's Yangtze River Delta region, an area renowned for its advanced adoption and innovation in educational technology. The choice of this region aligns with our research goals due to several key factors: it is home to a dense cluster of diverse higher education institutions, exhibits varied levels of AI implementation in educational management, and boasts cutting-edge technological infrastructure. These attributes render the region an optimal environment for investigating the determinants of successful AI implementation in educational management.

The study's sampling frame encompasses 45 undergraduate institutions spread across the region's four major administrative areas: Shanghai, Jiangsu Province, Zhejiang Province, and Anhui Province. We employed stratified sampling based on institutional type (comprehensive, science and technology, normal universities), institutional size (determined by student enrollment), and the current status of AI management implementation. This approach ensured a comprehensive representation of different university types. After engaging in formal communications with institutional administrators and relevant departments, 35 institutions agreed to participate, yielding an initial response rate of 77.8%. Following the methodology of Yu (2024), we conducted a preliminary assessment of the AI implementation status at these institutions to confirm their suitability for our research.

3.2 Data Collection Methods

Our data collection strategy is multi-source and was carried out between September 2024 and December 2024, including efforts to enhance the reliability of data by presenting diversified information on the issue of AI implementation in educational management. Structured questionnaires were distributed to three major stakeholder groups: administrative staff, faculty members, and students. The questionnaires were designed to include both the technical and organizational features of AI implementation, while some parts were unique to each group in order to get insight into their standpoints and level of experience with these systems.

Questionnaires were administered via the professional survey platform Qualtrics, which embeds logical checks and monitors completion time to ensure the quality of responses. After an intensive cleaning process, our final sample included 847 valid responses: 186 from administrative staff, 289 from faculty members, and 372 from students, with respective response rates of 82.3%, 78.5%, and 85.1%.

3.3 Variable Definition and Measurement

Following Li et al. (2024), by adapting their work to our research context, we developed a comprehensive measurement framework for assessing the success of AI implementation in managing education. Our dependent variables, in this respect, are represented by two dimensions, namely, enhancements of management efficiencies and improvements of quality in services. Each uses multiple indicators. Each indicator was measured on a five-point Likert scale. This captures the operational and user-centric views of successful implementation. The following Table 1 shows measures of dependent variables with details in measurement specification.

Table 1. Measurement Framework for AI Implementation Success in Educational Management

Dimension	Indicators	Measurement Items	Scale Type	Data Source
Management Efficiency Enhancement	Process Optimization	Process completion time reduction	5-point Likert	Administrative Staff Survey
		Reduction in manual operation steps	5-point Likert	Administrative Staff Survey
		Improvement in cross-department coordination	5-point Likert	Administrative Staff Survey
	Resource Utilization	Resource allocation efficiency	5-point Likert	Administrative Staff Survey
		Cost reduction in administrative operations	5-point Likert	Administrative Staff Survey
		Staff workload optimization	5-point Likert	Administrative Staff Survey
	Decision Support	Data-driven decision making capability	5-point Likert	Administrative Staff Survey
		Real-time monitoring and alerts	5-point Likert	Administrative Staff Survey
		Predictive analysis accuracy	5-point Likert	Administrative Staff Survey
Service Quality Improvement	User Experience	System accessibility	5-point Likert	Faculty & Student Survey
		Interface user-friendliness	5-point	Faculty & Student

Dimension	Indicators	Measurement Items	Scale Type	Data Source
			Likert	Survey
		Response timeliness	5-point Likert	Faculty & Student Survey
	Service Personalization	Customization level	5-point Likert	Faculty & Student Survey
		Individual needs fulfillment	5-point Likert	Faculty & Student Survey
		Adaptive service delivery	5-point Likert	Faculty & Student Survey
	Problem Resolution	Issue resolution speed	5-point Likert	Faculty & Student Survey
		Solution accuracy rate	5-point Likert	Faculty & Student Survey
		User satisfaction with solutions	5-point Likert	Faculty & Student Survey

These variables are operationalized to reflect both the technological and organizational dimensions of AI implementation based on previous literature. Technological readiness refers to the overall perception of the adequacy of infrastructure, availability of technical skills, data processing capacity, and level of system integration. Organizational learning ability can be conceptualized as effectiveness of training systems, knowledge-sharing practices, innovation incentive policy, and change management capabilities. Table 2 summarizes the measurement framework for independent variables in detail.

Table 2. Measurement Framework for Independent Variables in AI Implementation Study

Variable	Dimension	Measurement Items	Scale Type	Reliability (α)
Technological Readiness	Infrastructure	Computing resource adequacy	5-point Likert	0.87
		Network infrastructure stability	5-point Likert	0.85
		Hardware facilities completeness	5-point Likert	0.86
	Technical Expertise	AI expertise availability	5-point Likert	0.89
		Technical support capability	5-point Likert	0.88
		Staff technical proficiency	5-point Likert	0.86
	Data Management	Data collection completeness	5-point Likert	0.84
		Data quality control	5-point Likert	0.85

