The Impact of AI Adoption on Organizational Performance in Higher Vocational Institutions: Evidence from Guizhou, China

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Abstract: Artificial intelligence (AI) adoption has become increasingly important for improving management efficiency, service quality, and organizational performance in higher vocational institutions. However, limited empirical research has examined how AI adoption contributes to organizational performance in vocational higher education, particularly from an integrated theoretical perspective. Drawing on an extended technology–organization–environment (TOE) framework, this study investigates the relationship between AI adoption and organizational performance in higher vocational institutions. Individual innovation is incorporated into the TOE framework to capture the role of human-level innovation capability in institutional AI adoption. Guizhou Province, China, was selected as the research context because it represents a western region undergoing digital transformation while facing constraints in educational resources and institutional capacity, where higher vocational institutions play an important role in supporting regional industrial upgrading and skilled workforce development. Data were collected through a structured questionnaire survey and analyzed using structural equation modeling (SEM). The findings indicate that AI adoption has a significant positive effect on organizational performance. The results further show that technological, organizational, environmental, and individual innovation factors are important antecedents of AI adoption. By integrating individual innovation into the TOE framework, this study extends the explanatory scope of the framework and provides empirical evidence on AI-enabled organizational performance improvement in higher vocational education. The findings offer practical implications for institutional leaders and policymakers seeking to promote AI adoption and performance enhancement in vocational education institutions

Keywords: Higher vocational education institutions; AI adoption; TOE framework; organizational performance.

Introduction

Organizational performance constitutes a central indicator of institutional effectiveness in higher vocational institutions and reflects the extent to which these organizations transform resources into educational, social, and economic value (Marrucci et al., 2023). In vocational education, organizational performance cannot be adequately captured by single financial or academic indicators but instead represents a multidimensional construct encompassing operational efficiency, stakeholder satisfaction, and long term developmental capability (Rumanti et al., 2025). These dimensions are closely aligned with the vocational mission of higher vocational institutions, which emphasizes skills cultivation quality, industry education integration, responsiveness to labor market demand, and graduate employment outcomes. As a result, organizational performance occupies a pivotal position in determining institutional legitimacy, competitiveness, and sustainability within regional education and training systems (Lee et al., 2024).

Despite its strategic importance, organizational performance improvement remains a persistent challenge for higher vocational institutions. Many institutions face structural constraints such as limited resources, fragmented information systems, and rigid administrative routines that restrict their ability to respond effectively to external demands and internal governance pressures (Singun, 2025). These challenges are often intensified by growing accountability requirements, policy driven modernization agendas, and competition for students, funding, and employer partnerships (Mentini, 2024). In such environments, traditional management practices may be insufficient to support coordinated decision making, efficient resource allocation, and systematic performance monitoring. Performance disparities therefore tend to widen, particularly across regions characterized by uneven economic development and digital infrastructure.

Against this background, artificial intelligence adoption has attracted increasing attention as a potential mechanism for enhancing organizational performance. At the organizational level, ai adoption refers not merely to isolated or experimental tool usage but to the sustained integration of intelligent technologies into workflows, governance routines, and decision processes (Selten & Klievink, 2024). Through automation of routine tasks, enhancement of information processing capacity, and support for data informed decision making, ai adoption may contribute to improvements in administrative efficiency, service quality, and strategic coordination. In higher vocational institutions, such capabilities are especially relevant for addressing operational bottlenecks, strengthening internal management, and improving responsiveness to students and industry stakeholders. When embedded into organizational practices, ai adoption can therefore be conceptualized as a performance enabling capability rather than a purely instructional or technical innovation.

However, existing empirical research provides limited insight into the organizational performance implications of ai adoption in vocational education contexts. Much of the education related literature has focused on teaching effectiveness, learning outcomes, or individual level technology acceptance (Antonietti et al., 2022; Bailey et al., 2022), while the organizational consequences of ai adoption remain underexplored. Studies that do examine technology adoption and performance have often concentrated on corporate organizations or research oriented universities (Cui et al., 2022; Roy et al., 2022), offering limited applicability to higher vocational institutions with distinct governance structures, stakeholder configurations, and institutional objectives. Consequently, the conditions under which ai adoption contributes to organizational performance enhancement in higher vocational institutions remain insufficiently specified.

This limitation is particularly evident in the Chinese context, where vocational education operates within a strongly policy guided institutional environment and exhibits pronounced regional disparities. Policy initiatives associated with digital transformation and educational modernization generate strong incentives for technology adoption, yet the capacity of higher vocational institutions to implement and institutionalize ai varies substantially across regions. Guizhou Province constitutes a representative context in which higher vocational institutions simultaneously confront persistent constraints in organizational performance management and increasing expectations for digital and intelligent transformation. This combination of structural pressure and uneven institutional capability highlights the need for systematic investigation into how organizational performance is shaped and how ai adoption may contribute to performance enhancement under such conditions. Accordingly, the study is oriented toward three interrelated objectives:

RO1:To examine prevailing trends and key problems related to the factors influencing organizational performance management in higher vocational institutions.

RO2:To identify and analyze the factors that influence organizational performance in these institutions.

RO3:To develop an integrative model for enhancing organizational performance through organizational-level ai adoption in the context of higher vocational education.

Literature Review

2.1 Theoretical Framework

The study is grounded in an integrative theoretical framework that combines the technology organization environment framework (Baker, 2011), diffusion of innovations theory (Dearing & Cox, 2018), technology acceptance model (Davis et al., 1989), and balanced scorecard theory (Madsen, 2025) to explain the antecedents and consequences of organizational-level ai adoption in higher vocational institutions. This integrative approach enables a multilevel explanation in which external environmental pressures, internal organizational conditions, and individual characteristics jointly shape ai adoption, while adoption functions as a key mechanism through which these influences are translated into organizational performance outcomes.

