

PAPER

AI Adoption and Remote Teaching Supply Chain Efficiency: The Moderating Role of Digital Environment

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ABSTRACT

With the ongoing digital transformation of education and the pervasive integration of artificial intelligence, the remote teaching supply chain has emerged as a critical backbone supporting the flow of online educational resources, the delivery of instructional services, and the implementation of talent cultivation. Optimizing the efficiency of this supply chain is essential for addressing key practical challenges, including resource misallocation, procedural redundancies, and insufficient coordination in online education. Grounded in technology acceptance theory, this study investigates how basic artificial intelligence adoption and advanced artificial intelligence adoption influence remote teaching supply chain efficiency, as well as the moderating effect of the digital technology environment. Based on an analysis of 206 valid survey responses from practitioners in universities, vocational colleges, and online education institutions, both basic and advanced artificial intelligence adoption exert positive effects on remote teaching supply chain efficiency. In addition, the digital technology environment positively moderates the relationships between basic artificial intelligence adoption and supply chain efficiency, as well as between advanced artificial intelligence adoption and supply chain efficiency. Finally, theoretical guidance and managerial implications are provided for the intelligent development of educational institutions and platforms, as well as for the optimization of remote teaching supply chains.

KEYWORDS

artificial intelligence technology adoption, remote teaching supply chain, supply chain efficiency, digital technology environment

1 INTRODUCTION

With the deep integration of digital technologies into the educational sector, online remote teaching and blended learning models have been widely adopted, establishing themselves as critical pillars supporting the routine delivery of degree education, vocational training, and lifelong learning [1]. Educational services, when operated under corporate logic, are also characterized by a complete supply chain. The remote teaching supply chain encompasses multiple stakeholders, including teaching resource suppliers,

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online teaching platforms, institutional academic administration departments, instructors, learners, and operation and maintenance service entities. It spans the entire process from resource production, intelligent distribution, and instructional delivery to learning analytics, service feedback, and resource iteration, aiming to achieve the coordinated development of instructional, service, and operational efficiency [2]. However, the development of remote teaching supply chains in China remains at an early stage, with no standardized or intelligent management system yet established—from basic infrastructure to operational practices. Persistent issues include inefficient resource allocation, cumbersome operational workflows, and weak inter-stakeholder coordination [3].

To address these challenges, various educational institutions and online education platforms have increased investment in artificial intelligence technologies, introducing applications such as intelligent learning analytics, intelligent resource recommendation, automated assignment grading, and intelligent teaching scheduling. These efforts are aimed at restructuring the operational logic of the remote teaching supply chain through artificial intelligence [4]. Although the widespread adoption of artificial intelligence has, to some extent, simplified processes and upgraded the models of remote teaching supply chains [5], significant variation exists in the effectiveness of artificial intelligence implementation across different entities. In some cases, artificial intelligence investments have failed to translate into measurable improvements in supply chain efficiency [6]. Therefore, there is an urgent practical need to systematically investigate the mechanisms through which artificial intelligence technology adoption influences the efficiency of remote teaching supply chains.

Three distinct perspectives have been identified in the academic literature regarding the relationship between artificial intelligence technology adoption and remote teaching supply chain efficiency. According to the first perspective, artificial intelligence technologies—characterized by advantages in data mining, intelligent scheduling, and process automation—can streamline redundant procedures, optimize resource allocation, and significantly enhance the operational efficiency of remote teaching supply chains [7]. The second perspective suggests that artificial intelligence technology adoption entails high implementation costs and high compatibility thresholds. Given that existing teaching management systems and personnel competencies often fail to meet the technical requirements of artificial intelligence, the adoption of such technologies may instead increase operational burdens without yielding significant improvements in supply chain efficiency [8]. A third perspective posits that the relationship between artificial intelligence technology adoption and remote teaching supply chain efficiency is not simply linear. Instead, the strength of this association is contingent upon contextual factors, such as the external digital environment, rendering the nature of the relationship inherently uncertain [9].

Consequently, this study examines the effect of artificial intelligence technology adoption on remote teaching supply chain efficiency. Furthermore, to analyze the boundary constraints imposed by external environmental factors on this relationship, the digital technology environment is introduced as a moderating variable. Through this investigation, theoretical guidance and practical recommendations are provided for educational institutions and online education platforms regarding the optimization of artificial intelligence deployment and the improvement of remote teaching supply chain management.

