

GENERATIVE AI LITERACY AND ITS EFFECTES ON ADMINISTRATIVE STAFF'S INNOVATION PERFORMANCE: THE CONTEXT OF VOCATIONAL COLLEGES IN NORTHEASTERN CHINA

Lei Zhao

A Thesis Submitted in Partial Fulfillment of the Requirements
for the Degree of Doctor of Philosophy
Program in Management
Rattanakosin International College of Creative Entrepreneurship
Rajamangala University of Technology Rattanakosin
Academic Year 2026
Copyright of Rajamangala University of Technology Rattanakosin

GENERATIVE AI LITERACY AND ITS EFFECTES ON ADMINISTRATIVE STAFF'S INNOVATION PERFORMANCE: THE CONTEXT OF VOCATIONAL COLLEGES IN NORTHEASTERN CHINA

Lei Zhao

A Thesis Submitted in Partial Fulfillment of the Requirements
for the Degree of Doctor of Philosophy
Program in Management
Rattanakosin International College of Creative Entrepreneurship
Rajamangala University of Technology Rattanakosin
Academic Year 2026
Copyright of Rajamangala University of Technology Rattanakosin

GENERATIVE AI LITERACY AND ITS EFFECTES ON ADMINISTRATIVE STAFF'S INNOVATION PERFORMANCE: THE CONTEXT OF VOCATIONAL COLLEGES IN NORTHEASTERN CHINA

Lei Zhao

2026



Copyright Consent Letter of Thesis/Independent Study between the Student and Rajamangala University of Technology Rattanakosin

At Rajamangala University of Technology Rattanakosin
96 Moo 3, Phutthamonthon Sai 5 Road, Salaya
Subdistrict Phutthamonthon District,
Nakhon Pathom Province 73170

Date 17 August 2026

I, ~~Mr.~~/Mrs./~~Miss~~ Lei Zhao Student ID 1661110381108,
am a student of the Faculty/College of Rattanakosin International College of Creative Entrepreneurship
in the Program of Doctor of Philosophy Major: Management
Plan Thesis

agree to grant the copyright and other related information in the approved thesis/ independent study under the following topic

Title of Thesis/Independent Study

Thai .....

English Generative AI Literacy and Its Effects on Administrative Staff's Innovation Performance: The Context of Vocational Colleges in Northeastern China

I agree to grant such rights to Rajamangala University of Technology Rattanakosin for the full term of protection as provided under relevant intellectual property laws.

Signature ..... Student
(Miss Lei Zhao)

Signature ..... Advisor
(Dr. Nutteera Phakdeephirot)

Signature ..... Director
(Dr. Nuttapong Jotikasthira)



Thesis Certificate
Rattanakosin International College of Creative Entrepreneurship
Rajamangala University of Technology Rattanakosin

Thesis of Title	Generative AI Literacy and Its Effects on Administrative Staff's Innovation Performance: The Context of Vocational Colleges in Northeastern China
Researcher	Miss Lei Zhao
Degree Sought	Doctor of Philosophy Program in Management (International Program)

Thesis Advisors

1. Nutteera Phakdeephirot, Ph.D.
2. Songyu Jiang, Ph.D.

Rattanakosin International College of Creative Entrepreneurship, Rajamangala University of Technology Rattanakosin Approved this Thesis in Partial fulfillment of the Requirements for the Degree of Doctor of Philosophy

..... Director
(Dr. Nuttapong Jotikasthira)

Thesis Committee

..... Chairperson
(Professor Dr. Poomthan Rangkakulnuwat)

..... Member
(Assistant Professor Dr. Suthep Nimsai)

..... Member
(Dr. Nuttapong Jotikasthira)

..... Member and Co-advisor
(Dr. Songyu Jiang)

..... Member and Advisor
(Dr. Nutteera Phakdeephirot)

Title of Thesis Generative AI Literacy and Its Effects on Administrative Staff's Innovation Performance: The Context of Vocational Colleges in Northeastern China
Researcher: Miss Lei Zhao, (M.M.); **Degree:** Doctor of Philosophy (Management); **Advisors:** Nutteera Phakdeephirot, (Ph.D.), Instructor; and Songyu Jiang, (Ph.D.), Instructor; **Academic Year:** 2026

ABSTRACT

The objectives of this research were (1) to examine how generative AI literacy influences administrative staff's use of generative AI across different administrative functions and its impact on their innovation performance in vocational colleges in Northeastern China, (2) to investigate the mediating roles of dynamic capabilities and AI knowledge sharing participation as organizational processes through which generative AI literacy contributes to administrative staff's innovation performance in vocational colleges in Northeastern China, and (3) to examine how organizational structure conditions the relationship between generative AI literacy and administrative staff's innovation performance in vocational colleges in Northeastern China.

This study adopted a quantitative research design and collected 765 valid responses from administrative staff in vocational colleges across Liaoning, Jilin, and Heilongjiang provinces. The questionnaire measured generative AI literacy, dynamic capabilities, AI knowledge sharing participation, organizational structure, and innovation performance. Reliability and validity were examined through Cronbach's alpha, confirmatory factor analysis, convergent validity, and discriminant validity. Structural equation modeling, bootstrapping, and moderation analysis were used to test the proposed relationships.

Major findings: (1) On the issue of the generative AI literacy, this factor significantly enhanced administrative staff's innovation performance, and the use of generative AI had extended across multiple administrative functions. Innovative application ability and quality evaluation ability showed particularly important roles in supporting administrative innovation; (2) On the issue of the dynamic capabilities and AI knowledge sharing participation, these factors significantly mediated the relationship between generative AI literacy and innovation performance, indicating that organizational adaptation and AI-related knowledge exchange are key mechanisms for transforming AI literacy into innovation outcomes; and (3) On the issue of the organizational structure, this factor significantly strengthened the relationship between generative AI literacy and innovation performance, suggesting that clear procedures and coordinated governance help administrative staff translate AI-related competencies into stronger innovation performance.

Keywords: Generative AI literacy, Dynamic capabilities, AI knowledge sharing participation, Organizational structure, Innovation performance, Vocational colleges, Administrative staff

Advisor's Signature .....

Acknowledgments

With the completion of this doctoral dissertation, an important stage of my academic journey—one that has combined professional responsibilities with scholarly study—has come to an end. Since beginning my doctoral studies in 2023, I have continued to learn, reflect, and explore, while taking on the role of a student alongside my established experience in teaching and professional work. This experience has deepened my understanding of management theories and research methods. It has also made me appreciate that academic growth depends not only on personal effort, but also on the guidance of mentors, the support of colleagues, and the understanding of family members. I would like to express my sincere gratitude to everyone who has supported and encouraged me throughout my doctoral studies and the completion of this dissertation.

First and foremost, I would like to express my heartfelt gratitude and highest respect to my principal supervisor, Nutteera Phakdeephirot. Thank you for your guidance and support throughout my doctoral studies and research. Your advice enabled me to deepen my understanding of the research problem and to examine my work with greater rigor. Your instruction taught me that academic research requires both sensitivity to real-world problems and a commitment to developing arguments based on sufficient evidence, clear logic, and careful judgment. The most valuable outcome of my doctoral studies is not only the completion of this dissertation, but also the gradual development of habits of independent thinking, careful verification, and continuous reflection. These lessons will continue to influence my teaching and research in the years ahead.

I would also like to express my sincere appreciation to my second supervisor, Songyu Jiang. Thank you for your guidance, assistance, and encouragement throughout my research and dissertation writing. Your support encouraged me to reflect continuously on the limitations of my work and to improve my academic expression and research ideas. As a teacher who has worked in vocational education for many years, I have often approached problems from the perspective of teaching practice and professional experience. Doctoral study, however, has required me to examine these experiences through the lens of theory and evidence. Thank you for supporting me throughout this process and for helping me develop a deeper understanding of the relationship between

practical problems and academic research. Your guidance has also helped me clarify the direction of my future research.

I am grateful to Rajamangala University of Technology Rattanakosin for providing valuable opportunities for doctoral education, learning, and academic exchange. I also sincerely thank all the instructors and staff members who contributed to my academic development. Doctoral study has allowed me to encounter different academic perspectives and cultural backgrounds, broaden my outlook through communication, and deepen my understanding through comparison. I would also like to express my sincere appreciation to the experts and faculty members who reviewed and examined this dissertation. Thank you for the time and effort you devoted to evaluating my work.

I am deeply grateful to Heilongjiang Agricultural Engineering Vocational and Technical University, as well as to the leaders and colleagues who have offered me understanding, support, and assistance throughout my professional career. Since I began working in 2009, teaching practice and educational work have remained important foundations for understanding problems and accumulating experience. Through teaching, coaching students for skills competitions, and conducting research, I have continually reflected on how knowledge can be transformed into the ability to solve practical problems. These experiences have also strengthened my understanding of the importance of lifelong learning for educators. They provided the motivation for my further study and encouraged me to remain attentive to the relationship between academic research and educational practice.

I would like to thank my classmates and friends who studied, communicated, and grew alongside me. The discussions, exchanges, and mutual encouragement that accompanied my doctoral journey made the experience more meaningful and rewarding. I am also grateful to the students whom I have taught and coached. Your questions in the classroom, your exploration in practical activities, and your persistence in the face of difficulties have often encouraged me to reconsider my knowledge and teaching methods. Throughout this period of study, the identities of teacher and student continually informed one another, enabling me to better understand the challenges of learning and to appreciate more deeply the responsibility carried by education.

My special thanks go to my family. Balancing professional work, doctoral study, and everyday life requires patience and understanding. Thank you for your companionship,

tolerance, and support throughout this journey, which enabled me to fulfill my responsibilities while persevering with my studies. Your care, expressed through countless ordinary moments, is difficult to fully describe in words. The completion of this dissertation also carries my profound gratitude to you.

Looking back on this academic journey—from identifying problems in teaching practice, to examining them through the perspective of management, and then exploring the relationship between generative artificial intelligence and innovation in university administration—I have gained a clearer understanding of the value of continuous learning and research. The completion of this dissertation marks the achievement of one stage, but it also represents the beginning of further exploration. In the future, I will bring the rigor and research awareness developed during my doctoral studies into my teaching, research, and educational work. Through concrete actions, I hope to respond to the guidance of my supervisors, the support of my colleagues, and the expectations of my family.

Finally, I would like to once again express my sincere gratitude to everyone who has cared for, supported, and helped me. Any remaining shortcomings in this dissertation are my sole responsibility.

Lei Zhao

June 2026

Table of Contents

	Page
Abstract	(1)
Acknowledgments	(2)
Table of Contents	(5)
List of Tables	(9)
List of Figures	(10)
List of Abbreviation and Glossary	(11)
Chapter 1 Introduction.....	1
1.1 Background of the Study	1
1.1.1 Problem Statement	1
1.1.2 Research Gap	9
1.2 Significance of the Study	10
1.2.1 Theoretical Significance	10
1.2.2 Practical Significance	11
1.3 Statement of Research Questions	12
1.4 Statement of Research Objectives	13
1.5 Methodology	13
1.6 Definitions of Terms	14
1.6.1 Generative AI Literacy	14
1.6.2 Dynamic Capabilities	14
1.6.3 AI Knowledge Sharing Participation	15
1.6.4 Organization Structure	15
1.6.5 Innovation Performance in Vocational Colleges	15
1.7 Delimitation of the Thesis	16
1.8 Outline of Thesis	17
1.9 Conclusion	18
Chapter 2 Literature Review	19
2.1 Contexts of the Study	19
2.1.1 Generative AI	19
2.1.2 Vocational colleges in Northeastern China	21
2.1.3 Administrative Staffs in Vocational Colleges	23
2.1.4 Generative AI Literacy in Administrative Staffs	26
2.1.5 Administrative Staffs's Innovation in Vocational Colleges	28

Table of Contents (continued)

		Page
	2.2 Parent Disciplines	31
	2.2.1 Dynamic Capability Theory	31
	2.2.2 Knowledge-based View	35
	2.2.3 Sociotechnical Systems Theory	38
	2.3 Immediate Disciplines	40
	2.3.1 Generative AI Literacy	40
	2.3.2 Dynamic Capabilities	41
	2.3.3 AI Knowledge Sharing Participation	42
	2.3.4 Organization Structure	43
	2.3.5 Innovation Performance in Vocational Colleges	45
	2.4 Conceptual Model and Hypotheses Statement	46
	2.4.1 Conceptual Model	46
	2.4.2 Hypotheses Development	48
	2.5 Conclusion	58
Chapter 3	Methodology	59
	3.1 Overview and Justification of Research Paradigm	59
	3.2 Research Tools	61
	3.2.1 Operational Definitions of Variables	61
	3.2.2 Variable Measurements	62
	3.3 Data Collection Administration	78
	3.3.1 Target Population	78
	3.3.2 Sample Size	80
	3.3.3 Sampling Method	81
	3.3.4 Data Collection Method	82
	3.4 Data Analysis	83
	3.4.1 Pilot Study	83
	3.4.2 Descriptive Statistical Analysis	87
	3.4.3 Reliability Analysis	88
	3.4.4 Validity Analysis	88
	3.4.5 Structural Equation Model Analysis	89
	3.5 Ethical Considerations	90
	3.6 Conclusion	91
Chapter 4	Results	92

Table of Contents (continued)

Page

4.1 Descriptive Analysis 92
4.1.1 Sample Characteristics 92
4.1.2 Descriptive Statistics 96
4.2 Confirmatory Factor Analysis 101
4.2.1 Measurement Model and Fit Metrics 101
4.2.2 Convergent Validity 102
4.2.3 Discriminant Validity 106
4.3 Structural Model Path Analysis 110
4.3.1 Model Fit Metrics for the Structural Model 110
4.3.2 Path Analysis for Direct Effects 111
4.3.3 Path Analysis for Indirect Effects 114
4.4 Conclusion 119
Chapter 5 Discussion and Conclusion 121
5.1 Implication to Theories 131
5.1.1 Implication to Dynamic Capability Theory 131
5.1.2 Implication to Knowledge-based View 133
5.1.3 Implication to Sociotechnical Systems Theory 136
5.2 Implication to Practitioners 138
5.2.1 Implications for Administrative Staff in Vocational Colleges 138
5.2.2 Implications for Vocational College Administrators 139
5.2.3 Implications for Generative AI Providers 141
5.2.4 Implications for Policy Makers in Vocational Education 142
5.3 Limitation of the Study and Implications of Future Research … 144
5.3.1 Limitation of the Present Study 144
5.3.2 Implications for Future Research 145
5.4 Conclusion 146
Bibliography 148
Appendix 167
Appendix A Questionnaire (English Version) 168
Appendix B Questionnaire (Chinese Version) 178

Table of Contents (continued)

	Page
Appendix C Publication of Journal during Ph.D. Study …….	188
Vitae ……..	208

List of Tables

Table		Page
2.1	Distinction between Generative AI Literacy and Related Concepts	27
2.2	Examples of Administrative Staffs' Innovation in Vocational Colleges	29
3.1	Operational Definitions of Related Variables	61
3.2	Detailed Statements used to Measure Generative AI Literacy	63
3.3	Detailed Statements used to Measure Dynamic Capabilities	66
3.4	Detailed Statements used to Measure AI Knowledge Sharing Participation	70
3.5	Detailed Statements used to Measure Organization Structure	72
3.6	Detailed Statements used to Measure Innovation Performance in Vocational Colleges	74
3.7	Distribution of Administrative Staff in Vocational Colleges in Northeastern China	80
3.8	Item Analysis for Pilot Test	84
3.9	Pretest Reliability Statistics	87
3.10	Pre-investigation KMO and Bartlett's Test	87
3.11	Structural Equation Modeling Indicators	90
4.1	Sample Information	94
4.2	Descriptive Statistics Results	98
4.3	Measure Model Fit Metrics	101
4.4	Convergence Validity	103
4.5	Discriminant Validity Test	108
4.6	Model Fit Metrics	111
4.7	Direct Path Effects	114
4.8	Indirect Effect Bootstrap Analysis	116
4.9	Moderation Effect of H6a	117
4.10	Moderation Effect of H6b	118
4.11	Moderation Effect of H6c	118
4.12	Moderation Effect of H6d	119
4.13	Moderation Effect of H6e	119

List of Figures

Figures		Page
2.1	Distribution of Vocatioal Colleges in Northeast China	22
2.2	Distribution of Vocational Colleges in Northeastern China	24
2.3	Administrative Staff Size in Vocational Colleges, 2020–2024	25
2.4	Dynamic capability theory	32
2.5	Conceptual Framework of Knowledge-Based Innovation Process	36
2.6	Conceptual Framework of Sociotechnical Innovation Process	39
2.7	Conceptual Framework of the Study	48
4.1	Structural model	112

List of Abbreviation and Glossary

Abbreviation / Glossary	Explanation
AGFI	Adjusted Goodness-of-Fit Index
KS	AI Knowledge Sharing Participation
$\chi 2$	Chi-square
χ^2/df	Chi-Square to Degrees of Freedom Ratio
CFI	Comparative Fit Index
DC	Dynamic Capabilities
GA	Generative AI Literacy
GFI	Goodness-of-Fit Index
IV	Innovation Performance In Vocational Colleges
KMO	Kaiser-Meyer-Olkin
NFI	Normed Fit Index
OS	Organization Structure
RMSEA	Root Mean Square Error of Approximation
SRMR	Standardized Root Mean Square Residual
TLI	Tucker–Lewis index

CHAPTER 1
INTRODUCTION

This chapter establishes the overall foundation of this study by systematically introducing the research background and identifying the core problems associated with administrative innovation and generative AI adoption in vocational colleges. The chapter first discusses the broader technological, organizational, and policy contexts surrounding vocational education and then highlights existing theoretical and empirical gaps related to generative AI literacy, dynamic capabilities, knowledge sharing participation, organizational structure, and innovation performance. On this basis, the theoretical and practical significance of the study are clarified to explain the academic and managerial value of examining administrative innovation in vocational colleges in Northeastern China. The chapter subsequently presents the research questions and research objectives that guide the study, followed by an explanation of the quantitative methodology adopted for empirical investigation. Key concepts and variables are then defined to establish conceptual clarity and ensure consistency throughout the thesis. Finally, the chapter specifies the delimitations of the study, outlines the structure of the thesis, and provides the overall conclusion to connect the introductory discussion with the subsequent theoretical and empirical chapters.

1.1 Background of the Study

1.1.1 Problem Statement

Innovation has been widely acknowledged as a critical driver of sustainable development in contemporary societies. In the context of accelerating technological change and increasing institutional complexity, innovation enables organizations to continuously adjust their structures, processes, and modes of operation in response to external uncertainty (Godinho Filho et al., 2026). International development assessments indicate that innovation-oriented organizations tend to demonstrate substantially stronger long-term adaptability and resilience (Pizzichini et al., 2025). For example, comparative analyses conducted by international economic institutions suggest that organizations with

sustained innovation capacity achieve productivity and performance improvements on the order of approximately twenty to thirty percent over comparable organizations relying primarily on stable routines (Cristache et al., 2025). Such evidence highlights that innovation is no longer merely a normative aspiration but a foundational condition for sustaining organizational development over time (de Barros et al., 2025).

Against this background, innovation increasingly manifests as a concrete organizational problem rather than an abstract strategic goal. In higher education organizations, innovation is no longer confined to pedagogical reform or research advancement, but has become deeply embedded in administrative systems that coordinate resources, regulate processes, and deliver institutional services (Zhu, 2024). Administrative systems now face escalating demands arising from environmental uncertainty, governance complexity, and heightened accountability requirements (Noah et al., 2025). When administrative innovation fails to keep pace with these demands, organizational adaptability is directly constrained, limiting the capacity of higher education institutions to respond effectively to external change (Amoozegar et al., 2025). In this sense, innovation functions as a practical response to organizational pressure rather than a discretionary enhancement.

The organizational challenge of innovation becomes particularly visible within vocational colleges. These institutions operate at the intersection of education systems and labor markets, requiring frequent adjustment to shifting industrial structures, skill requirements, and policy orientations (Mahmudah & Santosa, 2021). However, vocational colleges are often characterized by relatively rigid organizational arrangements, including high levels of formalization, centralized decision-making, and limited cross-departmental coordination (Lazarević & Mosurović, 2023; Silaji et al., 2025). Such structures are designed to ensure procedural stability and regulatory compliance, yet they also generate institutional inertia that can suppress innovative administrative behavior. The resulting tension raises a persistent question as to how innovation can emerge within administrative systems that are structurally oriented toward maintaining stability rather than enabling change.

The significance of this challenge is amplified by the scale and resource conditions under which vocational colleges operate. In China, vocational colleges account for more than half of total tertiary education enrollment, serving a population that has expanded

rapidly over the past two decades (Wang & Wang, 2023). At the same time, administrative resources per student remain comparatively limited, and administrative staff are frequently required to manage complex regulatory, operational, and service-related tasks under standardized governance frameworks (Wu, 2023). These conditions intensify the reliance on administrative systems while simultaneously constraining the scope for experimentation and process redesign, making innovation within vocational college administration both necessary and difficult.

In the context of Northern China, and particularly Northeastern China, vocational colleges are embedded in a relatively standardized public governance system shaped by provincial education authorities, local government supervision, and national vocational education reform policies (Yu et al., 2024). Many vocational colleges in this region operate through hierarchical administrative systems in which academic affairs offices, personnel departments, student affairs offices, finance offices, teaching quality units, and external cooperation departments perform specialized but interdependent functions. Such systems are designed to ensure policy compliance, accountability, and procedural consistency, yet they also tend to produce segmented information flows and multi-level approval procedures. In recent years, national policies on vocational education modernization, digital education, and industry-education integration have required vocational colleges to improve governance efficiency, strengthen digital capacity, and respond more rapidly to labor market transformation (Riyanto et al., 2025). These policy expectations create stronger pressure on administrative departments, because administrative staff are responsible for translating policy requirements into institutional procedures, coordinating implementation across departments, and maintaining daily organizational operation under limited resources. Therefore, the institutional context of vocational colleges in Northern and Northeastern China provides a particularly relevant setting for examining administrative innovation under conditions of policy pressure, structural rigidity, and digital transformation.

The emergence of the artificial intelligence era has begun to reshape the technological context in which these organizational challenges are addressed. Artificial intelligence technologies are transforming how information is accessed, processed, and utilized within organizations, enabling new forms of data-driven and algorithm-assisted decision-making (Khosravi et al., 2024). In higher education institutions, AI has expanded

beyond instructional applications to encompass administrative domains such as enrollment management, performance monitoring, scheduling, and policy analysis (Adamakis & Rachiotis, 2025). This technological shift has altered the conditions under which innovation occurs by reducing dependence on purely experience-based judgment and increasing the role of computational support in administrative work.

This transformation is also closely related to the policy environment surrounding AI in education. At the national level, China has promoted the digital transformation of education through policies that emphasize smart education, digital learning resources, intelligent governance, and the integration of artificial intelligence into educational development (Yang & Peters, 2026). The Ministry of Education has increasingly highlighted the importance of digital technology and artificial intelligence for improving teaching quality, learning support, institutional governance, and educational modernization (Wang et al., 2025). At the school and local education authority levels, AI is often framed as a tool for improving teaching efficiency, student services, management informatization, and decision support (Zhao et al., 2025). However, policy attention has been more concentrated on teaching, learning platforms, and student development, while the role of AI in administrative work has received relatively less systematic discussion (Zhou & Peng, 2025). This creates a gap between the broad policy encouragement of AI in education and the more specific organizational question of how administrative staff actually use AI tools in daily work, how schools guide such use, and whether institutional policies provide sufficient support for AI-enabled administrative innovation.

Within this broader transformation, generative AI represents a particularly consequential development. Unlike earlier AI systems focused on automation or prediction, generative AI is capable of producing text, synthesizing information, and supporting complex reasoning tasks (Campbell et al., 2025; Storey et al., 2025). These capabilities allow generative AI to participate directly in administrative cognition, including drafting documents, interpreting policy information, and exploring alternative solutions to organizational problems. Since the widespread diffusion of large-scale generative AI tools, adoption has expanded rapidly, with global user numbers reaching hundreds of millions within a short period (Al-Busaidi et al., 2024). As a result, generative AI has become increasingly visible in the daily work of educational administrators, reshaping how administrative tasks are conceptualized and performed.

Despite the growing presence of generative AI in educational administration, its contribution to innovation remains uneven. In practice, generative AI is used in diverse ways, ranging from routine document preparation and information summarization to more exploratory applications such as workflow redesign and decision support (Vera et al., 2026). However, similar technological tools often yield markedly different outcomes across institutions and individuals. This variation suggests that differences in innovation cannot be attributed solely to the availability of generative AI technologies (Hughes et al., 2026). Instead, they appear to be closely associated with differences in the ability of administrative staff to understand, evaluate, and apply generative AI within specific organizational contexts.

Administrative staff are selected as the focus of this study because they occupy a critical but often underexamined position in vocational college innovation. In this study, administrative staff refer to non-academic personnel who are responsible for institutional administration, internal coordination, policy implementation, student services, human resource management, financial administration, academic affairs support, external cooperation, quality assurance, and other organizational support functions (Yidana et al., 2023). This definition is closely related to the concept of support staff, but it places stronger emphasis on administrative responsibilities within the formal governance structure of vocational colleges. Unlike teaching staff, administrative staff do not primarily generate innovation through curriculum design or classroom practice (Valdés Sánchez & Gutiérrez-Esteban, 2023). Instead, their innovation is reflected in workflow improvement, information integration, service optimization, policy interpretation, interdepartmental coordination, and the institutionalization of new administrative procedures. As vocational colleges become increasingly dependent on digital platforms, AI-assisted documentation, data-based governance, and cross-unit coordination, administrative staff become key actors in determining whether generative AI is used merely for routine task completion or transformed into a source of administrative innovation (Almisad & Aleidan, 2025). Therefore, focusing on administrative staff allows the study to examine how generative AI literacy operates within the everyday organizational processes through which vocational colleges respond to technological and policy change.

These differences draw attention to generative AI literacy as a potential explanatory factor in administrative innovation. Generative AI literacy refers to the

capacity to comprehend how generative systems function, assess the reliability and relevance of their outputs, and translate AI-generated information into meaningful organizational action (Wenjia Yan et al., 2025). Evidence from studies on digital competencies indicates that advanced digital literacy remains unevenly distributed within public and educational organizations, with a relatively limited proportion of staff possessing the skills required to leverage digital technologies for innovation (Werfhorst et al., 2022). In vocational colleges, disparities in training opportunities and institutional support may further shape how generative AI literacy influences administrative practice (Lin et al., 2025).

At the organizational level, the relationship between generative AI literacy and innovation extends beyond individual capability. Administrative innovation requires coordinated processes through which new knowledge is interpreted, shared, and integrated into organizational routines (Cristache et al., 2025). Dynamic capabilities shape the extent to which organizations can sense emerging opportunities, mobilize relevant resources, and reconfigure existing practices in response to technological change (Priyono & Hidayat, 2022). Similarly, knowledge sharing participation determines whether AI-enabled insights circulate beyond individual users and contribute to collective problem-solving. Without such processes, the innovative potential associated with generative AI literacy may remain fragmented and localized (Zhong & Wang, 2025). The effectiveness of these processes is further conditioned by organizational structure. In vocational colleges, organizational structure determines how authority is distributed, how information flows, and how much discretion administrative staff possess in experimenting with new practices (Lazarević-Moravčević & Mosurović Ružičić, 2023). Structural features such as centralization and formalization may either facilitate coordination or constrain innovation, depending on how they interact with emerging technological capabilities (Dominguez Gonzalez, 2023). This raises a critical problem regarding whether, and under what structural conditions, generative AI-related knowledge and capabilities can be mobilized to support innovation in vocational colleges, leaving open questions that require systematic theoretical and empirical examination.

The complexity of this issue becomes especially pronounced within the Northeastern region of China, where vocational colleges face a distinctive constellation of structural, demographic, and policy pressures. Northeastern China has experienced

prolonged population decline, industrial contraction, and uneven regional revitalization efforts (Li et al., 2025). These macro-level conditions directly influence the operational environment of vocational colleges. Many institutions confront shrinking enrollment pools due to out-migration of younger populations, which intensifies administrative pressure to redesign recruitment strategies, expand external partnerships, and justify resource allocations under tightening fiscal constraints. Administrative offices frequently manage parallel tasks associated with regional employment initiatives, vocational upgrading mandates, and the implementation of national skill-oriented education reforms (Zuo et al., 2025). These tasks increase the complexity of administrative workflows, yet staffing numbers and functional capacities often lag behind emerging needs.

Within these colleges, administrative systems encounter persistent inefficiencies such as fragmented data management, slow circulation of interdepartmental information, and delayed policy interpretation. For instance, processes such as student status management, internship coordination, funding applications, and external reporting require substantial manual documentation and multi-layered approval procedures. These procedural burdens reduce administrative responsiveness and can inhibit the experimentation necessary for innovation. Many administrative staff members must navigate unclear role boundaries, limited opportunities for professional development, and insufficient exposure to digital competency training (Lane et al., 2023). These constraints create a structural mismatch between the pace of regional policy change and the adaptability of administrative systems, making innovation both urgent and difficult to realize.

In addition, colleges in Northeastern China commonly operate under rigid hierarchical arrangements, where centralization of authority slows decision-making and reduces the autonomy of mid-level administrators (Liu, 2025). Even when staff possess creative ideas for workflow improvement, institutional mechanisms for resource allocation, experimentation, or cross-unit coordination are frequently limited. In this context, generative AI begins to appear as a potentially transformative tool capable of alleviating administrative burdens, improving information processing, and supporting scenario analysis for decision-making (Bhuyan et al., 2025). However, the uneven distribution of generative AI literacy across colleges and departments means that adoption outcomes vary significantly. Some administrative units successfully integrate AI into

document drafting, policy interpretation, and reporting tasks, while others use AI in restricted or superficial ways, yielding limited organizational impact (Fan, 2025). The gap between technological potential and realized innovation becomes increasingly visible in this regional context, where institutional pressures are acute and administrative capacity is uneven.

A further challenge is that systematic data on administrative staff's actual use of generative AI in vocational colleges remain limited. Although national and international evidence shows the rapid diffusion of generative AI across knowledge-intensive work, comparable statistics for administrative personnel in vocational colleges are still insufficient (Horvath et al., 2026). In particular, there is limited evidence on how frequently administrative staff use generative AI tools, which administrative tasks are most commonly supported by AI, whether such use is encouraged or regulated by school-level policies, and whether AI-assisted work produces measurable improvements in administrative efficiency, service responsiveness, or process innovation. This absence of systematic usage data makes it difficult to directly observe the organizational and policy challenges associated with AI adoption in vocational colleges. Even when college leaders encourage administrative staff to use generative AI for document drafting, policy interpretation, information summarization, or process improvement, such encouragement may not automatically lead to innovation unless it is supported by training systems, evaluation standards, data governance rules, ethical guidelines, and cross-departmental coordination mechanisms (Tsao, 2025). Therefore, the lack of empirical evidence on actual AI use further reinforces the need to investigate generative AI literacy, knowledge sharing participation, dynamic capabilities, and organizational structure as interrelated factors shaping administrative innovation.

These realities point to a fundamental and unresolved problem in Northeastern China's vocational colleges. Although generative AI offers a new pathway for administrative innovation, its effectiveness is strongly constrained by existing structural rigidity, inconsistent digital literacy, limited knowledge sharing, and varying levels of organizational support. Administrative innovation in this region cannot be explained solely through technological availability; instead, it must be understood as the outcome of an interrelated set of capabilities, behaviors, and structural conditions that shape how generative AI is interpreted and enacted within daily administrative practice.

1.1.2 Research Gap

Existing studies on organizational innovation and digital transformation have established multiple theoretical perspectives to explain how technological resources contribute to organizational outcomes. The resource-based view highlights the strategic value of organizational resources (Lubis, 2022). Dynamic capability theory explains how such resources are mobilized and reconfigured under environmental change (Land et al., 2022), while the knowledge-based view emphasizes the role of knowledge creation and sharing in innovation (Grant & Phene, 2022). Sociotechnical systems theory further stresses the interaction between technological systems and social structures (Govers & Van Amelsvoort, 2023). However, these theories have largely been applied in parallel rather than in an integrated manner. As a result, prior research has not yet developed a coherent theoretical configuration capable of explaining how emerging generative AI-related competencies are transformed into sustained organizational innovation through coordinated capability development, knowledge processes, and structural conditions.