The technology organization environment framework provides the primary analytical foundation for explaining organizational ai adoption (Baker, 2011). This framework conceptualizes adoption as the result of the combined influence of technological characteristics, organizational conditions, and environmental pressures. In the study, technological conditions are reflected in perceived relative advantage and compatibility, organizational conditions are represented by leadership support, and environmental pressures are associated with policy orientation and market competition. Prior research has demonstrated that these dimensions interact to shape both the likelihood and the extent of technology adoption, particularly in institutional settings where adoption decisions are embedded in formal governance structures and policy-driven reform agendas, as is the case in higher vocational education (Zhang et al., 2025; Zheng & Wu, 2025).

Diffusion of innovations theory complements this structural perspective by introducing an individual-level explanation of adoption behavior (Dearing & Cox, 2018). Central to this theory is personal innovativeness, which captures differences in individuals' willingness to experiment with new technologies and tolerate uncertainty. In organizational contexts, higher levels of personal innovativeness facilitate the translation of contextual drivers into substantive adoption behavior. Within higher vocational institutions, individual innovativeness among staff members strengthens implementation depth and supports the institutionalization of ai applications beyond initial trial use.

Technology acceptance model further informs the study by clarifying the cognitive and behavioral processes underlying ai adoption. The model distinguishes between adoption intention and actual adoption behavior, thereby explaining how favorable perceptions of usefulness and ease of use are transformed into sustained use (Davis et al., 1989). This perspective supports the conceptualization of ai adoption as a process rather than a single decision and aligns with the study's focus on organizational-level adoption that reflects both intention and practical integration into work routines.

Balanced scorecard theory is employed to conceptualize organizational performance as a multidimensional construct. This theory emphasizes that organizational performance encompasses internal process efficiency, stakeholder satisfaction, and long-term developmental capability in addition to financial outcomes (Madsen, 2025). Such a perspective is particularly appropriate for higher vocational institutions, whose missions prioritize service quality, stakeholder engagement, and sustainable capacity development. By adopting balanced scorecard logic, the study establishes a comprehensive framework for assessing the performance implications of organizational ai adoption.

Taken together, these theories provide a coherent conceptual foundation for the study. The integrated framework positions organizational ai adoption as a central mechanism through which technological, organizational, environmental, and individual factors influence organizational performance, thereby supporting systematic hypothesis development and empirical analysis within the context of higher vocational institutions in Guizhou Province, China.

2.2 Hypothesis Development

Figure 1 presents the conceptual framework of this study. The model is developed based on the extended Technology–Organization–Environment (TOE) framework by incorporating personal innovativeness as an additional individual-level factor. Specifically, relative advantage, compatibility, top management support, market competition pressure, and personal innovativeness are proposed as antecedent variables influencing AI adoption in higher vocational institutions (H1–H5). In turn, AI adoption is hypothesized to have a positive effect on organizational performance (H6). Furthermore, AI adoption is proposed to mediate the relationships between the five antecedent factors and organizational performance (H7a–H7e).

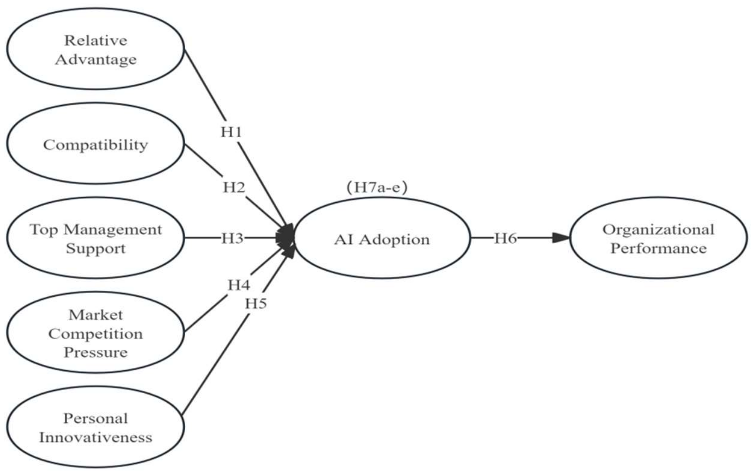


Figure 1 Conceptual Framework of the Study

Artificial intelligence adoption is conceptualised as an organizational level outcome reflecting the extent to which higher vocational institutions transform technological willingness into actual and sustained use of AI tools in teaching, administration, and decision support (Zuo et al., 2025). Prior empirical research on organizational innovation consistently suggests that favorable contextual conditions do not automatically generate performance improvement unless they are translated into routinised technology use embedded within daily organizational practices (Prasetyo et al., 2025; Todorovic et al., 2022). Especially in educational institutions, technologies are frequently introduced symbolically or experimentally, while their performance potential remains unrealised when adoption does not extend beyond isolated usage (Feng et al., 2025). Accordingly, the hypothesis development proceeds from the premise that artificial intelligence adoption constitutes the most immediate outcome of technological, organizational, environmental, and individual conditions, and serves as the direct antecedent through which these conditions influence organizational performance.