2 THEORETICAL ANALYSIS AND RESEARCH HYPOTHESES

Technology acceptance theory has been widely applied to explain the adoption and effectiveness of emerging digital technologies within educational organizations [10].

According to this theory, an organization's perceived ease of use and perceived usefulness of a new technology determine the willingness to adopt it and the depth of its application, which in turn reshape business processes and improve operational performance [11]. As a core enabling tool in the digital era, artificial intelligence provides support for process optimization, resource integration, and multi-stakeholder coordination in remote teaching supply chains. However, the adoption of artificial intelligence is confronted with dual logics of implementation at both the application level and the operational level, and the effectiveness of technological enablement varies significantly under different digital environmental conditions [12]. Based on this theoretical foundation, a conceptual model is constructed, and research hypotheses are proposed.

2.1 Artificial intelligence adoption and remote teaching supply chain efficiency

Artificial intelligence technology adoption is primarily manifested in two forms: basic artificial intelligence adoption and advanced artificial intelligence adoption. Both forms are posited to significantly influence remote teaching supply chain efficiency [13].

Basic artificial intelligence adoption may have a positive effect on remote teaching supply chain efficiency. It is characterized by low implementation thresholds and strong generalizability, relying primarily on standardized intelligent tools. These tools include basic functions such as intelligent attendance tracking, automated courseware generation, automatic assignment grading, fundamental intelligent question-answering, and smart monitoring of live-streamed classes. Basic artificial intelligence applications are highly deterministic and easy to deploy; they do not require large-scale modifications to existing remote teaching supply chain architectures. Instead, they directly replace repetitive manual tasks, compress intermediate management links within the supply chain, and reduce both labor investment and time consumption [14]. Once an educational institution has deployed basic artificial intelligence tools, the automatic aggregation of foundational teaching data and the rapid reorganization of course resources can be achieved. This accelerates the flow of resources among supply chain stakeholders and steadily improves the baseline operational efficiency of remote teaching supply chains. Accordingly, the following hypothesis is proposed:

H1: Basic artificial intelligence adoption has a positive effect on remote teaching supply chain efficiency.

Advanced artificial intelligence adoption may also have a positive effect on remote teaching supply chain efficiency. Unlike basic artificial intelligence adoption, which is limited to point-based tool applications, advanced artificial intelligence adoption relies on machine learning and big data analytics algorithms to be deeply embedded into the core operational links of the remote teaching supply chain. These advanced applications include intelligent student learning profiling, intelligent supply-demand matching of teaching resources, multi-stakeholder collaborative scheduling within the supply chain, intelligent teaching quality assessment, and dynamic iterative optimization of teaching resources [15]. Rather than being confined to point-based process optimization, advanced artificial intelligence restructures the business logic of the remote teaching supply chain, breaks down information barriers among stakeholders, and addresses persistent challenges such as resource misallocation, supply-demand imbalances, and information silos. Furthermore, advanced artificial intelligence possesses capabilities for dynamic monitoring,

intelligent early warning, and autonomous optimization, thereby enabling the long-term efficient operation of the supply chain. In addition, advanced artificial intelligence applications are characterized by long-term stability; they do not become ineffective due to changes in administrative personnel or minor adjustments in teaching models. Consequently, educational institutions are supported in steadily optimizing the operational model of the remote teaching supply chain [16]. Accordingly, the following hypothesis is proposed:

H2: Advanced artificial intelligence adoption has a positive effect on remote teaching supply chain efficiency.

2.2 Moderating role of the digital technology environment

The external digital technology environment is considered a foundational condition for the operation and development of both remote teaching supply chains and artificial intelligence applications. Shaped by factors such as regional network infrastructure, teaching platform compatibility, cross-stakeholder data-sharing mechanisms, the digital literacy of instructors and students, and educational digitalization policies, the degree of completeness and stability of this environment influences educational organizations' capabilities in resource acquisition, data integration, and technology implementation [17]. Consequently, the relationship between artificial intelligence technology adoption and remote teaching supply chain efficiency is affected by this environment.