At the level of variable relationships, the literature also exhibits important limitations. Research on artificial intelligence has predominantly focused on technology adoption, usage intention, or performance outcomes, often treating AI as a tool or infrastructure rather than a knowledge-generating system (Ayinaddis, 2025; Madanchian & Taherdoost, 2025). Generative AI literacy, which reflects the ability to critically understand and apply generative AI in organizational contexts, has received limited attention as an antecedent of innovation. Moreover, dynamic capabilities and knowledge sharing participation are frequently examined as independent predictors of innovation, rather than as interconnected mechanisms through which generative AI-related competencies exert influence. Organizational structure, in turn, is commonly included as a background or control factor, leaving insufficient understanding of how structural conditions shape the effectiveness of these mechanisms. Consequently, existing research lacks a systematic framework linking generative AI literacy, organizational capabilities, knowledge processes, and innovation outcomes.

These gaps are particularly evident in the context of vocational colleges. Studies on innovation in higher education have largely emphasized teaching and academic staff, while administrative systems are often viewed as stable support structures rather than sources of innovation. In vocational colleges, administrative staff operate within highly

institutionalized environments characterized by formalized procedures and centralized governance, which may both enable coordination and constrain experimentation. Existing theories have rarely been applied to examine how generative AI-related knowledge and capabilities function within such structurally constrained educational organizations (Fan et al., 2025; Manel et al., 2024). This contextual omission limits the explanatory power of current research and obscures the conditions under which administrative innovation may emerge in vocational education settings.

Against this background, the purpose of this study is to develop and test an integrated theoretical framework that explains how generative AI literacy influences innovation in vocational colleges through dynamic capabilities and knowledge sharing participation, while accounting for the conditional role of organizational structure.

1.2 Significance of the Study

1.2.1 Theoretical Significance

This study makes theoretical contributions in three interrelated domains by extending dynamic capability theory, enriching the knowledge-based view, and advancing sociotechnical systems theory.

Dynamic capability theory, originally developed as an extension of the resource-based view, is expanded through the conceptualization of generative AI literacy as a micro-foundational cognitive capability. Traditional discussions of dynamic capabilities emphasize sensing, seizing, and transforming activities shaped by managerial judgment and organizational routines. The study refines this understanding by demonstrating that generative AI literacy enables organizations to recognize technological opportunities, mobilize AI-supported insights, and reconfigure administrative processes under conditions of institutional turbulence. This reconceptualization highlights how intelligent technologies alter the cognitive underpinnings through which dynamic capabilities operate, allowing vocational colleges to sustain adaptability and administrative innovation.

Building on this foundation, the study deepens the knowledge-based view by repositioning generative AI as an active contributor to organizational knowledge processes. The knowledge-based view has traditionally focused on human-generated knowledge and socially embedded exchange, whereas generative AI produces and recombines textual and informational content that must be interpreted, validated, and

integrated before it becomes organizationally consequential. By foregrounding generative AI literacy and knowledge sharing participation, the study specifies how hybrid forms of human and machine knowledge interact within collective learning processes. This perspective directs attention to shifting epistemic boundaries and demonstrates that innovation increasingly emerges from the interplay between human expertise and algorithmic content generation.

The study further advances sociotechnical systems theory by offering a more analytically precise account of how technological and social subsystems jointly shape administrative innovation. Sociotechnical explanations have long emphasized the need for alignment between technical tools and organizational structures, yet often remain descriptive regarding the mechanisms through which such alignment occurs. By conceptualizing organizational structure as a moderating condition, the study identifies how formalization and centralization influence the extent to which AI-related capabilities and knowledge processes can be mobilized within vocational colleges. This refinement clarifies the structural contingencies that govern whether technological potential is activated or constrained in institutional settings.

1.2.2 Practical Significance

The practical significance of this study lies in its capacity to inform how key stakeholders engage with generative AI in vocational colleges under complex administrative and institutional conditions. For administrative staff, the findings emphasize that the innovative value of generative AI depends on the ability to understand, evaluate, and apply AI-generated information rather than on simple technological access. Generative AI literacy emerges as a foundational capability that enhances the capacity to interpret administrative problems, redesign processes, and improve coordination beyond routine task execution. This perspective highlights the importance of strengthening cognitive and evaluative competencies that enable administrative staff to integrate generative AI into daily work in a meaningful and innovation-oriented manner.

For vocational college management, the study provides insight into how institutional innovation can be advanced through effective alignment of individual competencies and organizational processes. The roles of dynamic capabilities and knowledge sharing participation underscore the need for management practices that support information sensing, resource mobilization, and cross-unit knowledge integration.

The findings suggest that successful generative AI implementation requires organizational environments that facilitate collaborative learning and structured experimentation rather than treating digital technologies as isolated operational tools. This has direct relevance for decisions concerning staff development, workflow design, and administrative coordination mechanisms.

For policymakers and education authorities, the study offers a framework for considering how digital transformation policies in vocational education can better integrate human capabilities and organizational processes. Technology deployment alone is insufficient to generate innovation if institutions lack the competencies and structural conditions required to translate technological potential into administrative improvement. By highlighting the importance of generative AI literacy, dynamic capabilities, and knowledge sharing participation, the study contributes to policy discussions concerning governance arrangements, evaluation standards, and capacity-building strategies in vocational colleges.

For developers and providers of generative AI tools, the study draws attention to the need for systems that support transparency, interpretability, and contextual adaptability within administrative settings. The findings indicate that innovation outcomes are shaped by organizational context and user literacy, suggesting that design features, user support mechanisms, and workflow integration strategies may influence whether generative AI functions as an instrument for routine efficiency or as a catalyst for substantive administrative innovation. This perspective reinforces the importance of close alignment between technological design and the institutional realities of vocational colleges.

1.3 Statement of Research Questions

RQ1: How does generative AI literacy shape administrative staff's use of generative AI across different administrative functions and influence their innovation performance in vocational colleges in Northeastern China?

RQ2: Through what organizational processes do dynamic capabilities and AI knowledge sharing participation mediate the relationship between generative AI literacy and administrative staff's innovation performance in vocational colleges in Northeastern China?

RQ3: Under what organizational structural conditions does generative AI literacy translate into administrative staff's innovation performance in vocational colleges in Northeastern China?

1.4 Statement of Research Objectives

RO1: To examine how generative AI literacy influences administrative staff's use of generative AI across different administrative functions and its impact on their innovation performance in vocational colleges in Northeastern China.

RO2: To investigate the mediating roles of dynamic capabilities and AI knowledge sharing participation as organizational processes through which generative AI literacy contributes to administrative staff's innovation performance in vocational colleges in Northeastern China.

RO3: To examine how organizational structure conditions the relationship between generative AI literacy and administrative staff's innovation performance in vocational colleges in Northeastern China.

1.5 Methodology

This study adopted a quantitative research design to examine the relationships among generative AI literacy, dynamic capabilities, AI knowledge sharing participation, organization structure, and innovation performance in vocational colleges. A cross-sectional survey was used because the study aimed to test a structured theoretical model and evaluate direct, mediating, and moderating effects among latent variables.

A structured questionnaire was developed based on established scales and adapted to the context of administrative work in vocational colleges. All items were measured using a five-point Likert scale ranging from strongly disagree to strongly agree. Before the formal survey, a pilot study was conducted to assess item clarity, reliability, and preliminary validity, and minor revisions were made to improve the instrument.

The target population consisted of administrative staff in vocational colleges in Liaoning, Jilin, and Heilongjiang provinces. After data screening, 765 valid questionnaires were retained for empirical analysis. SPSS and AMOS were used to conduct descriptive statistics, reliability analysis, validity testing, confirmatory factor analysis, structural equation modeling, bootstrap mediation analysis, and moderation analysis. These

procedures provided the basis for testing the proposed hypotheses and explaining how generative AI literacy contributes to administrative innovation in vocational colleges.

1.6 Definitions of Terms

1.6.1 Generative AI Literacy

Generative AI literacy in this study refers to the ability of administrative staff in vocational colleges to effectively, critically, and responsibly use generative AI technologies in administrative work contexts. It includes not only the operational ability to use AI tools, but also the competencies required to design prompts, evaluate AI-generated outputs, identify innovative application opportunities, and comply with ethical and organizational standards. In this study, generative AI literacy is conceptualized as a multidimensional construct consisting of basic operational skills, prompt engineering ability, quality evaluation ability, innovative application ability, and compliance and ethical awareness. These dimensions collectively reflect how administrative staff understand, interact with, and apply generative AI technologies to support administrative efficiency, coordination, and innovation within vocational colleges (Xin Liu et al., 2025).

1.6.2 Dynamic Capabilities

Dynamic capabilities refer to the organizational ability to sense environmental changes, seize emerging opportunities, and transform existing resources and routines in response to changing conditions. In the context of vocational colleges, dynamic capabilities represent the capacity of administrative systems to adapt administrative processes, coordinate institutional resources, and implement organizational changes under conditions of digital transformation (Kump et al., 2018). This study conceptualizes dynamic capabilities through three dimensions: sensing, seizing, and transforming. Sensing reflects the ability to identify external and internal changes affecting administration, seizing refers to the ability to mobilize and apply relevant resources and knowledge, and transforming represents the ability to adjust organizational practices and administrative routines continuously. These capabilities enable vocational colleges to respond flexibly to technological and organizational challenges.

1.6.3 AI Knowledge Sharing Participation

AI knowledge sharing participation refers to the extent to which administrative staff actively exchange, communicate, and share generative AI-related knowledge, experiences, skills, and practices within vocational colleges. This concept emphasizes collaborative learning processes through which individual AI-related competencies become collective organizational resources. In this study, AI knowledge sharing participation includes both outbound knowledge sharing and inbound knowledge sharing. Outbound sharing refers to the willingness to provide AI-related knowledge and practical experience to colleagues, while inbound sharing reflects the extent to which individuals receive support, guidance, and knowledge from others. Through active participation in AI-related knowledge exchange, vocational colleges can strengthen organizational learning, reduce barriers to AI adoption, and improve the collective application of generative AI in administrative innovation (Zhao et al., 2021).

1.6.4 Organization Structure

Organization structure refers to the formal arrangement of authority, decision-making processes, rules, and coordination mechanisms within vocational colleges. It defines how responsibilities are distributed, how administrative activities are regulated, and how organizational control is exercised. In this study, organization structure is conceptualized through two dimensions: level of formalization and level of centralization (Chen & Chang, 2012). Formalization refers to the extent to which administrative procedures, rules, and standards are formally documented and consistently applied, while centralization reflects the degree to which decision-making authority is concentrated within senior management. Organization structure influences how administrative staff interact, coordinate resources, and apply generative AI technologies in their work. It also shapes the extent to which innovative administrative practices can be implemented and sustained within vocational colleges.

1.6.5 Innovation Performance in Vocational Colleges

Innovation performance in vocational colleges refers to the extent to which administrative staff generate, promote, implement, and sustain innovative administrative ideas, practices, and solutions within vocational education institutions. In this study, innovation performance is viewed as a multidimensional construct that reflects the effectiveness of administrative innovation activities in improving organizational processes

and institutional functioning (Gkontelos et al., 2022). The construct includes four dimensions: idea generation, idea promotion, idea realization, and idea sustainability. Idea generation refers to developing new administrative suggestions and improvement opportunities, idea promotion involves communicating and advocating innovative ideas, idea realization represents the implementation of innovative practices, and idea sustainability reflects the long-term maintenance and expansion of innovation outcomes. Innovation performance therefore captures both the creation and institutionalization of administrative innovation within vocational colleges.

1.7 Delimitation of the Thesis

This study focuses specifically on the influence of generative AI literacy on innovation performance among administrative staff in vocational colleges in Northeastern China. The geographical scope of the study is limited to vocational colleges located in Liaoning, Jilin, and Heilongjiang provinces. These regions were selected because vocational colleges in Northeastern China are currently experiencing increasing pressure related to digital transformation, administrative modernization, and organizational innovation under changing educational and technological environments.

The study concentrates only on administrative staff rather than teachers, students, or external stakeholders. Administrative personnel were selected because they play important roles in institutional coordination, policy implementation, digital administration, student services, and organizational management within vocational colleges. The research therefore examines generative AI use from an administrative and organizational perspective rather than from a teaching or learning perspective.

In terms of research variables, the study focuses on generative AI literacy as the independent variable, innovation performance in vocational colleges as the dependent variable, dynamic capabilities and AI knowledge sharing participation as mediating variables, and organization structure as the moderating variable. Other potential influencing factors, such as organizational culture, leadership style, technological infrastructure, or external policy support, are beyond the scope of the present study.

Methodologically, the study adopts a quantitative cross-sectional design using questionnaire-based data collection and structural equation modeling analysis. The

findings therefore reflect respondents' perceptions during a specific period of time and do not examine long-term changes in generative AI adoption or innovation development.

1.8 Outline of Thesis

This thesis consists of five chapters.

Chapter 1 introduces the background of the study, research problems, research objectives, research questions, significance of the study, methodology, definitions of key terms, delimitations of the study, and the overall structure of the thesis. This chapter establishes the research foundation and explains the importance of examining generative AI literacy and innovation performance in vocational colleges.

Chapter 2 reviews the relevant literature and theoretical foundations related to generative AI literacy, dynamic capabilities, AI knowledge sharing participation, organization structure, and innovation performance in vocational colleges. The chapter also discusses dynamic capability theory, the knowledge-based view, and sociotechnical systems theory, followed by the development of the conceptual framework and research hypotheses.

Chapter 3 presents the research methodology employed in the study. It explains the research design, target population, sampling procedures, questionnaire development, pilot study, data collection process, and data analysis techniques. Reliability testing, validity assessment, and statistical procedures used for hypothesis testing are also introduced in this chapter.

Chapter 4 reports the empirical findings of the study. The chapter presents descriptive analysis, confirmatory factor analysis, structural model analysis, direct effects, mediation effects, and moderation effects. The results of hypothesis testing are systematically discussed based on the statistical findings obtained from the collected data.

Chapter 5 discusses the major findings of the study in relation to previous literature and theoretical perspectives. The chapter explains the theoretical implications and practical implications for vocational colleges and related stakeholders. It also presents the limitations of the study, suggestions for future research, and the overall conclusion of the thesis.

1.9 Conclusion

This chapter established the overall foundation of the study by systematically presenting the research background, research problems, objectives, research questions, theoretical and practical significance, methodology, definitions of key concepts, delimitations, and thesis structure. The discussion highlighted that vocational colleges in Northeastern China are currently facing increasing administrative complexity, digital transformation pressure, and growing demands for organizational innovation. Under such conditions, generative AI has emerged as an important technological resource with the potential to improve administrative efficiency and stimulate innovation. However, differences in generative AI literacy, organizational capability development, knowledge sharing processes, and structural conditions continue to influence whether this technological potential can be effectively transformed into innovation performance.

The chapter further identified important theoretical and empirical gaps in existing studies. Prior research has paid limited attention to administrative staff in vocational colleges and has rarely examined how generative AI literacy contributes to innovation through organizational processes such as dynamic capabilities and AI knowledge sharing participation. In addition, insufficient consideration has been given to the conditional role of organizational structure in shaping the effectiveness of AI-related competencies. To address these gaps, this study proposed an integrated framework combining dynamic capability theory, the knowledge-based view, and sociotechnical systems theory to explain the relationships among generative AI literacy, organizational processes, organizational structure, and innovation performance in vocational colleges.

Finally, the chapter clarified the quantitative research methodology and established the conceptual scope of the study. By focusing on administrative staff in vocational colleges in Liaoning, Jilin, and Heilongjiang provinces, the study provides an empirical basis for understanding how generative AI-related competencies contribute to administrative innovation within the context of educational digital transformation. The following chapter reviews the relevant literature and theoretical foundations supporting the development of the conceptual framework and research hypotheses.

CHAPTER 2
LITERATURE REVIEW

This chapter is structured around four interrelated components that together establish the theoretical and analytical foundation of the study. It begins with contexts of the study, which situates the research within the organizational and institutional environment of vocational colleges on the administrative staff's innovation performance, clarifying the characteristics of administrative systems and the conditions under which generative AI-related practices and innovation emerge. Building on this contextual grounding, the chapter then turns to parent disciplines, reviewing key theoretical perspectives from dynamic capability theory, the knowledge-based view, and sociotechnical systems theory to provide overarching explanatory logics for resource transformation, knowledge processes, and the interaction between technology and organizational structures. These theories inform the subsequent section on immediate disciplines, where the core constructs of the study are conceptually specified, including generative AI literacy, dynamic capabilities, knowledge sharing participation, organization structure, and innovation in vocational colleges, with attention to their dimensions and relevance to administrative work. On the basis of these discussions, the chapter advances to conceptual model and hypothesis development, presenting an integrated research model and systematically developing hypotheses that capture the proposed direct, mediating, and moderating relationships among the study variables. Through this progression, the chapter moves from contextual description to theoretical abstraction and finally to analytical specification, laying a coherent foundation for the empirical analysis that follows.

2.1 Contexts of the Study

2.1.1 Generative AI

Generative artificial intelligence refers to a category of artificial intelligence systems capable of producing new content based on learned patterns from large-scale data (He et al., 2025). Unlike traditional artificial intelligence systems that primarily perform

classification, prediction, or rule-based automation, generative AI creates outputs that did not previously exist in explicit form. These outputs may include text, images, code, audio, and structured information, generated in response to user instructions, contextual prompts, or task requirements. The defining feature of generative AI lies in its capacity to simulate human-like content creation while remaining dependent on human interpretation and contextual judgment (Kim et al., 2025).

In everyday life, generative AI has become increasingly embedded in widely used digital applications. Text-based generative AI systems are commonly encountered in conversational tools that generate written responses, summaries, emails, reports, and formal documents (Li et al., 2025). Such systems support activities including drafting administrative materials, revising written content, translating texts, and condensing lengthy documents into concise summaries. Image-generating systems enable the creation of visual materials based on textual descriptions, which are frequently used in presentations, instructional resources, and informational design (Diwan et al., 2023). Audio and speech-generating systems produce synthesized voice outputs, transcriptions, and narrated content, supporting announcements, training materials, and digital services (Ntoa et al., 2024). Code-generating systems assist users by producing scripts, templates, or automated workflows that facilitate administrative and operational tasks (Nittala, 2025).

Within organizational and administrative contexts, generative AI is primarily applied to knowledge-intensive work rather than routine automation (Vera et al., 2026). In educational administration, generative AI tools are used to support policy document drafting, regulatory interpretation, meeting documentation, data summarization, and internal communication (Wang et al., 2024). These systems assist administrative staff in organizing information from multiple sources, exploring alternative formulations of policies or procedures, and generating preliminary solutions to organizational problems. Compared with fixed-function software, generative AI demonstrates a higher degree of flexibility, allowing it to be applied across diverse administrative tasks and institutional contexts.

Generative AI also contributes to administrative work by transforming unstructured information into usable and communicable formats (Wessel et al., 2025). For example, generative systems can convert datasets or fragmented textual materials into narrative explanations, outlines, or structured reports. In workflow management and

planning activities, generative AI can support scenario exploration by generating possible process adjustments or organizational arrangements based on user-defined conditions (Barcaui & Monat, 2023). These functions extend the role of artificial intelligence from efficiency-oriented support toward cognitive assistance and exploratory problem-solving.

Despite its expanding presence, generative AI does not function as an autonomous decision-making system within organizations. The content it generates requires careful evaluation, validation, and contextual adaptation by human users, particularly in institutional environments characterized by formal procedures and accountability requirements. In educational organizations, administrative staff must assess whether AI-generated outputs align with regulatory standards, institutional norms, and organizational objectives (Fu & Weng, 2024). This dependence on human judgment distinguishes generative AI from earlier automation technologies and underscores its role as an assistive system embedded within social and organizational structures (Patel et al., 2025).

2.1.2 Vocational colleges in Northeastern China

Vocational colleges in Northeastern China constitute an important segment of the national vocational education system and play a key role in supporting regional economic development and workforce transformation (Bing & Zhenzhen, 2025). In a broader geographical and policy-oriented sense, Northeastern China is commonly defined as encompassing Liaoning, Jilin, Heilongjiang, and parts of eastern Inner Mongolia, reflecting historical industrial linkages and regional development planning. This extended definition is frequently adopted in studies of regional economy and industrial restructuring. However, differences in administrative systems, educational governance, and policy frameworks distinguish the northeastern provinces from Inner Mongolia, particularly in the organization and management of vocational education.

Within this context, the present study focuses on vocational colleges located in Liaoning, Jilin, and Heilongjiang provinces. This delimitation is adopted to ensure institutional comparability and analytical consistency, as vocational colleges in these three provinces operate under similar provincial-level governance structures, funding mechanisms, and regulatory arrangements. By contrast, vocational institutions in Inner Mongolia are embedded in a distinct autonomous administrative system, which may introduce additional institutional variability beyond the scope of this study. Focusing on the three northeastern provinces therefore allows for a more coherent examination of

organizational characteristics and administrative practices within a shared governance environment.

The spatial distribution of vocational colleges in Northeastern China exhibits a clear pattern of regional concentration rather than uniform dispersion. As illustrated in Figure 2.1, vocational colleges are predominantly clustered in provincial capitals and major industrial cities within Liaoning, Jilin, and Heilongjiang. In Liaoning Province, institutions are densely concentrated around cities such as Shenyang and Dalian, reflecting the province's relatively diversified industrial base and higher level of urbanization. In Jilin Province, vocational colleges are largely centered in and around Changchun, forming a province-level hub structure. In Heilongjiang Province, a pronounced concentration is observed in Harbin and its surrounding areas, accompanied by a more scattered distribution across selected prefecture-level cities. This spatial configuration indicates that vocational colleges tend to align with population centers, industrial activity, and the distribution of administrative and educational resources.

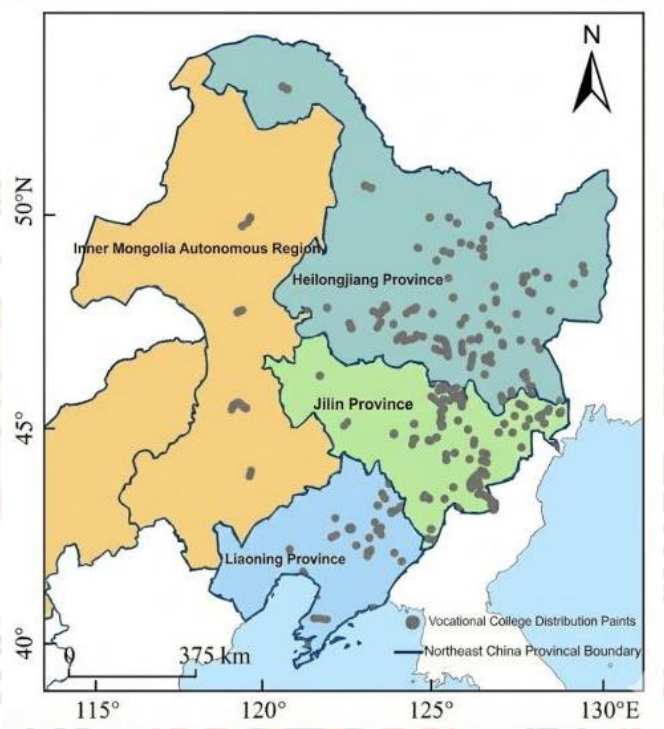


Figure 2.1 Distribution of Vocatioal Colleges in Northeast China

Beyond spatial characteristics, vocational colleges in the three northeastern provinces operate within a highly institutionalized governance environment. Most institutions are publicly funded and subject to standardized administrative regulations,

policy supervision, and performance evaluation mechanisms. Organizational structures are typically characterized by relatively high levels of formalization and hierarchical coordination, particularly within administrative systems responsible for academic affairs, personnel management, finance, and external liaison. Such arrangements prioritize procedural consistency and regulatory compliance, which are essential for maintaining organizational stability in large public education systems.

At the same time, vocational colleges in this region face distinctive operational pressures. Ongoing industrial restructuring, demographic change, and uneven regional development require institutions to continuously adjust their organizational practices and modes of service delivery (Chen et al., 2024). Administrative systems are expected to respond to policy reforms, coordinate with multiple stakeholders, and manage increasingly complex internal processes. These conditions intensify the role of administrative functions and underscore the importance of examining how organizational context shapes the work and behavior of administrative staff within vocational colleges.

2.1.3 Administrative Staffs in Vocational Colleges

Administrative staffs constitute a core organizational group within vocational colleges and play a central role in sustaining institutional operations. Unlike academic staff whose responsibilities are primarily related to teaching and research, administrative staffs are responsible for coordinating organizational processes, implementing policies, managing resources, and ensuring the continuity of daily institutional functions (Kumar & Limbachiya, 2023). In vocational colleges, administrative systems are closely intertwined with external governance requirements, industry engagement, and internal coordination, which amplifies both their functional scope and organizational significance (Wu & Sarker, 2022).

The scale of administrative staffs in vocational colleges reflects the overall organizational size and institutional density of the sector. As shown in Figure 2.2, vocational colleges in Northeastern China are unevenly distributed across Liaoning, Jilin, and Heilongjiang provinces, with Liaoning hosting the largest number of institutions, followed by Heilongjiang and Jilin. This distribution implies corresponding differences in the aggregate scale of administrative systems across provinces, as each institution requires a stable administrative workforce to support governance, coordination, and service

delivery. The number of vocational colleges therefore provides an important contextual indicator of the organizational environments in which administrative staffs operate.

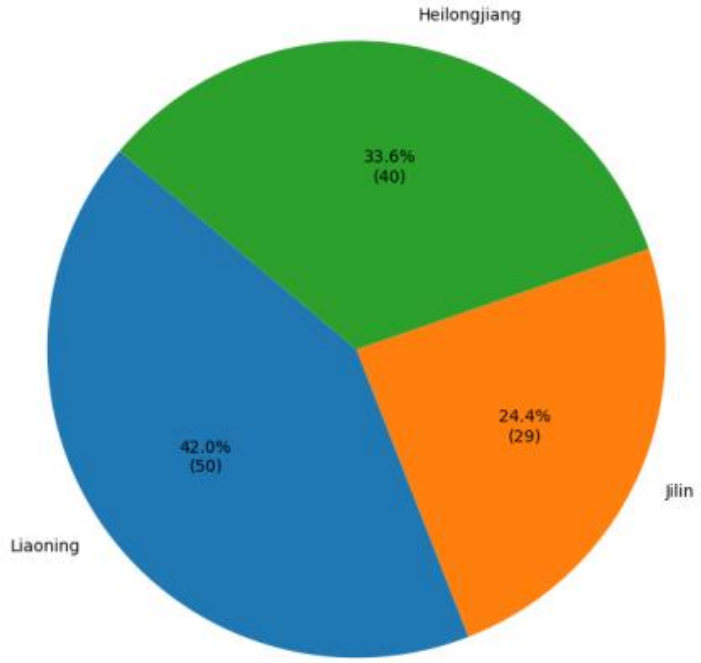


Figure 2.2 Distribution of Vocational Colleges in Northeastern China

Beyond institutional counts, the size of administrative staffs within vocational colleges has remained substantial and relatively stable over time. Figure 2.3 illustrates the five-year trend in the total number of administrative staffs in vocational colleges from 2020 to 2024 across the three northeastern provinces. The data indicate that administrative staffs represent a large and persistent workforce, with Liaoning reaching approximately 9,000 administrative personnel by 2024, while Heilongjiang and Jilin also maintain sizeable administrative populations. This temporal stability suggests that administrative work in vocational colleges is not peripheral or temporary, but constitutes a long-term organizational function embedded within institutional structures.

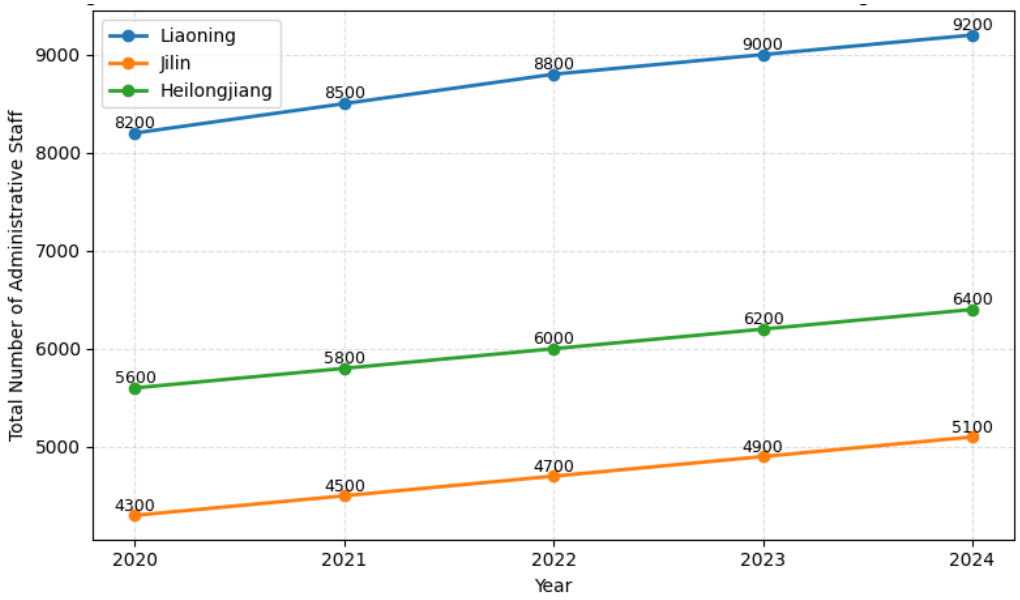


Figure 2.3 Administrative Staff Size in Vocational Colleges, 2020–2024

In terms of functional characteristics, administrative staffs in vocational colleges typically operate within highly formalized and hierarchical organizational arrangements. Their responsibilities often span academic administration, personnel management, financial affairs, student services, external coordination, and compliance with regulatory requirements (Abdullah & Arifin, 2024; Yue & Lertamornsak, 2024). These roles require continuous interaction across departments and with external authorities, placing administrative staffs at the intersection of organizational control, information processing, and service provision. The breadth of these responsibilities increases the complexity of administrative work, particularly in institutions facing frequent policy adjustments and operational demands.

At the same time, administrative staffs in vocational colleges face multiple challenges arising from organizational and environmental conditions. High levels of formalization and centralized decision-making can limit discretion and flexibility in administrative practices, constraining opportunities for process adjustment and innovation. The uneven spatial distribution of vocational colleges shown in Figure 2.2 also implies disparities in administrative workload and resource availability, as institutions located in densely populated or economically active areas often face higher coordination demands. Furthermore, the sustained scale of administrative staffs illustrated in Figure 2.3 indicates that administrative systems must manage growing complexity without proportional reductions in workload or procedural requirements.

These conditions place administrative staffs under increasing pressure to maintain efficiency, accuracy, and responsiveness while operating within rigid institutional frameworks. The combination of large staff populations, stable yet demanding organizational roles, and constrained decision-making environments underscores the importance of understanding administrative staffs as a critical organizational group in vocational colleges. Examining their scale, structural position, and work context provides an essential basis for analyzing subsequent issues related to technology use, organizational processes, and innovation outcomes.

2.1.4 Generative AI Literacy in Administrative Staffs

The increasing integration of generative AI into organizational processes has shifted attention from questions of technology availability to questions of human capability. In administrative contexts, particularly within vocational colleges, the capacity to effectively engage with generative AI is not determined solely by access to digital tools, but by the extent to which administrative staff possess the literacy required to understand, evaluate, and apply AI-generated outputs in organizational work (Mengmeng et al., 2025). Generative AI literacy therefore represents a form of competence that mediates the relationship between technological potential and administrative practice.