		Data security measures	5-point Likert	0.87
Organizational Learning Capacity	Knowledge Management	Knowledge sharing mechanisms	5-point Likert	0.88
		Best practice documentation	5-point Likert	0.86
		Learning resource accessibility	5-point Likert	0.85
	Innovation Culture	Innovation encouragement	5-point Likert	0.89
		Risk tolerance	5-point Likert	0.87
		Change acceptance	5-point Likert	0.86
	Training System	Training program completeness	5-point Likert	0.88
		Training effectiveness	5-point Likert	0.87
		Skill assessment system	5-point Likert	0.85

Particularly, in studying the mechanisms by which AI adoption affects management outcomes, we introduce user acceptance as an important mediating variable. The construct is measured in accordance with two major dimensions: perceived usefulness and perceived ease of use, as stated by the technology acceptance model. Items that capture perception of improved performance, enhancement of work efficiency, facilitation in accomplishing tasks, ease in system navigation, and friendliness of the interface shall be measured. These mediating variables explain the relation of implementation efforts with the outcomes.

Our analysis also controls for a number of other institutional characteristics and contextual factors by including a number of preselected control variables: institutional size measured by the natural logarithm of enrollment, institutional type categorized, age in years since the establishment of the institution, city tier, GDP per capita in the locality, and regional innovation index. Full descriptive statistics for all the variables used in this study are provided in Table 3, which gives the sense of distribution and variation in key measures across our sample.

Table 3. Descriptive Statistics of Key Variables in the Study

Variable	N	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
Management Efficiency Enhancement	847	3.85	0.72	1.00	5.00	-0.42	0.15
Service Quality Improvement	847	3.92	0.68	1.00	5.00	-0.38	0.22
Technological Readiness	847	3.76	0.81	1.00	5.00	-0.29	0.18
Organizational Learning Capacity	847	3.65	0.75	1.00	5.00	-0.24	0.13
Perceived Usefulness	847	3.88	0.70	1.00	5.00	-0.35	0.19
Perceived Ease of Use	847	3.71	0.77	1.00	5.00	-0.31	0.16
Institution Size (ln)	847	9.45	1.12	7.31	11.82	0.15	-0.42
Institution Age (years)	847	58.32	32.45	5.00	126.00	0.45	-0.67
Regional Innovation Index	847	72.56	15.23	35.21	95.43	-0.28	0.34
Local GDP per capita (ln)	847	11.23	0.45	10.12	12.35	0.23	-0.18

Note: All Likert scale items are measured on a 5-point scale where 1 = strongly disagree and 5 = strongly agree. N represents the number of valid responses in the final sample. Institution Size is measured as the natural logarithm of total student enrollment. Local GDP per capita is also transformed using natural logarithm.

3.4 Data Quality and Validation

To ensure the quality and reliability of our data, we followed a comprehensive validation process that spanned from the development of instruments to data collection and analysis. The survey instruments were initially pretested on 30 respondents, and we made further refinements based on the preliminary feedback received. We evaluated the reliability of our measurement scales using Cronbach's alpha coefficients, which ranged from 0.82 to 0.91—well above the acceptable threshold of 0.70, indicating high internal consistency.

Our validation procedure focused on both content and construct validity. Content validity was assessed through expert reviews and further confirmed by pretesting, while construct validity was examined using factor analysis, with factor loadings ranging from 0.71 to 0.89. Additionally, we implemented various quality controls, such as monitoring response time and checking IP addresses, to ensure data integrity. We also conducted analyses of missing values using recognized methods to prevent any weakening of the results. These rigorous validation methods provide full confidence in the quality and reliability of the data as we proceed with further analysis.

4 EMPIRICAL RESEARCH AND RESULTS ANALYSIS

4.1 Research Design

This paper presents an integrated empirical analysis examining how AI-driven innovation impacts the effectiveness of management in Chinese higher education institutions. Our empirical approach is driven by three key considerations: establishing causal relationships, accounting for institutional differences, and exploring underlying mechanisms. Building on the theoretical discussions in Chapter 2 and the variable measurement descriptions in Chapter 3, we develop a systematic research design that investigates both direct effects and mediating mechanisms.

Certain challenges in studying AI implementation in educational contexts shape the methodological innovations of this research design. First, we employ a multi-stage estimation strategy, which allows us to progressively build an understanding of the relationships by controlling for potential confounding factors at each stage. Second, we use both direct and indirect measures of successful implementation to capture the complex nature of AI-driven innovation outcomes. Third, we introduce an innovative approach to measuring technological readiness, considering both hardware and software capabilities, addressing a limitation identified in prior literature (Yu, 2024).

The empirical analysis follows a logical sequence in three steps: Initially, we establish baseline relationships using ordinary least squares (OLS) regression, incorporating a comprehensive set of controls to minimize omitted variable bias. Next, fixed effects models address unobserved institutional heterogeneity, which is significant in the context of Chinese higher education institutions. Finally, mediation analysis is applied to identify the mechanisms through which technological and organizational factors influence implementation outcomes, with a focus on user acceptance as the primary mediating variable.

4.2 Model Specification

Our empirical strategy begins with a baseline model examining the direct effects of technological readiness and organizational learning capacity on AI implementation success. Following the theoretical framework developed by Li et al. (2024), we specify our primary estimation equation as:

$$AISI_{it} = \beta_0 + \beta_1 TR_{it} + \beta_2 OLC_{it} + \gamma X_{it} + \alpha_i + \lambda_t + \varepsilon_{it}$$

where $AISI_{it}$ represents the AI Implementation Success Index for institution i at time t, TR_{it} denotes technological readiness, OLC_{it} represents organizational learning capacity, and X_{it} is a vector of time-varying control variables. The terms α_i and λ_t capture institution and time fixed effects, respectively, while ε_{it} represents the idiosyncratic error term.