Relative advantage reflects the extent to which artificial intelligence is perceived to outperform existing practices in improving efficiency, service quality, and decision making (Chen et al., 2025). Across organizational technology studies, perceived relative advantage has repeatedly been shown to play a central role in adoption decisions, as organizations are more willing to tolerate uncertainty and implementation costs when clear performance benefits are anticipated (Kurup & Gupta, 2022). When AI is perceived to enhance instructional management, administrative coordination, or information processing efficiency, institutions are more likely to allocate resources and adjust workflows to support its use (Yusuf et al., 2024). In higher vocational institutions, where operational efficiency and governance quality are critical performance concerns, perceived advantage provides the primary justification for adopting AI beyond trial use (Ruano-Borbalan, 2025).On this basis, it is reasonable to expect that perceived relative advantage will increase the level of AI adoption. Accordingly, the following hypothesis is advanced:

H1: Relative advantage has a direct effect on AI adoption in higher vocational institutions.

Compatibility refers to the perceived alignment between AI tools and existing technological infrastructure, operational routines, and institutional values (Bankins et al., 2024). Prior research on organizational innovation indicates that compatibility reduces perceived implementation difficulty, lowers disruption to established workflows, and facilitates organizational acceptance (Faiz et al., 2024; Zhang et al., 2023). Technologies that fit existing systems and practices are more likely to be integrated into routine operations, whereas misaligned technologies often remain marginal or abandoned after initial experimentation. In higher vocational institutions, where legacy systems and standardized procedures shape daily operations, compatibility is especially important for determining whether AI adoption becomes stable and sustainable (Ejjami, 2024).Taken together, these considerations suggest that greater compatibility will facilitate deeper and more sustained AI adoption. Thus, the following hypothesis is proposed:

H2: Compatibility has a direct effect on AI adoption in higher vocational institutions.

Top management support represents organizational leadership commitment manifested through strategic guidance, policy endorsement, and resource allocation (Lo et al., 2024). Organizational innovation research consistently demonstrates that leadership support is a decisive factor in converting technological potential into organizational adoption (Huang et al., 2022). When senior leaders actively endorse AI initiatives, provide resources, and legitimise experimentation, employees are more likely to engage with new technologies and incorporate them into their work (Azizah Zamir, 2025). Conversely, insufficient leadership support often results in fragmented adoption driven solely by individual initiative, limiting organizational impact. In higher vocational institutions, where AI adoption may involve changes in governance processes, teaching practices, and ethical norms, sustained top management support is critical for institutionalising AI use (Ionica & Bularca, 2025).Following this line of reasoning, it can be inferred that stronger top management support will enhance AI adoption. Therefore, the study puts forward the following hypothesis:

H3: Top management support has a direct effect on AI adoption in higher vocational institutions.

Market competition pressure reflects the external intensity faced by institutions in attracting students, resources, and reputational recognition (Hart & Rodgers, 2024). Prior studies on organizational innovation indicate that competitive pressure motivates organizations to adopt new technologies by increasing the perceived cost of inaction and highlighting the strategic value of modernization (Tajuddin, 2025). In educational environments characterised by benchmarking and performance comparison, institutions may adopt AI not only to improve internal efficiency but also to signal innovation capacity and responsiveness to external stakeholders (Mai, 2024). For higher vocational institutions operating in competitive regional contexts, market pressure is likely to strengthen incentives to adopt AI as a means of enhancing service quality and institutional competitiveness (Hannan & Liu, 2023).Accordingly, heightened market competition pressure is expected to translate into stronger motivation for AI adoption. This expectation leads to the following hypothesis:

H4: Market competition pressure has a direct effect on AI adoption in higher vocational institutions.

Personal innovativeness reflects an individual's tendency to experiment with and embrace new technologies. Prior empirical evidence suggests that innovative individuals experience lower psychological resistance, engage in exploratory learning, and act as early adopters who facilitate internal diffusion (Basileo & Lyons, 2024). In educational organizations, faculty and administrative staff are the primary users of AI tools, and their willingness to experiment plays a crucial role in determining whether adoption intentions are translated into actual use (Razzouki et al., 2025). Individuals with higher innovativeness are more likely to integrate AI into their work practices and influence peers through demonstration and knowledge sharing, thereby increasing overall organizational adoption levels (Daly et al., 2025).From this perspective, higher levels of personal innovativeness are expected to contribute positively to AI adoption. Therefore, the following hypothesis is formulated:

H5: Personal innovativeness has a direct effect on AI adoption in higher vocational institutions.

Organizational performance in higher vocational institutions encompasses improvements in operational efficiency, internal process effectiveness, stakeholder satisfaction, and long term development capability (Riza et al., 2025). Research on digital transformation suggests that technology contributes to performance only when adoption is realised as sustained use embedded in organizational routines rather than sporadic experimentation (Chen & Kim, 2023). AI adoption can enhance performance by improving information processing, supporting data driven decision making, and streamlining administrative workflows (Raina et al., 2026). When AI becomes integrated into teaching and management practices, its impact is more likely to be reflected in multidimensional organizational performance outcomes (Bankins et al., 2024).In light of this reasoning, AI adoption is expected to play a direct role in enhancing organizational performance. Accordingly, the following hypothesis is proposed:

H6: AI adoption has a direct effect on organizational performance in higher vocational institutions.

The integrated framework further implies that AI adoption functions as a mediating mechanism linking contextual antecedents to organizational performance. Technological characteristics, leadership support, competitive pressure, and individual innovativeness shape organizational readiness and motivation, but their performance effects depend on whether they result in actual adoption. Without sustained adoption, favorable conditions remain latent and fail to generate measurable outcomes. By contrast, AI adoption represents the behavioural and organizational translation of these antecedents into operational practice, making it the most proximate pathway through which contextual factors influence performance.Based on this integrative reasoning, AI adoption is expected to mediate the relationships between key antecedents and organizational performance. Therefore, the following hypotheses are advanced:

H7a:Relative Advantage indirectly influences Organizational Performance of higher vocational institutions through the mediating role of AI Adoption.