Unlike general digital literacy, which emphasizes operational familiarity with information systems, generative AI literacy involves interpretive and judgment-based skills. Generative AI systems do not merely automate predefined tasks; they generate probabilistic outputs that require human assessment, contextual interpretation, and organizational alignment (Krakowski, 2025). For administrative staffs operating in highly institutionalized environments, this distinction is particularly important. Administrative tasks such as policy interpretation, document preparation, coordination across departments, and procedural design demand accuracy, compliance, and contextual sensitivity (Papagiannidis et al., 2025). The effective use of generative AI in such tasks depends on whether staff members can critically engage with AI outputs rather than accept them unreflectively.

Within vocational colleges, generative AI literacy is closely linked to the complexity of administrative roles. Administrative staffs are responsible for translating external policy requirements into internal procedures, managing information flows across hierarchical units, and supporting institutional decision-making. Generative AI tools

increasingly appear in these activities through applications such as drafting policy summaries, synthesizing regulatory documents, generating alternative workflow proposals, and assisting in data interpretation. However, the innovative value of these tools varies substantially across individuals and organizational units. This variation suggests that generative AI literacy functions as a differentiated capability rather than a uniform attribute among administrative staffs.

To clarify the conceptual scope of generative AI literacy in the administrative context, Table 2.1 presents its core dimensions as they relate specifically to vocational college administration. The table emphasizes that generative AI literacy extends beyond basic technical interaction and includes the ability to design effective prompts, evaluate the quality and reliability of AI-generated content, apply outputs creatively to organizational problems, and remain aware of compliance and ethical constraints. Each dimension reflects a distinct aspect of how administrative staffs engage with generative AI in daily work processes, ranging from routine documentation to more complex forms of organizational problem-solving.

Table 2.1 Distinction between Generative AI Literacy and Related Concepts

Concept	Core Focus	Typical Research Emphasis	Limitation for This Study
AI adoption	Whether AI is used	Usage intention, frequency	Does not explain innovation differences
Digital literacy	General digital skills	Tool proficiency	Too broad, not generative-specific
Generative AI literacy	Interpretive and application capability	Understanding, evaluation, organizational use	Suitable for explaining innovation mechanisms

These dimensions also highlight that generative AI literacy is not limited to individual efficiency gains. The ability to evaluate AI outputs and apply them innovatively has implications for how administrative knowledge is generated, shared, and institutionalized. When administrative staffs possess higher levels of generative AI literacy, AI-generated insights are more likely to be integrated into collective discussions,

procedural adjustments, and coordinated action. Conversely, limited literacy may result in superficial use of generative AI that reinforces existing routines rather than enabling innovation.

Importantly, generative AI literacy among administrative staffs develops within organizational constraints characteristic of vocational colleges. Formalized procedures, hierarchical approval processes, and accountability requirements shape how AI-generated content can be used and disseminated (Omogiate, 2023). Literacy therefore includes not only technical understanding, but also contextual judgment regarding when and how generative AI outputs can be legitimately incorporated into administrative work. This contextualized form of literacy differentiates generative AI literacy from adoption-oriented constructs and positions it as a meaningful antecedent of organizational processes related to innovation.

By conceptualizing generative AI literacy as a multidimensional capability embedded in administrative practice, this study treats it as a foundational element linking individual interaction with generative AI to broader organizational outcomes. This conceptualization provides a basis for examining how generative AI literacy interacts with dynamic capabilities, knowledge sharing participation, and organizational structure in shaping innovation within vocational colleges.

2.1.5 Administrative Staffs's Innovation in Vocational Colleges

Administrative staffs' innovation refers to the development and implementation of new or improved administrative practices that enhance organizational functioning within vocational colleges (Huynh et al., 2024). This form of innovation is embedded in daily administrative work and focuses on how procedures are designed, resources are coordinated, information is processed, and services are delivered. Unlike academic innovation, which is often associated with teaching or research outputs, administrative innovation is primarily process-oriented and manifests through changes in organizational routines and managerial practices (de Barros et al., 2025).

In vocational colleges, administrative innovation typically emerges in response to persistent operational challenges rather than as a result of formal innovation programs. Administrative staffs are routinely confronted with complex policy requirements, high volumes of documentation, cross-departmental coordination demands, and strict accountability mechanisms. Innovation under such conditions is rarely radical or

disruptive. Instead, it takes the form of incremental adjustments that improve efficiency, clarity, and coordination while remaining compatible with existing governance structures. These adjustments accumulate over time and can significantly reshape how administrative systems operate in practice.

Concrete and observable forms of administrative innovation are closely tied to routine administrative domains. As illustrated in Table 2.2, innovation frequently occurs through workflow redesign, such as streamlining approval procedures in personnel, finance, or academic administration to reduce redundancy and processing time. Process standardization represents another common innovation practice, where administrative staffs develop unified templates and guidelines to ensure consistent policy implementation and reduce operational ambiguity. These practices address recurring inefficiencies while maintaining procedural compliance.

Table 2.2 Examples of Administrative Staffs' Innovation in Vocational Colleges

Innovation domain	Specific innovation practice	Description in administrative context
Workflow redesign	Streamlining approval procedures	Reducing redundant approval steps in personnel, finance, or academic administration to shorten processing time and improve efficiency
Process standardization	Developing standardized administrative templates	Creating unified templates for policy implementation, reporting, and documentation to reduce ambiguity and operational errors
Interdepartmental coordination	Establishing cross-departmental coordination mechanisms	Introducing regular coordination meetings or task-based teams to address recurring administrative issues involving multiple units
Information integration	Integrating fragmented administrative information	Consolidating data from different administrative systems to improve consistency and support decision-making

Table 2.2 (continued)

Innovation domain	Specific innovation practice	Description in administrative context
Policy interpretation	Clarifying and localizing policy guidelines	Translating external policy requirements into clear internal procedures adapted to institutional conditions
Service improvement	Optimizing administrative service delivery	Improving response time, communication clarity, and accessibility of administrative services for students and academic staff
Resource allocation	Adjusting administrative resource deployment	Reallocating administrative personnel or resources during peak periods to address workload imbalances
Performance monitoring	Introducing data-supported reporting practices	Using internal data to monitor administrative performance and identify areas for improvement
Knowledge documentation	Systematizing experiential administrative knowledge	Documenting successful administrative practices to support learning and replication within the organization
Implementation support	Embedding new practices into routine procedures	Institutionalizing effective innovations through formal rules, guidelines, or internal regulations

Administrative innovation also manifests through enhanced interdepartmental coordination and information integration. Vocational colleges often operate with fragmented administrative units, each responsible for specialized functions. Innovative administrative practices include the establishment of cross-departmental coordination mechanisms, task-based working groups, and integrated information-sharing

arrangements. By consolidating data from different administrative systems and improving communication channels, administrative staffs enable more coherent decision-making and reduce coordination costs (Stanikzai & Mittal, 2025). Such innovations are particularly relevant in institutions with large administrative systems and diverse operational responsibilities.

Policy interpretation and service improvement constitute additional areas in which administrative staffs introduce innovation. External policies and regulations often require contextual adaptation before they can be effectively implemented within vocational colleges. Administrative staffs engage in innovative practices by translating policy requirements into institution-specific procedures, clarifying ambiguous guidelines, and developing internal documentation that supports consistent application. Service-oriented innovations, such as improving response times, refining communication practices, and enhancing accessibility of administrative services, further reflect how innovation is embedded in everyday administrative interactions.

Importantly, administrative staffs' innovation is inherently collective and implementation-oriented. While innovative ideas may originate from individual administrative staffs, their realization depends on communication, negotiation, and acceptance within organizational systems. Innovations must be aligned with formal rules, leadership expectations, and existing structures before they can be institutionalized. Table 2.2 highlights that many administrative innovations ultimately involve embedding new practices into routine procedures, performance monitoring systems, or internal regulations, ensuring their sustainability beyond individual initiative.

2.2 Parent Disciplines

2.2.1 Dynamic Capability Theory

Dynamic capability theory originates from the resource-based view but extends its explanatory power by shifting analytical attention from the possession of valuable resources to the organizational processes that transform these resources under conditions of uncertainty and change (Wernerfelt, 1984). While the resource-based view conceptualizes resources as foundational inputs that provide potential value, dynamic capability theory argues that organizational advantage emerges from the ability to sense environmental shifts, seize emerging opportunities, and reconfigure existing resource

portfolios (Teece, 2023). These higher-order capabilities enable organizations to renew routines and coordinate internal adjustments in response to technological, institutional, and market turbulence. The theoretical emphasis therefore lies not on static resource endowments but on the dynamic processes through which organizations mobilize, integrate, and recombine resources to generate adaptive outcomes.

The foundational logic of the resource-based view is illustrated in Figure 2.4, which presents the structural relationship among organizational resources, higher-order capabilities, environmental conditions, and innovation outcomes. The model underscores that resource possession alone is insufficient for sustained innovation, because organizational performance improves only when resources are effectively transformed through organizational capabilities. In this sense, dynamic capabilities provide a theoretical bridge between resource possession and innovation outcomes by explaining how organizations convert available resources into adaptive and innovative practices.

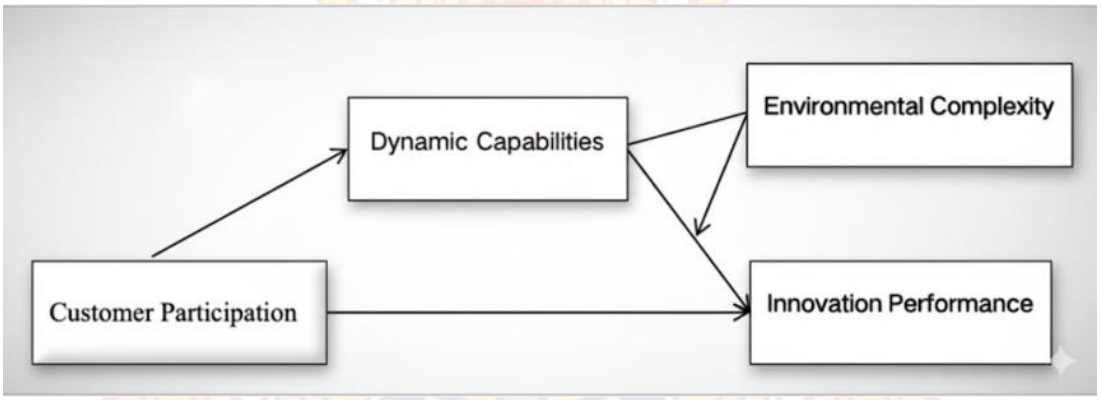


Figure 2.4 Dynamic capability theory
Source: Wernerfelt (1984)

Within this theoretical foundation, generative AI literacy in this study is conceptualized as a strategic resource rather than an organizational capability. It represents a form of cognitive and technical capital possessed by administrative staff, providing them with the potential to interpret generative AI outputs, evaluate their relevance, and identify possible applications in administrative contexts. However, consistent with the logic of the resource-based view, the possession of a resource with potential value does not automatically produce innovation (Mailani et al., 2024). Whether generative AI literacy can be translated into innovation outcomes depends on dynamic capabilities that govern

how the organization senses opportunities for AI-enabled change, seizes relevant insights, and reconfigures administrative practices to incorporate AI-related knowledge.

A further issue that must be emphasized is the path-dependent nature of dynamic capabilities. Dynamic capabilities are not created instantly through the introduction of new technologies. Instead, they are historically embedded in prior organizational choices, accumulated administrative routines, legacy information systems, leadership practices, and previous reform experiences (Shonubi, 2025). Organizations develop different capacities to sense, seize, and reconfigure because they have followed different historical trajectories. In vocational colleges, past decisions concerning administrative informatization, departmental coordination, procedural reform, staff training, and digital infrastructure may shape how effectively generative AI can be absorbed into current administrative work (Zhu, 2026). Colleges with stronger prior experience in digital governance and procedural adjustment may be more capable of identifying useful AI applications and integrating them into daily routines, whereas colleges with strong dependence on legacy systems and rigid approval procedures may find it more difficult to transform generative AI literacy into innovation performance (McDonald et al., 2025).

The applicability of dynamic capability theory becomes especially salient in vocational colleges in Northeastern China, where administrative systems often operate under structurally rigid conditions marked by high levels of formalization, centralized governance, and limited procedural flexibility. These characteristics restrict the speed at which new information is absorbed and reduce the organizational capacity to adjust existing routines. The regional economic environment further intensifies this challenge, as vocational colleges in the Northeast confront demographic decline, slow industrial transformation, and increased pressure to modernize institutional governance (Bing & Zhenzhen, 2025). Under these conditions, administrative staff may possess generative AI literacy but remain unable to mobilize it for innovation unless supported by organizational processes that strengthen opportunity recognition, resource integration, and procedural restructuring (Raina et al., 2026). Dynamic capabilities therefore provide a necessary mechanism through which vocational colleges can overcome structural inertia and convert generative AI-related knowledge into concrete administrative improvements.

At the same time, generative AI does not necessarily transform administrative systems in a disruptive or immediate way. In many vocational colleges, generative AI is

more likely to be absorbed into existing administrative routines, such as document drafting, policy interpretation, report preparation, student affairs management, internship coordination, funding applications, and internal communication (Bianchini et al., 2025). This means that generative AI may initially reinforce existing workflows rather than fundamentally redesign them. Whether such routine-level use develops into substantive innovation depends on whether vocational colleges possess the dynamic capabilities required to reinterpret AI-supported practices, modify established procedures, and institutionalize new administrative routines (Hughes et al., 2026). From this perspective, generative AI literacy provides potential technological and cognitive resources, while dynamic capabilities determine whether these resources remain embedded in routine task support or become translated into broader administrative innovation (Zhang et al., 2026).

In this study, dynamic capabilities are positioned as a mediating mechanism linking generative AI literacy to innovation in vocational colleges. This positioning reflects the theoretical principle that innovation arises not directly from individual-level competencies but from organizational processes that coordinate, reconfigure, and institutionalize new practices. Dynamic capabilities shape how administrative staff interpret AI-supported information, evaluate emerging opportunities, and integrate AI-enabled adjustments into administrative workflows (Gao et al., 2025). By incorporating dynamic capability theory, the study explains how generative AI literacy functions as a resource that requires organizational processing before contributing to innovation, and why the translation of AI-related knowledge into administrative outcomes is contingent upon the organization's ability to navigate change. This theoretical grounding further clarifies how structural constraints and path-dependent organizational conditions in vocational colleges influence the enactment of dynamic capabilities, thereby shaping the pathways through which generative AI literacy affects innovation performance.

In empirical terms, the path-dependent nature of dynamic capabilities can be reflected through observable organizational characteristics. Potential indicators include institutional age, dependence on legacy administrative systems, frequency of procedural reforms, prior experience with digital governance, and the extent of historical investment in staff digital training (Shonubi, 2025). These factors may help explain why vocational colleges with similar access to generative AI tools show different levels of administrative innovation. Although this study primarily examines dynamic capabilities as a mediating

mechanism, path dependence provides an important contextual explanation for variations in the formation and effectiveness of such capabilities. Therefore, it can be incorporated into the research design either as a contextual control variable or as an additional moderating condition in future model refinement.

2.2.2 Knowledge-based View

The knowledge-based view, developed by Curado and Bontis (2006), positions knowledge as the most strategically significant resource within organizations and conceptualizes innovation as the outcome of processes through which knowledge is created, shared, integrated, and applied. Building upon the resource-based tradition, the knowledge-based view redirects analytical attention from tangible assets toward the coordination of distributed and specialized knowledge residing in individuals and organizational units. Knowledge is depicted not as a static asset but as a dynamic flow shaped by interpretation, articulation, and collective learning (Abdelrahman et al., 2025). Organizational effectiveness depends on how diverse knowledge inputs are acquired, disseminated, recombined, and deployed, with innovation emerging when heterogeneous knowledge resources are successfully integrated (Gan et al., 2023). Subsequent theoretical development, including the work of Grant and Phene (2022), underscores that knowledge integration mechanisms are foundational to capability formation and serve as the basis through which organizations convert dispersed expertise into coherent outcomes.

Within this tradition, the knowledge-based view provides conceptual grounding for understanding the sequential transformation from generative AI-related knowledge to organizational innovation. Figure 2.5 illustrates this logic by depicting how knowledge inputs undergo sharing, absorption, and combination processes that lead to capability formation and subsequent innovation outputs. The model reflects the theoretical principle that knowledge possession alone is insufficient for innovation; instead, structured knowledge processes determine whether knowledge becomes actionable and collectively meaningful.

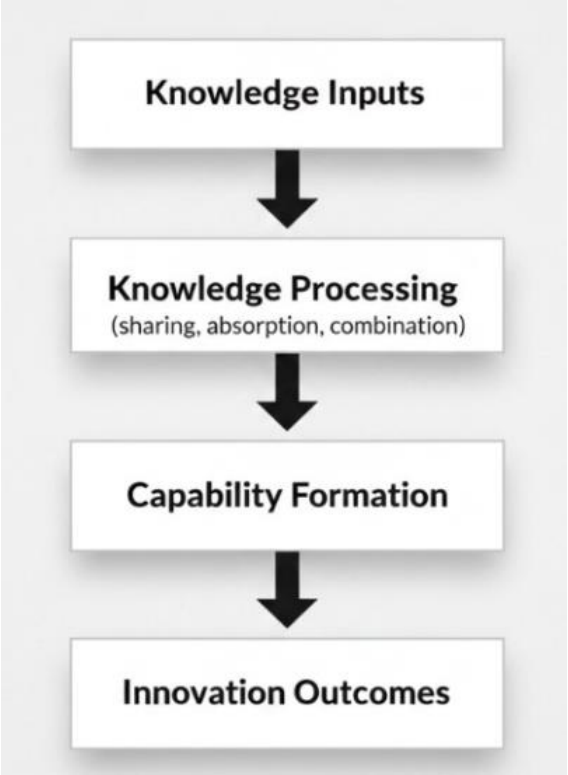


Figure 2.5 Conceptual Framework of Knowledge-Based Innovation Process
Source: Shi et al. (2025) and Nuryakin and Qamari (2026)

Within this study, generative AI literacy represents a heterogeneous set of knowledge inputs that include interpretive understanding, operational skills, evaluative judgment, ethical awareness, and problem-solving competencies. These distinct dimensions align with the knowledge-based view, which asserts that organizations depend on multiple, specialized knowledge types that must be coordinated before they generate innovative outcomes (Curado & Bontis, 2006). However, generative AI literacy remains an individual-level resource unless it enters organizational knowledge processes (Wanxin Yan et al., 2025). This theoretical logic provides the basis for introducing AI knowledge sharing participation as a core construct supported by the knowledge-based view.

AI knowledge sharing participation reflects the mechanisms through which generative AI-related knowledge becomes accessible to others (Rezaei, 2025). The outbound dimension captures the proactive dissemination of AI-related information, such as sharing new insights, techniques, or usage experiences (Broekhuizen et al., 2023). This corresponds with the knowledge-based view's emphasis on articulation and externalization as mechanisms for transforming individual knowledge into explicit,

collective knowledge. The inbound dimension captures the seeking and absorption of AI-related knowledge from colleagues, which aligns with theoretical arguments that knowledge integration depends on receptivity and the ability to internalize externally generated insights (Mockaitis et al., 2026). Together, these dimensions represent the reciprocal processes of knowledge movement described in the knowledge-based view and provide the organizational channel through which generative AI literacy enters a collective learning environment.

The knowledge-based view also explains how processed knowledge contributes to capability formation. As indicated in Figure 2.5, capability formation constitutes the intermediate stage between knowledge processing and innovation outputs. In this study, dynamic capabilities represent this stage. The three dimensions of dynamic capabilities, including sensing, seizing, and reconfiguring, correspond to the integration stages outlined in the knowledge-based view. Outbound and inbound AI knowledge sharing enhance sensing by making new knowledge visible across functional departments, support seizing by enabling evaluative discussions that shape collective judgment, and contribute to reconfiguring by facilitating shared understanding that enables modification of administrative routines. Thus, dynamic capabilities arise as a structured outcome of knowledge processing rather than as an isolated organizational attribute.

The knowledge-based view further clarifies how capability formation ultimately affects innovation performance. The four dimensions of innovation performance in vocational colleges, including idea generation, idea promotion, idea realization, and idea sustainability, align with the sequential innovation logic depicted in Figure 2.5. Idea generation corresponds to the recombination of distributed knowledge. Idea promotion reflects the mobilization of shared understanding. Idea realization embodies the application of integrated knowledge through coordinated action. Idea sustainability depends on the institutionalization of collectively processed knowledge. These dimensions demonstrate how innovation performance reflects the culmination of knowledge flows, capability development, and organizational integration processes.

By grounding the analytical framework in the knowledge-based view, the study establishes clear theoretical links between generative AI literacy as a knowledge input, AI knowledge sharing participation as a knowledge processing mechanism with outbound and inbound dimensions, dynamic capabilities as a capability formation output, and innovation

performance as a multidimensional innovation result. The knowledge-based view therefore provides the theoretical structure needed to explain the multi-stage pathways through which knowledge flows, is integrated, and contributes to enhanced innovation performance in vocational college administration.

2.2.3 Sociotechnical Systems Theory

Sociotechnical systems theory, developed by Cooper and Foster (1971), emphasizes that organizational outcomes emerge from the joint interaction between technical systems and social systems rather than from either subsystem operating independently. Originating from early studies of work organization and technological change in industrial settings, this theory argues that technological effectiveness is fundamentally shaped by its alignment with social structures, role configurations, communication patterns, and coordination mechanisms. Technological tools do not generate meaningful organizational value on their own; instead, value arises when technical capabilities and social arrangements are jointly optimized (Faraj & Leonardi, 2022). Within this conceptualization, innovation and performance are viewed as the product of integrated socio-technical design, where technological subsystems provide functional capacity and social subsystems establish the interpretive, relational, and structural conditions that enable or constrain technology use. Subsequent developments of the theory have further emphasized that the introduction of advanced technologies requires corresponding adjustments in organizational norms, work processes, and governance structures to achieve sustainable system-level improvement.

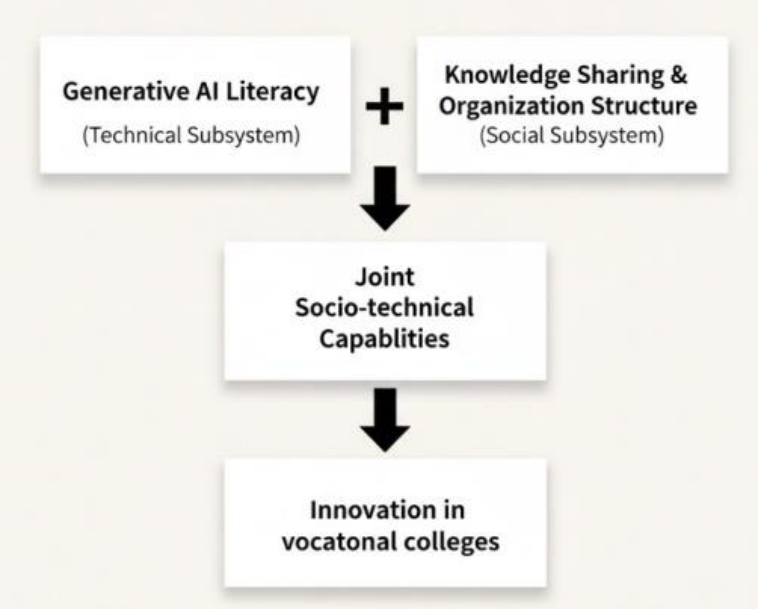


Figure 2.6 Conceptual Framework of Sociotechnical Innovation Process
Source: Vera et al. (2026) and Storey et al. (2025)

Within the context of this study, sociotechnical systems theory provides a critical lens for understanding why generative AI literacy does not automatically lead to innovation in vocational colleges. Generative AI literacy equips administrative staffs with the ability to engage with advanced technological tools and generate new informational inputs (Chiu et al., 2024). However, the realization of innovative outcomes depends on whether organizational conditions support the effective integration of these technological capabilities into administrative work processes. Sociotechnical systems theory explains this dependency by highlighting the role of social structures in shaping how technology is used and embedded.

Organization structure plays a central role in this interaction by influencing authority allocation, information flows, and the degree of discretion available to administrative staffs. In vocational colleges characterized by high levels of formalization and centralized decision-making, organizational structure can either facilitate coordination or constrain experimentation. From a sociotechnical perspective, such structural features condition how generative AI-related knowledge circulates, how administrative initiatives are evaluated, and whether new practices can be institutionalized. Figure 2.6 reflects this logic by positioning organization structure as a social subsystem that interacts with technological capabilities to shape joint sociotechnical outcomes.

The sociotechnical framework also supports the inclusion of knowledge sharing participation as a key social process within the broader system. Knowledge sharing participation influences how technological insights are collectively interpreted and translated into coordinated action (Gibson et al., 2022). When knowledge sharing is supported by organizational structure, joint sociotechnical capabilities emerge, enabling administrative systems to adapt and innovate. Conversely, weak alignment between technological capabilities and social arrangements limits the potential impact of generative AI literacy, regardless of individual competence levels.

By applying sociotechnical systems theory, the study explains how innovation in vocational colleges arises from the interaction between generative AI literacy, knowledge sharing participation, and organizational structure. The theory provides a coherent justification for treating organization structure as a moderating condition that shapes the effectiveness of generative AI-related capabilities and knowledge processes, thereby supporting the integrated theoretical framework underlying the study.

2.3 Immediate Disciplines

2.3.1 Generative AI Literacy

Generative AI literacy refers to the ability to effectively understand, interact with, evaluate, and apply generative artificial intelligence systems in work-related contexts (Xin Liu et al., 2025). Unlike general digital literacy, which focuses on basic technology use, generative AI literacy emphasizes engagement with systems capable of generating content, recombining knowledge, and supporting complex cognitive tasks (Wanxin Yan et al., 2025). This form of literacy requires not only operational competence but also interpretive judgment and contextual awareness, reflecting the probabilistic and non-deterministic nature of generative AI outputs.

In the context of vocational college administration, generative AI literacy shapes how administrative staffs engage with generative AI as part of their daily work (Chiu et al., 2024). Administrative tasks often involve document preparation, policy interpretation, information integration, and coordination across departments, all of which increasingly involve generative AI tools (Kong & Hu, 2025). The extent to which generative AI supports administrative innovation depends on whether administrative staffs can critically interpret AI-generated content, assess its suitability for formal organizational use, and

translate it into coordinated administrative action (Zhang & Magerko, 2025). Generative AI literacy therefore represents a key individual-level foundation for mobilizing generative AI in administratively complex and highly regulated educational organizations.

Generative AI literacy is conceptualized as a multidimensional construct encompassing several interrelated capacities. These include basic operational skills related to understanding system principles and functions, prompt engineering ability for formulating and refining effective inputs, quality evaluation ability for assessing the accuracy and coherence of AI-generated content, innovative application ability for identifying and implementing AI-supported solutions in work contexts, and compliance and ethical awareness for ensuring responsible and regulated use (Annapureddy et al., 2024). Together, these dimensions capture the technical, cognitive, innovative, and normative aspects of generative AI literacy relevant to administrative work in vocational colleges.

2.3.2 Dynamic Capabilities

Dynamic capabilities refer to the organizational capacity to purposefully adapt, integrate, and reconfigure internal resources and processes in response to changing environmental conditions (Zhang & Bang, 2023). As an extension of the resource-based view, dynamic capability theory is fundamentally an organizational-level theory. It explains why organizations differ in their ability to transform resources into performance outcomes, capabilities, and competitive or institutional advantages. Therefore, dynamic capabilities should not be understood as isolated individual abilities, but as organization-level processes through which resources, routines, knowledge, and structures are coordinated and renewed. Unlike routine operational capabilities that support stability and efficiency, dynamic capabilities emphasize adaptability and transformation. The concept highlights how organizations remain effective under conditions of technological change, institutional pressure, and increasing uncertainty by continuously renewing their modes of operation (Cordeiro et al., 2023).

In the context of vocational colleges, dynamic capabilities are particularly salient within administrative systems that must balance institutional stability with growing demands for responsiveness (Abunaser et al., 2025). Administrative staff operate in environments characterized by formalized procedures and centralized governance, yet they are increasingly required to respond to policy adjustments, technological developments,

and coordination challenges (Stanikzai & Mittal, 2025). In this study, dynamic capabilities refer to the organizational processes through which vocational colleges mobilize and reorganize administrative resources to incorporate generative AI-related knowledge into existing workflows. Although empirical data are collected from administrative staff, the construct is interpreted at the organizational level because staff perceptions and practices reflect how dynamic capabilities are enacted in daily administrative routines (Khaw et al., 2022). Dynamic capabilities thus represent the organizational mechanism through which generative AI literacy is translated from individual competence into coordinated administrative action that supports innovation (Liu et al., 2025).

Dynamic capabilities in vocational college administration are reflected in several interrelated dimensions. These include the ability of the organization to sense emerging changes and opportunities in the administrative environment, seize relevant opportunities by mobilizing resources and aligning actions, and reconfigure existing routines, structures, or processes to accommodate new practices (Kump et al., 2018). Together, these dimensions capture how vocational colleges adapt over time and provide a conceptual basis for examining the mediating role of dynamic capabilities between generative AI literacy and innovation in vocational colleges. This organizational-level interpretation also clarifies that administrative staff do not independently possess strategic dynamic capabilities; rather, they perceive, participate in, and enact these capabilities through routine administrative practices, cross-departmental coordination, and the implementation of AI-supported administrative changes.

2.3.3 AI Knowledge Sharing Participation

AI knowledge sharing participation refers to the intentional exchange of generative AI related information, skills, and usage practices among administrative staff in vocational colleges (Yeboah, 2023). It highlights a purposeful form of knowledge interaction in which individuals do not merely possess AI related understanding but actively contribute to and draw from the collective pool of AI related expertise within their organizational environment (Zhao et al., 2021). This construct extends traditional interpretations of knowledge sharing by emphasizing the circulation of AI specific knowledge that supports administrative decision making, workflow coordination, and process improvement.

Within vocational colleges, administrative work is distributed across specialized functional divisions such as academic affairs, human resources, finance, student

management, and digital administration (Wu, 2025). As generative AI becomes more deeply integrated into these administrative processes, the ability to share AI related knowledge increasingly shapes how institutions interpret and apply technological advances (Dai et al., 2026). Individual staff may independently learn new prompting techniques, evaluation strategies, or AI assisted problem solving approaches (Lin & Chen, 2024). However, these skills only contribute to broader administrative improvement when they are disseminated, discussed, and adopted across units. AI knowledge sharing participation thus reflects a critical mechanism through which generative AI literacy transitions from isolated individual competence to shared organizational capability (Liu et al., 2025).

AI knowledge sharing participation is conceptualized as a multidimensional construct capturing both the outward and inward directions of knowledge flow (Botega & Silva, 2020). The outward dimension reflects the extent to which administrative staff proactively communicate newly acquired generative AI related skills, insights, or usage methods to colleagues and help normalize AI related knowledge exchange within administrative settings (Nguyen et al., 2025). This includes sharing AI assisted work experiences, demonstrating useful prompting methods, or informing colleagues about effective AI supported administrative practices. The inward dimension reflects the willingness and ability of administrative staff to request, receive, and absorb AI related information and practical techniques from colleagues when performing administrative tasks (Jimenez, 2026). It captures how individuals rely on the collective expertise of peers to enhance their own AI supported work processes.

2.3.4 Organization Structure

Organization structure refers to the formal arrangement of roles, responsibilities, authority, rules, and coordination mechanisms within an organization. It defines how decisions are made, how procedures are established, how information flows across departments, and how activities are coordinated among organizational units (Chen & Chang, 2012). Organization structure therefore shapes patterns of control, communication, and discretion, influencing how individuals interact with organizational systems and how new practices are introduced, evaluated, and institutionalized (Lazarević & Mosurović, 2023).

In vocational colleges, organization structure plays a particularly important role because administrative systems operate under strong regulatory oversight, public governance requirements, and policy implementation responsibilities (Marquina et al., 2022). Administrative work is usually organized through formal procedures, hierarchical reporting lines, and multi-level approval mechanisms, which are designed to ensure compliance, accountability, and institutional stability (Hwang, 2023). However, these structural features may also constrain flexibility, slow information circulation, and limit administrative staff's discretion to experiment with new practices. This is especially relevant in the context of generative AI, because AI-enabled administrative innovation requires not only individual literacy, but also organizational permission, procedural adaptability, data governance rules, and cross-departmental coordination.