When the digital technology environment is less developed—characterized by lagging network infrastructure, inconsistent platform standards, and limited data interoperability—basic artificial intelligence applications may fail to achieve stable integration with the various stakeholders in the remote teaching supply chain. Frequent system lags and data discontinuities are observed, thereby weakening the positive effect of basic artificial intelligence adoption on supply chain efficiency [18]. Conversely, a well-developed digital technology environment provides a stable operational foundation for basic intelligent tools, amplifying their value in streamlining processes and replacing manual labor. Accordingly, the following hypothesis is proposed:

H3: The digital technology environment positively moderates the relationship between basic artificial intelligence adoption and remote teaching supply chain efficiency.

When the digital technology environment is underdeveloped, the existing data systems, technical architectures, and personnel competencies within remote teaching supply chains are often unable to meet the advanced algorithmic and computational demands of advanced artificial intelligence adoption. Consequently, functions such as intelligent profiling, resource matching, and collaborative scheduling may fail to be effectively implemented, thereby hindering the realization of artificial intelligence-enabled value [19]. Furthermore, when the external digital environment is highly variable and characterized by inconsistent standards, data-sharing mechanisms tend to break down. Under such conditions, market-oriented intelligent incentives and resource allocation mechanisms are unable to operate effectively across supply chain stakeholders, thereby impeding the positive effect of advanced artificial intelligence adoption on supply chain efficiency [20]. Conversely, a well-developed digital technology environment—characterized by unified data standards, sufficient computational support, and a favorable atmosphere of digital literacy—strengthens the enabling effect of advanced artificial intelligence. Accordingly, the following hypothesis is proposed:

H4: The digital technology environment positively moderates the relationship between advanced artificial intelligence adoption and remote teaching supply chain efficiency.

In summary, the theoretical model of this study is presented in Figure 1.

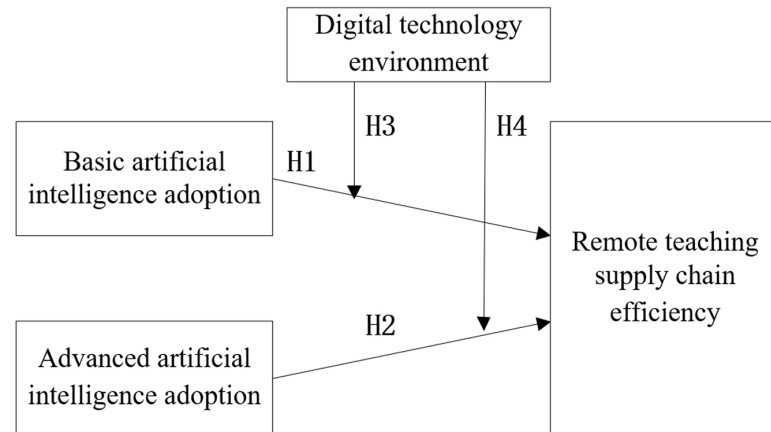


Fig. 1. Theoretical model of this study

3 RESEARCH METHODOLOGY

3.1 Data collection

1. Sample selection

The selection criteria for survey respondents in this study were established below. First, broad contextual coverage was ensured. Educational institutions that conduct remote teaching or blended learning—including four-year universities, vocational colleges, adult education institutions, and dedicated online education platforms—were selected, covering relevant disciplinary fields such as science and engineering, humanities and social sciences, economics and management, and vocational education. When the questionnaires were distributed, only those individuals with at least two years of work experience and familiarity with remote teaching operations and supply chain processes—such as teaching administrators, information technology staff, and front-line instructors—were chosen, thereby ensuring the professionalism and validity of the responses. Second, stakeholder representativeness was emphasized. Given that this study investigates the relationship between artificial intelligence technology adoption and remote teaching supply chain efficiency, educational institutions varying in years of operation, scale, and public versus private ownership were selected as the survey sample, enabling the full capture of differential characteristics across these variables.

2. Questionnaire distribution and collection

Two primary methods were employed for questionnaire distribution: on-site distribution and online distribution. The questionnaire distribution period commenced in March 2026 and concluded in May 2026. A total of 260 questionnaires were distributed, of which 223 were returned, yielding a response rate of 85.77%. Among the returned questionnaires, 206 were identified as valid, resulting in a valid response rate of 79.23%. A summary of the collection methods and the number of valid responses obtained is presented in Table 1.