H7b:Compatibility indirectly influences the Organizational Performance of higher vocational institutions through the mediating role of AI Adoption.

H7c:Top Management Support indirectly influences the Organizational Performance of higher vocational institutions through the mediating role of AI Adoption.

H7d:Market Competition Pressure indirectly influences the Organizational Performance of higher vocational institutions through the mediating role of AI Adoption.

H7e:Personal Innovativeness indirectly influences the Organizational Performance of higher vocational institutions through the mediating role of AI Adoption.

Method

3.1 Sample

This study was conducted in Guizhou Province, China, covering higher vocational institutions across all nine prefecture-level administrative regions. Guizhou Province was selected as the research setting because it represents an underdeveloped regional context where higher vocational institutions face constraints in resources, governance capacity, and digital transformation (Li et al., 2025). The target population consisted of academic and administrative staff employed in higher vocational institutions. As the study focuses on artificial intelligence adoption, only staff members with prior experience using AI tools in teaching, administration, or decision support were included. Respondents without AI usage experience were excluded to ensure alignment between the research constructs and the sample.

A stratified sampling strategy was employed to enhance representativeness and methodological rigor. The nine prefecture-level regions of Guizhou Province were treated as independent strata to ensure comprehensive geographic coverage and to capture regional heterogeneity. Prior to formal data collection, the required sample size was determined to ensure sufficient statistical power for structural equation modeling analysis. Based on the number of observed variables in the research model, the baseline sample size was set at twenty times the number of observed variables. An additional redundancy margin was incorporated to account for invalid or incomplete responses. Following this procedure, the final target sample size was determined to be 480.

To allocate the sample across regions, the study adopted a stratified sampling strategy with reference to the Neyman allocation principle (Mukherjee, 2023). This approach accounts for intra-regional variability and improves sampling efficiency compared with equal or proportional allocation strategies. During the preliminary survey stage, one higher vocational institution was randomly selected from each region, and five faculty members from each institution completed the questionnaire. Based on these preliminary responses, the standard deviation of key measurement variables was calculated for each region and used to determine the final sample allocation under the Neyman principle. This procedure ensured that regions with greater variability received proportionally larger sample sizes, thereby reducing overall estimation error.

Formal data collection was subsequently conducted in accordance with the stratified allocation plan. Questionnaires were distributed to eligible academic and administrative staff across higher vocational institutions in all nine regions of Guizhou Province. A total of 480 questionnaires were distributed according to the planned stratified allocation, and 444 valid responses were retained for final analysis,with an effective recovery rate of 92.50%. The final sample provided adequate geographic coverage and sufficient statistical power for subsequent structural equation modeling analysis. The detailed sample allocation by region is presented in Table 1. Overall, the sampling design ensured representativeness, operational feasibility, and robustness for subsequent structural equation modeling analysis.

Table 1 Sample Distribution and Effective Recovery Rate by Region

ID	Region	Sent	Return	Valid Samples	Effective Recovery Rate
1	Gui Yang	42	42	41	97.62%
2	Zun Yi	73	73	70	95.89%
3	Bi Jie	43	43	39	90.70%
4	An Shun	32	32	31	96.88%
5	Liu Pan Shui	83	83	75	90.36%
6	Tong Ren	66	66	62	93.94%
7	Qian Nan	57	57	52	91.23%
8	Qian Dong Nan	28	28	23	82.14%
9	Qian Xi Nan	56	56	51	91.07%
Total		**480**	**480**	**444**	**92.50%**

3.2 Data Collection

Quantitative data for this study were collected via a questionnaire distributed and retrieved through an online survey platform (Quanxunxing). This approach streamlined questionnaire distribution, enhanced data collection efficiency, and effectively mitigated geographical constraints on sample acquisition.Compared to traditional paper questionnaires, online platforms enable automatic logical branching, mandatory field control, and real-time data monitoring, thereby enhancing data completeness and accuracy (Dillman et al., 2014). Additionally, these platforms support direct export of data files in Excel or SPSS formats, facilitating subsequent statistical analysis and data cleaning while reducing human input errors.

This collection method aligns closely with the questionnaire design of this study. First, a screening question was placed on the questionnaire's first page to distinguish target samples. Respondents selecting “NO” (indicating no prior AI tool usage) were automatically redirected to the questionnaire's end, thereby excluding non-target samples.Second, during the sampling phase, the study established sample quotas for different regions. Once the sample size for a specific region reached the predetermined number, the system automatically halted further questionnaire completion in that region, preventing sample distribution imbalance. All these functions were implemented through the online questionnaire platform, enhancing the precision of sample control and the standardization of data collection.

During the formal survey, researchers allocated quotas for each region based on the required sample size and taking “geographic area” as classification condition before distributing the questionnaire links, which can ensure data sources aligned with the research design. Questionnaire links were distributed to survey participants via work groups, email, and school academic affairs offices.To enhance questionnaire response quality, researchers included a brief study description at the beginning, clearly outlining data usage scope and anonymity guarantees to reduce participant anxiety. After data collection, questionnaires were screened to exclude invalid responses: those from participants who had never used AI tools, those with excessively short completion times, those with identical answers across all options, or those exhibiting logical inconsistencies. The collected data was then analyzed using advanced statistical analysis and structural equation modeling software.