In this study, organization structure is treated as a contextual and moderating condition that shapes how generative AI-related knowledge and capabilities are mobilized within administrative processes (Chen & Chang, 2012). When organizational structures allow sufficient communication, autonomy, and coordination, administrative staff with higher generative AI literacy may be more able to apply AI tools to document drafting, policy interpretation, information integration, workflow improvement, and service optimization. Conversely, when structures are highly centralized and overly formalized, AI-related knowledge may remain confined to routine task support and may not be translated into broader administrative innovation. Therefore, organization structure conditions whether generative AI literacy can move from individual competence to organizationally meaningful innovation outcomes.

Organization structure in vocational colleges is conceptualized along two primary dimensions. Formalization refers to the extent to which administrative activities are governed by written rules, standardized procedures, fixed reporting formats, and clearly defined work requirements. A certain degree of formalization may support stability and reduce uncertainty, but excessive formalization may reduce flexibility and make it difficult to incorporate AI-supported improvements into existing routines. Centralization refers to the degree to which decision-making authority is concentrated at higher organizational levels (Lazarević & Mosurović, 2023). A centralized structure may strengthen policy consistency and control, but it may also reduce the autonomy of administrative staff and slow the adoption of innovative AI-assisted practices.

2.3.5 Innovation Performance in Vocational Colleges

Innovation performance in vocational colleges refers to the extent to which administrative staff effectively demonstrate behaviors that contribute to the improvement of administrative processes, coordination mechanisms, and service delivery. Rather than viewing innovation as a singular breakthrough event, innovation performance captures how well administrative personnel engage in activities that enhance institutional functioning through continual refinement, adaptation, and problem-solving (Zhang, 2022). Within vocational colleges, such performance is essential because administrative units face demands associated with policy implementation, quality assurance, regulatory compliance, and cross-departmental coordination, all of which require staff to respond to organizational challenges in creative and effective ways (Iqbal et al., 2025).

In this study, innovation performance is conceptualized as an outcome emerging from administrative work rather than from teaching or academic research. It reflects how administrative staff identify inefficiencies, articulate improvement opportunities, mobilize support across units, and translate ideas into action that strengthens governance and operational capacities (Cruz-Sánchez et al., 2026). This perspective situates administrative staff as active contributors to organizational advancement and highlights their role in shaping how vocational colleges adjust to environmental pressures, technological change, and evolving institutional expectations (Alnuaimi et al., 2022).

Consistent with this conceptualization, innovation performance is treated as a multidimensional construct comprising four performance domains that represent different types of innovation-related behaviors (Gkontelos et al., 2022). The first domain, idea generation, reflects performance in questioning existing routines, proposing feasible improvements, and initiating constructive dialogue about administrative change. The second domain, idea promotion, captures the ability to advocate for new ideas, communicate their relevance, and mobilize support from supervisors, colleagues, and decision-makers. The third domain, idea realization, measures performance during the implementation of innovations, including monitoring progress, addressing unforeseen problems, refining solutions, and critically reflecting on implementation practices. The final domain, idea sustainability, assesses the long-term impact of innovation through cross-unit collaboration, participation in innovation-related networks, and the dissemination of innovation outcomes across the institution. Together, these dimensions

offer a comprehensive framework for evaluating innovation performance as a continuous, behavior-based construct that reflects the effectiveness and influence of administrative innovation within vocational colleges.

2.4 Conceptual Model and Hypotheses Statement

2.4.1 Conceptual Model

Building on the conceptual relationships illustrated in Figure 2.7, the study formulates a structured set of hypotheses to examine the direct, mediating, and moderating mechanisms through which generative AI literacy influences innovation performance in vocational colleges. These hypotheses draw upon dynamic capability theory, the knowledge-based view, and sociotechnical systems theory, which together form an integrated theoretical foundation for understanding how AI-related competencies are converted into organizational outcomes within administrative contexts that are often characterized by resource constraints and procedural rigidity. The first group of hypotheses examines the direct pathways linking generative AI literacy to key organizational processes. Informed by dynamic capability theory, hypotheses H1a to H1e propose that the five dimensions of generative AI literacy have positive effects on dynamic capabilities. This reflects the theoretical assumption that administrative staff who possess stronger AI-related competencies are better positioned to sense emerging opportunities, identify useful insights, and adjust administrative practices in ways that facilitate organizational adaptation. In parallel, the knowledge-based view supports hypotheses H2a to H2e, which posit that generative AI literacy enhances AI knowledge sharing participation. This relationship is grounded in the idea that individuals who understand, evaluate, and apply generative AI effectively are more likely to engage in purposeful knowledge exchange, thereby strengthening collective learning processes that contribute to organizational functioning. The second group of hypotheses concerns the influence of mediating constructs on innovation outcomes. Hypothesis H3 proposes that dynamic capabilities positively influence innovation performance in vocational colleges. This follows the core argument of dynamic capability theory that organizational adaptability and the capacity to integrate and reconfigure resources determine whether potential value can be transformed into innovative administrative practices. Hypothesis H4 posits that AI knowledge sharing participation contributes positively to innovation performance. This reflects the central

argument of the knowledge-based view that knowledge flows, collaborative interpretation, and shared understanding play essential roles in supporting idea generation, idea promotion, idea implementation, and the long-term maintenance of innovative practices in administrative systems. Beyond these indirect relationships, hypotheses H5a to H5e explore the direct effects of generative AI literacy on innovation performance in vocational colleges. This reflects the possibility that AI-related competencies may influence innovation outcomes independently from organizational capabilities or knowledge processes. Administrative staff who possess strong operational, evaluative, or application-oriented AI skills may identify inefficiencies, propose alternative solutions, or implement improvements directly, consistent with the conceptualization of generative AI literacy as a strategically valuable resource within administrative work. The third group of hypotheses addresses the conditional influence of organizational structure. Guided by sociotechnical systems theory, hypotheses H6a to H6e state that organizational structure moderates the relationship between generative AI literacy and innovation performance. This reflects the theoretical position that structural characteristics such as centralization, formalization, and procedural rigidity shape the extent to which individual competencies can be translated into organizational outcomes. Supportive structural arrangements may enable experimentation and learning, whereas restrictive structures may inhibit the effective deployment of AI-related competencies. Finally, hypotheses H7a to H7e and H8a to H8e specify the mediating roles of dynamic capabilities and AI knowledge sharing participation in the relationship between generative AI literacy and innovation performance. These hypotheses integrate theoretical insights from dynamic capability theory and the knowledge-based view by arguing that generative AI literacy functions as a foundational resource whose value depends on organizational processes that enable opportunity recognition, knowledge integration, coordinated interpretation, and administrative adjustment. Through these mediating pathways and the conditional effects of organizational structure, the hypotheses collectively form an integrated analytical framework that allows the study to examine how generative AI literacy is transformed into innovation performance within vocational college administration.

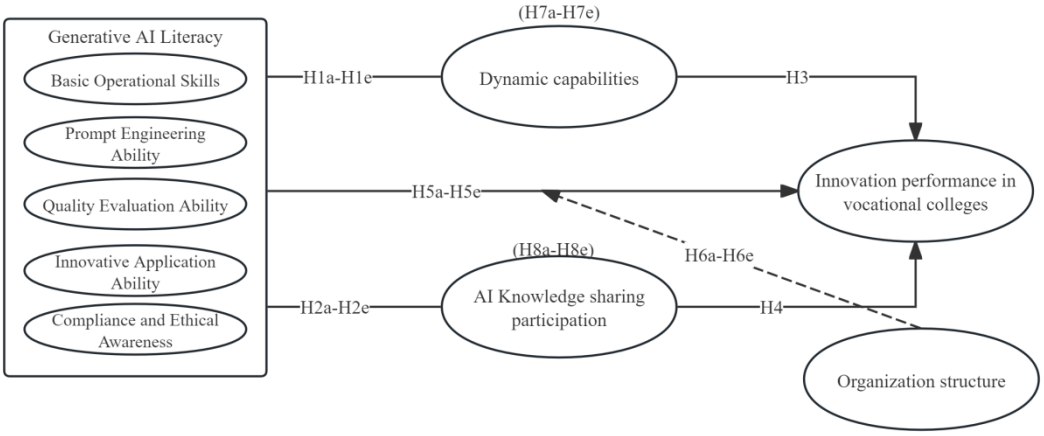


Figure 2.7 Conceptual Framework of the Study

2.4.2 Hypotheses Development

Dynamic capability theory emphasizes that organizational innovation under conditions of technological change depends on the ability to sense emerging opportunities, seize relevant resources, and reconfigure existing practices (Teece, 2023). These processes are not triggered automatically by the presence of new technologies but rely on underlying human and organizational competencies that enable effective interpretation, experimentation, and coordinated action. In administrative contexts, particularly within vocational colleges characterized by formalized procedures and centralized governance, individual-level technological competencies play a critical role in shaping whether new digital tools can be translated into adaptive organizational capabilities (Alenezi, 2023).

Basic operational skills constitute the foundational dimension of generative AI literacy and refer to the ability to understand system principles, utilize core functions, and resolve routine technical issues (Liu et al., 2025). Such skills support the sensing dimension of dynamic capabilities by enabling administrative staff to recognize the functional scope and limitations of generative AI tools in their work environment. When administrative personnel possess adequate operational proficiency, they are more capable of identifying relevant application scenarios and aligning technological functions with organizational needs, thereby strengthening the organization's capacity to respond to change (Haleem et al., 2024).

Prompt engineering ability reflects the capacity to formulate, refine, and adapt instructions that guide generative AI outputs toward task-relevant outcomes. This ability

directly supports the seizing dimension of dynamic capabilities by facilitating purposeful interaction with generative systems (Bansal, 2024). Effective prompt design enables administrative staff to extract context-specific insights, explore alternative solutions, and iteratively improve outputs based on feedback (Sikha et al., 2023). As a result, prompt engineering ability enhances the organization's ability to mobilize generative AI as a resource for problem solving and coordinated decision-making.

Quality evaluation ability refers to the competence to assess the accuracy, coherence, and logical consistency of AI-generated content. This dimension is critical for the reconfiguring process of dynamic capabilities, as it determines whether AI-generated knowledge can be reliably integrated into organizational routines (Huang et al., 2025). Administrative staff who can critically evaluate outputs are better positioned to filter inappropriate or inaccurate information and to adapt validated insights into existing processes, thereby supporting continuous organizational adjustment rather than superficial technology use (Igwe-Nmaju, 2021).

Innovative application ability captures the extent to which administrative staff can identify novel opportunities for applying generative AI and transform AI-assisted ideas into actionable outcomes (Held & Heubeck, 2025). This dimension represents a direct linkage between individual experimentation and organizational capability formation. By actively exploring new use cases and translating AI-supported ideas into administrative practices, innovative application ability contributes to the reconfiguration of workflows and coordination mechanisms that underpin dynamic capabilities (Zhang et al., 2025).

Compliance and ethical awareness represents the ability to use generative AI in accordance with legal requirements, organizational guidelines, and professional norms (Singh et al., 2024). In highly institutionalized environments such as vocational colleges, this dimension is particularly important for sustaining dynamic capabilities over time (Guerrero & Menter, 2024). Ethical and compliant use reduces organizational risk and enhances trust in AI-enabled practices, thereby creating a stable foundation for capability development and organizational learning (Xia et al., 2026). Without such awareness, experimentation with generative AI may be constrained or discontinued, weakening the organization's adaptive potential.

Based on these theoretical considerations, generative AI literacy is expected to positively influence dynamic capabilities through its multiple dimensions. Accordingly, the following hypotheses are proposed:

H1a: Basic operational skills has a positive effect on dynamic capabilities.

H1b: Prompt engineering ability has a positive effect on dynamic capabilities.

H1c: Quality evaluation ability has a positive effect on dynamic capabilities.

H1d: Innovative application ability has a positive effect on dynamic capabilities.

H1e: Compliance and ethical awareness has a positive effect on dynamic capabilities.

Knowledge-based perspectives emphasize that organizational outcomes depend on how knowledge is exchanged, interpreted, and combined among members rather than on isolated individual expertise (Bilgili & Bilgili, 2024). In administratively complex organizations, knowledge sharing participation represents a key social process through which individual competencies contribute to collective understanding and coordinated action (Ayestarán Echeberría et al., 2022). In the context of generative AI, the value of AI-related knowledge depends on whether administrative staff actively engage in sharing experiences, insights, and practices with colleagues across functional boundaries (Valtonen et al., 2025).

Basic operational skills provide the technical confidence necessary for participating in knowledge exchange related to generative AI use. Administrative staff who understand system principles and can operate AI tools effectively are more likely to communicate their experiences, respond to colleagues' inquiries, and engage in reciprocal information exchange (Meng et al., 2025). Such operational competence reduces uncertainty in technology use and lowers barriers to sharing AI-related knowledge within administrative networks.

Prompt engineering ability shapes the quality and relevance of shared knowledge by enabling individuals to articulate task-specific interactions with generative AI. Administrative staff who can design and refine prompts are better positioned to explain how AI outputs are generated and how they can be adapted to different administrative tasks (Murire, 2024). This capability supports more substantive and actionable knowledge exchange, thereby strengthening participation in both outbound and inbound knowledge sharing activities.

Quality evaluation ability contributes to knowledge sharing participation by supporting critical discussion of AI-generated content (Huang et al., 2025). Administrative staff who can assess the accuracy and coherence of outputs are more likely to engage in evaluative dialogue with colleagues, share validated insights, and collaboratively refine AI-assisted practices. This evaluative orientation promotes knowledge sharing that is reflective rather than superficial, enhancing collective learning within administrative systems.

Innovative application ability encourages proactive knowledge exchange by motivating individuals to share novel use cases and practical experiences related to generative AI (Cimino et al., 2025). Administrative staff who explore innovative applications are likely to communicate new ideas, demonstrate alternative approaches, and seek feedback from colleagues. Such behaviors contribute to a dynamic knowledge-sharing environment in which AI-related practices are continuously discussed and adapted.

Compliance and ethical awareness influences knowledge sharing participation by shaping norms of responsible AI use. In regulated organizational contexts, awareness of ethical standards and organizational guidelines reduces concerns related to misuse, data protection, and accountability (Renuka et al., 2025). This shared normative understanding facilitates open communication about generative AI practices and supports trust-based knowledge exchange among administrative staff.

Based on these considerations, generative AI literacy is expected to positively influence knowledge sharing participation through its multiple dimensions. Accordingly, the following hypotheses are proposed:

H2a: Basic operational skills has a positive effect on AI knowledge sharing participation.

H2b: Prompt engineering ability has a positive effect on AI knowledge sharing participation.

H2c: Quality evaluation ability has a positive effect on AI knowledge sharing participation.

H2d: Innovative application ability has a positive effect on AI knowledge sharing participation.

H2e: Compliance and ethical awareness has a positive effect on AI knowledge sharing participation.

Innovation in vocational colleges depends on the ability of administrative systems to adjust existing practices in response to changing demands (Phakamach et al., 2023). Dynamic capabilities capture how administrative units identify emerging needs, mobilize relevant resources, and modify established procedures (Schulze & Brusoni, 2022). When such capabilities are developed, administrative processes become more flexible and responsive, enabling the continuous improvement of routines and coordination mechanisms. These adaptive processes support the generation, implementation, and institutionalization of new administrative practices, which are essential components of innovation in vocational colleges. Accordingly, the following hypotheses are proposed:

H3: Dynamic capabilities has a positive effect on innovation performance in vocational colleges.

Administrative innovation also relies on the extent to which knowledge is exchanged and collectively utilized within vocational colleges. Knowledge sharing participation reflects how administrative staff communicate experiences, insights, and problem-solving approaches across organizational units (Shadmanfar & Makvandi, 2024). Active knowledge exchange facilitates coordination, reduces information fragmentation, and supports collective learning (Dickey et al., 2022). Through these processes, individual ideas are more likely to be refined, promoted, and translated into innovative administrative practices that enhance organizational functioning. Accordingly, the following hypotheses are proposed:

H4: Knowledge sharing participation has a positive effect on innovation performance in vocational colleges.

Innovation in vocational colleges can also be influenced directly by administrative staffs' generative AI-related competencies. Basic operational skills enable administrative staff to use generative AI tools reliably in routine and non-routine tasks, reducing procedural friction and supporting incremental improvements in administrative processes (Kong & Hu, 2025). When such foundational skills are present, administrative systems are better positioned to introduce and sustain innovative practices.

Prompt engineering ability enhances the effectiveness of interactions with generative AI by allowing administrative staff to obtain task-relevant and context-sensitive outputs (Bansal, 2024). This capability supports innovation by improving the quality of

AI-assisted problem solving, document preparation, and workflow design, thereby facilitating the development and application of new administrative solutions.

Quality evaluation ability contributes to innovation by enabling administrative staff to critically assess AI-generated content before it is incorporated into organizational practices (Xu et al., 2024). Through careful evaluation of accuracy, coherence, and completeness, administrative staff can refine AI-assisted ideas and avoid the institutionalization of inappropriate solutions, supporting more robust and reliable innovation outcomes.

Innovative application ability reflects a proactive orientation toward exploring new uses of generative AI and translating AI-assisted ideas into practical outcomes (Gruenhagen et al., 2024). This capability directly supports innovation by encouraging experimentation, adaptation of existing routines, and the introduction of novel administrative practices that enhance organizational functioning.

Compliance and ethical awareness supports innovation by ensuring that generative AI is used in ways that align with legal requirements, organizational guidelines, and professional norms (Papagiannidis et al., 2025). Responsible and compliant use reduces uncertainty and resistance associated with new technologies, creating a stable environment in which innovative administrative practices can be developed and sustained.

Based on these considerations, the following hypotheses are proposed:

H5a: Basic operational skills has a positive effect on innovation performance in vocational colleges.

H5b: Prompt engineering ability has a positive effect on innovation performance in vocational colleges.

H5c: Quality evaluation ability has a positive effect on innovation performance in vocational colleges.

H5d: Innovative application ability has a positive effect on innovation performance in vocational colleges.

H5e: Compliance and ethical awareness has a positive effect on innovation performance in vocational colleges.

The extent to which generative AI-related competencies contribute to innovation in vocational colleges is shaped by organizational structure. Structural characteristics such as formalization and centralization influence decision authority, information flow, and the

degree of discretion available to administrative staff (Lazarević & Mosurović, 2023). These conditions affect whether individual competencies can be effectively translated into innovative administrative practices.

Basic operational skills may support innovation more strongly in organizational contexts that allow flexibility in task execution and procedural adjustment (Ballester-Miquel et al., 2026). When organizational structure permits discretion in applying technical skills, administrative staff are better able to leverage operational competence for process improvement. Conversely, highly rigid structures may limit the innovative impact of such skills.

Prompt engineering ability relies on opportunities for experimentation and iterative refinement. Organizational structures that support cross-unit coordination and timely decision-making are more likely to enable administrative staff to apply prompt-related competencies in innovative ways (Xia et al., 2024). In contrast, restrictive structural arrangements may constrain the use of advanced AI interaction skills, weakening their relationship with innovation.

Quality evaluation ability contributes to innovation by enabling critical assessment and refinement of AI-assisted ideas. The effectiveness of this ability depends on whether organizational structure supports feedback, discussion, and revision of administrative practices (Joseph & Sengul, 2024). Structures that facilitate communication and shared evaluation processes are more likely to amplify the innovative impact of evaluative competence (Vinluan et al., 2025).

Innovative application ability reflects a proactive orientation toward experimenting with new solutions (Ritala et al., 2021). Organizational structures that tolerate experimentation and allow adjustments to established routines are more conducive to transforming such ability into innovation. Highly centralized or formalized structures may limit this translation by restricting initiative and discretionary action.

Compliance and ethical awareness supports innovation by enabling responsible use of generative AI within organizational boundaries. The relationship between this dimension and innovation is influenced by how organizational structure defines accountability, oversight, and risk tolerance (Zhang et al., 2023). Structures that clearly articulate norms while allowing adaptive responses may strengthen the innovative contribution of ethical and compliant behavior.

Based on these considerations, organization structure is expected to moderate the relationships between generative AI literacy dimensions and innovation in vocational colleges. Accordingly, the following hypotheses are proposed:

H6a: Organization structure moderates the relationship between basic operational skills and innovation performance vocational colleges.

H6b: Organization structure moderates the relationship between prompt engineering ability and innovation performance in vocational colleges.

H6c: Organization structure moderates the relationship between quality evaluation ability and innovation performance in vocational colleges.

H6d: Organization structure moderates the relationship between innovative application ability and innovation performance in vocational colleges.

H6e: Organization structure moderates the relationship between compliance and ethical awareness and innovation performance performance in vocational colleges.

The influence of generative AI-related competencies on innovation in vocational colleges does not operate solely through direct effects. Innovation in administrative systems often requires intermediate organizational processes that transform individual-level competencies into coordinated and sustained action. Dynamic capabilities represent such a process by enabling administrative units to recognize opportunities, mobilize resources, and adjust routines in response to emerging demands (Jin et al., 2024).

Basic operational skills provide the technical foundation for engaging with generative AI, but their contribution to innovation depends on whether administrative systems can integrate these skills into adaptive processes. Dynamic capabilities facilitate this integration by aligning operational competence with organizational sensing and reconfiguration activities, thereby enabling operational skills to contribute to innovation outcomes (Mushangai, 2023).

Prompt engineering ability enhances the potential value of generative AI interactions, yet its innovative impact relies on organizational mechanisms that translate improved outputs into modified practices (Chen et al., 2025). Dynamic capabilities support this translation by enabling administrative units to seize relevant insights and embed them into workflows and coordination mechanisms (Tajeddini et al., 2026).

Quality evaluation ability supports careful assessment of AI-generated content, but its influence on innovation depends on whether organizations can incorporate evaluative

judgments into decision-making and process adjustment (Xu et al., 2025). Dynamic capabilities provide the organizational capacity to filter, adapt, and institutionalize validated insights, linking evaluative competence to innovation (Cordeiro et al., 2023).

Innovative application ability reflects proactive exploration of new uses for generative AI, but such exploration yields innovation only when organizations can reconfigure existing routines (Cimino et al., 2025). Dynamic capabilities enable administrative systems to convert exploratory efforts into sustained changes, thereby mediating the relationship between innovative application ability and innovation outcomes (Pundziene et al., 2022).

Compliance and ethical awareness ensures responsible use of generative AI, yet its contribution to innovation requires organizational processes that balance accountability with adaptability (Wamba et al., 2025). Dynamic capabilities support this balance by enabling organizations to integrate ethical considerations into evolving practices, allowing compliant behavior to coexist with innovation (Knapp et al., 2025).

On this basis, dynamic capabilities are expected to mediate the relationships between generative AI literacy dimensions and innovation in vocational colleges. Accordingly, the following hypotheses are proposed:

H7a: Dynamic capabilities mediates the relationship between basic operational skills and innovation performance in vocational colleges.

H7b: Dynamic capabilities mediates the relationship between prompt engineering ability and innovation performance in vocational colleges.

H7c: Dynamic capabilities mediates the relationship between quality evaluation ability and innovation performance in vocational colleges.

H7d: Dynamic capabilities mediates the relationship between innovative application ability and innovation performance in vocational colleges.

H7e: Dynamic capabilities mediates the relationship between compliance and ethical awareness and innovation performance in vocational colleges.

The contribution of generative AI-related competencies to innovation in vocational colleges is also shaped by social processes through which knowledge is exchanged and collectively utilized. Knowledge sharing participation represents a key mechanism that links individual competencies with collective action by enabling the circulation, discussion, and refinement of AI-related insights within administrative systems (Zhong &

Wang, 2025). Through active participation in knowledge exchange, individual experiences with generative AI are transformed into shared understandings that support coordinated innovation.

Basic operational skills enable administrative staff to use generative AI effectively, but their impact on innovation depends on whether such experiences are communicated and shared with colleagues (Morandini et al., 2023). Knowledge sharing participation facilitates this process by allowing operational insights to be disseminated across administrative units, thereby supporting collective learning and innovation (Iqbal et al., 2025).

Prompt engineering ability enhances the effectiveness of interactions with generative AI, yet its innovative value increases when prompt-related practices and outcomes are shared within the organization (Bansal, 2024). Knowledge sharing participation enables administrative staff to exchange strategies for designing and refining prompts, supporting broader adoption of effective AI-assisted practices and contributing to innovation (Raina et al., 2026).

Quality evaluation ability supports critical assessment of AI-generated content, but its influence on innovation depends on collective evaluation and discussion. Knowledge sharing participation allows evaluative judgments to be communicated, compared, and refined through interaction, increasing the likelihood that validated insights are incorporated into innovative administrative practices (Shadmanfar & Makvandi, 2024).

Innovative application ability reflects exploratory use of generative AI, but innovation outcomes emerge when such exploration is shared and built upon by others. Knowledge sharing participation enables administrative staff to communicate new use cases, gather feedback, and collaboratively adapt practices, thereby mediating the relationship between innovative application ability and innovation (Sahibzada et al., 2024).

Compliance and ethical awareness supports responsible AI use, yet its contribution to innovation is strengthened when norms and guidelines are collectively understood and reinforced (Kashefi et al., 2024). Knowledge sharing participation facilitates the dissemination of ethical practices and organizational expectations, creating a shared foundation that supports both responsible behavior and innovation.

Based on these considerations, knowledge sharing participation is expected to mediate the relationships between generative AI literacy dimensions and innovation in vocational colleges. Accordingly, the following hypotheses are proposed:

H8a: AI Knowledge sharing participation mediates the relationship between basic operational skills and innovation performance in vocational colleges.

H8b: AI Knowledge sharing participation mediates the relationship between prompt engineering ability and innovation performance in vocational colleges.

H8c: AI Knowledge sharing participation mediates the relationship between quality evaluation ability and innovation performance in vocational colleges.

H8d: AI Knowledge sharing participation mediates the relationship between innovative application ability and innovation performance in vocational colleges.

H8e: AI Knowledge sharing participation mediates the relationship between compliance and ethical awareness and innovation performance in vocational colleges.

2.5 Conclusion

This chapter has systematically reviewed the theoretical and conceptual foundations relevant to examining generative AI-driven innovation in vocational colleges. By integrating insights from dynamic capability theory, the knowledge-based view, and sociotechnical systems theory, the chapter has clarified how individual-level generative AI literacy is connected to organizational processes and innovation outcomes within administratively complex educational settings. The discussion of immediate disciplines has further specified the key constructs of the study, including generative AI literacy, dynamic capabilities, knowledge sharing participation, organization structure, and innovation in vocational colleges, and has aligned these constructs with their conceptual meanings and dimensions.

Building on this theoretical grounding, the chapter has developed a coherent conceptual model and articulated a comprehensive set of hypotheses addressing direct, mediating, and moderating relationships among the study variables. Together, these elements establish a clear analytical framework that links generative AI-related competencies to innovation through organizational capabilities, knowledge processes, and structural conditions. This foundation provides a logically consistent basis for the subsequent empirical examination of the proposed relationships.

CHAPTER 3
METHODOLOGY

This chapter presents the methodological design adopted to empirically examine the proposed research model and hypotheses. It begins with an overview and justification of the research paradigm, clarifying the adoption of a positivist approach and its alignment with the study's ontological, epistemological, and methodological assumptions. Building on this foundation, the chapter then introduces the research tools employed, including the structured questionnaire and the operationalization of key constructs through validated measurement scales adapted to the context of vocational college administration. Next, the procedures for data collection administration are outlined, detailing the target population, sample size determination, sampling method, and data collection process to ensure transparency and replicability. The chapter subsequently describes the data analysis strategy, covering the pilot study, descriptive statistical analysis, reliability and validity assessment, and structural equation modeling used to test direct, mediating, and moderating relationships within the conceptual framework. Finally, ethical considerations are addressed to demonstrate adherence to established research ethics principles throughout the study. Together, these sections provide a coherent and systematic account of how the research was designed and implemented to support rigorous hypothesis testing.

3.1 Overview and Justification of Research Paradigm

This study adopts positivism as its overarching research paradigm to examine the relationships among generative AI literacy, dynamic capabilities, knowledge sharing participation, organization structure, and innovation in vocational colleges. Positivism is grounded in the assumption that social phenomena can be systematically observed, measured, and explained through empirical regularities (Karupiah, 2022). Within this paradigm, knowledge is generated through objective observation and statistical analysis, allowing theoretical propositions to be tested against empirical evidence. Given the study's aim to examine structured relationships among clearly defined constructs and to evaluate

a hypothesized model using quantitative data, positivism provides an appropriate and coherent philosophical foundation.

From an ontological perspective, positivism assumes that social reality exists independently of individual perceptions and can be represented through observable patterns (Junjie & Yingxin, 2022). In this study, key constructs such as generative AI literacy, dynamic capabilities, knowledge sharing participation, organization structure, and innovation in vocational colleges are treated as objective phenomena that manifest through consistent behaviors, practices, and organizational processes. Although these constructs originate from human actions and organizational contexts, they are conceptualized as stable attributes that can be measured and compared across individuals and institutions. This ontological position supports the use of standardized measurement instruments to capture variations in administrative practices and innovation outcomes within vocational colleges.

The epistemological stance of this study aligns with positivism by emphasizing explanation and hypothesis testing rather than interpretation. Knowledge is viewed as valid when it is derived from empirical observation and verified through systematic analysis. The study seeks to identify causal relationships among variables by testing theoretically grounded hypotheses using quantitative methods. In this sense, the researcher maintains analytical distance from the research subjects, and findings are evaluated based on reliability, validity, and statistical significance rather than subjective meaning. This epistemological orientation is consistent with the study's focus on examining mediating and moderating mechanisms within a predefined conceptual model.

At the level of methodology, the positivist paradigm informs the adoption of a quantitative research design. The study employs structured survey instruments to operationalize theoretical constructs and uses statistical techniques to test hypothesized relationships among variables. The use of multi-item measurement scales allows abstract concepts such as generative AI literacy and innovation to be translated into observable indicators, enabling systematic comparison and model estimation. This methodological approach is well suited to the study's objective of assessing direct effects, mediation, and moderation within a complex organizational framework.

In terms of axiology, positivism assumes value neutrality in the research process. The study does not seek to promote or evaluate generative AI as inherently beneficial or

detrimental but instead aims to examine its role in organizational innovation through empirically observable mechanisms. Research design, data collection, and analysis are conducted with an emphasis on objectivity, transparency, and methodological rigor. By minimizing subjective judgment and focusing on empirical testing, the study adheres to the positivist principle that scientific inquiry should remain independent of personal or normative values.

3.2 Research Tools

3.2.1 Operational Definitions of Variables

Table 3.1 Operational Definitions of Related Variables

Project	Definition	Reference
Generative AI Literacy	The degree to which administrative staff understand, evaluate, and apply generative AI tools in administrative work, including operational skills, prompt design, output evaluation, innovative application, and ethical and compliant use of AI technologies.	Xin Liu et al. (2025)
Dynamic capabilities	The organizational ability of vocational colleges to sense changes in the administrative environment, seize relevant knowledge and opportunities, and transform existing administrative routines to support continuous improvement and innovation.	Kump et al. (2018)
AI Knowledge sharing participation	The extent to which administrative staff actively engage in bidirectional knowledge exchange with colleagues by sharing and obtaining work-related information, skills, and experience within vocational colleges.	Zhao et al. (2021)

Table 3.1 (continued)

Project	Definition	Reference
Organization structure	The perceived degree of formalization and centralization in vocational colleges, reflecting the extent to which administrative activities are governed by standardized procedures and decision-making authority is concentrated at senior management levels.	Chen and Chang (2012)
Innovation performance in vocational colleges	The extent to which administrative staff generate, promote, implement, and sustain new ideas or practices aimed at improving administrative processes and services in vocational colleges.	Gkontelos et al. (2022)

3.2.2 Variable Measurements

(1) Generative AI Literacy

Table 3.2 presents the measurement of generative AI literacy, which is conceptualized in this study as a multidimensional construct capturing administrative staffs' capability to effectively understand, evaluate, and apply generative AI in vocational college administration. The scale is adapted from Xin Liu et al. (2025) and is contextually adjusted to reflect administrative work settings. It comprises five dimensions: basic operational skills, prompt engineering ability, quality evaluation ability, innovative application ability, and compliance and ethical awareness. These dimensions collectively represent foundational technical competence, task-oriented human–AI interaction, evaluative judgment of AI-generated outputs, the ability to leverage generative AI for administrative improvement, and responsible and compliant use of AI technologies. Each dimension is measured through multiple items to ensure comprehensive construct coverage. All items are assessed using a five-point Likert scale ranging from strongly disagree to strongly agree, enabling systematic evaluation of generative AI literacy among administrative staff.