Table 1. Summary of questionnaire collection methods and valid response counts

	Online Distribution	On-Site Distribution	Total
Questionnaires distributed	170	90	260
Questionnaires returned	148	75	223
Valid questionnaires	127	79	206
Valid response rate	74.71%	87.78%	79.23%

The collected questionnaires were divided into two subsamples based on collection method. The mean values of the two subsamples were found to be 4.97 and 5.01, respectively, indicating that no significant difference in questionnaire responses was introduced by the different collection methods. Subsequently, an independent-samples t-test was performed on the two subsamples. The test yielded a between-group significance value of 0.612, which exceeded the threshold of 0.05. Therefore, it can be concluded that the two questionnaire collection methods employed in this study did not significantly influence the sample data.

3.2 Variable measurement

The independent variable, artificial intelligence technology adoption, was measured along two dimensions: basic artificial intelligence adoption and advanced artificial intelligence adoption. An established maturity scale for artificial intelligence technology adoption in educational settings, originally developed by Sova [21], was adapted for the context of the remote teaching supply chain. This adaptation resulted in a 10-item scale, with five items measuring basic artificial intelligence adoption and five items measuring advanced artificial intelligence adoption. All items were assessed using a 7-point Likert scale.

The dependent variable, remote teaching supply chain efficiency, was measured using a scale developed by Rahman et al. [22], which was revised to fit the remote teaching supply chain context. A total of 16 items were included, all measured on a 7-point Likert scale.

The moderating variable, digital technology environment, was measured using the digital education environment scale for online teaching contexts developed by Walker et al. [23]. This scale was adapted to the remote teaching supply chain research context of this study, resulting in a 6-item scale, with all items measured on a 7-point Likert scale.

Three control variables were included: institutional size, years of operation, and ownership type. Institutional size was measured as the logarithm of the total number of personnel in the educational institution. Years of operation were measured as the number of years the institution had been in operation from its establishment to the present. Ownership type was operationalized as a dummy variable, with public universities and public educational institutions coded as 2, and private institutions and commercial online education platforms coded as 1.

4 DATA ANALYSIS AND RESULTS

4.1 Reliability and validity analysis

1. Reliability analysis

Reliability testing was conducted using SPSS 22.0, in which Cronbach's α coefficients were calculated for each variable scale. As shown in Table 2, the Cronbach's

α value for each variable exceeded the threshold of 0.7. Furthermore, the corrected item-total correlation values for all items across the scales were found to be above the recommended threshold of 0.5, indicating a high degree of inter-item correlation within each scale. In summary, the reliability and internal consistency of the variables within each scale were determined to be satisfactory.

Table 2. Reliability analysis of the scales

Variable Name	Item	Corrected Item-Total Correlation	Cronbach's α if Item Deleted	Cronbach's α
Basic artificial intelligence adoption	AI1	0.634	0.81	0.842
	AI2	0.655	0.795	
	AI3	0.629	0.804	
	AI4	0.641	0.792	
	AI5	0.636	0.801	
Advanced artificial intelligence adoption	AJ1	0.648	0.82	0.854
	AJ2	0.665	0.806	
	AJ3	0.654	0.812	
	AJ4	0.639	0.825	
	AJ5	0.642	0.818	
Remote teaching supply chain efficiency	GY1	0.654	0.835	0.868
	GY2	0.649	0.84	
	GY3	0.637	0.844	
	GY4	0.651	0.838	
	GY5	0.646	0.841	
	GY6	0.635	0.846	
	GY7	0.653	0.837	
	GY8	0.642	0.843	
	GY9	0.638	0.845	
	GY10	0.647	0.84	
	GY11	0.65	0.839	
	GY12	0.643	0.842	
	GY13	0.636	0.847	
	GY14	0.652	0.838	
	GY15	0.645	0.841	
	GY16	0.639	0.844	
Digital technology environment	SZ1	0.639	0.814	0.85
	SZ2	0.643	0.808	
	SZ3	0.635	0.816	
	SZ4	0.647	0.805	
	SZ5	0.641	0.811	
	SZ6	0.638	0.813	

2. Validity analysis and factor analysis

A confirmatory factor analysis was conducted using Mplus 8.3 to further assess the validity of the scales. As shown in Table 3, the standardized factor loadings for all items exceeded 0.7, the composite reliability values for all variables exceeded 0.8, and the average variance extracted values for all variables exceeded 0.6. Both exploratory factor analysis and confirmatory factor analysis met the required thresholds, indicating that the selected variables and corresponding items possessed good convergent validity.