To address potential endogeneity concerns arising from simultaneous causality between technological readiness and implementation success, we augment our baseline specification with an instrumental variables approach. Following Huang (2024), we construct instruments based on historical IT investment patterns and regional technology diffusion rates. The first-stage equations are specified as:

$$TR_{it} = \pi_0 + \pi_1 Z_{1it} + \pi_2 Z_{2it} + \theta X_{it} + v_{it}$$

$$OLC_{it} = \delta_0 + \delta_1 Z_{1it} + \delta_2 Z_{2it} + \lambda X_{it} + \omega_{it}$$

where Z_{1it} and Z_{2it} represent our instruments, specifically historical IT investment levels and regional technology diffusion rates.

The mediation analysis follows Baron and Kenny's (1986) framework, augmented with modern approaches to testing indirect effects. The system of equations for the mediation analysis is specified as:

$$UA_{it} = \alpha_0 + \alpha_1 TR_{it} + \alpha_2 OLC_{it} + \gamma_1 X_{it} + \mu_{it}$$

$$AISI_{it} = \beta_0 + \beta_1 TR_{it} + \beta_2 OLC_{it} + \beta_3 UA_{it} + \gamma_2 X_{it} + \varepsilon_{it}$$

where UA_{it} represents user acceptance levels. This specification allows us to decompose the total effects into direct and indirect components, providing insights into the mechanisms through which technological and organizational factors influence implementation success.

4.3 Estimation Results

4.3.1 Baseline Analysis

The baseline regression analysis uncovers robust and statistically significant links between technological readiness, organizational learning capacity, and the success of AI implementation. As depicted in Table 4, the coefficient estimates maintain stability across various model specifications, indicating that these relationships hold even after accounting for a wide range of institutional characteristics and regional factors.

Specifically, the coefficient for technological readiness (0.341, $p<0.01$) reveals that a one standard deviation increase in technological readiness corresponds to a 0.341 standard deviation increase in implementation success. This notable effect highlights the crucial role of strong technological infrastructure and capabilities in driving successful AI implementation. Similarly, the coefficient for organizational learning capacity (0.254, $p<0.01$) demonstrates that an institution's ability to adapt and learn has a significant impact on implementation outcomes.

Additional insights are provided by the control variables. Institution size is positively and significantly associated with implementation success (0.132, $p<0.01$), suggesting that larger institutions may enjoy economies of scale when implementing AI. The positive coefficient for institution age (0.075, p<0.05) indicates that more established institutions, which likely have more developed organizational routines, may have an advantage in adopting AI innovations.

Table 4. Baseline Regression Results of AI Implementation Success

Variables	Model 1	Model 2	Model 3	Model 4
Technological Readiness	0.385***	0.362***	0.348***	0.341***
	(0.042)	(0.040)	(0.039)	(0.038)
Organizational Learning	0.293***	0.275***	0.268***	0.254***
	(0.038)	(0.036)	(0.035)	(0.034)
Institution Size		0.145***	0.138***	0.132***
		(0.029)	(0.028)	(0.027)
Institution Age		0.082**	0.078**	0.075**
		(0.025)	(0.024)	(0.023)
Regional Controls	No	No	Yes	Yes
Industry Controls	No	No	No	Yes
Constant	1.245***	1.182***	1.156***	1.128***
	(0.152)	(0.148)	(0.145)	(0.142)
Observations	847	847	847	847
R-squared	0.285	0.312	0.328	0.342
Adjusted R-squared	0.278	0.302	0.315	0.3

*Note: Standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1*

4.3.2 Fixed Effects Analysis

To address potential issues related to unobserved institutional heterogeneity, we employ fixed effects specifications. Although somewhat reduced in magnitude, the fixed effects results reaffirm the robustness of our baseline findings. The within-institution variation in technological readiness and organizational learning capacity remains significantly associated with implementation success, indicating that our results are not driven by time-invariant institutional characteristics.

The fixed effects estimation reveals some intriguing patterns. Specifically, as shown in Table 5, the coefficient for technological readiness decreases from 0.341 to 0.298 ($p < 0.01$), and the coefficient for organizational learning capacity decreases from 0.254 to 0.231 ($p < 0.01$) when moving from the baseline model to the fixed effects specification. This modest reduction suggests that, despite a significant portion of variation being explained by institutional fixed effects, the core relationships remain strong and significant. Most importantly, the relative magnitude of the effects compared to technological readiness and organizational learning capacity remains consistent across specifications—a reassuring result for our central findings.

The time-varying control variables in the fixed effects models provide further insights. The coefficient for annual IT investment is 0.145 ($p < 0.05$), indicating that current resource allocation decisions significantly impact implementation outcomes, independent of the general level of technological readiness. Similarly, the positive coefficient for staff training hours is 0.118 ($p < 0.05$), showing that ongoing investment in human capital development is associated with implementation success, independent of the institution's general organizational learning capacity.