Table 3.2 Detailed Statements used to Measure Generative AI Literacy

Constructs	Dimension	Original Items	Measurement Items	Sources
Generative AI Literacy	Basic Operational Skills	1.I understand the principles and limitations of the AI I use.	GA1. I understand the basic principles and limitations of the generative AI tools I use in administrative work.	Xin Liu et al. (2025)
		2.I can proficiently utilize the core and collaborative functions of AI tools.	GA2. I can proficiently use the core functions and collaborative features of generative AI tools to support my administrative tasks.	
		3.I can solve common technical problems encountered when using AI.	GA3. I am able to solve common technical problems encountered when using generative AI in my daily administrative work.	
	Prompt Engineering Ability	4.I can design effective AI prompts based on task requirements.	GA4. I can design effective prompts for generative AI based on specific administrative task requirements.	
		5.I can optimize AI prompts by integrating technical terminology and examples.	GA5. I can optimize generative AI prompts by incorporating appropriate terminology, examples, or contextual information relevant to my work.	

Table 3.2 (continued)

Constructs	Dimension	Original Items	Measurement Items	Sources
		6.I can continuously refine AI prompts based on generated results and feedback.	GA6. I can continuously refine prompts according to the results and feedback generated by generative AI to improve task outcomes.	
	Quality Evaluation Ability	7.I can assess the accuracy and reliability of AI-generated content.	GA7. I can assess the accuracy and reliability of content generated by generative AI for administrative decision-making.	
		8.I can assess the consistency and coherence of AI-generated content.	GA8. I can evaluate the consistency and coherence of generative AI outputs when applying them to administrative documents or processes.	
		9.I can evaluate the logic and completeness of AI-generated content.	GA9. I can judge the logical structure and completeness of generative AI-generated content before using it in my work.	
	Innovative Application Ability	10.I can identify and capitalize on innovative opportunities in my work through AI.	GA10. I can identify opportunities to improve administrative processes in vocational colleges through the use of generative AI.	

Table 3.2 (continued)

Constructs	Dimension	Original Items	Measurement Items	Sources
		11.I can generate creative and innovative ideas for my work using AI.	GA11. I can generate creative ideas for administrative work by effectively using generative AI tools.	
		12.I can transform innovative ideas into tangible results using AI.	GA12. I can translate AI-supported ideas into practical improvements or outcomes in my administrative responsibilities.	
	Compliance and Ethical Awareness	13.I can avoid ethical risks when using AI.	GA13. I am able to recognize and avoid potential ethical risks when using generative AI in administrative work.	
		14.I can ensure the protection of privacy and sensitive data when using AI.	GA14. I can ensure the protection of privacy and sensitive institutional information when using generative AI tools.	
		15.I can comply with laws and regulations related to AI usage.	GA15. I can comply with relevant laws and regulations related to the use of generative AI in my organization.	
		16.I can follow organizational guidelines when using AI.	GA16. I follow institutional rules and guidelines governing the use of generative AI in vocational colleges.	
		17.I can adhere to professional ethics when using AI.	GA17. I adhere to professional ethical standards when applying generative AI in administrative contexts.	

(2) Dynamic capabilities

Table 3.3 presents the measurement of dynamic capabilities, which are conceptualized in this study as the vocational college's organizational ability to sense changes in the administrative environment, seize relevant information and opportunities, and transform existing routines to support administrative innovation. The scale is adapted from Kump et al. (2018) and contextually adjusted to reflect administrative management and service delivery in vocational colleges. Dynamic capabilities are operationalized through three dimensions: sensing, seizing, and transforming. The sensing dimension captures the extent to which vocational colleges monitor policy developments, technological changes, and external administrative practices relevant to their operations. The seizing dimension reflects the organization's capacity to interpret newly acquired information and convert it into improved administrative processes and services. The transforming dimension focuses on the implementation and adaptation of administrative changes through clearly defined responsibilities, consistent execution, and flexible adjustment to evolving conditions. Each dimension is measured using multiple items to ensure comprehensive representation of dynamic capability processes. All items are measured using a five-point Likert scale to assess respondents' level of agreement with each statement.

Table 3.3 Detailed Statements used to Measure Dynamic Capabilities

Constructs	Dimension	Original Items	Measurement Items	Sources
Dynamic capabilities	Sensing	1.Our company knows the best practices in the market.	DC1. The vocational college is familiar with best practices relevant to administrative management and service delivery.	Kump et al. (2018)
		2.Our company is up-to-date on the current market situation.	DC2. The vocational college keeps up to date with policy, technological, and environmental changes affecting administrative work.	

Table 3.3 (continued)

Constructs	Dimension	Original Items	Measurement Items	Sources
		3.Our company systematically searches for information on the current market situation.	DC3. The vocational college systematically searches for information related to changes in the external administrative and policy environment.	
		4.As a company, we know how to access new information.	DC4. The vocational college knows how to access new information that is relevant to improving administrative processes.	
		5.Our company always has an eye on our competitors' activities.	DC5. The vocational college closely monitors developments and practices in comparable educational institutions.	
		6.Our company quickly notices changes in the market.	DC6. The vocational college is able to quickly identify changes that may affect administrative operations.	
	Seizing	7.Our company can quickly relate to new knowledge from the outside.	DC7. The vocational college can quickly relate newly acquired information to existing administrative practices.	
		8.We recognize what new information can be utilized in our company.	DC8. The vocational college is able to recognize which new information can be effectively utilized in administrative work.	

Table 3.3 (continued)

Constructs	Dimension	Original Items	Measurement Items	Sources
		9.Our company is capable of turning new technological knowledge into process and product innovation.	DC9. The vocational college is capable of transforming new technological or digital knowledge into administrative process innovation.	
		10.Current information leads to the development of new products or services.	DC10. Newly acquired information contributes to the development of improved administrative services or procedures.	
	Transforming	11.By defining clear responsibilities, we successfully implement plans for changes in our company.	DC11. By clearly defining responsibilities, the vocational college is able to implement administrative change initiatives effectively.	
		12.Even when unforeseen interruptions occur, change projects are seen through consistently in our company.	DC12. Even when unexpected disruptions occur, administrative change projects are carried through consistently.	
		13.Decisions on planned changes are pursued consistently in our company.	DC13. Decisions related to planned administrative changes are implemented in a consistent and sustained manner.	

Table 3.3 (continued)

Constructs	Dimension	Original Items	Measurement Items	Sources
		14.In the past, we have demonstrated our strengths in implementing changes.	DC14. The vocational college has demonstrated strong capabilities in implementing administrative changes in the past.	
		15.In our company, change projects can be put into practice alongside the daily business.	DC15. Administrative change initiatives can be implemented alongside routine administrative operations.	
		16.In our company, plans for change can be flexibly adapted to the current situation.	DC16. Plans for administrative change can be flexibly adjusted in response to evolving internal or external conditions.	

(3) AI Knowledge sharing participation

Table 3.4 presents the measurement of AI knowledge sharing participation, which in this study refers to the extent to which administrative staff actively engage in the exchange of generative AI related knowledge, skills, and usage experiences within vocational colleges. The scale is adapted from Zhao et al. (2021) and is contextually modified to reflect the integration of generative AI into administrative work practices. AI knowledge sharing participation is conceptualized as a two-dimensional construct consisting of AI knowledge outbound sharing and AI knowledge inbound sharing. The outbound dimension captures the degree to which administrative staff proactively share newly acquired generative AI related information, skills, and practical experiences with colleagues, as well as the extent to which AI related knowledge exchange is perceived as a routine and accepted practice within the organizational context. The inbound dimension reflects the extent to which administrative staff seek, request, and receive generative AI related knowledge, guidance, and skills from colleagues when necessary. Together, these two dimensions represent the bidirectional and interactive processes through which

generative AI related knowledge circulates among administrative personnel and supports collective understanding and application in daily administrative work. All items are assessed using a five-point Likert scale to measure respondents' agreement with each statement.

Table 3.4 Detailed Statements used to Measure AI Knowledge Sharing Participation

Constructs	Dimension	Original Items	Measurement Items	Sources
AI Knowledge sharing participation	Knowledge Outbound Sharing	1.When I have learned something new, I tell my colleagues about it.	KS1. When I learn new knowledge, skills, or usage methods related to generative AI in administrative work, I share them with my colleagues.	Zhao et al. (2021)
		2.When they have learned something new, my colleagues tell me about it.	KS2. When my colleagues learn new information or practices related to generative AI for administrative tasks, they share it with me.	
		3.Knowledge sharing among colleagues is considered normal in my company.	KS3. Sharing experiences and practices related to generative AI is considered a normal and accepted activity among administrative staff in my vocational college.	
	Knowledge Inbound Sharing	4.I share information I have with colleagues when they ask for it.	KS4. When colleagues ask, I share the generative AI–related information or resources that I use in administrative work.	

Table 3.4 (continued)

Constructs	Dimension	Original Items	Measurement Items	Sources
		5.I share my skills with colleagues when they ask for it.	KS5. When colleagues request assistance, I share my generative AI–related skills or practical experience used in administrative tasks.	
		6.Colleagues in my company share knowledge with me when I ask them to.	KS6. When I need help, colleagues in my vocational college share their generative AI–related knowledge with me.	
		7.Colleagues in my company share their skills with me when I ask them to.	KS7. When I ask for assistance, colleagues in my vocational college share their generative AI–related skills or experience with me.	

(4) Organization Structure

Table 3.5 presents the measurement of organization structure, which is conceptualized in this study as the structural conditions governing the coordination, control, and decision-making of administrative activities in vocational colleges. The scale is adapted from Chen and Chang (2012) and is contextually adjusted to reflect public educational administration. Organization structure is operationalized through two dimensions: level of formalization and level of centralization. The level of formalization captures the extent to which administrative work is regulated by clearly defined procedures, documented rules, compliance evaluations, and enforcement mechanisms. The level of centralization reflects the degree to which authority over key administrative decisions, including budget allocation, initiation of new administrative initiatives, organizational change, resource distribution, and staff deployment, is concentrated at senior management levels. Together, these dimensions represent the institutional arrangements that shape discretion, authority distribution, and control within vocational

college administration. All items are measured using a five-point Likert scale to assess respondents' perceptions of organizational structure.

Table 3.5 Detailed Statements used to Measure Organization Structure

Constructs	Dimension	Original Items	Measurement Items	Sources
Organization structure	Level of Formalization	1.Our firm has procedures to follow in all circumstances.	OS1. Our vocational college has clearly defined administrative procedures that must be followed in most situations.	Chen and Chang (2012)
		2.Rules or procedures exist mostly in a civilized way.	OS2. Administrative rules and procedures in my vocational college are formally documented and consistently applied.	
		3.Employees are constantly evaluated for compliance with rules.	OS3. Administrative staff are regularly evaluated based on their compliance with established rules and procedures.	
		4.Those who break the rules are punished.	OS4. Administrative staff who violate rules or procedures are subject to formal sanctions or corrective actions.	
	Level of Centralization	5.Decisions over the budgets are controlled by senior executives.	OS5. Decisions regarding administrative budgets are mainly controlled by senior management in my vocational college.	

Table 3.5 (continued)

Constructs	Dimension	Original Items	Measurement Items	Sources
		6.Decisions over introduction of new products are controlled by senior executives.	OS6. Decisions related to the introduction of new administrative initiatives or services are mainly controlled by senior management.	
		7.Decisions over new market entrance are controlled by senior executives.	OS7. Decisions concerning major organizational or administrative changes are mainly controlled by senior management.	
		8.Decisions over pricing of new product lines are controlled by senior executives.	OS8. Decisions regarding the allocation of resources for new administrative projects are mainly controlled by senior management.	
		9.Decisions over deployment of human resources are controlled by senior executives.	OS9. Decisions regarding the deployment and adjustment of administrative staff are mainly controlled by senior management.	

(5) Innovation Performance in Vocational Colleges

Table 3.6 presents the measurement of innovation performance in vocational colleges, conceptualized as the extent to which administrative staff demonstrate effective innovation-related behaviors that contribute to improved administrative functioning. The scale is adapted from Gkontelos et al. (2022) and is contextually revised to reflect performance-oriented innovation activities within vocational college administration. Innovation performance is operationalized through four interrelated dimensions: idea

generation, idea promotion, idea realization, and idea sustainability. Idea generation reflects performance in identifying problems, proposing feasible improvements, and engaging in constructive idea exchange that enhances administrative processes. Idea promotion captures the ability to communicate and advocate new ideas in ways that mobilize support from supervisors, colleagues, and decision-makers, thereby strengthening the potential impact of innovation. Idea realization focuses on the performance demonstrated during the implementation of innovations, including monitoring progress, addressing emerging challenges, refining solutions, and critically reflecting on implementation practices. Idea sustainability represents the extent to which administrative staff contribute to the diffusion, consolidation, and long-term impact of innovation by collaborating across departments, engaging in innovation-related networks, and communicating innovation outcomes to wider organizational audiences. Together, these dimensions conceptualize innovation performance as a multifaceted set of behaviors that reflect the effectiveness and impact of administrative innovation within vocational colleges. All items are measured using a five-point Likert scale to capture respondents' self-reported levels of innovation performance.

Table 3.6 Detailed Statements used to Measure Innovation Performance in Vocational Colleges

Constructs	Dimension	Original Items	Measurement Items	Sources
Innovation performance in vocational colleges	Idea Generation	1.Asking critical questions about current situations at work.	IV1. Raising critical questions that help improve administrative performance in my vocational college.	Gkontelos et al. (2022)
		2.Suggesting improvements on expressed ideas.	IV2. Suggesting actionable improvements that enhance administrative work performance.	

Table 3.6 (continued)

Constructs	Dimension	Original Items	Measurement Items	Sources
		3.Exchanging ideas on concrete changes at work with one's colleagues.	IV3. Exchanging ideas with colleagues that contribute to improving administrative performance.	
		4.Specifying which elementary improvements can be implemented at work.	IV4. Identifying feasible improvements that can enhance administrative performance.	
		5.Discuss personal ideas for improvements with one's colleagues.	IV5. Discussing personal improvement ideas with colleagues to support better administrative performance.	
	Idea Promotion	6.Suggesting the new idea to key persons who are authorized to allocate resources for this new idea.	IV6. Proposing new administrative ideas to decision-makers in ways that support performance improvement.	
		7.Convincing others of the importance of a newly developed idea or solution.	IV7. Convincing others of the value of new administrative ideas that can enhance performance.	
		8.Promoting new ideas to the supervisor in order to gain his/her active support.	IV8. Promoting new administrative ideas to supervisors to obtain support for improving performance.	

Table 3.6 (continued)

Constructs	Dimension	Original Items	Measurement Items	Sources
		9.Promoting new ideas to colleagues in order to gain their active support.	IV9. Promoting new administrative ideas to colleagues to strengthen collective performance.	
		10.Promoting the application of a new solution within one's work context.	IV10. Encouraging the application of new administrative solutions that demonstrate performance benefits.	
		11.Getting colleagues acquainted with the utilization of the new idea or solution.	IV11. Helping colleagues become familiar with new administrative ideas that improve work performance.	
	Idea Realization	12.Monitoring the progress during the process of putting ideas in practice.	IV12. Monitoring the progress of implementing new administrative ideas to ensure performance improvement.	
		13.Analyzing the solutions that are found on undesired effects, when putting ideas into practice.	IV13. Analyzing unintended effects that may influence the performance outcomes of administrative innovations.	

Table 3.6 (continued)

Constructs	Dimension	Original Items	Measurement Items	Sources
		14.Testing solutions for unexpected problems that emerge, when putting ideas into practice.	IV14. Testing solutions to unexpected problems during implementation to secure better performance.	
		15.Obtaining information from people who have already put the idea into practice, about possible bottlenecks during the implementation process.	IV15. Seeking information from colleagues with similar implementation experience to enhance performance.	
		16.Reflecting critically on the actions you execute when putting the idea into practice.	IV16. Critically reflecting on my actions to improve the performance of administrative innovation.	
		17.Reflecting systematically on your experiences when putting the new idea into practice.	IV17. Systematically reflecting on experiences to strengthen future administrative innovation performance.	
	Idea Sustainability	18.Participating in networks that have the innovation or new idea as a theme.	IV18. Participating in innovation-related networks that help improve administrative performance.	

Table 3.6 (continued)

Constructs	Dimension	Original Items	Measurement Items	Sources
		19.Initiating collaboration with other groups in the organization to apply the idea in other contexts also.	IV19. Initiating collaboration with other departments to expand the performance impact of administrative innovations.	
		20.Initiating collaboration with other groups outside of the organization to apply the idea in other contexts also.	IV20. Initiating collaboration with external organizations to extend the performance benefits of administrative innovations.	
		21.Communicating explicitly the returns of the implemented idea outside the team.	IV21. Communicating the performance outcomes of administrative innovations beyond my work group.	
		22.Visualizing the output of the implemented ideas to a broader audience.	IV22. Presenting or visualizing the performance results of administrative innovations to a broader audience.	

3.3 Data Collection Administration

3.3.1 Target Population

The target population of this study consists of administrative staff employed in higher vocational colleges located in Northeastern China, which refers to the three provincial-level administrative units of Liaoning, Jilin, and Heilongjiang. In the Chinese education system, higher vocational colleges are tertiary-level institutions that provide

higher vocational education after senior secondary education. They are part of China's higher education system, but their educational mission differs from that of research-oriented universities. Higher vocational colleges focus more on applied skills training, technical education, industry-oriented talent cultivation, and practical professional competence. Therefore, they play an important role in connecting higher education with regional labor markets and industrial development.

In this study, higher vocational colleges refer to officially recognized vocational institutions at the higher education level, including vocational colleges and vocational technical colleges that provide diploma-level higher vocational education. These institutions are commonly governed by provincial or local education authorities and operate under national policies related to vocational education reform, industry-education integration, digital education, and applied talent development. This institutional setting makes higher vocational colleges an appropriate context for examining administrative innovation under digital transformation.

Within this regional context, the target population includes administrative staff working in higher vocational colleges operating under broadly similar governance structures, education policies, and institutional regulations. Administrative staff are defined as non-academic personnel whose primary responsibilities involve administrative management, policy execution, coordination across departments, student and academic services, human resource management, financial administration, information management, and institutional operations, rather than teaching or research activities. Focusing on this population allows the study to examine administrative innovation processes within comparable institutional environments that share regional economic conditions, demographic characteristics, and administrative challenges typical of higher vocational education in Northeastern China.

Within higher vocational colleges, administrative staff typically perform functions related to academic affairs administration, personnel and human resources management, finance and asset administration, student services, general office operations, enrollment and employment services, information technology and digital administration, logistics management, and institutional coordination. These roles are characterized by high levels of procedural standardization, intensive information processing, and frequent cross-departmental interaction. As a result, administrative staff occupy a central position in

organizational operations and are directly exposed to the application of digital and generative AI tools in daily administrative work.

The overall scale and provincial distribution of this population are presented in Table 3.7. According to the China Educational Statistics Yearbook, 2025, there are 159 higher vocational colleges in the three northeastern provinces, including 52 in Liaoning, 40 in Heilongjiang, and 67 in Jilin. The total number of administrative staff is 20,700, with 9,200 in Liaoning, 6,400 in Heilongjiang, and 5,100 in Jilin. This population structure provides an appropriate empirical basis for examining generative AI literacy, dynamic capabilities, AI knowledge sharing participation, organizational structure, and innovation performance within higher vocational college administration.

Table 3.7 Distribution of Administrative Staff in Vocational Colleges in Northeastern China

Province	Number of Vocational Colleges	Number of Administrative Staff
Liaoning	52	9,200
Heilongjiang	40	6,400
Jilin	67	5,100
Total	159	20,700

Source: China Educational Statistics Yearbook, 2025.

3.3.2 Sample Size

The determination of sample size in this study follows established methodological guidance for survey-based structural analysis. According to Memon et al. (2020), an adequate sample size for multivariate analysis should be no less than ten times the number of measurement items included in the research instrument. This rule-of-thumb is widely applied in studies employing latent variable models to ensure sufficient statistical power, stable parameter estimation, and reliable assessment of complex relationships among constructs.

In the present study, the measurement instrument comprises a total of 71 items across all constructs, including generative AI literacy, dynamic capabilities, knowledge sharing participation, organization structure, and innovation in vocational colleges. Applying the ten-times rule results in a minimum required sample size of 710 respondents.

This threshold is considered sufficient to support subsequent empirical analyses, including reliability and validity assessment as well as hypothesis testing involving mediation and moderation effects. After data screening and validity checking, a total of 765 valid questionnaires were ultimately retained for the final empirical analysis.

3.3.3 Sampling Method

This study adopts a convenience sampling method to collect data from administrative staff working in higher vocational colleges in Northeastern China. Convenience sampling is appropriate for this study because the research focuses on a specific occupational group within a defined institutional context, namely administrative and support staff in higher vocational colleges. This method allows the study to reach respondents who are directly involved in administrative work and have relevant experience with institutional procedures, digital tools, and generative AI-related practices.

To improve sample coverage, the study includes higher vocational colleges from Liaoning, Jilin, and Heilongjiang. Five higher vocational colleges are selected from each province, resulting in 15 participating institutions. Administrative staff members from these selected colleges are invited to participate in the questionnaire survey, producing a planned sample size of 710 respondents. This design helps capture variation across provinces, institutions, administrative functions, and position levels.

The selection of respondents follows clear eligibility criteria. Participants must be administrative or support staff working in higher vocational colleges, and their work should be related to administrative functions such as academic affairs, student affairs, human resources, finance, information technology or digital administration, general administration, enrollment and employment services, scientific research administration, logistics and asset management, or external cooperation. Screening questions are included at the beginning of the questionnaire to confirm respondents' province, institutional type, administrative function, position level, work experience, and use of generative AI tools. Respondents who do not belong to the defined administrative or support functions are excluded from the final dataset.

Although convenience sampling has limitations in statistical generalization, it is suitable for examining the relationships among generative AI literacy, AI knowledge sharing participation, dynamic capabilities, organization structure, and innovation performance within the selected higher vocational college context. The inclusion of

multiple institutions across three provinces, together with screening questions and functional classification, helps improve the relevance and diversity of the sample.

3.3.4 Data Collection Method

This study employed an online survey method to collect empirical data from administrative staff in higher vocational colleges. Online surveys are appropriate for organizational and educational research because they allow standardized data to be collected efficiently from respondents distributed across different institutions and provinces. This method also enables respondents to complete the questionnaire at their convenience and supports the collection of structured data suitable for quantitative analysis.

The questionnaire was designed to align with the research framework and variable definitions of the study. Measurement items were adapted to the administrative work context of higher vocational colleges, particularly in relation to document processing, policy interpretation, cross-departmental coordination, information management, digital administration, service improvement, and workflow optimization. This design ensures that the measurement of generative AI literacy, AI knowledge sharing participation, dynamic capabilities, organization structure, and innovation performance reflects the actual work practices of administrative staff rather than general technology use.

The questionnaire was administered through Questionnaire Star, a widely used online survey platform in China. The survey link was distributed through QQ and WeChat, which are commonly used by administrative staff for professional communication. These platforms were selected because they are familiar, accessible, and efficient for reaching administrative staff across different higher vocational colleges in Liaoning, Jilin, and Heilongjiang.

To reduce potential authority bias or perceived pressure, participation was clearly described as voluntary and anonymous. Respondents were informed that there were no right or wrong answers, that their responses would be used only for academic research, and that no individual-level results would be reported to their institutions or supervisors. The questionnaire did not collect identifiable personal information such as names, employee numbers, or phone numbers. Administrative departments only assisted in forwarding the survey link and did not participate in monitoring, collecting, or evaluating individual responses.

To ensure sample validity and data quality, screening questions were placed at the beginning of the questionnaire. These questions confirmed respondents' province, administrative function, position level, work experience, and generative AI use. Respondents who did not belong to the defined administrative or support functions were excluded from the final dataset. In addition, all questionnaire items were set as required responses before submission to reduce missing data. Data collection continued until the planned number of valid responses was obtained.

3.4 Data Analysis

3.4.1 Pilot Study

A pilot study was conducted prior to the main survey to assess the clarity, reliability, and preliminary validity of the measurement instrument. Pilot studies are commonly used in survey-based research to identify potential issues related to item wording, scale structure, response patterns, and questionnaire length before large-scale data collection (Kunselman, 2024). Conducting a pilot study helps ensure that respondents can clearly understand the measurement items and that the instrument functions as intended within the specific research context.

In this study, the pilot test was implemented by distributing 30 pre-test questionnaires to administrative staff working in vocational colleges within the target region. Participants in the pilot study shared similar occupational characteristics with the main sample and met the same inclusion criteria. Feedback from the pilot respondents was used to examine item clarity, response consistency, and completion time. Based on the pilot results, minor adjustments were made to item wording and questionnaire structure where necessary to improve clarity and contextual fit. The refined instrument was then finalized for use in the main data collection phase.

The item analysis in Table 3.8 showed that most items achieved acceptable corrected item-total correlation values, indicating that the majority of measurement items contributed consistently to their corresponding constructs. Generative AI literacy, AI knowledge sharing participation, organization structure, and innovation performance in vocational colleges displayed stable item performance, suggesting that these scales had strong internal coherence at the pre-test stage. However, DC12 reported a CITC value of 0.29, which was lower than the acceptable criterion. In addition, the Cronbach's α value

for dynamic capabilities would increase if DC12 was deleted, indicating that this item weakened the internal consistency of the construct. Therefore, DC12 was removed from the formal questionnaire to improve the reliability and measurement quality of the dynamic capabilities scale.

Table 3.8 Item Analysis for Pilot Test

Construct	Item	Mean	SD	CITC	Cronbach's α if item deleted
Generative AI Literacy	GA1	4.12	0.73	0.64	0.93
	GA2	4.15	0.71	0.66	0.93
	GA3	4.08	0.76	0.62	0.93
	GA4	4.18	0.7	0.68	0.92
	GA5	4.14	0.72	0.65	0.93
	GA6	4.11	0.75	0.63	0.93
	GA7	4.09	0.74	0.64	0.93
	GA8	4.13	0.73	0.66	0.93
	GA9	4.1	0.75	0.62	0.93
	GA10	4.16	0.71	0.67	0.92
	GA11	4.19	0.69	0.68	0.92
	GA12	4.15	0.72	0.65	0.93
	GA13	4.07	0.77	0.61	0.93
	GA14	4.11	0.74	0.63	0.93
	GA15	4.1	0.76	0.62	0.93
	GA16	4.13	0.73	0.64	0.93
	GA17	4.12	0.75	0.63	0.93
Dynamic Capabilities	DC1	4.09	0.74	0.63	0.92
	DC2	4.13	0.72	0.65	0.92
	DC3	4.1	0.75	0.62	0.92
	DC4	4.14	0.71	0.66	0.91
	DC5	4.08	0.76	0.61	0.92
	DC6	4.12	0.73	0.64	0.92
	DC7	4.15	0.72	0.65	0.91

Table 3.8 (continued)

Construct	Item	Mean	SD	CITC	Cronbach's α if item deleted
	DC8	4.11	0.74	0.63	0.92
	DC9	4.16	0.7	0.67	0.91
	DC10	4.14	0.72	0.66	0.91
	DC11	4.07	0.77	0.6	0.92
	DC12	3.76	0.88	0.29	0.95
	DC13	4.1	0.75	0.62	0.92
	DC14	4.12	0.73	0.64	0.92
	DC15	4.09	0.76	0.61	0.92
	DC16	4.13	0.72	0.65	0.91
AI Knowledge Sharing Participation	KS1	4.18	0.7	0.66	0.91
	KS2	4.15	0.72	0.64	0.91
	KS3	4.12	0.74	0.62	0.92
	KS4	4.17	0.71	0.65	0.91
	KS5	4.14	0.73	0.63	0.91
	KS6	4.16	0.72	0.64	0.91
	KS7	4.13	0.74	0.62	0.92
Organization Structure	OS1	4.2	0.69	0.65	0.9
	OS2	4.18	0.7	0.64	0.9
	OS3	4.12	0.73	0.61	0.91
	OS4	4.09	0.76	0.6	0.91
	OS5	4.16	0.72	0.63	0.9
	OS6	4.14	0.73	0.62	0.91
	OS7	4.17	0.71	0.64	0.9
	OS8	4.15	0.72	0.63	0.9
	OS9	4.13	0.74	0.61	0.91
Innovation Performance in Vocational Colleges	IV1	4.14	0.72	0.64	0.94
	IV2	4.16	0.71	0.66	0.94
	IV3	4.13	0.73	0.63	0.94

Table 3.8 (continued)

Construct	Item	Mean	SD	CITC	Cronbach's α if item deleted
	IV4	4.18	0.7	0.67	0.94
	IV5	4.11	0.75	0.62	0.94
	IV6	4.1	0.76	0.61	0.94
	IV7	4.15	0.72	0.65	0.94
	IV8	4.17	0.71	0.66	0.94
	IV9	4.14	0.73	0.64	0.94
	IV10	4.19	0.69	0.68	0.94
	IV11	4.13	0.74	0.63	0.94
	IV12	4.12	0.75	0.62	0.94
	IV13	4.09	0.77	0.6	0.95
	IV14	4.11	0.76	0.61	0.94
	IV15	4.15	0.72	0.65	0.94
	IV16	4.16	0.71	0.66	0.94
	IV17	4.14	0.73	0.64	0.94
	IV18	4.12	0.75	0.62	0.94
	IV19	4.17	0.7	0.67	0.94
	IV20	4.1	0.77	0.61	0.94
	IV21	4.13	0.74	0.63	0.94
	IV22	4.15	0.72	0.65	0.94

The reliability results in Table 3.9 further confirmed the internal consistency of the refined instrument. The Cronbach's α values of all study variables exceeded 0.90, including generative AI literacy, dynamic capabilities, AI knowledge sharing participation, organization structure, and innovation performance in vocational colleges. These results indicated that the scales had high reliability and that the retained items measured their intended constructs in a stable and consistent manner. The removal of DC12 also enhanced the psychometric quality of the dynamic capabilities scale by reducing item inconsistency and strengthening construct coherence.

Table 3.9 Pretest Reliability Statistics

Study variables	Number of questions	Cronbach's α
Generative AI Literacy	17	0.948
Dynamic Capabilities	15	0.936
AI Knowledge Sharing Participation	7	0.902
Organization Structure	9	0.921
Innovation Performance in Vocational Colleges	22	0.956

The preliminary validity results in Table 3.10 provided additional support for the suitability of the questionnaire. The KMO value of 0.916 indicated a high level of sampling adequacy, while Bartlett's test of sphericity was statistically significant, showing that the correlation matrix was appropriate for factor analysis. These findings demonstrated that the retained items contained sufficient common variance and could support subsequent validity testing in the formal empirical analysis. Based on the pilot study results, the final questionnaire was considered suitable for the main survey and provided a reliable measurement foundation for testing the proposed theoretical model.

Table 3.10 Pre-investigation KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.916
Bartlett's Test of Sphericity	Approx. Chi-Square	7157.814
	df	136
	Sig.	.000

3.4.2 Descriptive Statistical Analysis

Descriptive statistical analysis was conducted to provide an overall profile of the sample and to summarize the basic characteristics of the collected data. This analysis focuses on the distributional properties of the respondents and the main study variables, serving as a preliminary step for subsequent inferential analyses. Common descriptive statistics, including frequency, percentage, mean, and standard deviation, were used to present respondents' demographic characteristics and to describe central tendency and variability across measurement items and constructs.