3.3 Data Analysis Methods

The data were processed and analyzed using advanced statistical software packages following a structured analytical procedure. First, descriptive statistical analysis was conducted to summarize the demographic characteristics of respondents and to examine the distributional properties of the observed variables, with means, standard deviations, skewness, and kurtosis calculated to assess central tendency, dispersion, and normality. Normality was evaluated based on skewness and kurtosis criteria, and the results indicated that the data satisfied the assumptions required for factor analysis and structural equation modeling. Pearson correlation analysis was subsequently performed to examine linear relationships among the study variables and to assess potential multicollinearity. Second, the reliability and validity of the measurement instruments were evaluated prior to hypothesis testing. Internal consistency reliability was assessed using Cronbach’s alpha and composite reliability, while the suitability of the data for factor analysis was examined using the Kaiser Meyer Olkin measure and Bartlett’s test of sphericity. Confirmatory factor analysis was then conducted to evaluate the measurement model, with convergent validity assessed through standardized factor loadings and average variance extracted values, and discriminant validity examined using the Fornell Larcker criterion (Fornell & Larcker, 1981). Items with insufficient factor loadings were excluded to improve measurement quality. Lastly, structural equation modeling was employed to test the hypothesized relationships among latent constructs after the measurement model demonstrated acceptable reliability and validity. Model fit was evaluated using multiple goodness of fit indices, including the chi square to degrees of freedom ratio, comparative fit index, Tucker Lewis index, root mean square error of approximation, and standardized root mean square residual. Path analysis were adopted to examine effects encompassing direct, indirect, and total effects. Direct effects denote the immediate influence of independent variables (e.g., Relative Advantage) on dependent variables (Organizational Performance). Indirect effects represent the mediated impact of independent variables on dependent variables through intermediary variables (e.g., AI Adoption).The total effect represents the sum of direct and indirect effects, reflecting the overall influence of the independent variable on the dependent variable. To ensure comparability of results and clarity of interpretation, all effect values presented in this study are based on standardized coefficients.

Results

4.1 Descriptive Statistics and Demographic Analysis

The demographic characteristics of the respondents are presented in Table 3. The sample shows a predominance of female respondents, who account for 70.50% of the total, while male respondents account for 29.50%. In terms of age, the largest group is respondents aged 31–40 years old (46.17%), followed by those aged 21–30 years old (26.80%), indicating that the sample is mainly composed of early- and mid-career professionals. Respondents aged 41–50 and 51–60 account for 18.24% and 8.78%, respectively. Regarding work experience, more than half of the respondents have ten years or less of service, including 25.00% with less than five years and 29.73% with five to ten years of experience. In addition, 22.07% have 11–15 years of work experience, 9.46% have 16–20 years, and 13.74% have more than 20 years. In terms of educational attainment, 46.85% of respondents hold a bachelor's degree and 43.69% hold a master's degree, while smaller proportions have qualifications below the bachelor's level (6.98%) or doctoral degrees (2.48%). With regard to academic rank, lecturers constitute the largest group (42.34%), followed by teaching assistants (17.12%), associate professors (16.89%), and professors (2.25%). For administrative positions, 45.50% of respondents do not hold administrative roles, while frontline administrative staff and general administrative staff each account for 20.50%. Mid-level managers account for 10.14%, and senior leaders account for 3.38%. Overall, the demographic profile indicates that the sample includes respondents with diverse backgrounds in terms of gender, age, work experience, educational attainment, academic rank, and administrative responsibility, providing an appropriate basis for examining AI adoption and organizational performance in higher vocational institutions in Guizhou Province.

Table 3. Demography Summary

Demographics	**Frequency**	**Percent**
Gender		
Male	131	29.50%
Female	313	70.50%
Age		
21-30 years old	119	26.80%
31-40 years old	205	46.17%
41-50 years old	81	18.24%
51-60 years old	39	8.78%
Work Experiences		
Under 5 years	111	25.00%
5-10 years	132	29.73%
11-15 years	98	22.07%
16-20 years	42	9.46%
Above 20 years	61	13.74%
Education Qualification		
Below bachelor's degree	31	6.98%
Bachelor's degree	208	46.85%
Master's degree	194	43.69%
Doctoral degree	11	2.48%
Academic title		

Unrated	95	21.40%
Teaching Assistant	76	17.12%
Lecturer	188	42.34%
Associate Professor	75	16.89%
Professor	10	2.25%
Job Position		
Senior Leadership	15	3.38%
Mid-level management	45	10.14%
Frontline administrative staff	91	20.50%
General administrative staff	91	20.50%
No administrative position	202	45.50%

Table 4 presents the descriptive statistics of the latent variables included in the study. Except for Top Management Support (TMS), all constructs had mean values above the midpoint of 3 on the five-point Likert scale, indicating generally positive perceptions among respondents. AI Adoption (AIA) recorded the highest mean score (M = 4.027, SD = 0.693), followed by Compatibility (CMP), Market Competition Pressure (MCP), Organizational Performance (OP), Personal Innovativeness (PI), and Relative Advantage (RA). These six constructs fell within the high-level range based on five-point Likert scale interpretation criteria. In contrast, TMS had a mean value of 2.264, placing it in the low-level range and suggesting that respondents perceived insufficient senior management support. The standard deviations ranged from 0.618 to 0.721, all below 1, indicating a high degree of response convergence. TMS showed the largest standard deviation, suggesting relatively greater variation in respondents' perceptions of senior management support. Overall, the descriptive statistics indicate acceptable response consistency for subsequent analysis.