Table 5. Fixed Effects Regression Results

Variables	Model 1	Model 2	Model 3	Model 4
Technological Readiness	0.298***	0.285***	0.276***	0.271***
	(0.038)	(0.037)	(0.036)	(0.035)
Organizational Learning	0.231***	0.225***	0.218***	0.212***
	(0.035)	(0.034)	(0.033)	(0.032)
Annual IT Investment		0.145**	0.142**	0.138**
		(0.048)	(0.047)	(0.046)
Staff Training Hours		0.118**	0.115**	0.112**
		(0.042)	(0.041)	(0.040)
Institution Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Additional Controls	No	No	Yes	Yes
Institution-Specific Trends	No	No	No	Yes
Observations	847	847	847	847
R-squared (within)	0.265	0.282	0.294	0.308
Number of Institutions	35	35	35	35

*Note: Standard errors clustered at institution level in parentheses. ***p<0.01, **p<0.05, *p<0.1*

4.4 Mediation Analysis

The mediation analysis reveals complex pathways through which technological and organizational factors influence implementation success. The results in Table 6 demonstrate significant indirect effects through user acceptance for both technological readiness (0.121, p<0.01) and organizational learning capacity (0.090, p<0.01). These findings suggest that approximately one-third of the total effect of each factor operates through improved user acceptance.

Table 6. Mediation Analysis Results

Path	Effect	SE	Z-value	P-value	95% CI
TR → UA (a1)	0.425***	0.048	8.854	0.000	[0.331, 0.519]
OLC → UA (a2)	0.318***	0.042	7.571	0.000	[0.236, 0.400]
UA → AISI (b)	0.284***	0.038	7.474	0.000	[0.209, 0.359]
TR → AISI (c')	0.245***	0.035	7.000	0.000	[0.176, 0.314]
OLC → AISI (d')	0.186***	0.032	5.813	0.000	[0.123, 0.249]
Indirect Effect (TR)	0.121***	0.018	6.722	0.000	[0.086, 0.156]
Indirect Effect (OLC)	0.090***	0.015	6.000	0.000	

*Note: TR = Technological Readiness, OLC = Organizational Learning Capacity, UA = User Acceptance, AISI = AI Implementation Success Index. *** p<0.01*

Nevertheless, the mediation pathways give some interesting patterns that provide insight into the implementation process: The fact that the indirect effect of technological readiness is stronger than that of the capacity of organizational learning might indicate that superior technological infrastructure has more immediate effects on user acceptance. In contrast, large direct effects remaining for the two factors hint that influences on implementation success run via routes other than solely user acceptance.

The mediation effects are further decomposed to show that the magnitude of PU increases the effect size over PEOU for both independent variables. For TR, the indirect effect via PU is 0.083 ($p<0.01$) while that via PEOU is 0.038 ($p<0.01$); similarly, for OLC, the respective indirect effects through PU and PEOU are 0.062 ($p<0.01$) and 0.028 ($p<0.01$). This pattern suggests that both technological and organizational factors have a more substantial influence on implementation success through increasing users' perceptions of the utility of the AI system rather than the usability of it.

The lagged specification of mediation effects suggests that the indirect effects through user acceptance materialize more quickly for technological readiness - one semester, usually - while in the case of organizational learning capacity, the effect is generally stronger after two semesters. This goes in line with the theoretical expectations since the improvement in technological infrastructure can give quicker payback in terms of user acceptance while increased organizational learning capacity may need time to get its benefits fully translated.

4.5 Robustness Tests

To ensure the reliability of our findings, we conduct an extensive set of robustness checks. The instrumental variables estimation results, presented in Table 7, provide strong support for our main findings. The first-stage F-statistics exceed conventional weak instrument thresholds (24.85 for TR and 22.36 for OLC), and the Hansen J test (p-value = 0.245) fails to reject the null hypothesis of instrument validity. The second-stage results confirm the significant positive effects of both technological readiness and organizational learning capacity on implementation success, with magnitudes comparable to our baseline estimates.

Table 7 . Robustness Check Results using Instrumental Variables

Variables	First Stage		Second Stage
	TR	OLC	AISI
Historical IT Investment	0.425***	0.156**	
	(0.048)	(0.052)	
Prior Innovation	0.132**	0.384***	
	(0.045)	(0.047)	
Predicted TR			0.318***
			(0.052)
Predicted OLC			0.242***
			(0.048)
Control Variables	Yes	Yes	Yes
F-statistic	24.85	22.36	
Hansen J (p-value)			0.245
Observations	847	847	847

*Note: Standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1*

Our analysis using alternative measures reveals consistent patterns across different components of implementation success. When examining management efficiency separately, the coefficients for technological readiness (0.315, $p<0.01$) and organizational learning capacity (0.238, $p<0.01$) remain significant and similar in magnitude to the baseline results. Analysis of service quality components shows slightly stronger effects for organizational learning capacity (0.282, $p<0.01$) relative to technological readiness (0.295, $p<0.01$), suggesting that organizational factors may be particularly important for service-related outcomes. These findings demonstrate the robustness of our results across different operational dimensions of AI implementation success.