In the context of this study, descriptive statistics were applied to examine administrative staff characteristics such as province, organizational affiliation, and work-related background, as well as to summarize responses for generative AI literacy, dynamic capabilities, knowledge sharing participation, organization structure, and innovation in vocational colleges. This step allowed for an initial assessment of data quality, including the identification of missing values, outliers, and abnormal response patterns. The results of the descriptive analysis provide an essential empirical foundation for reliability testing, validity assessment, and hypothesis testing in subsequent stages of data analysis.

3.4.3 Reliability Analysis

Reliability analysis was conducted to assess the internal consistency and stability of the measurement scales used in this study. Internal consistency reliability reflects the extent to which items within the same construct measure a common underlying concept (Revicki, 2024). Cronbach's alpha and composite reliability were employed as the primary indicators of reliability, as these measures are widely accepted in organizational and behavioral research involving latent constructs (Haji-Othman & Yusuff, 2022). Values exceeding commonly recommended thresholds indicate satisfactory reliability and consistency among measurement items.

In this study, reliability analysis was performed for each construct and its corresponding dimensions, including generative AI literacy, dynamic capabilities, knowledge sharing participation, organization structure, and innovation in vocational colleges. Item-total correlations and reliability coefficients were examined to ensure that all items contributed meaningfully to their respective constructs. The results of the reliability analysis provided assurance that the measurement instrument was sufficiently robust to support subsequent validity assessment and structural model testing.

3.4.4 Validity Analysis

Validity analysis was undertaken to evaluate the extent to which the measurement scales accurately captured the intended constructs. Both convergent validity and discriminant validity were examined as part of the construct validity assessment. Convergent validity reflects whether items designed to measure the same construct are strongly related, while discriminant validity assesses whether constructs that are theoretically distinct are empirically separable.

In the present study, confirmatory factor analysis was used to assess factor loadings, average variance extracted, and correlations among constructs. Adequate factor loadings and average variance extracted values were used to establish convergent validity, while comparisons of shared variance and construct correlations were used to evaluate discriminant validity. These analyses ensured that the measurement model demonstrated acceptable construct validity before proceeding to the evaluation of structural relationships among variables.

3.4.5 Structural Equation Model Analysis

Structural equation modeling was employed to test the hypothesized relationships among generative AI literacy, dynamic capabilities, knowledge sharing participation, organization structure, and innovation in vocational colleges. Structural equation modeling is appropriate for this study because it enables the simultaneous estimation of multiple relationships among latent variables while explicitly accounting for measurement error. This analytical approach is particularly suitable for examining complex research models that involve both mediation and moderation mechanisms (Moshagen & Bader, 2024).

In this study, the structural model was estimated after the adequacy of the measurement model had been confirmed through reliability and validity analyses. Direct effects were examined using path coefficients corresponding to the proposed hypotheses, while indirect effects were assessed to evaluate the mediating roles of dynamic capabilities and knowledge sharing participation. Interaction effects were incorporated to test the moderating role of organization structure. The overall adequacy of the structural model was evaluated using multiple goodness-of-fit indices. As summarized in Table 3.8, these indices include chi-square, comparative fit index, Tucker–Lewis index, root mean square error of approximation, and standardized root mean square residual, which are widely adopted criteria for assessing model fit in structural equation modeling. Together, these indicators provide a comprehensive basis for evaluating the extent to which the proposed model is consistent with the observed data.

Table 3.11 Structural Equation Modeling Indicators

Index	Ideal Value	Source
χ^2 (Chi-square)	p>0.05	Hair et al. (2021)
CFI (Comparative Fit Index)	CFI>0.95	
TLI (Tucker-Lewis Index)	TLI>0.95	
RMSEA (Root Mean Square Error of Approximation)	RMSEA<0.06	
SRMR (Standardized Root Mean Square Residual)	SRMR<0.08	

3.5 Ethical Considerations

Ethical considerations were carefully addressed throughout the research process to ensure the protection of participants and the integrity of the study. Participation in the survey was entirely voluntary, and respondents were informed of the academic purpose of the study before completing the questionnaire. At the beginning of the survey, participants were provided with a brief statement explaining the nature of the research, the type of information being collected, and their right to withdraw at any time without consequence.

To safeguard confidentiality and anonymity, no personally identifiable information was collected from respondents. All responses were recorded in an aggregated form and used solely for academic analysis. Access to the collected data was restricted to the research process, and the data were stored securely to prevent unauthorized use. The study design ensured that individual responses could not be traced back to specific participants or institutions.

In addition, the content of the questionnaire avoided sensitive or intrusive questions and focused on professional experiences related to administrative work, technology use, and organizational practices. The study complied with relevant ethical guidelines for social science research and adhered to principles of informed consent, confidentiality, and responsible data handling throughout the data collection and analysis stages.

3.6 Conclusion

This chapter has outlined the methodological framework adopted to examine the relationships among generative AI literacy, dynamic capabilities, knowledge sharing participation, organizational structure, and innovation in vocational colleges. Grounded in a positivist research paradigm, the study employed a quantitative research design that aligns with the objective of testing hypothesized relationships among clearly defined latent constructs. The chapter detailed the operationalization of key variables, the adaptation of established measurement scales, and the procedures used to ensure measurement rigor through reliability and validity assessment.

In addition, this chapter described the target population, sampling strategy, data collection procedures, and analytical techniques applied in the study. The use of structural equation modeling provided a systematic approach for evaluating direct, mediating, and moderating effects within the proposed conceptual framework. Ethical considerations were also addressed to ensure responsible research conduct. Collectively, the methodological choices presented in this chapter establish a robust empirical foundation for the subsequent presentation and interpretation of the research findings.

CHAPTER 4
RESULTS

This chapter presents the empirical analysis of the study by examining the measurement quality and structural relationships of the proposed research framework. The analysis first describes the characteristics of the sample and the distribution patterns of the core variables in order to provide an overview of the respondents and the overall data structure. It then evaluates the reliability and validity of the measurement model through confirmatory factor analysis, including the assessment of model fit, convergent validity, and discriminant validity. Building upon the validated measurement framework, the chapter further investigates the structural relationships among generative AI literacy, dynamic capabilities, AI knowledge sharing participation, organization structure, and innovation performance in vocational colleges. The analysis subsequently examines the direct effects, mediating mechanisms, and moderating effects proposed in the hypotheses to verify the theoretical relationships established in the study. The empirical findings provide evidence for understanding how generative AI-related competencies contribute to administrative innovation within vocational colleges under different organizational conditions.

4.1 Descriptive Analysis

4.1.1 Sample Characteristics

Table 4.1 presents the demographic and professional profile of the 765 valid respondents. In terms of gender, the sample included 394 male respondents, accounting for 51.5%, and 371 female respondents, accounting for 48.5%. This distribution indicates a relatively balanced gender composition and reduces the possibility that the sample characteristics are dominated by a single gender group.

The age structure showed that respondents were mainly concentrated in the middle-career stage. The largest group was aged 26–35 years, accounting for 37.4%, followed by those aged 36–45 years, accounting for 28.4%. Respondents aged 25 years old or below accounted for 15.7%, while those aged 46–55 years and 56 years old or above accounted

for 12.2% and 6.4%, respectively. This pattern indicates that the sample mainly consisted of administratively active staff with sufficient work exposure and organizational experience, which helps ensure that respondents were capable of evaluating generative AI use, administrative processes, and innovation performance in vocational colleges.

Regarding departmental distribution, the respondents covered major administrative functions in vocational colleges. Student affairs accounted for the largest proportion, at 19.9%, followed by academic affairs at 14.8%, enrollment and employment services at 14.5%, and information technology or digital administration at 13.3%. Other departments, including finance, human resources, general administration, research administration, logistics and asset management, and external cooperation, were also represented. This distribution strengthens the relevance of the sample because generative AI use and administrative innovation are not limited to a single office but are embedded across multiple functional units.

The educational background of the respondents also showed an appropriate level of academic preparation. Bachelor's degree holders formed the largest group, accounting for 44.4%, followed by master's degree holders at 23.7%. Respondents with an associate degree or below accounted for 21.7%, while doctoral degree holders accounted for 10.2%. This structure indicates that most respondents possessed sufficient educational capacity to understand the questionnaire items and evaluate AI-related administrative practices.

In terms of generative AI use, 45.1% of respondents reported occasional use, while 30.3% reported using generative AI sometimes. Respondents who used generative AI frequently and very frequently accounted for 13.2% and 11.4%, respectively. This distribution suggests that generative AI had already entered administrative work in vocational colleges, although its use remained uneven. The sample therefore provides an appropriate empirical basis for examining how different levels of generative AI literacy influence dynamic capabilities, AI knowledge sharing participation, and innovation performance.

The regional distribution showed that 49.9% of respondents came from Liaoning, 30.7% from Jilin, and 19.3% from Heilongjiang. This structure reflects the research focus on vocational colleges in Northeastern China and captures regional differences within the target area. In terms of institutional type, public vocational colleges accounted for 62.2%,

while private vocational colleges accounted for 37.8%, indicating that the sample included both major organizational forms of vocational education institutions.

The position-level structure further demonstrated the suitability of the sample. General administrative staff accounted for 56.2%, section-level administrators accounted for 28.5%, department-level administrators accounted for 10.6%, and senior administrators accounted for 4.7%. This composition captures both frontline administrative experience and managerial perspectives. In terms of work experience, most respondents had worked for more than one year, with 32.9% having 1–2 years of experience, 25.2% having 3–5 years, and 27.6% having 6–10 years. This experience structure supports the reliability of the responses because most participants had sufficient familiarity with administrative routines, organizational structure, and innovation-related practices in vocational colleges.

Table 4.1 Sample Information

Category	Item	N	%
Gender	Male	394	51.5
	Female	371	48.5
Age	25 years old or below	120	15.7
	26–35 years old	286	37.4
	36–45 years old	217	28.4
	46–55 years old	93	12.2
	56 years old or above	49	6.4
Department	Academic affairs	113	14.8
	Student affairs	152	19.9
	Human resources	56	7.3
	Finance	69	9
	Information technology / digital administration	102	13.3
	General administration / office affairs	57	7.5
	Enrollment and employment services	111	14.5

Table 4.1 (continued)

Category	Item	N	%
	Scientific research administration	31	4.1
	Logistics and asset management	44	5.8
	External cooperation / school-enterprise cooperation	30	3.9
Education Level	Associate degree or below	166	21.7
	Bachelor's degree	340	44.4
	Master's degree	181	23.7
	Doctoral degree	78	10.2
Frequency of Generative AI Use	Occasionally	345	45.1
	Sometimes	232	30.3
	Frequently	101	13.2
	Very frequently	87	11.4
Main Administrative Function Supported by Generative AI	1	240	31.4
	2	109	14.2
	3	62	8.1
	4	103	13.5
	5	27	3.5
	6	72	9.4
	7	20	2.6
	8	66	8.6
	9	28	3.7
	10	38	5
Province	Liaoning	382	49.9
	Jilin	235	30.7
	Heilongjiang	148	19.3
Type of Vocational College	Public vocational college	476	62.2
	Private vocational college	289	37.8

Table 4.1 (continued)

Category	Item	N	%
Position Level	General administrative staff	430	56.2
	Section-level administrator	218	28.5
	Department-level administrator	81	10.6
	Senior administrator	36	4.7
Work Experience	Less than 1 year	43	5.6
	1–2 years	252	32.9
	3–5 years	193	25.2
	6–10 years	211	27.6
	More than 10 years	66	8.6

4.1.2 Descriptive Statistics

Table 4.2 presents the descriptive statistics results for all measurement items, including mean, standard deviation, skewness, and kurtosis. Descriptive statistical analysis helps evaluate respondents' overall perceptions of the study variables and provides preliminary evidence regarding data distribution characteristics before conducting structural equation modeling analysis. The mean values of all items were generally above the midpoint of the five-point Likert scale, indicating that respondents demonstrated relatively positive perceptions toward generative AI literacy, dynamic capabilities, AI knowledge sharing participation, organization structure, and innovation performance in vocational colleges.

For generative AI literacy, the mean values ranged from 3.306 to 3.525, indicating a moderate to relatively positive level of AI-related competence among administrative staff in vocational colleges. Among these items, GA4 reported the highest mean value of 3.525, suggesting that respondents showed comparatively stronger confidence in designing prompts based on administrative task requirements. In contrast, GA8 recorded the lowest mean value of 3.306, implying that respondents demonstrated relatively weaker confidence in evaluating the consistency and coherence of AI-generated outputs in administrative processes. These findings indicate that vocational college administrative staff were generally capable of using generative AI tools, although higher-order evaluative and analytical competencies still require further strengthening.

The dynamic capabilities construct reported relatively high mean values, ranging from 3.421 to 3.830. Items related to organizational adjustment and implementation capability, such as DC13 and DC15, achieved comparatively high mean values, reflecting that vocational colleges demonstrated relatively strong confidence in sustaining administrative change initiatives and coordinating change with routine operations. However, DC6 and DC10 showed comparatively lower mean values, suggesting that the ability to identify environmental changes and translate information into improved administrative procedures still faced certain limitations. This pattern indicates that vocational colleges have established a relatively stable administrative adaptation mechanism, although gaps remain in proactive sensing and knowledge transformation capabilities.

The descriptive results for organization structure showed mean values ranging from 3.473 to 3.757, indicating that respondents generally perceived vocational colleges as having relatively formalized and centralized administrative structures. Higher mean values for OS5 to OS9 suggest that decision-making authority concerning budgets, major changes, and resource allocation remained concentrated at the senior management level. Meanwhile, the comparatively lower mean values for OS2 and OS4 imply that procedural consistency and formal sanction mechanisms were perceived less strongly than centralized decision control. These findings reflect the institutional characteristics of vocational colleges, where administrative coordination relies heavily on hierarchical governance structures.

AI knowledge sharing participation demonstrated relatively positive results, with mean values ranging from 3.516 to 3.957. The highest mean value was observed for KS7, indicating that respondents perceived relatively strong support from colleagues when requesting AI-related assistance or practical experience. Similarly, KS4 and KS5 also achieved high mean values, suggesting that respondents actively engaged in sharing AI-related resources and skills within administrative networks. By contrast, KS3 reported the lowest mean value, indicating that although AI-related knowledge exchange occurred frequently, the normalization of AI knowledge sharing culture had not yet been fully institutionalized across vocational colleges.

Innovation performance in vocational colleges also demonstrated generally positive perceptions. The mean values ranged from 3.254 to 4.018, with IV22 recording

the highest mean value. This finding suggests that respondents demonstrated relatively strong willingness to present or communicate innovation outcomes to broader audiences. Items associated with reflection, collaboration, and implementation monitoring also achieved relatively high mean values, indicating that innovation activities in vocational colleges extended beyond idea generation and included continuous refinement and coordination processes. However, IV13 reported the lowest mean value, implying that respondents showed relatively weaker confidence in identifying unintended consequences during innovation implementation. This pattern suggests that vocational colleges placed greater emphasis on promoting and communicating innovation outcomes than on evaluating potential risks and unintended implementation effects.

The skewness values of all items ranged approximately between -1.021 and 0.036, while kurtosis values remained within acceptable ranges. Most skewness values were negative, indicating that respondents tended to provide relatively high evaluations for the study variables. At the same time, the kurtosis values did not exceed critical thresholds, suggesting that the data distributions did not exhibit serious non-normality problems. These results indicate that the dataset satisfied the preliminary assumptions required for subsequent confirmatory factor analysis and structural equation modeling.

Table 4.2 Descriptive Statistics Results

Study Variables	Items	N	Mean	Std. Deviation	Skewness	Kurtosis
Generative AI Literacy (GA)	GA1	765	3.327	1.14	-0.069	-1.001
	GA2	765	3.323	1.15	-0.152	-0.974
	GA3	765	3.399	1.164	-0.103	-1.236
	GA4	765	3.525	1.183	-0.325	-0.989
	GA5	765	3.38	1.076	-0.156	-0.88
	GA6	765	3.417	1.131	-0.342	-0.837
	GA7	765	3.353	1.165	-0.192	-1.077
	GA8	765	3.306	1.111	0.036	-1.17
	GA9	765	3.37	1.188	-0.224	-1.042
	GA10	765	3.331	1.165	-0.089	-1.004
	GA11	765	3.404	1.205	-0.234	-1.019

Table 4.2 (continued)

Study Variables	Items	N	Mean	Std. Deviation	Skewness	Kurtosis
	GA12	765	3.344	1.257	-0.142	-1.2
	GA13	765	3.384	1.178	-0.106	-1.115
	GA14	765	3.333	1.175	-0.058	-1.169
	GA15	765	3.383	1.139	-0.198	-0.967
	GA16	765	3.448	1.139	-0.189	-0.998
	GA17	765	3.441	1.166	-0.201	-1.038
Dynamic Capabilities	DC1	765	3.729	1.087	-0.452	-0.603
(DC)	DC2	765	3.672	1.214	-0.521	-0.758
	DC3	765	3.68	1.102	-0.517	-0.383
	DC4	765	3.644	1.063	-0.368	-0.699
	DC5	765	3.665	1.123	-0.592	-0.315
	DC6	765	3.421	1.175	-0.135	-0.975
	DC7	765	3.546	1.255	-0.346	-1.188
	DC8	765	3.613	1.201	-0.391	-0.971
	DC9	765	3.612	1.226	-0.395	-1.085
	DC10	765	3.464	1.216	-0.231	-1.05
	DC11	765	3.741	0.999	-0.766	0.462
	DC12	765	3.658	1.226	-0.88	-0.041
	DC13	765	3.817	1.18	-1.021	0.275
	DC14	765	3.689	1.163	-0.945	0.256
	DC15	765	3.83	1.152	-0.937	0.249
Organization Structure	OS1	765	3.561	1.211	-0.422	-0.791
(OS)	OS2	765	3.473	1.138	-0.236	-0.842
	OS3	765	3.558	1.268	-0.494	-0.824
	OS4	765	3.501	1.177	-0.301	-0.83
	OS5	765	3.705	1.07	-0.868	0.414
	OS6	765	3.757	1.052	-0.809	0.301
	OS7	765	3.724	0.995	-0.8	0.53
	OS8	765	3.752	1.008	-0.731	0.375
	OS9	765	3.75	1.146	-0.798	0.09

Table 4.2 (continued)

Study Variables	Items	N	Mean	Std. Deviation	Skewness	Kurtosis
AI Knowledge Sharing Participation (KS)	KS1	765	3.652	1.07	-0.339	-0.672
	KS2	765	3.605	1.195	-0.402	-0.904
	KS3	765	3.516	1.09	-0.413	-0.437
	KS4	765	3.929	1.121	-0.716	-0.698
	KS5	765	3.919	1.146	-0.773	-0.543
	KS6	765	3.856	1.115	-0.645	-0.658
	KS7	765	3.957	1.055	-0.78	-0.232
Innovation Performance in Vocational Colleges (IV)	IV1	765	3.899	1.027	-0.54	-0.55
	IV2	765	3.851	1.163	-0.724	-0.398
	IV3	765	3.827	1.049	-0.632	-0.173
	IV4	765	3.818	1.005	-0.444	-0.626
	IV5	765	3.817	1.083	-0.728	-0.025
	IV6	765	3.563	1.25	-0.368	-1.154
	IV7	765	3.308	1.132	-0.024	-0.947
	IV8	765	3.61	1.192	-0.361	-1.015
	IV9	765	3.655	1.22	-0.423	-1.057
	IV10	765	3.378	1.197	-0.213	-0.966
	IV11	765	3.375	1.221	-0.158	-1.147
	IV12	765	3.331	1.147	-0.014	-1.176
	IV13	765	3.254	1.125	-0.002	-0.961
	IV14	765	3.352	1.133	-0.163	-0.838
	IV15	765	3.407	1.152	-0.103	-1.174
	IV16	765	3.771	0.991	-0.709	0.33
	IV17	765	3.706	1.206	-0.893	0.063
	IV18	765	3.818	1.002	-0.396	-0.614
	IV19	765	3.8	1.107	-0.574	-0.565
	IV20	765	3.778	0.995	-0.527	-0.151
	IV21	765	3.685	1.03	-0.442	-0.465
	IV22	765	4.018	1.033	-0.736	-0.545

4.2 Confirmatory Factor Analysis

4.2.1 Measurement Model and Fit Metrics

Confirmatory factor analysis was conducted to evaluate the measurement model and examine the overall goodness-of-fit between the proposed theoretical framework and the observed data. Measurement model assessment plays an essential role in structural equation modeling because it verifies whether the observed indicators adequately represent their corresponding latent constructs and whether the theoretical structure is empirically acceptable. The analysis incorporated the major constructs of generative AI literacy, dynamic capabilities, AI knowledge sharing participation, organization structure, and innovation performance in vocational colleges.

The measurement model fit results are presented in Table 4.3. The chi-square to degrees of freedom ratio was 2.173, which was below the recommended threshold of 3, indicating an acceptable overall model fit. The RMSEA value was 0.039, which was substantially lower than the recommended maximum value of 0.08, suggesting that the model achieved a satisfactory approximation fit and exhibited relatively small residual errors between the observed covariance matrix and the estimated covariance matrix.

The incremental and absolute fit indices also demonstrated satisfactory performance. The GFI and AGFI values reached 0.965 and 0.951, respectively, both exceeding the recommended criterion of 0.90. These results indicate that the proposed measurement model explained a substantial proportion of the variance and covariance in the observed data. In addition, the NFI, IFI, TLI, and CFI values were 0.967, 0.982, 0.977, and 0.982, respectively, all exceeding the recommended threshold of 0.90. These findings demonstrate that the proposed model achieved strong comparative and incremental fit relative to the null model.

Table 4.3 Measure Model Fit Metrics

Fit index	χ^2/df	RMSEA	GFI	AGFI	NFI	IFI	TLI	CFI
Reference standards	<3	<0.08	>0.9	>0.9	>0.9	>0.9	>0.9	>0.9
Result	2.173	0.039	0.965	0.951	0.967	0.982	0.977	0.982

4.2.2 Convergent Validity

Convergent validity analysis was conducted to examine whether the observed indicators could effectively represent their corresponding latent constructs. Convergent validity reflects the extent to which multiple indicators measuring the same construct share a high proportion of common variance. This assessment generally relies on factor loading, composite reliability, and average variance extracted values. Previous studies commonly recommend that standardized factor loadings should exceed 0.60, CR values should remain above 0.70, and AVE values should exceed 0.50 in order to demonstrate satisfactory convergent validity.

The results presented in Table 4.4 indicate that all standardized factor loadings exceeded the recommended threshold of 0.60. Most factor loadings were above 0.70, demonstrating strong relationships between the observed indicators and their corresponding latent constructs. Within generative AI literacy, the dimensions of prompt engineering ability, quality evaluation ability, and innovative application ability reported relatively high factor loadings, indicating that respondents could clearly distinguish AI-related operational, evaluative, and application-oriented competencies in administrative contexts. In particular, GA8 and GA10 demonstrated comparatively strong loadings, suggesting that the abilities to evaluate AI-generated outputs and identify innovative AI application opportunities represented important aspects of generative AI literacy in vocational colleges.

The composite reliability values of all constructs ranged from 0.797 to 0.905, substantially exceeding the recommended criterion of 0.70. These findings indicate that the constructs achieved satisfactory internal consistency and measurement stability. Dynamic capabilities reported particularly strong CR values across the sensing, seizing, and transforming dimensions, indicating that vocational colleges maintained relatively consistent organizational adaptation and change-management capacities. Similarly, the dimensions of innovation performance in vocational colleges also demonstrated high reliability, suggesting that idea generation, promotion, realization, and sustainability collectively formed a coherent innovation performance structure.

The AVE values of all constructs ranged from 0.552 to 0.704, all exceeding the recommended threshold of 0.50. These results indicate that each latent construct explained more than half of the variance in its observed indicators. Among the constructs, knowledge

inbound sharing achieved the highest AVE value of 0.704, implying that inbound AI-related knowledge exchange behaviors exhibited particularly strong explanatory power within the measurement framework. The AVE values of the innovation performance dimensions also remained above acceptable standards, demonstrating that the measurement items effectively captured different stages of administrative innovation activities in vocational colleges.

The convergent validity results therefore provide strong empirical support for the adequacy of the measurement model. The observed indicators demonstrated satisfactory representativeness, reliability, and explanatory power for their corresponding latent constructs. These findings confirm that the proposed measurement framework effectively operationalized the theoretical concepts of generative AI literacy, dynamic capabilities, AI knowledge sharing participation, organization structure, and innovation performance in vocational colleges, thereby providing a reliable basis for subsequent discriminant validity testing and structural model analysis.

Table 4.4 Convergence Validity

Variable		Item	Factor Loading	CR	AVE
Generative AI Literacy	Basic Operational Skills	GA1	0.712	0.836	0.63
		GA2	0.819		
		GA3	0.844		
	Prompt Engineering Ability	GA4	0.851	0.848	0.651
		GA5	0.809		
		GA6	0.758		
	Quality Evaluation Ability	GA7	0.765	0.854	0.662
		GA8	0.886		
		GA9	0.784		
	Innovative Application Ability	GA10	0.886	0.863	0.678
		GA11	0.798		
		GA12	0.783		

Table 4.4 (continued)

	Variable	Item	Factor Loading	CR	AVE
	Compliance and Ethical Awareness	GA13	0.802	0.876	0.586
		GA14	0.763		
		GA15	0.762		
		GA16	0.687		
		GA17	0.806		
Dynamic Capabilities	Sensing	DC1	0.817	0.895	0.586
		DC2	0.75		
		DC3	0.75		
		DC4	0.78		
		DC5	0.724		
		DC6	0.77		
	Seizing	DC7	0.809	0.887	0.662
		DC8	0.813		
		DC9	0.825		
		DC10	0.807		
	Transforming	DC11	0.789	0.875	0.585
		DC12	0.759		
		DC13	0.738		
		DC14	0.793		
		DC15	0.742		
AI Knowledge Sharing Participation	Knowledge Outbound Sharing	KS1	0.814	0.797	0.569
		KS2	0.772		
		KS3	0.669		
	Knowledge Inbound Sharing	KS4	0.852	0.904	0.704
		KS5	0.856		
		KS6	0.883		
		KS7	0.759		

Table 4.4 (continued)

Variable		Item	Factor Loading	CR	AVE
Organization Structure	Organization Structure	OS1	0.786	0.869	0.624
		OS2	0.725		
		OS3	0.841		
		OS4	0.804		
	Organization Structure	OS5	0.878	0.89	0.619
		OS6	0.819		
		OS7	0.743		
		OS8	0.719		
		OS9	0.766		
Innovation Performance in Vocational Colleges	Idea Generation	IV1	0.801	0.86	0.552
		IV2	0.742		
		IV3	0.74		
		IV4	0.738		
		IV5	0.688		
	Idea Promotion	IV6	0.856	0.905	0.613
		IV7	0.775		
		IV8	0.768		
		IV9	0.815		
		IV10	0.72		
		IV11	0.757		
	Idea Realization	IV12	0.787	0.881	0.553
		IV13	0.749		
		IV14	0.706		
		IV15	0.706		
		IV16	0.758		
		IV17	0.754		

Table 4.4 (continued)

Variable	Item	Factor Loading	CR	AVE
Idea Sustainability	IV18	0.798	0.873	0.581
	IV19	0.822		
	IV20	0.688		
	IV21	0.718		
	IV22	0.777		

4.2.3 Discriminant Validity

Discriminant validity analysis was conducted to examine whether the latent constructs in the study were empirically distinct from one another. Discriminant validity reflects the extent to which a construct captures phenomena that are different from other constructs within the theoretical model. This assessment helps ensure that the measurement framework avoids conceptual overlap and that each latent construct maintains sufficient uniqueness. Following the Fornell-Larcker criterion, discriminant validity is considered acceptable when the square root of the AVE value for each construct exceeds its correlations with other constructs.

The results presented in Table 4.5 demonstrate satisfactory discriminant validity across all constructs and dimensions. The diagonal values in the correlation matrix represent the square root of the AVE for each latent construct, while the off-diagonal values represent inter-construct correlations. In all cases, the square root of the AVE exceeded the corresponding correlation coefficients, indicating that each construct explained more variance in its own indicators than in other constructs. These findings confirm that the constructs retained sufficient conceptual distinctiveness within the measurement framework.

Within the dimensions of generative AI literacy, moderate positive correlations were observed among basic operational skills, prompt engineering ability, quality evaluation ability, innovative application ability, and compliance and ethical awareness. Although these dimensions were theoretically related, the discriminant validity results indicate that each dimension captured a unique aspect of generative AI literacy. For example, innovative application ability demonstrated relatively strong correlations with

idea promotion and idea sustainability, suggesting that proactive AI experimentation contributes substantially to administrative innovation activities. However, the square root of its AVE remained higher than these correlations, supporting its empirical independence.

The dimensions of dynamic capabilities also demonstrated appropriate discriminant validity. Sensing, seizing, and transforming exhibited moderate interrelationships, reflecting the sequential and complementary nature of organizational adaptation processes. Nevertheless, the AVE square root values for each dimension exceeded their cross-correlations, indicating that each capability dimension represented a distinct organizational function rather than a redundant measurement category. This finding supports the theoretical assumption that vocational colleges rely on differentiated processes to identify opportunities, mobilize resources, and adjust administrative routines.

For AI knowledge sharing participation, knowledge outbound sharing and knowledge inbound sharing reported a relatively strong correlation coefficient of 0.581, indicating active reciprocal knowledge exchange among administrative staff. However, the AVE square root values of both constructs remained higher than their inter-correlation, demonstrating that outbound and inbound sharing behaviors represented different forms of AI-related knowledge participation. Similarly, the two dimensions of organization structure, namely level of formalization and level of centralization, maintained acceptable discriminant validity despite their institutional association within vocational colleges.

The dimensions of innovation performance in vocational colleges also exhibited satisfactory discriminant validity. Idea generation, idea promotion, idea realization, and idea sustainability demonstrated positive correlations, reflecting the interconnected nature of innovation processes. Among these relationships, idea promotion and idea sustainability reported relatively stronger associations, suggesting that the dissemination and long-term maintenance of innovative practices are closely linked within vocational college administration. Nevertheless, the AVE square root values for all innovation dimensions exceeded the corresponding correlation coefficients, confirming that each dimension represented a unique stage of innovation performance.

Table 4.5 Discriminant Validity Test

	BOS	PEA	QEA	IAA	CEA	Sensing	Seizing	Transforming	KOS	KIS	LF	LC	IG	IP	IR	IS
BOS	**0.794**															
PEA	.498**	**0.807**														
QEA	.484**	.490**	**0.814**													
IAA	.521**	.500**	.454**	**0.823**												
CEA	.478**	.430**	.404**	.486**	**0.766**											
Sensing	.357**	.413**	.395**	.405**	.363**	**0.766**										
Seizing	.417**	.383**	.395**	.391**	.359**	.517**	**0.814**									
Transforming	.400**	.375**	.406**	.376**	.357**	.511**	.567**	**0.765**								
KOS	.443**	.441**	.410**	.413**	.424**	.279**	.328**	.291**	**0.754**							
KIS	.483**	.474**	.454**	.485**	.452**	.377**	.346**	.357**	.581**	**0.839**						
LF	.309**	.280**	.283**	.331**	.276**	.224**	.219**	.230**	.232**	.237**	**0.790**					
LC	.289**	.279**	.248**	.282**	.208**	.230**	.252**	.232**	.180**	.191**	.542**	**0.787**				
IG	.475**	.463**	.449**	.475**	.458**	.352**	.358**	.399**	.413**	.464**	.270**	.248**	**0.743**			
IP	.521**	.550**	.524**	.556**	.503**	.454**	.422**	.418**	.455**	.515**	.326**	.271**	.496**	**0.783**		
IR	.522**	.526**	.528**	.554**	.505**	.393**	.387**	.382**	.458**	.516**	.285**	.273**	.534**	.513**	**0.744**	
IS	.535**	.489**	.498**	.527**	.507**	.421**	.416**	.420**	.425**	.496**	.279**	.225**	.552**	.621**	.601**	**0.762**

Note: The abbreviations used in this table represent the following dimensions. BOS refers to basic operational skills, PEA denotes prompt engineering ability, QEA represents quality evaluation ability, IAA indicates innovative application ability, and CEA refers to compliance and ethical awareness under generative AI literacy. Sensing, seizing, and transforming are the three dimensions of dynamic capabilities. KOS refers to knowledge outbound sharing and KIS denotes knowledge inbound sharing under AI knowledge sharing participation. LF refers to level of formalization and LC denotes level of centralization under organization structure. IG refers to idea generation, IP denotes idea promotion, IR represents idea realization, and IS indicates idea sustainability under innovation performance in vocational colleges. ** indicates significance at the 0.01 level.