Table 4. Descriptive Statistics of Latent Variables

Variable	**Mean**	**SD**
Relative Advantage (RA)	3.783	0.618
Compatibility (CMP)	3.915	0.668
Top Management Support (TMS)	2.264	0.721
Market Competition Pressure (MCP)	3.871	0.714
Personal Innovativeness (PI)	3.818	0.658
AI Adoption (AIA)	4.027	0.693
Organizational Performance (OP)	3.844	0.639

4.2 Measurement Model: Reliability and Validity Assessment

Confirmatory factor analysis was conducted to assess the reliability and validity of the measurement model. Internal consistency reliability was evaluated using Cronbach's alpha. As reported in Table 5, all constructs exhibit satisfactory reliability, with Cronbach's alpha values exceeding the recommended threshold, indicating strong internal consistency among the measurement items. In addition, the Kaiser–Meyer–Olkin measures and Bartlett's test of sphericity confirm that the data are appropriate for factor analysis, demonstrating adequate sampling adequacy and significant correlations among variables (Shrestha, 2021).

Table 5. The Results of Reliability and Validity Testing

Variable	**Cronbach's Alpha**	**KMO**	**Bartlett's Test**		
			Chi-Square	**f**	**Significance**
Relative Advantage	0.890	0.891	2003.288	6	<0.001
Compatibility	0.930	0.920	2854.738	6	<0.001
Top Management Support	0.941	0.875	2532.081	5	<0.001
Market Competition Pressure	0.957	0.934	4037.955	6	<0.001
Personal Innovativeness	0.946	0.923	4186.906	5	<0.001
AI Adoption	0.900	0.838	1805.981	5	<0.001
Organizational Performance	0.949	0.928	4591.021	6	<0.001

Discriminant validity was assessed using the Fornell–Larcker criterion by comparing the square roots of the average variance extracted with the inter-construct correlations (Fornell & Larcker, 1981). As shown in Table 6, the square root of the AVE for each construct is greater than its correlations with all other constructs, satisfying the established criterion for discriminant validity. These results indicate that the constructs are empirically distinct and capture unique dimensions within the measurement model. Overall, the findings support the robustness of the measurement model and provide a sound basis for subsequent structural equation modelling.

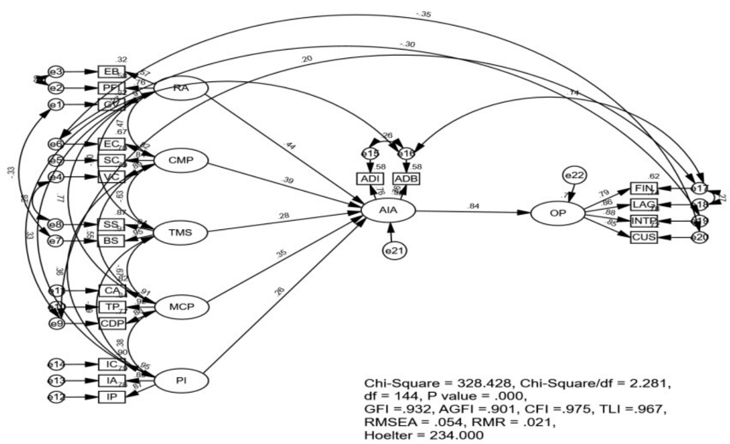
Table 6. Discriminant Validity

	RA	**CMP**	**TMS**	**MCP**	**PI**	**AIA**	**OP**
RA	**0.808**						
CMP	0.459***	**0.849**					
TMS	-0.462***	-0.632***	**0.944**				
MCP	0.735***	0.556***	-0.671***	**0.900**			
PI	0.322***	0.368***	-0.293***	0.376***	**0.903**		
AIA	0.734***	0.613***	-0.381***	0.735***	0.597***	**0.833**	
OP	0.663***	0.662***	-0.472***	0.656***	0.436***	0.754***	**0.861**

Note: *** $p < 0.001$

4.3 Structural Model and Hypothesis Testing

Figure 2 presents the structural model estimation results, demonstrating an adequate overall fit after model adjustment. The chi-square-to-degrees-of-freedom ratio was 2.281, which falls within the accepted threshold for structural equation modeling. Additional fit indices confirmed model adequacy, including GFI = 0.932, AGFI = 0.901, CFI = 0.975, and TLI = 0.967. The RMSEA value of 0.054 and the RMR value of 0.021 were also within the recommended thresholds, indicating acceptable absolute and residual fit.



Figur 2 SEM Model

Table 7 presents the structural path results, which show that all antecedent constructs exert positive effects on AI adoption. Relative Advantage demonstrates the strongest direct effect on AI Adoption, with a standardized coefficient of 0.442, followed by Compatibility with a coefficient of 0.390, Market Competition Pressure with a coefficient of 0.349, Top Management support with a coefficient of 0.276, and Personal Innovativeness with a coefficient of 0.261. These results indicate that technological, organizational, environmental, and individual factors all contribute to AI adoption in higher vocational institutions. Besides, AI Adoption exhibits a strong positive effect on Organizational Performance, with a standardized coefficient of 0.837.

Regarding the indirect influence of independent variables on Organizational Performance, Relative Advantage (β=0.370) exerted the largest indirect effect, followed by Compatibility (β=0.327). Meanwhile, the path coefficient of Market Competition Pressure on Organizational Performance is 0.292. In contrast, the path coefficients for Top Management Support (β=0.231) and Personal Innovativeness with a coefficient of 0.218. These findings demonstrate that AI Adoption mediates the influence of technological, organizational, environmental and personal factors on Organizational Performance.