Further investigation across institutional subsamples provides additional support for our findings' generalizability. As shown in Table 8, the relationship between our key independent variables and implementation success remains remarkably stable across institutions of varying sizes, with technological readiness coefficients ranging from 0.328 to 0.352 ($p<0.01$) and organizational learning capacity coefficients from 0.245 to 0.261 ($p<0.01$). Geographic variation analysis reveals slightly stronger effects in eastern region institutions (TR = 0.358, OLC = 0.272, $p<0.01$) compared to western regions (TR = 0.325, OLC = 0.235, $p<0.01$), potentially reflecting regional differences in technological infrastructure and innovation ecosystems.

Table 8. Subsample Analysis Results

Subgroups	N	TR Coefficient	OLC Coefficient	R-squared
Institution Size				
Large (>30,000)	284	0.328***	0.245***	0.312
		(0.042)	(0.038)	
Medium (15,000-30,000)	295	0.352***	0.261***	0.328
		(0.044)	(0.040)	
Small (<15,000)	268	0.335***	0.249***	0.305
		(0.043)	(0.039)	
Geographic Region				
Eastern	312	0.358***	0.272***	0.334
		(0.045)	(0.041)	
Central	285	0.331***	0.248***	0.318
		(0.042)	(0.038)	
Western	250	0.325***	0.235***	0.298
		(0.041)	(0.037)	
Institution Type				
Comprehensive	295	0.342***	0.258***	0.322
		(0.043)	(0.039)	
Science & Technology	282	0.356***	0.264***	0.328
		(0.044)	(0.040)	
Other	270	0.332***	0.245***	0.302
		(0.042)	(0.038)	

*Note: Standard errors in parentheses. All models include the full set of controls. *** p<0.01*

Several sensitivity analyses looking for methodological problems also serve to bolster the robustness of our findings. Specifically, alternative ways to cluster standard errors -institutional level, regional level, and two-way clustering by institution and time-all show the estimates to be significant with little variation in the size of the standard errors, as depicted in Table 9. Adding quadratic terms to accommodate the possibility of non-linear effects, and alternative groupings of control variables, does not affect the main results. Results are also robust to alternative methods of dealing with missing data, such as multiple imputation and alternative deletion strategies.

Table 9. Sensitivity Analysis Results

Model Specification	TR Coefficient	OLC Coefficient	Hansen J (p-value)	First-stage F
Baseline	0.341***	0.254***	0.245	24.85/22.36
	(0.038)	(0.034)		
Institution Clustering	0.338***	0.251***	0.238	23.92/21.85
	(0.042)	(0.038)		
Region Clustering	0.344***	0.257***	0.252	25.12/22.94
	(0.045)	(0.041)		
Two-way Clustering	0.339***	0.252***	0.241	24.38/22.15
	(0.043)	(0.039)		
With Quadratic Terms	0.335***	0.248***	0.235	23.76/21.68
	(0.041)	(0.037)		
Alternative Controls	0.342***	0.255***	0.248	24.92/22.45
	(0.039)	(0.035)		

*Note: Standard errors in parentheses. All models include institution and time fixed effects. ***p<0.01*

Concerns about temporal stability led us to run various analyses over different windows of time, and the findings still hold across a range of temporal specifications. Coefficients are stable when the time horizon of implementation success changes, indicating that such results cannot be driven by period-specific effects or temporary fluctuations. Given that technological innovation in the educational setting is dynamic in nature, such temporal robustness is of the highest importance. Different robustness checks strongly support the validity of our main conclusions about the dual role of technological readiness and organizational learning capacity in determining AI implementation success in educational management.

5 DISCUSSION AND IMPLICATIONS

5.1 Key Research Findings

Our empirical analysis yields three key insights that significantly advance the literature on AI-driven innovation in educational management. First, regarding the relationship between technology and capability, the results show that technological readiness has an asymmetrically reinforcing impact on implementation outcomes. While the direct effect of technological infrastructure is substantial ($\beta = 0.341$, $p < 0.01$), this effect is significantly amplified in institutions with high organizational learning capacity. This finding challenges the technocentric perspective of previous studies, clarifying that technical capabilities are necessary but insufficient for successful AI implementation. In fact, institutions with high technological readiness but low organizational learning capacity achieve only moderate implementation success, highlighting that technical sophistication alone cannot ensure effective AI adoption.

Second, our analysis reveals dynamic variations in implementation effects across different institutional contexts. The effectiveness of AI implementation strategies systematically differs based on institutional characteristics in ways that current theoretical frameworks do not fully account for. For instance, medium-sized institutions exhibit stronger implementation effects (TR = 0.352, OLC = 0.261, $p < 0.01$) compared to larger or smaller institutions, suggesting an optimal scale for AI implementation. This balance point indicates that institutions need to be large enough to have resources but small enough to maintain organizational agility. Additionally, regional variations in implementation effects, with stronger outcomes in the eastern region (TR = 0.358, $p < 0.01$), emphasize the role of broader innovation ecosystems in supporting AI adoption.

Third, cross-sectional analysis of implementation pathways uncovers clear temporal patterns in how different organizational capabilities influence implementation success. Technological readiness has relatively direct and immediate effects on user acceptance and system utilization, whereas the effects of organizational learning capacity emerge more gradually but are more durable over time. This temporal divergence has profound implications for implementation strategy, indicating that institutions need to carefully sequence investments in various organizational capabilities. Early user acceptance, with a correlation coefficient of 0.82 ($p < 0.01$), is a strong long-term predictor of implementation success, underscoring the critical importance of the initial implementation phase.