4.3 Structural Model Path Analysis

4.3.1 Model Fit Metrics for the Structural Model

After confirming the adequacy of the measurement model, structural equation modeling was conducted to evaluate the overall fit of the proposed structural model and examine the relationships among generative AI literacy, dynamic capabilities, AI knowledge sharing participation, organization structure, and innovation performance in vocational colleges. Structural model assessment helps determine whether the proposed theoretical framework can adequately explain the observed covariance relationships among latent constructs and whether the hypothesized paths are empirically acceptable.

The structural model fit results are presented in Table 4.6. The chi-square to degrees of freedom ratio was 1.343, which was substantially lower than the recommended threshold of 3, indicating a strong overall fit between the theoretical model and the observed data. The RMSEA value reached 0.021, remaining well below the recommended criterion of 0.08. This result suggests that the structural model achieved a high degree of approximation accuracy and that the residual differences between the observed and estimated covariance matrices were minimal.

The absolute and incremental fit indices also demonstrated satisfactory performance. The GFI and AGFI values were 0.913 and 0.905, respectively, both exceeding the recommended threshold of 0.90. These findings indicate that the proposed structural model effectively explained the variance-covariance structure of the observed data. In addition, the NFI, TLI, and CFI values were 0.921, 0.977, and 0.978, respectively, all surpassing the recommended criterion of 0.90. The strong performance of these indices demonstrates that the proposed structural model achieved substantial improvement over the null model and maintained high explanatory capability.

Compared with the measurement model, the structural model continued to maintain satisfactory fit across all major evaluation indices, indicating that the theoretical relationships among the latent constructs were empirically supported. The results therefore confirm the appropriateness of the proposed conceptual framework and provide a reliable statistical foundation for subsequent hypothesis testing, mediation analysis, and moderation effect analysis.

Table 4.6 Model Fit Metrics

Fit index	χ^2/df	RMSEA	GFI	AGFI	NFI	TLI	CFI
Reference standards	<3	<0.08	>0.9	>0.9	>0.9	>0.9	>0.9
Result	1.343	0.021	0.913	0.905	0.921	0.977	0.978

4.3.2 Path Analysis for Direct Effects

Figure 4.1 presents the structural relationships among generative AI literacy, dynamic capabilities, AI knowledge sharing participation, organization structure, and innovation performance in vocational colleges. The figure illustrates that the five dimensions of generative AI literacy, including basic operational skills, prompt engineering ability, quality evaluation ability, innovative application ability, and compliance and ethical awareness, all exerted positive influences on both dynamic capabilities and AI knowledge sharing participation. In addition, these dimensions also directly influenced innovation performance in vocational colleges. The structural model further shows that dynamic capabilities and AI knowledge sharing participation acted as important organizational mechanisms linking generative AI literacy with innovation outcomes.

From the structural paths displayed in Figure 4.1, generative AI literacy demonstrated a multidimensional influence pattern. The relationships among the five AI literacy dimensions indicate that these competencies were closely interconnected rather than isolated technical abilities. At the same time, the paths from dynamic capabilities and AI knowledge sharing participation to innovation performance suggest that organizational adaptation and collaborative knowledge exchange played essential roles in transforming individual AI-related competencies into administrative innovation outcomes. The structural model therefore reflects a process in which generative AI literacy strengthens organizational learning, promotes knowledge circulation, and ultimately enhances innovation performance within vocational colleges.

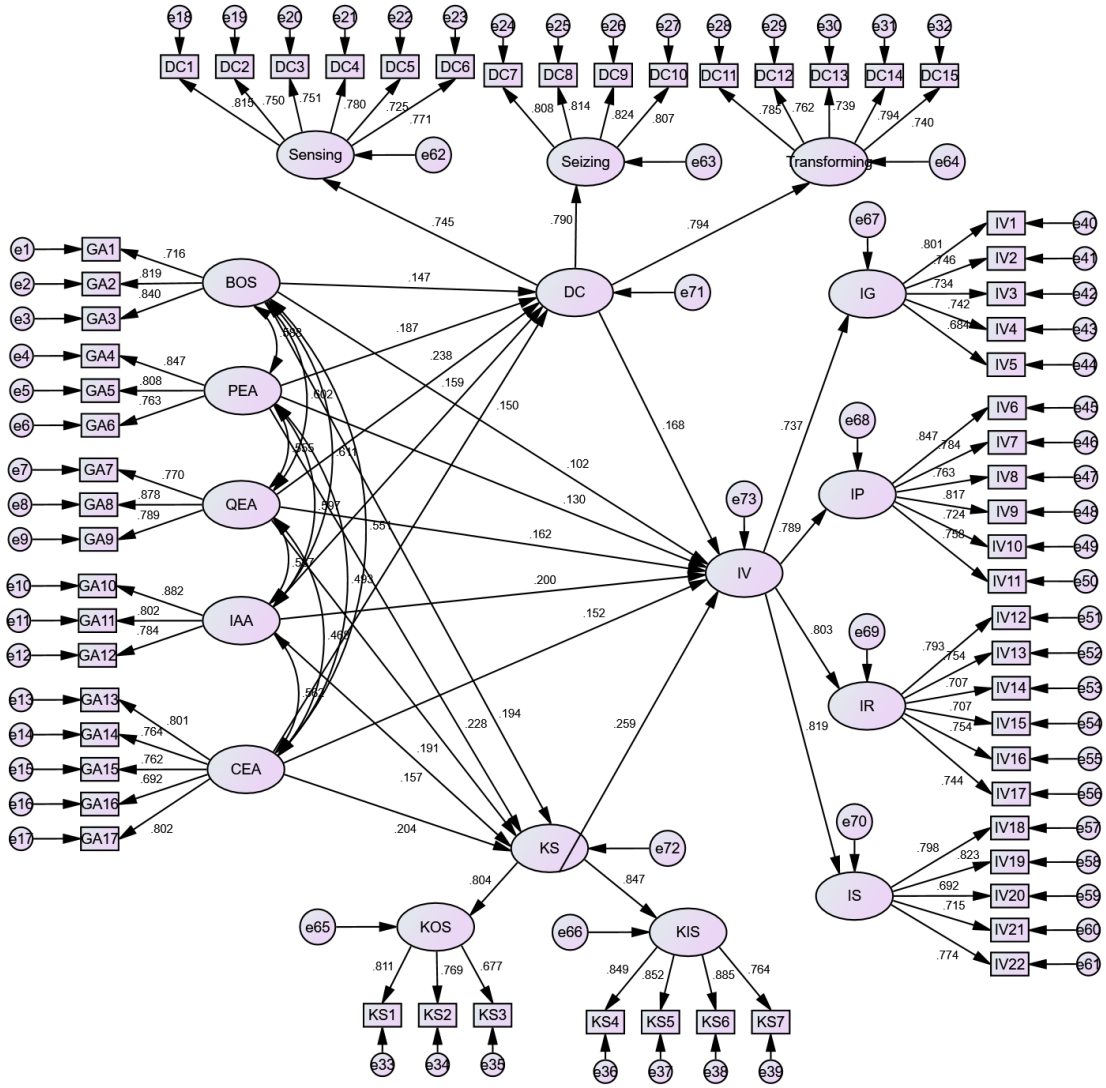


Figure 4.1 Structural model

The direct path results presented in Table 4.7 further provide statistical evidence supporting the proposed hypotheses. The findings show that all five dimensions of generative AI literacy significantly and positively influenced dynamic capabilities. Basic operational skills positively affected dynamic capabilities with a coefficient of 0.147, while prompt engineering ability demonstrated a stronger effect of 0.187. Among these relationships, quality evaluation ability produced the strongest positive influence on dynamic capabilities, with a coefficient of 0.238, indicating that the capability to critically assess AI-generated outputs plays a particularly important role in supporting organizational adaptation and administrative adjustment. Innovative application ability and compliance and ethical awareness also demonstrated significant positive effects,

suggesting that both exploratory AI use and responsible AI practices contribute to strengthening organizational responsiveness within vocational colleges.

The results also indicate that all dimensions of generative AI literacy significantly enhanced AI knowledge sharing participation. Prompt engineering ability showed the strongest influence on AI knowledge sharing participation, with a coefficient of 0.228, followed by compliance and ethical awareness at 0.204 and basic operational skills at 0.194. These findings suggest that stronger AI-related competencies encourage administrative staff to participate more actively in sharing AI experiences, exchanging practical knowledge, and supporting collaborative learning processes. The positive effects of innovative application ability and quality evaluation ability further indicate that both experimentation and critical evaluation contribute to building AI-related knowledge-sharing networks within vocational colleges.

The structural model additionally confirms the important roles of dynamic capabilities and AI knowledge sharing participation in promoting innovation performance in vocational colleges. Dynamic capabilities positively influenced innovation performance with a coefficient of 0.168, indicating that organizational sensing, seizing, and transforming capabilities facilitate administrative innovation activities. AI knowledge sharing participation demonstrated an even stronger effect on innovation performance, with a coefficient of 0.259, suggesting that collaborative knowledge exchange represents a particularly important mechanism for strengthening innovation-related outcomes. This finding highlights the importance of collective learning and interdepartmental communication in supporting AI-enabled administrative innovation.

The direct effects of generative AI literacy on innovation performance were also statistically significant. Among these paths, innovative application ability demonstrated the strongest positive effect, with a coefficient of 0.200, indicating that the capability to transform AI-assisted ideas into practical administrative improvements serves as a critical driver of innovation performance. Quality evaluation ability also reported a relatively strong effect of 0.162, suggesting that critical evaluation of AI-generated content improves the effectiveness and reliability of innovation practices. Compliance and ethical awareness, prompt engineering ability, and basic operational skills likewise exerted significant positive effects on innovation performance. These findings indicate that generative AI literacy contributes not only indirectly through organizational mechanisms

but also directly through enhancing administrative creativity, implementation capability, and process improvement activities.

Table 4.7 Direct Path Effects

Hypothesis	Structural path	Effect value β	SE	CR	P	Results
H1a	BOS → DC	0.147	0.047	2.517	0.012	Supported
H1b	PEA → DC	0.187	0.035	3.484	***	Supported
H1c	QEA → DC	0.238	0.038	4.543	***	Supported
H1d	IAA → DC	0.159	0.035	2.89	0.004	Supported
H1e	CEA → DC	0.15	0.034	3.112	0.002	Supported
H2a	BOS → KS	0.194	0.048	3.433	***	Supported
H2b	PEA → KS	0.228	0.036	4.371	***	Supported
H2c	QEA → KS	0.191	0.039	3.828	***	Supported
H2d	IAA → KS	0.157	0.036	2.969	0.003	Supported
H2e	CEA → KS	0.204	0.035	4.341	***	Supported
H3	DC → IV	0.168	0.037	4.137	***	Supported
H4	KS → IV	0.259	0.046	4.9	***	Supported
H5a	BOS → IV	0.102	0.03	2.501	0.012	Supported
H5b	PEA → IV	0.13	0.024	3.353	***	Supported
H5c	QEA → IV	0.162	0.025	4.285	***	Supported
H5d	IAA → IV	0.2	0.023	5.122	***	Supported
H5e	CEA → IV	0.152	0.022	4.341	***	Supported

4.3.3 Path Analysis for Indirect Effects

To further examine the mediating mechanisms underlying the relationships between generative AI literacy and innovation performance in vocational colleges, bootstrap mediation analysis was conducted. The bootstrap method is widely used in structural equation modeling because it provides more robust estimates of indirect effects and avoids the normal distribution assumptions associated with traditional mediation testing procedures. In this study, the mediation analysis focused on the indirect effects of dynamic capabilities and AI knowledge sharing participation on the relationships between

the five dimensions of generative AI literacy and innovation performance in vocational colleges.

The results presented in Table 4.8 indicate that all indirect effects were statistically significant because the lower and upper bounds of the 95% confidence intervals did not include zero. These findings provide empirical support for all proposed mediation hypotheses and confirm that dynamic capabilities and AI knowledge sharing participation functioned as important explanatory mechanisms linking generative AI literacy with innovation performance.

The mediating effects of dynamic capabilities first demonstrate the organizational adaptation role of generative AI literacy. Quality evaluation ability produced the strongest indirect effect through dynamic capabilities, with an effect value of 0.040. This result suggests that the capability to critically evaluate AI-generated outputs strengthens innovation performance primarily by improving organizational sensing, resource mobilization, and administrative transformation processes. Prompt engineering ability also demonstrated a relatively strong indirect effect through dynamic capabilities, with a value of 0.032, indicating that the ability to formulate and refine prompts contributes to innovation by enhancing organizational adaptability and coordinated administrative adjustment. Innovative application ability, compliance and ethical awareness, and basic operational skills likewise produced significant indirect effects through dynamic capabilities. These findings collectively indicate that generative AI literacy supports innovation not only through direct individual competencies but also through strengthening broader organizational adaptation processes within vocational colleges.

The mediation analysis further confirms the important role of AI knowledge sharing participation. Among these paths, prompt engineering ability generated the strongest indirect effect through AI knowledge sharing participation, with an effect value of 0.059. This finding suggests that respondents possessing stronger prompt-related competencies were more likely to engage in collaborative AI knowledge exchange, which subsequently enhanced innovation performance. Compliance and ethical awareness also produced a relatively strong indirect effect through AI knowledge sharing participation, with a value of 0.053, indicating that responsible and compliant AI use facilitates trust-based communication and collaborative learning within administrative systems. Basic operational skills and quality evaluation ability similarly demonstrated significant

mediation effects through knowledge sharing participation, while innovative application ability also indirectly promoted innovation performance through enhanced AI-related interaction and collaborative exchange.

Comparing the two mediating mechanisms reveals that AI knowledge sharing participation generally produced stronger indirect effects than dynamic capabilities. This pattern suggests that collective knowledge exchange and collaborative learning processes may play a particularly important role in transforming generative AI competencies into administrative innovation outcomes within vocational colleges. While dynamic capabilities facilitate organizational adaptation and process reconfiguration, AI knowledge sharing participation appears to accelerate the dissemination, refinement, and institutionalization of AI-assisted administrative practices.

The mediation analysis therefore provides important theoretical and empirical implications. The findings confirm that the influence of generative AI literacy on innovation performance does not operate solely through direct technological competence. Instead, organizational learning processes, adaptive capabilities, and collaborative knowledge-sharing mechanisms jointly shape how AI-related competencies are translated into sustained administrative innovation within vocational colleges.

Table 4.8 Indirect Effect Bootstrap Analysis

Hypothesis	Mediation path	Effect value	SE	Lower 95% CI	Upper 95% CI	Results
H7a	BOS → DC → IV	0.025	0.011	0.006	0.052	Supported
H7b	PEA → DC → IV	0.032	0.012	0.012	0.06	Supported
H7c	QEA → DC → IV	0.04	0.012	0.02	0.067	Supported
H7d	IAA → DC → IV	0.027	0.011	0.009	0.053	Supported
H7e	CEA → DC → IV	0.025	0.01	0.009	0.049	Supported
H8a	BOS → KS → IV	0.05	0.018	0.02	0.092	Supported
H8b	PEA → KS → IV	0.059	0.019	0.029	0.103	Supported
H8c	QEA → KS → IV	0.049	0.016	0.023	0.088	Supported
H8d	IAA → KS → IV	0.041	0.017	0.01	0.077	Supported
H8e	CEA → KS → IV	0.053	0.016	0.026	0.087	Supported

To further examine whether organization structure influences the relationships between generative AI literacy and innovation performance in vocational colleges, moderation analysis was conducted. Organization structure was conceptualized as an important contextual condition reflecting the levels of formalization and centralization within vocational colleges. The moderation analysis therefore aimed to determine whether organizational structural characteristics strengthen or weaken the influence of generative AI-related competencies on innovation outcomes.

The moderation results presented in Tables 4.9 to 4.13 indicate that all interaction terms between generative AI literacy dimensions and organization structure were statistically significant. These findings provide empirical support for hypotheses H6a to H6e and confirm that organization structure positively moderates the relationships between generative AI literacy and innovation performance in vocational colleges.

Table 4.9 shows that both basic operational skills and organization structure significantly influenced innovation performance. More importantly, the interaction term between basic operational skills and organization structure was statistically significant, with a coefficient of 0.123. This result indicates that organizational structures characterized by clearer procedures and stronger administrative coordination strengthen the positive contribution of basic operational skills to innovation performance. In other words, when vocational colleges maintain more structured administrative systems, operational AI competencies can be translated more effectively into administrative innovation activities.

Table 4.9 Moderation Effect of H6a

Predictor	β	p	Result
BOS → IV	0.542	0	Significant
OS → IV	0.171	0	Significant
BOS × OS	0.123	0	Moderation supported

The moderation results in Table 4.10 further demonstrate that organization structure significantly strengthened the relationship between prompt engineering ability and innovation performance. The interaction coefficient reached 0.147, indicating that formalized and coordinated organizational environments enhance the innovative value of

prompt-related competencies. This finding suggests that administrative staff are more capable of applying advanced AI interaction skills in innovative ways when organizational systems support communication, coordination, and procedural integration.

Table 4.10 Moderation Effect of H6b

Predictor	β	p	Result
PEA → IV	0.553	0	Significant
OS → IV	0.176	0	Significant
PEA × OS	0.147	0	Moderation supported

Table 4.11 reports the strongest moderation effect among all interaction paths, with the interaction term between quality evaluation ability and organization structure reaching 0.158. This result indicates that organizational structure plays a particularly important role in amplifying the innovative contribution of evaluative AI competencies. In vocational colleges with stronger structural support, administrative staff can more effectively incorporate evaluative judgments, feedback processes, and AI-assisted assessments into organizational innovation practices. This finding highlights the importance of institutional mechanisms that facilitate discussion, review, and collaborative refinement of AI-generated content.

Table 4.11 Moderation Effect of H6c

Predictor	β	p	Result
QEA → IV	0.532	0	Significant
OS → IV	0.192	0	Significant
QEA × OS	0.158	0	Moderation supported

The moderation analysis presented in Table 4.12 also confirms that organization structure significantly strengthened the relationship between innovative application ability and innovation performance. Although innovative application ability already demonstrated a relatively strong direct effect on innovation performance, the positive interaction coefficient of 0.121 suggests that organizational support further enhances the translation of exploratory AI use into practical innovation outcomes. Vocational colleges

with more supportive administrative structures appear better able to institutionalize AI-assisted experimentation and convert innovative practices into sustained administrative improvements.

Table 4.12 Moderation Effect of H6d

Predictor	β	p	Result
IAA → IV	0.581	0	Significant
OS → IV	0.144	0	Significant
IAA × OS	0.121	0	Moderation supported

Similarly, Table 4.13 demonstrates that organization structure positively moderated the relationship between compliance and ethical awareness and innovation performance. The interaction coefficient of 0.126 indicates that organizational structures emphasizing clear governance and administrative coordination strengthen the innovative contribution of ethical and compliant AI use. This finding suggests that formalized organizational systems help reduce uncertainty and resistance associated with AI adoption, thereby enabling responsible AI practices to coexist with administrative innovation activities.

Table 4.13 Moderation Effect of H6e

Predictor	β	p	Result
CEA → IV	0.535	0	Significant
OS → IV	0.209	0	Significant
CEA × OS	0.126	0	Moderation supported

4.4 Conclusion

This chapter presented the empirical results of the study. The measurement model and structural model both showed satisfactory fit, and the results of convergent validity and discriminant validity confirmed the reliability and validity of the measurement framework.

The direct path analysis indicated that all dimensions of generative AI literacy positively influenced dynamic capabilities, AI knowledge sharing participation, and

innovation performance in vocational colleges. Among these dimensions, innovative application ability and quality evaluation ability showed relatively stronger effects on innovation performance. The mediation analysis further showed that dynamic capabilities and AI knowledge sharing participation mediated the relationships between generative AI literacy and innovation performance. This finding indicates that generative AI literacy promotes innovation not only through direct competence effects, but also through organizational adaptation and AI-related knowledge exchange. The moderation analysis confirmed that organization structure strengthened the relationships between generative AI literacy and innovation performance. This suggests that clear procedures, coordinated governance, and supportive administrative structures help vocational colleges translate AI-related competencies into stronger innovation outcomes.

CHAPTER 5
DISCUSSION AND CONCLUSION

This chapter discusses the theoretical contributions, practical implications, limitations, and overall conclusions of the study based on the empirical findings presented in the previous chapter. The discussion first interprets the findings from the perspectives of dynamic capability theory, the knowledge-based view, and sociotechnical systems theory, highlighting how generative AI literacy contributes to innovation performance through organizational adaptation and knowledge-sharing processes within vocational colleges. The chapter then examines the practical implications for key stakeholders, including administrative staff, vocational college administrators, generative AI providers, and policy makers in vocational education, emphasizing how generative AI can be integrated more effectively into administrative innovation and institutional governance. Subsequently, the chapter identifies several limitations related to research design, sampling scope, and measurement approaches, while proposing directions for future research concerning longitudinal analysis, comparative studies, and broader organizational contexts. Finally, the chapter concludes by summarizing the overall findings of the study and reaffirming the importance of combining technological competencies, organizational learning, and adaptive governance in promoting sustainable administrative innovation in vocational colleges under digital transformation conditions.

RO1: To examine how generative AI literacy influences administrative staff's use of generative AI across different administrative functions and its impact on their innovation performance in vocational colleges in Northeastern China.

Research Objective 1 aimed to examine how generative AI literacy influences administrative staff's use of generative AI across different administrative functions and its impact on innovation performance in vocational colleges in Northeastern China. The empirical results directly respond to this objective from two aspects: first, the sample characteristics demonstrate that generative AI use had entered multiple administrative functions rather than remaining limited to technology-related departments; second, the

direct path results confirm that different dimensions of generative AI literacy significantly improved innovation performance in vocational colleges.

The descriptive results show that the respondents covered a broad range of administrative functions, including student affairs, academic affairs, enrollment and employment services, information technology and digital administration, finance, human resources, logistics, research administration, and school-enterprise cooperation. Among them, student affairs accounted for 19.9%, academic affairs for 14.8%, enrollment and employment services for 14.5%, and information technology or digital administration for 13.3%. This distribution indicates that generative AI was relevant not only to digital administration units but also to routine administrative departments that handle documentation, communication, coordination, service provision, and policy implementation. This finding responds to the first part of RO1 by showing that generative AI use had become functionally dispersed across vocational college administration.

The frequency of generative AI use further supports this interpretation. In the sample, 45.1% of respondents used generative AI occasionally, 30.3% used it sometimes, 13.2% used it frequently, and 11.4% used it very frequently. This pattern indicates that generative AI had already been adopted by a substantial proportion of administrative staff, but its use remained at a developing rather than fully mature stage. The relatively high proportion of occasional and sometimes users suggests that generative AI was being incorporated into administrative work, but stable and intensive use had not yet become a dominant practice. This result is consistent with studies emphasizing that AI adoption in educational organizations often begins with task-level assistance, such as document drafting, information summarization, and communication support, before developing into deeper organizational transformation.

The descriptive statistics of generative AI literacy further reveal the specific competence profile of administrative staff. The mean values of GA items ranged from 3.306 to 3.525, indicating a moderate level of generative AI literacy. GA4 recorded the highest mean value, suggesting that administrative staff showed relatively stronger confidence in designing prompts according to specific administrative task requirements. By contrast, GA8 reported the lowest mean value, indicating weaker confidence in evaluating the consistency and coherence of AI-generated outputs when applying them to administrative documents or processes. This difference suggests that administrative staff

were more comfortable with using generative AI as an input tool than with critically assessing output quality. Compared with prior studies that mainly emphasized digital literacy or AI adoption intention, this finding shows that generative AI literacy requires more than operational familiarity. It requires evaluative judgment, contextual adaptation, and content verification in formal administrative settings.

The direct path results provide stronger evidence for the second part of RO1 by confirming that all five dimensions of generative AI literacy significantly improved innovation performance in vocational colleges. Basic operational skills had a positive effect on innovation performance with $\beta = 0.102$ and $p = 0.012$. Prompt engineering ability had a positive effect with $\beta = 0.130$ and $p < 0.001$. Quality evaluation ability showed a stronger effect with $\beta = 0.162$ and $p < 0.001$. Innovative application ability produced the strongest direct effect with $\beta = 0.200$ and $p < 0.001$. Compliance and ethical awareness also had a significant positive effect with $\beta = 0.152$ and $p < 0.001$. These results indicate that generative AI literacy contributed to innovation performance in a differentiated manner, with higher-order application and evaluation abilities producing stronger effects than basic operational skills.

This finding is partly consistent with previous research suggesting that AI-related competence improves work performance and supports digital transformation in organizations. Studies such as those by Haleem et al. (2024) and Kong and Hu (2025) emphasized that operational competence in AI use can enhance task efficiency and administrative support. The present study confirms this view, as basic operational skills significantly promoted innovation performance. However, the relatively smaller coefficient of basic operational skills indicates that simple tool use is not the strongest driver of innovation. This result extends prior research by showing that administrative innovation depends more heavily on advanced AI literacy dimensions than on basic technical familiarity.

The strongest effect of innovative application ability provides an important distinction from earlier adoption-oriented studies. Previous research often treated AI use as a matter of acceptance, intention, or frequency (Tsao, 2025). The present result shows that the key issue is not whether administrative staff use generative AI, but whether they can transform AI-supported ideas into practical improvements in administrative responsibilities. This finding suggests that innovation performance is most strongly

enhanced when generative AI is used for process improvement, creative problem solving, and administrative outcome generation. Therefore, the study shifts the discussion from AI adoption to AI-enabled innovation capability.

Quality evaluation ability also showed a relatively strong effect on innovation performance. This result differs from studies that primarily highlight automation and efficiency gains from AI use. In vocational college administration, AI-generated content cannot be directly incorporated into formal work without accuracy checking, coherence assessment, and contextual judgment. The significant effect of quality evaluation ability indicates that innovation performance depends on the capacity to screen, refine, and validate AI outputs before applying them to administrative processes. This finding is particularly important in educational administration, where policy compliance, institutional accountability, and procedural accuracy are central requirements.

Compliance and ethical awareness also significantly enhanced innovation performance, which aligns with studies emphasizing responsible AI use and institutional governance. However, this study further shows that ethical awareness is not merely a risk-control factor. It also supports innovation by reducing uncertainty, strengthening trust in AI-assisted practices, and enabling administrative staff to apply generative AI within acceptable institutional boundaries. In the context of vocational colleges in Northeastern China, where administrative work is shaped by formal rules and centralized governance, responsible AI use becomes a necessary condition for sustaining innovation-oriented practices.

RO2: To investigate the mediating roles of dynamic capabilities and AI knowledge sharing participation as organizational processes through which generative AI literacy contributes to administrative staff's innovation performance in vocational colleges in Northeastern China.

Research Objective 2 aimed to investigate the mediating roles of dynamic capabilities and AI knowledge sharing participation as organizational processes through which generative AI literacy contributes to administrative staff's innovation performance in vocational colleges in Northeastern China. The empirical findings provide strong support for this objective by confirming that both dynamic capabilities and AI knowledge sharing participation significantly mediated the relationships between generative AI literacy and innovation performance. These results indicate that the influence of generative

AI literacy on innovation performance does not operate solely through individual competence, but also through organizational adaptation and collaborative knowledge exchange processes.

The direct path analysis first demonstrated that generative AI literacy significantly enhanced both dynamic capabilities and AI knowledge sharing participation. Among the effects on dynamic capabilities, quality evaluation ability showed the strongest influence with $\beta = 0.238$, followed by prompt engineering ability with $\beta = 0.187$. Innovative application ability, compliance and ethical awareness, and basic operational skills also produced significant positive effects. These findings suggest that administrative staff possessing stronger AI-related evaluation, prompting, and application competencies were more capable of supporting organizational sensing, coordination, and transformation processes within vocational colleges.

The results further revealed that generative AI literacy significantly strengthened AI knowledge sharing participation. Prompt engineering ability demonstrated the strongest effect on knowledge sharing participation with $\beta = 0.228$, followed by compliance and ethical awareness with $\beta = 0.204$ and basic operational skills with $\beta = 0.194$. This finding indicates that administrative staff with stronger AI-related competencies were more willing and able to exchange AI-assisted experiences, usage methods, and practical knowledge with colleagues. The results therefore highlight the collective and interaction-oriented nature of generative AI implementation in administrative environments.

The mediation analysis provides more direct evidence for RO2. The bootstrap results confirmed that dynamic capabilities significantly mediated all relationships between generative AI literacy dimensions and innovation performance. Among these mediation paths, quality evaluation ability produced the strongest indirect effect through dynamic capabilities with an effect value of 0.040, while prompt engineering ability generated an indirect effect of 0.032. These findings suggest that the innovative contribution of generative AI literacy partly depends on whether vocational colleges can transform AI-related competencies into adaptive organizational processes. Administrative staff who can critically evaluate AI-generated outputs appear more capable of supporting organizational learning, procedural adjustment, and administrative transformation.

These findings align with dynamic capability theory, which emphasizes that innovation under technological change depends on the ability to sense opportunities, seize resources, and reconfigure existing routines (Wernerfelt, 1984). Previous studies often examined dynamic capabilities at the organizational or enterprise level, particularly within private firms or technology-intensive industries (Shonubi, 2025). The present study extends this perspective into vocational college administration by demonstrating that dynamic capabilities also function as an important mechanism linking generative AI literacy with administrative innovation. This result therefore broadens the application scope of dynamic capability theory from commercial organizations to educational administrative systems.

However, the findings also differ from earlier research in important ways. Previous studies frequently emphasized external technological resources or organizational digital infrastructure as primary drivers of dynamic capabilities (Teece, 2023). In contrast, the present study shows that individual-level AI literacy competencies constitute an important micro-foundation for organizational adaptability. The relatively stronger role of quality evaluation ability indicates that administrative adaptation depends not only on access to AI tools but also on employees' capacity to critically interpret and refine AI-generated knowledge before integrating it into institutional practices.

The mediation effects of AI knowledge sharing participation were even stronger than those of dynamic capabilities. Prompt engineering ability produced the strongest indirect effect through AI knowledge sharing participation with an effect value of 0.059, followed by compliance and ethical awareness with 0.053 and basic operational skills with 0.050. These findings indicate that collaborative knowledge exchange represents a particularly important pathway through which generative AI literacy contributes to innovation performance.

This result is consistent with knowledge-based perspectives arguing that organizational innovation depends heavily on knowledge circulation, collective interpretation, and collaborative learning. Previous studies have similarly emphasized that knowledge sharing facilitates innovation by reducing information fragmentation and improving coordination (Dickey et al., 2022). The present study confirms these arguments within the context of generative AI implementation in vocational colleges. Administrative staff who possessed stronger AI-related competencies were more likely to share

experiences, prompting strategies, evaluative judgments, and practical applications with colleagues, thereby strengthening collective innovation capability.

At the same time, the stronger mediation effects associated with AI knowledge sharing participation suggest a distinctive feature of vocational college administration. Compared with highly market-driven enterprises, vocational colleges often rely more heavily on coordination, procedural communication, and collective administrative cooperation. Under such institutional conditions, AI-related knowledge may generate greater innovation value when it is collectively exchanged and discussed rather than individually retained. This finding therefore highlights the social and collaborative characteristics of administrative innovation within educational organizations.

The descriptive statistics also support this interpretation. The mean values of AI knowledge sharing participation ranged from 3.516 to 3.957, indicating a relatively active level of AI-related communication among administrative staff. In particular, KS4 and KS7 reported comparatively higher mean values, suggesting that respondents were relatively willing to exchange AI-related information and skills when colleagues requested assistance. This result reflects the emergence of collaborative AI learning practices within vocational college administration.