Table 3. Variable validity analysis results (N = 206)

Variable Name	Items	Factor Loadings	Composite Reliability	Average Variance Extracted
Basic artificial intelligence adoption	AI1–AI5	0.715~0.826	0.851	0.642
Advanced artificial intelligence adoption	AJ1–AJ5	0.723~0.831	0.858	0.650
Remote teaching supply chain efficiency	GY1–GY16	0.708~0.819	0.876	0.654
Digital technology environment	SZ1–SZ6	0.712~0.824	0.854	0.645

Discriminant validity was assessed by examining whether the square root of the average variance extracted for each variable was greater than the absolute value of the inter-variable correlation coefficients. If the square root of the average variance extracted exceeded the absolute correlation coefficient, the scale was considered to have good discriminant validity [24]. As shown in Table 3, the square root of the average variance extracted for each variable (presented on the diagonal) was substantially larger than the maximum absolute correlation coefficient. Therefore, the scale was determined to have good discriminant validity.

4.2 Descriptive statistics and correlation analysis

From the sample data, it was observed that the surveyed educational institutions were predominantly those with more than 15 years of operation. In terms of institutional size, large and medium-sized institutions and platforms constituted the majority. Regarding ownership type, public educational institutions were the most represented. A summary of the sample characteristics is presented in Table 4.

Table 4. Sample characteristics

Variable	Category	Frequency	Percentage (%)	Cumulative Percentage (%)
Institutional size	Below 100 persons	18	8.74	8.74
	100–500 persons	45	21.84	30.58
	500–1,000 persons	62	30.1	60.68
	Above 1,000 persons	81	39.32	100
Years of operation	Below 5 years	12	5.83	5.83
	5–15 years	38	18.45	24.28
	15–30 years	76	36.89	61.17
	Above 30 years	80	38.83	100
Ownership type	Public institution	142	68.93	68.93
	Private/platform	64	31.07	100

To further examine the data and provide preliminary assessments, basic descriptive statistics for the measurement items were analyzed. Using SPSS 22.0 statistical software, skewness and kurtosis values for the measurement items were computed. The results showed that the absolute values of skewness for all variables were below 2, while the absolute values of kurtosis were below 5. These findings preliminarily indicated that the sample data were of high quality and satisfied the basic statistical assumptions required for empirical testing, thereby establishing a foundation for subsequent statistical testing and regression analysis.

Table 5. Correlation analysis of the sample (N = 206)

	Institutional Size	Years of Operation	Ownership Type	Basic Artificial Intelligence Adoption	Advanced Artificial Intelligence Adoption	Digital Technology Environment	Remote Teaching Supply Chain Efficiency
Institutional size	—						
Years of operation	0.061	—					
Ownership type	0.083	−0.024	—				
Basic artificial intelligence adoption	−0.086	0.053	0.012	0.801			
Advanced artificial intelligence adoption	−0.057	0.026	−0.008	0.382**	0.806		
Digital technology environment	0.025	0.031	0.048	0.316**	0.327**	0.803	
Remote teaching supply chain efficiency	−0.105	−0.021	−0.063	0.482**	0.479**	0.415**	0.809
Mean	3.31	3.29	1.82	5.26	5.34	5.18	5.25
Standard deviation	0.93	0.76	0.47	1.68	1.52	1.45	1.42

Notes: (1) *indicates that $p < 0.05$, **indicates that $p < 0.01$, and ***indicates that $p < 0.001$. (2) The diagonal values represent the square root of the average variance extracted for each variable. For control variables, which do not have average variance-extracted values, this is indicated by “—”.

A correlation analysis was conducted among the variables of basic artificial intelligence adoption, advanced artificial intelligence adoption, digital technology environment, and remote teaching supply chain efficiency, as presented in Table 5. The statistical results indicated that most pairwise correlations among the variables were relatively high, suggesting that subsequent regression analysis could be appropriately performed.