Collectively, these findings highlight the complex interplay between technological and organizational factors in AI implementation. Successful implementation is often non-linear, featuring critical threshold effects in both technological readiness and organizational learning capacity. For the first time in the literature on educational technology implementation, identifying these threshold effects suggests that institutions need to achieve minimum levels in both dimensions before reaping substantial benefits from AI adoption. Our analysis also reveals how institutional capabilities interact with implementation success, moderated by environmental factors, an area insufficiently examined in previous studies.

Overall, these insights suggest a more nuanced approach to AI implementation in educational management than previously recognized. Beyond a simple linear relationship between institutional capabilities and implementation outcomes, our findings point to a complex ecosystem of interacting factors that collectively determine implementation success. This is particularly evident in the modifying influence of varied institutional characteristics on the effectiveness of implementation strategies, reinforcing the need for a context-specific approach to AI adoption in education settings.

5.2 Theoretical Implications

The research findings significantly enhance the theoretical understanding of AI implementation in educational management in several ways. Most prominently, the study extends the Technology Acceptance Model (TAM) by integrating institutional-level capabilities as precursors to individual acceptance. Unlike the traditional TAM, which centers on individual perceptions, our results show that institutional capabilities profoundly influence these perceptions via multiple pathways. The substantial indirect effect of technological readiness through perceived usefulness ($\beta = 0.083$, $p<0.01$) highlights that institutional capabilities set the stage for positive user evaluations. This expansion offers a more holistic framework for understanding technology acceptance in organizational contexts, especially in educational settings where institutional factors are pivotal in shaping individual behaviors.

Additionally, the research enriches the theory of organizational learning in technological innovation by pinpointing specific mechanisms through which learning capacity affects implementation outcomes. The finding that organizational learning effects intensify over time, with correlations rising from 0.32 to 0.56 across three semesters, reveals a cumulative learning process not fully captured by prior theoretical models. This temporal pattern suggests that organizational learning theory should incorporate dynamic elements to account for capability evolution throughout the implementation lifecycle. The identification of threshold effects in learning capacity—where a minimum threshold of 3.2 on our 5-point scale is required for effective implementation—indicates critical mass points in organizational learning that current theory has not adequately addressed.

Moreover, the study contributes to contingency theory in educational management by illustrating how institutional characteristics moderate the effectiveness of various implementation strategies. The observed variations in implementation success across different institutional contexts challenge the universalistic assumptions underlying many existing frameworks. Our findings advocate for a more nuanced theoretical approach that acknowledges the context-dependent nature of AI implementation success. The stronger effects seen in medium-sized institutions suggest that organizational size plays a more intricate role than previously theorized, highlighting the need for more sophisticated models of technology implementation that consider organizational scale and complexity.

5.3 Practical Implications

The empirical results offer several important insights for educational administrators and managers when implementing AI systems. Our analysis indicates that successful AI implementation requires a carefully orchestrated approach, balancing technological infrastructure development with organizational capability building. A notable threshold effect in technological readiness suggests that institutions must attain a minimum level of infrastructure (TR score > 3.4) before they can effectively deploy sophisticated AI systems. Conversely, our data reveal a point of diminishing returns in technology investments when the TR score exceeds 4.2, highlighting the need for strategic resource allocation in infrastructure development.

The temporal dynamics observed in our study have significant implications for implementation strategies. Institutions that achieved the most successful implementations followed a sequential approach to capability development, starting with basic technical infrastructure and progressively building organizational capabilities. This pattern was markedly superior to simultaneous implementation of all initiatives, with sequenced implementations being 34.2% more likely to succeed. The temporal analysis further shows that in the early stages, focusing on technical training and system familiarization can create especially favorable conditions for successful implementation, to be followed by comprehensive organizational development initiatives.

Our findings on organizational learning capacity underscore the critical role of systematic knowledge management in implementation success. Institutions that implemented formal knowledge-sharing systems demonstrated 28.5% higher implementation success compared to those relying on informal knowledge management mechanisms. The success of formal knowledge management appears to stem from its ability to systematically capture and disseminate implementation experience, reduce error rates, and provide consistent user support. Additionally, the data highlight that structured documentation and formal mentoring programs are significant facilitators of sustainable implementation success. These practices seem particularly effective in maintaining high levels of user satisfaction and system use over time.

5.4 Policy Recommendations

Based on the empirical findings, we propose a comprehensive policy framework targeting both institutional and governmental levels for AI implementation in educational management. Our analysis at the institutional level advocates for integrated policies that address technological standards and organizational development needs simultaneously. Given that formal documentation of technical standards significantly reduces implementation failure, there is a clear need for well-defined yet adaptable technological guidelines. These guidelines should be comprehensive but flexible enough to accommodate specific institutional contexts while maintaining a core set of requirements to ensure successful implementation.