In addition, the model explained 95.3% of the variance in AI adoption and 70.0% of the variance in organizational performance. Collectively, the structural coefficients provide empirical support for the hypothesized relationships and demonstrate a coherent mechanism linking contextual and individual factors to organizational performance through AI adoption.

Table 7. Standardized Direct, Indirect and Total Effects

	Effect	**RA**	**CMP**	**TMS**	**MCP**	**PI**	**AIA**
AIA	DE	0.442	0.390	0.276	0.349	0.261	-
	IDE	-	-	-	-	-	-
	TE	0.442	0.39	0.276	0.349	0.261	-
	R^2	0.953					
OP	DE	-	-	-	-	-	0.837
	IDE	0.370	0.327	0.231	0.292	0.218	-
	TE	0.370	0.327	0.231	0.292	0.218	0.837
	R^2	0.700					

Note: DE means direct effect, IDE means indirect effect, TE means total effect.

The hypothesis testing outcomes reported in Table 8 indicate that all proposed direct effect hypotheses are supported. Relative advantage, compatibility, top management support, market competition pressure, and personal innovativeness each show statistically significant positive effects on AI adoption, confirming H1 through H5. The results further demonstrate that AI adoption exerts a positive and significant impact on organizational performance, providing support for H6. The mediating hypotheses are also verified, as AI adoption is shown to transmit the effects of all five antecedent constructs to organizational performance. Accordingly, H7a through H7e are accepted, indicating that relative advantage, compatibility, top management support, market competition pressure, and personal innovativeness influence organizational performance through the indirect pathway of AI adoption.

Table 8. Summary of Hypothesis Results

Hypothesis	**Result**
H1:Relative Advantage has a direct impact on AI adoption of higher vocational institutions.	Accepted
H2:Compatibility has a direct impact on AI adoption of higher vocational institutions.	Accepted
H3:Top Management Support has a direct impact on AI adoption of higher vocational institutions.	Accepted
H4: Market Competition Pressure has a direct impact on AI adoption of higher vocational institutions.	Accepted
H5: Personal Innovativeness has a direct impact on AI adoption of higher vocational institutions.	Accepted
H6: AI adoption has a direct impact on Organizational Performance of higher vocational institutions.	Accepted
H7a:Relative Advantage indirectly influences Organizational Performance of higher vocational institutions through the mediating role of AI Adoption.	Accepted

H7b:Compatibility pindirectly influences the Organizational Performance of higher vocational institutions through the mediating role of AI Adoption.	Accepted
H7c:Top Management Support indirectly influences the Organizational Performance of higher vocational institutions through the mediating role of AI Adoption.	Accepted
H7d:Market Competition Pressure indirectly influences the Organizational Performance of higher vocational institutions through the mediating role of AI Adoption.	Accepted
H7e:Personal Innovativeness indirectly influences the Organizational Performance of higher vocational institutions through the mediating role of AI Adoption.	Accepted

Discussion

5.1 Research Findings

This study confirms that technological factors are important drivers of AI adoption in higher vocational institutions. Consistent with previous technology adoption and TOE-based studies, relative advantage and compatibility significantly promote AI adoption, indicating that institutions are more likely to adopt AI when it is perceived as useful, efficient, and aligned with existing work practices. However, this study extends prior findings by showing that these technological factors further contribute to organizational performance through AI adoption. Thus, the study moves beyond explaining adoption intention or adoption behavior alone and clarifies how technological perceptions are transformed into institutional performance outcomes.

The findings also support the importance of organizational and environmental factors in AI adoption. Top management support has a significant positive effect on AI adoption, which is consistent with prior studies emphasizing leadership commitment and resource allocation in technology implementation. Market competition pressure also encourages AI adoption, reflecting the role of external demands in promoting digital transformation. Nevertheless, this study adds a more nuanced explanation by showing that leadership support and environmental pressure do not automatically generate performance improvement; rather, their effects are realized mainly when they are translated into actual and sustained AI adoption within institutional processes.

A key contribution of this study is the incorporation of personal innovativeness into the TOE framework. While traditional TOE studies mainly focus on technological, organizational, and environmental conditions, the present findings show that individual-level innovation capacity is also a significant predictor of AI adoption. Personal innovativeness not only promotes AI adoption but also indirectly enhances organizational performance through adoption mechanisms. This finding extends the explanatory scope of the TOE framework and highlights the importance of staff willingness, openness, and ability to experiment with AI tools in enabling organizational transformation.

Finally, this study demonstrates that AI adoption has a significant positive effect on organizational performance and serves as a mediating mechanism linking contextual and individual factors to performance outcomes. Previous studies have often treated technology adoption as an outcome variable, whereas this study positions AI adoption as both an outcome of antecedent factors and a pathway through which institutional performance is improved. By doing so, the study provides empirical evidence on AI-enabled performance improvement in higher vocational institutions and contributes to the limited literature examining AI adoption, extended TOE factors, and organizational performance within the vocational education context..

5.2 Theoretical Contributions

The empirical findings are consistent with recent theoretical developments in research on technology adoption and organizational performance within educational and public sector organizations. Prior studies have increasingly emphasized that the effects of technological, organizational, and environmental conditions on performance outcomes are not necessarily direct but are often transmitted through internal adoption mechanisms. Recent research has demonstrated that the influence of technological characteristics and organizational conditions on performance can be fully mediated by digital technology adoption processes (Kallmuenzer et al., 2025; Zhou et al., 2023). Similar patterns have been identified in studies examining digital transformation in educational institutions, where contextual conditions shape organizational outcomes primarily through the depth and effectiveness of technology use. The present findings provide strong empirical support for this emerging theoretical perspective by demonstrating that the effects of relative advantage, compatibility, top management support, market competition pressure, and personal innovativeness on organizational performance are entirely transmitted through AI adoption. The convergence of these findings across institutional types and regional settings suggests that indirect performance pathways mediated by technology adoption represent a stable and generalizable mechanism of organizational change rather than a context specific phenomenon.