4.3 Multiple regression analysis

To adequately ensure the stability and reliability of the multiple regression model results, it is necessary to test for potential issues of multicollinearity, serial correlation, and heteroscedasticity before the regression analysis. The results of the tests conducted for these three issues are presented below. First, multicollinearity was assessed. The variance inflation factor values for each regression model in this study ranged from 1.003 to 1.042 (variance inflation factor < 10), indicating that no severe multicollinearity was present. Second, with respect to serial correlation, the Durbin-Watson values for all models ranged from 1.660 to 1.940, falling within the acceptable critical range of $1 < \text{Durbin-Watson values} < 3$. Therefore, no serial correlation was detected. Third, heteroscedasticity was examined by plotting

standardized residual scatterplots for each model, with the standardized residual used as the Y variable and the standardized predicted value as the X variable. Upon inspection, the scatterplots for all models were found to be randomly distributed, with no discernible pattern. Consequently, no heteroscedasticity was identified.

1. Regression analysis of direct effects

Artificial intelligence technology adoption (basic artificial intelligence adoption and advanced artificial intelligence adoption) exerts a direct influence on remote teaching supply chain efficiency. The regression analysis of these direct relationships is presented in Table 6.

As shown in Table 6, Model 1 and Model 2 indicate that basic artificial intelligence adoption has a positive effect on remote teaching supply chain efficiency. Thus, Hypothesis H1 is supported. Model 1 and Model 3 indicate that advanced artificial intelligence adoption has a positive effect on remote teaching supply chain efficiency. Thus, Hypothesis H2 is supported.

2. Regression analysis of moderating effects

The digital technology environment exerts a moderating effect on the relationship between artificial intelligence technology adoption and remote teaching supply chain efficiency. The regression analysis of the moderating effects is presented in Table 7.

Table 6. Regression analysis of the direct relationship between artificial intelligence adoption and remote teaching supply chain efficiency (N = 206)

Dependent Variable		Remote Teaching Supply Chain Efficiency		
		Model 1	Model 2	Model 3
Control variables	Institutional size	−0.153	−0.087	−0.031
	Years of operation	−0.025	−0.068	−0.045
	Ownership type	−0.149	−0.173	−0.021
Independent variables	Basic artificial intelligence adoption		0.402***	
	Advanced artificial intelligence adoption			0.491***
<i>F</i>		1.482	23.956	25.137
<i>R</i> ²		0.013	0.235	0.244
ΔR^2			0.222***	0.231***

Notes: *indicates that $p < 0.05$, **indicates that $p < 0.01$, and ***indicates that $p < 0.001$.

Table 7. Regression analysis of the moderating role of the digital technology environment on the relationship between artificial intelligence adoption and supply chain efficiency (N = 206)

Dependent Variable		Remote Teaching Supply Chain Efficiency	
		Model 1	Model 2
Control variables	Institutional size	−0.033	−0.061
	Years of operation	−0.024	−0.022
	Ownership type	−0.078	−0.075

(Continued)

Table 7. Regression analysis of the moderating role of the digital technology environment on the relationship between artificial intelligence adoption and supply chain efficiency (N = 206) (*Continued*)

Dependent Variable		Remote Teaching Supply Chain Efficiency	
		Model 1	Model 2
Main effects	Basic artificial intelligence adoption	0.534***	
	Advanced artificial intelligence adoption		0.481***
	Digital technology environment	0.021	0.112
Two-way interaction	Basic artificial intelligence adoption × digital technology environment	0.163**	
	Advanced artificial intelligence adoption × digital technology environment		0.192***
<i>F</i>		25.126	30.153
<i>R</i> ²		0.328	0.369
ΔR^2		0.018**	0.045***

Notes: *indicates that $p < 0.05$, **indicates that $p < 0.01$, and ***indicates that $p < 0.001$.

As shown in Table 7, Model 1 indicates that the digital technology environment exerts a positive and statistically significant moderating effect on the relationship between basic artificial intelligence adoption and remote teaching supply chain efficiency. Thus, Hypothesis H3 is supported. Model 2 indicates that the digital technology environment exerts a positive and statistically significant moderating effect on the relationship between advanced artificial intelligence adoption and remote teaching supply chain efficiency. Thus, Hypothesis H4 is supported.

The robustness of the moderating effect of the digital technology environment was further tested using simple slope tests and slope difference tests within the bootstrapping method [25]. As shown in Table 8, for the paths from basic artificial intelligence adoption to remote teaching supply chain efficiency and from advanced artificial intelligence adoption to remote teaching supply chain efficiency, the effect sizes in the high moderator group were significantly larger than those in the low moderator group. Consequently, the positive moderating effects of the digital technology environment on these paths were confirmed, thereby providing additional support for Hypotheses H3 and H4.