The governmental policy implications highlight the necessity for differentiated support strategies based on institutional characteristics and regional contexts. Our analysis suggests that regions with less developed innovation ecosystems require targeted interventions focused on infrastructure development and sharing of technical capabilities. Moreover, optimal resource allocation should be tailored to the size and existing capabilities of institutions. For instance, smaller institutions benefit most from focused infrastructure support, whereas larger institutions thrive with balanced capability development programs. This indicates that customized support packages, rather than uniform assistance, are essential.

The temporal patterns observed have profound implications for policy timing and resource allocation. From a policy perspective, the data suggest that implementation policies should account for different phases in the AI adoption process, with varying support needs at each stage. In the early phase, policies should prioritize infrastructure and capability development, while in the later phase, the focus should shift to optimization and sustainable development. This phased approach promotes the sustainable adoption of AI technologies in educational management. Additionally, our results emphasize the need for continuous assessment and adaptation within the policy framework to swiftly address emerging implementation challenges and opportunities.

5.5 Future Research Directions

Although this study has significantly advanced our understanding of AI implementation in educational management, several important research directions remain open for future exploration. One key area is the long-term sustainability of AI implementations in educational institutions. While our findings have uncovered significant patterns in initial implementation success, questions remain about how these effects evolve over extended periods. Specifically, the observed increase in organizational learning effects from 0.32 to 0.56 over three semesters suggests that longer-term dynamics may exist beyond our current research timeframe. Future multi-year longitudinal studies could investigate whether these learning effects continue to accumulate, plateau, or decline over time, providing valuable insights for planning long-term implementation strategies.

Another promising research avenue is the role of external innovation ecosystems in supporting AI implementation. The stronger treatment effects observed in institutions in the eastern region (TR = 0.358, $p < 0.01$) hint at the presence of regional innovation network effects. However, the precise mechanisms by which external environments shape implementation success are not yet fully understood. Future research could explore the impact of various forms of partnerships, such as industry collaborations, inter-institutional networks, and government-fostered innovation clusters. Network analysis methodologies could be particularly useful for mapping and quantifying these relationships and their impacts on implementation success.

A third critical area for future research is the interaction between AI implementation and institutional change processes. While our study highlights the importance of organizational learning capacity, further research is needed to explore how AI implementation reciprocally influences organizational structure and processes. The optimal scale effect observed for medium-sized institutions suggests complex relationships between organizational size, structure, and implementation success that warrant deeper investigation. Research on how institutions adapt their structures based on AI implementation experiences and how these adjustments affect outcomes would be particularly insightful.

Another area ripe for further exploration is the psychological and social dimensions of AI implementation. Our findings on user-acceptance patterns raise intriguing questions about the social dynamics of technology adoption in educational settings. Future studies could employ mixed-method approaches, combining quantitative measures with qualitative case studies, to examine how different stakeholder groups—administrators, faculty, staff, and students—experience and influence the implementation process. Special attention should be given to the contributions of informal social networks and opinion leaders, which extend beyond the current focus on formal organizational structures.

Finally, cross-cultural comparisons of AI implementation in educational management are essential. While our focus on Chinese higher education institutions has been valuable, it raises questions about the generalizability of our findings to other cultural and institutional contexts. Cross-national comparative studies could investigate how national education systems, cultural values, and institutional traditions shape the relationship between organizational capabilities and implementation success, allowing for more culturally informed modeling of educational technology implementation.

These research directions would not only enhance theoretical understanding but also provide practical insights for improving AI implementation in educational settings. Methodologically, combining traditional quantitative analysis with novel methodologies such as social network analysis, digital ethnography, and longitudinal case studies could capture the complexity of AI implementation, providing both breadth and depth in understanding the dynamics involved.

6 CONCLUSION AND RECOMMENDATIONS

This paper explores the adoption of AI-driven innovations in educational management through a multi-case study of Chinese higher education institutions, revealing the intricate interplay between technological capability and organizational factors in shaping implementation outcomes. Our investigation demonstrates that AI implementation is not merely a straightforward deployment of technology but rather necessitates a delicate balance among technical infrastructure, organizational learning capabilities, and user engagement. Our empirical analysis establishes that the influence of institutional capabilities on implementation success is not linear but contingent upon specific institutional contexts and temporal dynamics.

Our findings expand current theoretical frameworks related to educational technology management by uncovering previously unidentified threshold effects and interaction patterns. The asymmetric nature of technological readiness and organizational learning capacity suggests that institutions need to fundamentally reconsider their approach to AI implementation. The temporal patterns observed imply that institutions should adopt a more nuanced, phased strategy for innovation, recognizing that different capabilities may develop and deliver benefits at varying rates. This insight challenges the conventional wisdom of simultaneous capability development and points toward a more strategically sequenced implementation approach.

This research makes a particularly novel contribution to understanding the optimal scale effects for AI implementation. The stronger implementation effects observed in medium-sized institutions suggest that organizational scale may play a more complex role than previously recognized, potentially reflecting a balance between resource availability and organizational agility. This insight could be crucial for how institutions structure their AI initiatives and how policymakers design support mechanisms for diverse educational institutions.

Moving forward, educational institutions deploying AI should adopt a holistic approach to adoption, acknowledging that successful innovation is multivariate. This requires an approach that encompasses not only the development of technical infrastructure but also systematic organizational capability building and careful attention to user acceptance dynamics. Institutions should also recognize that successful implementation demands sustained commitment beyond the initial deployment phase, with a particular focus on developing robust knowledge management systems and continuous learning mechanisms.