These findings also extend the theoretical understanding of the technology organization environment framework by repositioning AI adoption as a central explanatory mechanism linking contextual conditions to organizational performance. While the framework has traditionally been employed to explain adoption decisions, the results indicate that its explanatory power can be significantly enhanced by embedding adoption within a broader performance oriented causal structure. The evidence suggests that technological attributes, organizational support, and environmental pressure do not independently produce performance improvement unless they are effectively transformed into sustained AI adoption (Li & Jin, 2024). This extension advances the framework beyond its conventional use and establishes a clearer causal logic connecting environmental and organizational readiness to performance outcomes through technology enabled transformation.

In addition, the findings offer important theoretical implications for diffusion of innovations theory by demonstrating that personal innovativeness exerts influence beyond individual level adoption behavior. Existing research has primarily treated innovativeness as a predictor of individual acceptance or early use of technology (Marikyan et al., 2023). The present results indicate that personal innovativeness contributes to organizational performance indirectly by facilitating institutional level AI adoption. This aggregation of individual innovation tendencies into organizational outcomes supports the extension of diffusion based theories toward multilevel explanations of performance. The results suggest that individual psychological traits can function as distal antecedents within organizational performance models when mediated by collective adoption processes.

The study also contributes to the theoretical development of performance management in educational organizations through the application of balanced scorecard logic in an AI enabled context. Previous research in vocational education has often relied on limited outcome indicators, thereby constraining theoretical understanding of how digital technologies affect organizational performance (Lu, 2024; Zuo et al., 2025). The findings demonstrate that AI adoption exerts influence across financial efficiency, internal process optimization, learning and growth capacity, and stakeholder related outcomes simultaneously. This multidimensional effect supports the theoretical relevance of balanced scorecard perspectives for analyzing digital transformation in educational institutions and indicates that AI adoption should be conceptualized as a systemic performance driver rather than a narrowly operational tool.

5.3 Practical Implications

First, the findings indicate that effective AI adoption constitutes a core element of organizational performance enhancement in higher vocational institutions. Given the strong and consistent influence of AI adoption on multiple performance dimensions, institutions are advised to prioritize the systematic integration of AI tools into teaching, administrative, and management processes. Rather than treating AI as an auxiliary technological resource, institutions should embed AI applications within routine work practices and performance management systems. Emphasis should be placed on practical usability and functional relevance, ensuring that AI adoption directly supports efficiency improvement, service quality enhancement, and organizational learning capacity.

Second, although top management support plays a significant role in creating favorable conditions and allocating resources for AI adoption, the findings indicate that leadership alone is insufficient to generate meaningful performance improvement. The role of institutional leadership should therefore shift from symbolic endorsement toward facilitating and sustaining AI adoption at the operational level. This includes providing clear strategic direction, establishing institutional policies for AI use, and supporting professional development initiatives that enable staff to integrate AI tools into daily work activities. Leadership engagement should focus on enabling adoption rather than relying on top down directives to produce performance outcomes.

Third, the results imply that higher vocational institutions need to actively cultivate individual innovativeness among faculty and administrative staff. Since personal innovativeness significantly contributes to AI adoption and indirectly affects organizational performance, institutions should create environments that encourage experimentation, skill development, and knowledge sharing related to AI use. This may involve providing training opportunities, recognizing innovative practices, and fostering peer learning mechanisms that allow innovative behaviors to diffuse across departments. Strengthening individual level innovation capacity can enhance collective adoption outcomes and reinforce organizational performance improvement.

Fourth, the findings suggest that AI adoption initiatives should be structured not only to introduce technological capabilities but also to translate these capabilities into concrete performance oriented practices. While general awareness of AI potential is important, it is insufficient to produce sustained organizational impact. Institutions should therefore focus on developing clear application scenarios, operational guidelines, and performance linked objectives for AI use. Aligning AI adoption with specific institutional goals can support the formation of actionable strategies that enhance efficiency, decision quality, and service delivery.

Conclusion

This study contributes to the literature on AI adoption in higher vocational institutions by extending the TOE framework with personal innovativeness and by explaining how contextual and individual factors influence organizational performance through AI adoption. The findings show that AI adoption has a strong positive effect on organizational performance, while relative advantage, compatibility, market competition pressure, and personal innovativeness mainly enhance performance through their influence on AI adoption. In contrast, top management support alone does not directly generate performance improvement unless it is translated into sustained and routinized AI use within institutional processes. These results highlight the central role of AI adoption as a mechanism linking institutional readiness, individual innovation capacity, and organizational outcomes. Practically, higher vocational institutions should move beyond symbolic support for AI by providing clear strategic guidance, supportive policies, staff training, and concrete application scenarios that enable generative AI to be integrated into teaching, administration, and decision-making. However, this study is limited by its focus on generative AI adoption without further distinguishing among different generative AI tools or specific application scenarios. In addition, its cross-sectional survey design and focus on higher vocational institutions in Guizhou Province may affect the generalizability and temporal interpretation of the findings. Future research could adopt longitudinal designs, include broader regional samples, and compare different generative AI application scenarios to explain how generative AI adoption becomes institutionalized and contributes to sustainable performance improvement in vocational education.

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