Table 8. Results of simple slope tests and slope difference tests for the moderating effect of the digital technology environment (N = 206)

Path	Moderator Level	Effect Size	Standard Error	<i>p</i>
Basic artificial intelligence adoption → supply chain efficiency	Low moderator group	0.3126***	0.0692	0.0000
	Intermediate group	0.4435***	0.0513	0.0000
	High moderator group	0.5721***	0.0685	0.0000
Advanced artificial intelligence adoption → supply chain efficiency	Low moderator group	0.2985***	0.0612	0.0000
	Intermediate group	0.4492***	0.0476	0.0000
	High moderator group	0.6017***	0.0624	0.0000

Notes: *indicates that $p < 0.05$, **indicates that $p < 0.01$, and ***indicates that $p < 0.001$.

5 CONCLUSIONS

5.1 Research conclusions

In this study, the direct effects of the two dimensions of artificial intelligence technology adoption—basic artificial intelligence adoption and advanced artificial intelligence adoption—on remote teaching supply chain efficiency, as well as the moderating role of the digital technology environment, were analyzed. The results of the analysis revealed the findings below. First, basic artificial intelligence adoption was found to have a positive effect on remote teaching supply chain efficiency. Second, advanced artificial intelligence adoption was found to have a positive effect on remote teaching supply chain efficiency. Third, a positive moderating effect of the digital technology environment on the relationship between basic artificial intelligence adoption and remote teaching supply chain efficiency was identified. Fourth, a positive moderating effect of the digital technology environment on the relationship between advanced artificial intelligence adoption and remote teaching supply chain efficiency was also identified.

5.2 Theoretical contributions

Given the inconsistency of findings in the existing literature regarding the effect of artificial intelligence technology adoption on remote teaching supply chain efficiency, a new research perspective was adopted in this study. Two distinct dimensions of artificial intelligence adoption—basic artificial intelligence adoption and advanced artificial intelligence adoption—were distinguished, and their respective effects on remote teaching supply chain efficiency were analyzed. Furthermore, the digital technology environment was introduced as a moderating variable. Based on this approach, two theoretical contributions were made. First, the two dimensions of artificial intelligence technology adoption were introduced into the remote teaching supply chain research context, thereby enriching the application scenarios and empirical findings of technology acceptance theory within the domain of educational supply chains. Second, whereas previous studies have generally overlooked the contextual constraints imposed by the external digital environment, a positive moderating effect of the digital technology environment was demonstrated in this study. This finding provides a contextual boundary condition that helps explain the divergent findings reported in prior research, thereby extending the relevant theoretical framework.

5.3 Managerial implications

Instead of indiscriminately investing in high-end artificial intelligence systems, educational institutions and online education platforms should promote intelligent construction in a phased manner. Priority should be given to the deployment of basic intelligent tools to replace manual labor and streamline processes, followed by the gradual implementation of advanced artificial intelligence applications, thereby aligning investment with efficiency gains. Educational entities should place greater emphasis on the development of the external digital technology environment. Proactive efforts should be made to adapt to regional digital infrastructure, standardize data protocols across teaching platforms, and improve internal data-sharing mechanisms. When the digital environment is well developed, artificial intelligence

technologies should be fully leveraged to enhance supply chain efficiency. When the digital environment is underdeveloped, priority should be given to strengthening the underlying digital foundation before intelligent technologies are introduced. In addition, governments and educational authorities should coordinate the balanced development of regional educational digitalization. Increased support should be provided to grassroots institutions and educational organizations in remote areas to narrow regional disparities in the digital technology environment, thereby creating favorable external conditions for empowering remote teaching supply chains through artificial intelligence technologies.

5.4 Limitations and future research directions

Although the sample in this study covered multiple types of educational institutions and online education platforms, no subgroup comparisons were performed based on institutional level or disciplinary category. In future research, institutional type and educational level could be introduced as control variables, or focused studies could be conducted within a single industry sector, thereby further validating the generalizability of the findings. In addition, only a single moderating variable—the digital technology environment—was introduced in this study. Future research could incorporate additional variables such as organizational innovation climate, digital leadership, and dynamic capabilities, through which mediating effects or moderated mediating effects could be examined. Such efforts would allow the underlying mechanisms of the observed relationships to be further elucidated.

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