Policymakers, in turn, should design support strategies that consider both institutional characteristics and regional contexts. Support mechanisms should be tailored to institutional size, existing capabilities, and regional innovation ecosystems, with policy frameworks allowing flexibility to accommodate the varied developmental trajectories that different institutions will experience in their AI journey.

As educational institutions globally continue to navigate technological transformation, these findings offer a guide to overcoming challenges in AI implementation. The ongoing evolution of the Educational Technology industry is likely to present new threats and opportunities, necessitating continuous research to understand how institutions can best leverage AI innovations for improved educational management. Given the nature of technological progress, the findings and recommendations from this research should be seen as a catalyst for ongoing investigation rather than a definitive conclusion.

REFERENCES

[1] Ashrafi, A., Zareravasan, A., Rabiee Savoji, S., et al. (2020). Exploring factors influencing students' continuance intention to use the learning management system (LMS): A multi-perspective framework. Interactive Learning Environments, 1-23. https://doi.org/10.1080/10494820.2020.1734028

[2] Barari, N., RezaeiZadeh, M., Khorasani, A., et al. (2020). Designing and validating educational standards for e-teaching in virtual learning environments (VLEs). Interactive Learning Environments, 1-13. https://doi.org/10.1080/10494820.2020.1739078

[3] Blundell, C., Lee, K.-T., & Nykvist, S. (2020). Moving beyond enhancing pedagogies with digital technologies: Frames of reference, habits of mind and transformative learning. Journal of Research on Technology in Education, 52(2), 178-196. https://doi.org/10.1080/15391523.2020.1726235

[4] Chan, R. Y., Bista, K., Allen, R. M., et al. (2021). Online teaching and learning in higher education during COVID-19 - International perspectives and experiences. Routledge. https://doi.org/10.4324/9781003125921

[5] Cheng, Y.-M. (2019). How does task-technology fit influence cloud-based e-learning continuance and impact? Education & Training, 61, 480-499. https://doi.org/10.1108/ET-09-2018-0203

[6] Dodgson, M., Ash, S., Andrews, J., et al. (2021). Managing technology-enabled innovation in a professional services firm: A cooperative case study. Academy of Management Discoveries. https://doi.org/10.5465/amd.2020.0217

[7] Flavin, M. (2020). Re-imagining technology-enhanced learning. Springer Nature. https://doi.org/10.1007/978-3-030-55785-0

[8] Green, W., Anderson, V., Tait, K., et al. (2020). Precarity, fear and hope: Reflecting and imagining in higher education during a global pandemic. Higher Education Research & Development, 39(7), 1309-1312. https://doi.org/10.1080/07294360.2020.1826029

[9] Huang, D. (2024). Artificial intelligence driving innovation in higher education management and student training mechanisms. Applied Mathematics and Nonlinear Sciences, 9(1).

[10] Huang, J., Matthews, K. E., & Lodge, J. M. (2021). 'The university doesn't care about the impact it is having on us': Academic experiences of the institutionalisation of blended learning. Higher Education Research & Development. https://doi.org/10.1080/07294360.2021.1915965

[11] Jin, Y. Q., Lin, C. L., Zhao, Q., et al. (2021). A study on traditional teaching method transferring to e-learning under the COVID-19 pandemic: From Chinese students' perspectives. Frontiers in Psychology, 12, 632787. https://doi.org/10.3389/fpsyg.2021.632787

[12] Lanford, M., Corwin, Z. B., Maruco, T., et al. (2019). Institutional barriers to innovation: Lessons from a digital intervention for underrepresented students applying to college. Journal of Research on Technology in Education, 51(3), 203-216. https://doi.org/10.1080/15391523.2019.1576558

[13] Li, N., Zhang, X., Limniou, M., et al. (2024). Meaning-making in virtual learning environment enabled educational innovations: A 13-year longitudinal case study. Interactive Learning Environments, 32(1), 168-182. https://doi.org/10.1080/10494820.2022.2081582

[14] Luan, S., Reb, J., & Gigerenzer, G. (2019). Ecological rationality: Fast-and-frugal heuristics for managerial decision-making under uncertainty. Academy of Management Journal, 62(6), 1735-1759. https://doi.org/10.5465/amj.2018.0172

[15] Pelletier, K., Brown, M., Brooks, D. C., et al. (2021). 2021 EDUCAUSE Horizon Report, Teaching and Learning Edition. EDUCAUSE.

[16] Yu, T.-Y. (2010). Modelling the factors that affect individuals' utilisation of online learning systems: An empirical study combining the task-technology fit model with the theory of planned behaviour. British Journal of Educational Technology, 41, 1003-1017. https://doi.org/10.1111/j.1467-8535.2009.01003.x

[17] Yu, W. (2024). Artificial intelligence-driven innovation in adult education management and student training mechanisms. Applied Mathematics and Nonlinear Sciences, 9(1).

[18] Zhang, M., & Huang, Z. (2022). Crowdsourcing used in higher education: An empirical study on a sustainable translation teaching mode based on crowdsourced translation. Sustainability, 14(6), 3140. https://doi.org/10.3390/su14063140