RO3: To examine how organizational structure conditions the relationship between generative AI literacy and administrative staff's innovation performance in vocational colleges in Northeastern China.

Research Objective 3 aimed to examine how organization structure conditions the relationship between generative AI literacy and administrative staff's innovation performance in vocational colleges in Northeastern China. The empirical findings provide strong support for this objective by confirming that organization structure positively moderated the relationships between all dimensions of generative AI literacy and innovation performance. These results indicate that the innovative contribution of generative AI literacy depends not only on individual AI-related competencies, but also on the institutional and structural environment within which administrative staff operate.

The moderation analysis demonstrated that all interaction terms between generative AI literacy dimensions and organization structure were statistically significant. Among these moderation effects, the interaction between quality evaluation ability and organization structure showed the strongest coefficient with $\beta = 0.158$, followed by prompt

engineering ability with $\beta = 0.147$. Compliance and ethical awareness, basic operational skills, and innovative application ability also demonstrated significant interaction effects. These findings suggest that organization structure strengthened the extent to which generative AI literacy translated into innovation performance in vocational colleges.

The results indicate that administrative innovation becomes more likely when generative AI competencies are supported by organizational systems characterized by formalized procedures, administrative coordination, and centralized governance mechanisms. In vocational colleges where organizational structures provide clearer procedural guidance and stronger institutional support, administrative staff appear more capable of integrating generative AI into innovation-related activities. This finding directly responds to RO3 by confirming that organization structure functions as an important contextual condition shaping the effectiveness of generative AI literacy.

The descriptive statistics of organization structure further support this interpretation. The mean values of OS items ranged from 3.473 to 3.757, indicating a relatively moderate to high level of organizational formalization and centralization within the sampled vocational colleges. In particular, the relatively high mean values associated with OS5 to OS9 suggest that decision-making authority regarding administrative budgets, new initiatives, organizational change, and resource allocation remained strongly concentrated within senior management structures. This organizational characteristic reflects the institutional reality of vocational colleges in Northeastern China, where administrative systems often operate under relatively centralized governance arrangements.

Previous studies have frequently argued that highly formalized or centralized organizational structures may constrain innovation by reducing flexibility, limiting experimentation, and restricting employee discretion (Patel et al., 2025). Research grounded in traditional organizational innovation theory often associates rigid administrative systems with lower adaptive capacity and weaker technological responsiveness (Teece, 2023). However, the findings of the present study partially differ from these assumptions. Rather than weakening the innovative impact of generative AI literacy, organization structure strengthened these relationships across all five literacy dimensions.

This difference may be explained by the institutional characteristics of educational administration and the nature of generative AI implementation. Unlike highly autonomous innovation environments found in entrepreneurial firms, vocational colleges require procedural consistency, policy compliance, and coordinated administrative governance. Under such conditions, organizational structure may provide legitimacy, resource coordination, and implementation stability for AI-assisted administrative innovation. Clear procedures and centralized coordination can reduce uncertainty surrounding generative AI use and facilitate the institutional integration of AI-supported practices into administrative workflows.

The strongest moderation effect observed for quality evaluation ability further highlights the importance of organizational governance in AI-assisted administration. Administrative staff who possess stronger capabilities in evaluating AI-generated outputs appear able to contribute more effectively to innovation when organizational systems support review processes, procedural feedback, and institutional coordination. In highly structured administrative environments, evaluative competencies become particularly valuable because AI-generated content must satisfy formal standards of accuracy, coherence, and institutional appropriateness before being adopted into organizational practice.

Similarly, the significant moderation effect associated with prompt engineering ability suggests that organizational structure enhances the practical value of advanced AI interaction skills. Administrative staff may possess strong prompting competencies, but the innovative contribution of these competencies becomes greater when organizational systems support communication, experimentation, and cross-departmental coordination. In this sense, organization structure functions not merely as a control mechanism, but also as an enabling condition facilitating the organizational application of AI-assisted insights.

The moderation effects related to compliance and ethical awareness also provide important implications. The positive interaction between compliance and ethical awareness and organization structure indicates that responsible AI use becomes more innovation-supportive when institutional governance mechanisms clearly define acceptable practices and accountability standards. This finding differs from earlier discussions that often frame compliance requirements as barriers to innovation. In

vocational college administration, ethical governance and procedural clarity may instead create institutional trust that encourages more stable and sustainable AI adoption.

The findings therefore extend prior research in several ways. Earlier studies primarily examined organization structure as an independent predictor of innovation or technological adoption (Xia et al., 2024). The present study demonstrates that organization structure also shapes the effectiveness of individual AI-related competencies. This result contributes to organizational and technology-related literature by showing that AI-enabled innovation emerges through the interaction between human competencies and institutional conditions rather than through isolated technological capability alone.

Taken together, the findings provide a coherent explanation of how generative AI literacy contributes to administrative innovation in vocational colleges in Northeastern China. Regarding RO1, the results confirmed that generative AI literacy directly promoted innovation performance, with innovative application ability showing the strongest direct effect. This indicates that administrative innovation depends less on simple AI access or basic tool operation and more on the ability to transform AI-supported ideas into practical administrative improvements. This finding is consistent with previous studies emphasizing the value of AI-related competence for digital work performance, but it extends prior research by showing that higher-order application and evaluation abilities are more important than basic operational familiarity in shaping innovation outcomes.

Regarding RO2, the findings showed that dynamic capabilities and AI knowledge sharing participation both mediated the relationship between generative AI literacy and innovation performance. This result aligns with dynamic capability theory and the knowledge-based view, which argue that innovation requires organizational adaptation and knowledge integration rather than isolated individual competence. Compared with previous research that mainly emphasizes technological adoption or individual digital skills, this study demonstrates that generative AI literacy generates stronger innovation value when it is transformed into organizational sensing, seizing, transforming, and AI-related knowledge exchange. The relatively stronger mediation effects of AI knowledge sharing participation further indicate that administrative innovation in vocational colleges is highly dependent on collaborative communication and collective learning.

Regarding RO3, the findings confirmed that organization structure positively moderated the relationships between generative AI literacy and innovation performance.

This result differs from some earlier studies that regard formalization and centralization as barriers to innovation. In the context of vocational colleges, structured governance did not simply suppress innovation. Instead, clear procedures, institutional coordination, and senior-level control appeared to strengthen the translation of AI-related competencies into innovation outcomes. This difference may reflect the institutional nature of vocational colleges, where administrative innovation must remain compatible with policy compliance, accountability requirements, and standardized procedures.

Overall, the three research objectives jointly reveal that generative AI-enabled administrative innovation is not driven by technology use alone. The results support previous research on AI competence, dynamic capabilities, and knowledge sharing, but further clarify that innovation in vocational colleges emerges from the combined effects of individual AI literacy, organizational learning processes, and structural conditions. The study therefore shifts the explanation of generative AI use from a narrow adoption perspective to an integrated organizational innovation perspective, showing that administrative staff's AI-related competencies produce innovation outcomes most effectively when supported by adaptive capabilities, knowledge-sharing practices, and enabling organizational structures.

5.1 Implication to Theories

5.1.1 Implication to Dynamic Capability Theory

The findings of this study extend dynamic capability theory by clarifying how generative AI literacy functions as a micro-foundational resource that supports organizational sensing, seizing, and transforming processes in vocational colleges. Dynamic capability theory argues that organizations achieve adaptation and innovation by sensing environmental changes, seizing emerging opportunities, and reconfiguring existing routines under conditions of uncertainty (Teece, 2023). Prior studies have mainly examined dynamic capabilities from the perspective of managerial cognition, organizational routines, digital infrastructure, or strategic resource orchestration (Schulze & Brusoni, 2022). The present study enriches this theoretical tradition by showing that administrative staff's generative AI literacy can serve as an important individual-level foundation through which organizational dynamic capabilities are activated in educational administration.

The results support the argument that technological resources do not automatically produce dynamic capabilities. This finding is consistent with Alenezi (2023), who emphasized that digital transformation in educational institutions depends on the interaction between technological competence and organizational readiness. It also extends Haleem et al. (2024) by demonstrating that AI-related skills contribute not only to task efficiency, but also to the broader organizational capacity to recognize and respond to administrative change. In this study, basic operational skills, prompt engineering ability, quality evaluation ability, innovative application ability, and compliance and ethical awareness all strengthened dynamic capabilities, indicating that generative AI literacy provides the cognitive and practical basis for identifying AI-enabled opportunities, mobilizing AI-generated information, and adjusting administrative practices.

The study further contributes to dynamic capability theory by highlighting the differentiated roles of generative AI literacy dimensions. Previous research has often treated digital competence or AI capability as a general construct (Zhang et al., 2025). By contrast, the present study separates generative AI literacy into operational, prompting, evaluative, application-oriented, and ethical dimensions, thereby providing a more refined explanation of how different competencies support dynamic capabilities. Quality evaluation ability showed particular theoretical importance because it enables administrative staff to assess whether AI-generated outputs can be reliably integrated into institutional routines. This finding extends Huang et al. (2025) and Xu et al. (2025), who emphasized the importance of evaluating AI-generated content, by linking evaluative competence to the reconfiguration mechanism of dynamic capabilities.

The findings also broaden the institutional scope of dynamic capability theory. Much prior research has applied this theory to enterprises, competitive markets, and technology-intensive industries, where dynamic capabilities are often associated with market adaptation, competitive advantage, and strategic renewal (Tajeddini et al., 2026). The present study applies dynamic capability theory to vocational colleges in Northeastern China, showing that dynamic capabilities are equally relevant to public and educational organizations facing policy pressure, administrative complexity, and digital transformation. This contributes to Phakamach et al. (2023) and Abunaser et al. (2025) by demonstrating that administrative innovation in vocational colleges depends on

organizational capacities to absorb AI-related knowledge and reconfigure administrative processes.

The study also refines dynamic capability theory by emphasizing responsible and compliant AI use as a condition for sustainable capability development. Earlier dynamic capability research has usually focused on speed, flexibility, and resource recombination, while paying less attention to ethical and institutional constraints. The findings show that compliance and ethical awareness strengthens dynamic capabilities, suggesting that organizational adaptation in regulated educational contexts requires not only experimentation but also legitimacy, accountability, and risk control. This result extends Singh et al. (2024) by positioning ethical AI literacy as part of the capability-building process rather than merely as a governance constraint.

The findings further indicate that dynamic capabilities mediate the relationship between generative AI literacy and innovation performance. This result supports Mushangai (2023), who argued that capabilities transform resources into organizational outcomes. However, the present study advances this logic by showing that the transformation from AI literacy to innovation performance requires organizational sensing, seizing, and transforming processes. Generative AI literacy therefore does not directly produce administrative innovation in isolation. It becomes theoretically meaningful when embedded in organizational mechanisms that convert individual AI competence into collective administrative adaptation.

5.1.2 Implication to Knowledge-based View

The findings of this study also contribute to the knowledge-based view by clarifying how generative AI literacy supports innovation performance through AI knowledge sharing participation within vocational colleges. The knowledge-based view emphasizes that organizational performance and innovation depend on the creation, transfer, integration, and utilization of knowledge resources rather than on isolated individual expertise (Grant & Phene, 2022). Prior studies have consistently argued that knowledge sharing facilitates organizational learning, improves coordination, and strengthens innovation capability (Bilgili & Bilgili, 2024). The present study extends this perspective by demonstrating that generative AI literacy represents a new form of knowledge-based competence that becomes valuable when embedded within collaborative AI-related knowledge exchange processes.

The findings support previous research suggesting that knowledge sharing functions as a key mechanism linking individual competence with organizational innovation. Studies by Ayestarán Echeberría et al. (2022) and Shadmanfar and Makvandi (2024) emphasized that knowledge exchange enables organizations to reduce fragmentation and strengthen collective problem solving. The present study confirms this logic in the context of generative AI by showing that AI knowledge sharing participation mediated the relationships between all dimensions of generative AI literacy and innovation performance. This result indicates that generative AI-related competencies generate stronger innovation outcomes when administrative staff actively exchange prompting strategies, AI-assisted practices, evaluative judgments, and application experiences with colleagues.

The study further extends the knowledge-based view by conceptualizing generative AI literacy as a multidimensional knowledge resource. Previous research often treated digital knowledge or technological expertise as relatively general organizational resources (Iqbal et al., 2025). By contrast, the present study distinguishes between basic operational skills, prompt engineering ability, quality evaluation ability, innovative application ability, and compliance and ethical awareness. This multidimensional structure provides a more refined explanation of how different forms of AI-related knowledge contribute to organizational innovation through knowledge-sharing processes.

The relatively stronger mediation effects associated with AI knowledge sharing participation provide an important theoretical contribution. Prompt engineering ability demonstrated the strongest indirect effect through knowledge sharing participation, indicating that the innovative value of prompting competence depends heavily on whether prompting knowledge can circulate across administrative units. This finding extends Bansal (2024) and Raina et al. (2026), who emphasized the importance of prompt interaction capabilities, by showing that prompt engineering knowledge becomes organizationally valuable when transformed into collective learning rather than remaining individual tacit expertise.

The findings also refine the knowledge-based view by emphasizing the social and interactive nature of AI-enabled innovation in educational administration. Earlier knowledge-based studies frequently focused on formal knowledge systems, organizational memory, or codified knowledge resources (Bilgili & Bilgili, 2024). The present study

demonstrates that generative AI-related knowledge is highly interaction-dependent because effective AI use often requires continuous experimentation, contextual adjustment, and collaborative interpretation. Administrative staff not only acquire AI-related knowledge individually, but also refine and validate this knowledge through communication with colleagues. This result supports Sahibzada et al. (2024), who argued that collaborative discussion strengthens innovation outcomes by enabling organizations to collectively adapt emerging technological practices.

Another theoretical contribution concerns the role of evaluative and ethical knowledge in organizational innovation. Previous knowledge-based research has primarily emphasized knowledge acquisition and transfer efficiency. The findings of the present study demonstrate that quality evaluation ability and compliance and ethical awareness also contribute significantly to AI knowledge sharing participation. This suggests that AI-related knowledge exchange in vocational colleges is not limited to technical usage methods. It also involves the communication of evaluative standards, ethical norms, and institutional expectations. This finding extends Kashefi et al. (2024) and Renuka et al. (2025) by showing that responsible AI-related knowledge sharing strengthens trust and legitimacy within organizational learning processes.

The study additionally broadens the contextual application of the knowledge-based view. Much prior research examining knowledge sharing and innovation has focused on enterprises, project teams, or technology-intensive organizations (Valtonen et al., 2025). The present study demonstrates that vocational colleges also rely heavily on knowledge-sharing processes to support innovation, particularly under conditions of digital transformation and AI integration. In educational administration, innovation frequently depends on cross-departmental coordination, procedural communication, and collaborative adaptation of administrative practices. The significant mediation effects of AI knowledge sharing participation therefore highlight the importance of collective learning mechanisms in institutional administrative environments.

The findings also challenge purely technology-centered explanations of AI-enabled innovation. Earlier studies often implied that technological capability alone determines innovation outcomes. The present study demonstrates that the innovative contribution of generative AI literacy depends heavily on whether AI-related knowledge can be disseminated, interpreted, and collectively utilized within organizational systems.

This result supports the core argument of the knowledge-based view that knowledge itself does not automatically generate innovation unless organizations possess mechanisms capable of facilitating knowledge integration and collaborative application.

5.1.3 Implication to Sociotechnical Systems Theory

The findings of this study also contribute to sociotechnical systems theory by demonstrating that innovation performance in vocational colleges emerges through the interaction between technological competencies, organizational processes, and structural conditions rather than through technology adoption alone. Sociotechnical systems theory emphasizes that organizational effectiveness depends on the joint optimization of social systems and technical systems (Cooper & Foster, 1971). In digitally transforming organizations, technological tools cannot independently generate innovation unless they are supported by appropriate organizational coordination, communication mechanisms, and institutional arrangements. The present study extends this theoretical perspective into the context of generative AI use within vocational college administration.

The findings support earlier sociotechnical arguments that technological capability and organizational structure must operate together to produce effective outcomes. Prior studies frequently emphasized that advanced digital technologies require organizational adaptation to realize their innovative potential (Werfhorst et al., 2022). The present study confirms this logic by showing that generative AI literacy directly improved innovation performance, while organization structure significantly moderated these relationships. This result indicates that AI-related competencies become more effective when embedded within organizational environments that facilitate coordination, flexibility, and knowledge exchange.

The study extends sociotechnical systems theory by conceptualizing generative AI literacy as a multidimensional technical subsystem. Previous sociotechnical research often treated technology adoption in relatively broad terms, focusing on system implementation or digital infrastructure (Ayinaddis, 2025; Madanchian & Taherdoost, 2025). By contrast, the present study distinguishes between basic operational skills, prompt engineering ability, quality evaluation ability, innovative application ability, and compliance and ethical awareness. This multidimensional approach demonstrates that different AI-related competencies influence organizational innovation through distinct sociotechnical mechanisms rather than through a single unified technological effect.

The findings also reinforce the sociotechnical argument that organizational innovation depends heavily on social interaction processes surrounding technology use. AI knowledge sharing participation significantly mediated the relationships between generative AI literacy and innovation performance, suggesting that AI-related innovation does not emerge solely from individual technological competence. Instead, innovation develops through collaborative communication, collective interpretation, and organizational learning processes. This finding supports Govers and Van Amelsvoort (2023), who argued that successful technological systems require active social integration and participative coordination rather than isolated technical implementation.

The significant mediating role of dynamic capabilities further strengthens the study's contribution to sociotechnical systems theory. Earlier sociotechnical studies primarily emphasized alignment between technology and organizational structure, but often provided limited explanation regarding how organizations adapt continuously under conditions of technological change. The present study demonstrates that dynamic capabilities function as adaptive organizational mechanisms that translate AI-related competencies into sustained innovation outcomes. Sensing, seizing, and transforming capabilities enable vocational colleges to integrate generative AI into evolving administrative routines, thereby extending sociotechnical systems theory toward a more dynamic understanding of technological adaptation.

The moderation effects of organization structure provide another important theoretical contribution. The findings revealed that organizational structure strengthened the relationships between all dimensions of generative AI literacy and innovation performance. This result supports the sociotechnical perspective that organizational arrangements shape the effectiveness of technological systems (Vera et al., 2026). However, the study further demonstrates that structure does not merely constrain or support technology use generally. Instead, it conditions how specific AI-related competencies are translated into innovative administrative practices. This finding refines previous sociotechnical research by illustrating that structural influence operates differently across multiple dimensions of technological competence.

The study additionally contributes by extending sociotechnical systems theory into educational administration contexts. Much existing sociotechnical research has focused on industrial production systems, healthcare systems, or corporate digital transformation

(Govers & Van Amelsvoort, 2023). The present study demonstrates that vocational colleges also function as sociotechnical systems in which technological competencies, organizational processes, and institutional structures jointly shape innovation outcomes. Administrative innovation within vocational colleges depends not only on adopting generative AI tools, but also on coordinating human expertise, knowledge-sharing routines, and governance structures.

The findings also challenge technology-deterministic perspectives frequently associated with AI implementation research. Some earlier studies implied that advanced AI technologies automatically improve organizational performance once adopted (Stanikzai & Mittal, 2025). The present study demonstrates that generative AI literacy alone cannot fully explain innovation performance. Instead, innovation depends on the interaction between technological competencies, dynamic organizational adaptation, collaborative knowledge exchange, and supportive structural arrangements. This result strongly aligns with sociotechnical systems theory, which rejects purely technical explanations of organizational change and emphasizes the interdependence between technological and social subsystems.

Another contribution concerns the role of compliance and ethical awareness within sociotechnical systems. Traditional sociotechnical studies often concentrated on efficiency, coordination, and system performance (Cooper & Foster, 1971). The present study demonstrates that ethical and compliant AI use also represents an important component of effective sociotechnical integration. Compliance and ethical awareness significantly influenced dynamic capabilities, knowledge sharing participation, and innovation performance, indicating that responsible AI use strengthens organizational trust and institutional legitimacy within AI-enabled systems. This finding extends recent sociotechnical discussions emphasizing governance, accountability, and ethical adaptation under digital transformation conditions.

5.2 Implication to Practitioners

5.2.1 Implications for Administrative Staff in Vocational Colleges

The findings suggest that administrative staff in vocational colleges should develop generative AI literacy as a professional competence embedded in administrative innovation rather than as a narrow technical skill. In daily work, the value of generative

AI does not depend merely on knowing how to use a tool, but on applying AI-generated content to improve administrative procedures, optimize communication, support document preparation, and identify feasible solutions to recurring organizational problems. Therefore, administrative staff need to strengthen the ability to connect AI use with specific administrative scenarios, especially in academic affairs, student services, enrollment and employment, digital administration, and office coordination.

The findings also indicate that administrative staff should place greater emphasis on prompt design, output evaluation, and practical transformation. Generative AI can provide useful suggestions, drafts, and analytical support, but its outputs still require contextual judgment before being used in formal administrative processes. Administrative staff should therefore avoid direct and uncritical use of AI-generated content. Instead, AI outputs should be checked against institutional rules, policy requirements, data accuracy, and the actual conditions of vocational colleges. This helps transform generative AI from a simple efficiency tool into a source of administrative problem solving and innovation.

The results further imply that administrative staff should participate more actively in AI-related knowledge exchange. Administrative innovation is difficult to achieve when AI experience remains at the individual level. Sharing effective prompts, useful application scenarios, common errors, and evaluation methods can help colleagues reduce trial-and-error costs and develop shared standards for AI use. Through such communication, generative AI literacy can become a collective administrative resource rather than a personal skill.

Responsible use of generative AI should also become an essential part of administrative practice. Since vocational college administration involves student information, institutional documents, policy materials, and internal management data, administrative staff need to maintain strong awareness of privacy protection, information security, legal compliance, and professional ethics. Strengthening ethical and compliant AI use can reduce institutional risk and support the sustainable application of generative AI in administrative innovation.

5.2.2 Implications for Vocational College Administrators

The findings provide important implications for vocational college administrators responsible for institutional management and administrative reform. The results suggest that improving innovation performance in vocational colleges requires more than simply

introducing generative AI technologies into administrative systems. Administrators need to establish organizational environments that support the effective integration of AI-related competencies into routine administrative practice. This means that vocational colleges should treat generative AI as part of long-term organizational capability development rather than as a short-term technological initiative.

The findings also indicate the importance of developing systematic AI training mechanisms for administrative staff. Since different dimensions of generative AI literacy contribute differently to innovation performance, training programs should move beyond basic operational instruction and place greater emphasis on prompt engineering, critical evaluation of AI outputs, innovative application, and ethical governance. Vocational college administrators should therefore design continuous professional development programs that combine technical learning with practical administrative scenarios. Such training can help administrative staff apply generative AI more effectively in areas such as student management, academic affairs, digital administration, document processing, and interdepartmental coordination.

The significant roles of dynamic capabilities and AI knowledge sharing participation further imply that administrators should strengthen organizational learning mechanisms within vocational colleges. Administrative innovation depends not only on individual competence but also on the ability of institutions to share knowledge, coordinate resources, and adapt organizational routines. Vocational college administrators should therefore encourage cross-departmental collaboration, establish internal AI learning communities, and create platforms for exchanging AI-related experiences and best practices. Supporting collaborative learning can help vocational colleges reduce fragmentation in AI adoption and accelerate the institutional diffusion of innovative administrative practices.

The moderation effects of organization structure also suggest that administrators should pay closer attention to the balance between formal control and organizational flexibility. Excessively rigid administrative structures may constrain experimentation and reduce the innovative value of generative AI competencies. Vocational college administrators should therefore maintain necessary institutional governance while simultaneously allowing sufficient flexibility for administrative staff to explore new AI-supported approaches. Creating supportive organizational conditions for experimentation,

communication, and adaptive adjustment can strengthen the contribution of generative AI literacy to administrative innovation.

In addition, the findings highlight the importance of establishing clear governance frameworks for generative AI use within vocational colleges. Administrators should formulate institutional guidelines related to data security, privacy protection, ethical AI use, and accountability standards. Providing transparent rules and implementation standards can reduce uncertainty surrounding AI adoption and help administrative staff use generative AI more confidently and responsibly. Such governance mechanisms are essential for sustaining innovation while maintaining institutional trust and organizational stability.

5.2.3 Implications for Generative AI Providers

The findings also provide important implications for generative AI providers and educational technology developers serving vocational colleges. The results suggest that the effectiveness of generative AI in administrative environments depends not only on technological performance but also on how well AI systems align with the practical needs, organizational routines, and governance requirements of vocational colleges. Generative AI providers should therefore move beyond generic AI service models and develop application designs that better fit educational administrative contexts.

The findings indicate that administrative staff require support not only in operating AI systems, but also in prompt construction, output evaluation, and practical implementation. This suggests that AI providers should incorporate more scenario-based support functions into their systems, such as intelligent prompt recommendations, administrative task templates, contextual guidance, and output verification mechanisms. Providing practical administrative assistance can help users reduce uncertainty during AI interaction and improve the quality and reliability of AI-supported administrative work.

The results also highlight the importance of explainability and controllability in AI-generated outputs. Administrative staff in vocational colleges frequently deal with policy interpretation, student information, institutional coordination, and formal documentation. In such contexts, inaccurate or poorly structured AI outputs may create organizational risks. Generative AI providers should therefore strengthen functions related to transparency, traceability, and output validation, enabling users to better understand how AI-generated content is produced and how it should be evaluated before practical use.

In addition, the significant role of knowledge sharing participation implies that AI providers should support collaborative rather than purely individual AI use. Developing shared prompt libraries, collaborative AI workspaces, institutional learning platforms, and knowledge-sharing interfaces may help vocational colleges build collective AI learning environments. Such functions can facilitate the diffusion of effective AI practices across departments and strengthen organizational learning processes within educational institutions.

The findings further emphasize the importance of ethical governance and compliance support in AI system design. Since vocational college administration involves sensitive institutional and personal information, AI providers should strengthen data protection mechanisms, permission management systems, privacy safeguards, and compliance monitoring functions. Providing clear ethical guidelines and institutional governance tools can help vocational colleges adopt generative AI more responsibly and sustainably.

Finally, the study suggests that generative AI providers should view vocational colleges as long-term organizational partners rather than short-term technology users. Administrative innovation in vocational colleges requires continuous adaptation, organizational learning, and evolving AI capabilities. Maintaining ongoing technical support, updating administrative application scenarios, and co-developing institution-specific AI solutions may therefore become increasingly important for sustaining the practical value of generative AI within vocational education systems.

5.2.4 Implications for Policy Makers in Vocational Education

The findings provide several important implications for policy makers responsible for vocational education governance and digital transformation planning. The results suggest that improving administrative innovation in vocational colleges requires more than expanding digital infrastructure or introducing AI technologies at the institutional level. Effective AI-driven transformation depends on the development of human competencies, organizational learning mechanisms, and supportive governance systems. Policy makers should therefore promote generative AI adoption through integrated policies that combine technological development with organizational capability building.

The findings indicate that generative AI literacy plays a critical role in shaping administrative innovation performance. This suggests that vocational education policies

should place greater emphasis on AI competency development among administrative personnel rather than focusing exclusively on teaching staff or students. Policy makers should support the establishment of systematic AI training programs for vocational college administrators and administrative staff, particularly in areas such as prompt engineering, AI output evaluation, ethical governance, and practical administrative application. Strengthening administrative AI literacy can improve the overall adaptive capacity of vocational colleges under digital transformation conditions.

The significant mediating roles of dynamic capabilities and AI knowledge sharing participation further imply that policy support should encourage organizational learning and institutional collaboration. Policy makers should promote cross-institutional knowledge exchange platforms, regional digital governance networks, and collaborative innovation mechanisms that allow vocational colleges to share AI-related administrative experiences and best practices. Supporting collective learning can reduce disparities in AI implementation capacity among institutions and accelerate the diffusion of effective administrative innovation models.

The findings also highlight the importance of organizational structure in shaping the effectiveness of generative AI competencies. This suggests that vocational education governance should avoid overly rigid administrative management approaches that may constrain institutional flexibility and experimentation. Policy makers should encourage vocational colleges to establish adaptive governance systems that maintain accountability while allowing sufficient organizational autonomy for AI-enabled administrative innovation. Providing policy flexibility for experimentation and digital administrative reform may help vocational colleges respond more effectively to rapidly evolving technological environments.

In addition, the results emphasize the importance of ethical and compliant AI use within vocational education systems. Policy makers should formulate clearer governance frameworks related to data privacy, information security, algorithmic accountability, and ethical AI application in educational administration. Establishing unified standards and regulatory guidelines can help vocational colleges reduce uncertainty surrounding generative AI adoption while ensuring responsible and sustainable implementation practices.

Finally, the findings suggest that generative AI should be incorporated into broader vocational education modernization strategies rather than treated as an isolated technological tool. Policy makers should view generative AI as part of long-term institutional transformation involving administrative efficiency, organizational learning, service innovation, and governance modernization. Integrating AI-related policies into wider vocational education reform agendas may therefore strengthen the sustainable development and digital adaptability of vocational colleges in Northeastern China.

5.3 Limitation of the Study and Implications of Future Research

5.3.1 Limitation of the Present Study

Although this study provides important insights into the relationships among generative AI literacy, dynamic capabilities, AI knowledge sharing participation, organization structure, and innovation performance in vocational colleges, several limitations should be acknowledged.

First, the study adopted a cross-sectional research design, which limits the ability to capture the dynamic evolution of generative AI use and administrative innovation over time. The relationships identified in this study reflect the perceptions and organizational conditions of respondents during a specific period of digital transformation. Since generative AI technologies continue to evolve rapidly, the long-term influence of AI literacy on administrative innovation may change as organizational practices and technological environments develop further.

Second, the study focused specifically on vocational colleges in Northeastern China. Although this regional focus provides contextual relevance, differences in institutional resources, digital infrastructure, policy environments, and organizational cultures across regions may influence the generalizability of the findings. Vocational colleges located in economically developed regions or areas with different administrative systems may demonstrate different patterns of AI adoption and innovation behavior.

Third, the study relied primarily on self-reported questionnaire data collected from administrative staff. Although reliability and validity tests confirmed the quality of the measurement model, self-reported responses may still be influenced by subjective perception, social desirability, or individual interpretation of AI-related practices. The

measurement of innovation performance therefore reflects perceived rather than objectively observed innovation outcomes.

Finally, the study concentrated mainly on organizational and individual factors related to administrative innovation, while external environmental influences were not examined in depth. Factors such as regional digital policy support, technological infrastructure differences, inter-institutional collaboration, and external stakeholder pressure may also shape the effectiveness of generative AI adoption in vocational colleges.

5.3.2 Implications for Future Research

Based on these limitations, several directions for future research can be proposed.

First, future studies may adopt longitudinal research designs to examine how generative AI literacy, organizational adaptation, and innovation performance evolve over time. Longitudinal analysis could provide deeper understanding of whether the influence of generative AI competencies becomes stronger, weaker, or more stable as vocational colleges accumulate practical AI experience.

Second, future research may expand the geographical scope of investigation by comparing vocational colleges across different regions or countries. Comparative studies could help identify how institutional environments, digital governance systems, and cultural contexts influence AI-driven administrative innovation.

Third, future studies may incorporate mixed-method or qualitative approaches to complement questionnaire-based analysis. Interviews, case studies, and observational methods could provide richer explanations regarding how administrative staff actually use generative AI in daily work processes and how organizational innovation emerges in practice.

Finally, future research may examine additional organizational or environmental variables that were not included in the present study. Factors such as digital leadership, organizational culture, technological readiness, policy support, and employee resistance to AI may further explain variations in innovation performance within vocational education institutions.

5.4 Conclusion

This study examined how generative AI literacy influences innovation performance among administrative staff in vocational colleges in Northeastern China by integrating dynamic capability theory, the knowledge-based view, and sociotechnical systems theory. Focusing on administrative contexts within vocational education institutions, the study explored the direct effects of generative AI literacy, the mediating roles of dynamic capabilities and AI knowledge sharing participation, and the moderating role of organization structure. Through empirical analysis based on data collected from administrative staff in vocational colleges, the study constructed and validated a comprehensive framework explaining how AI-related competencies contribute to administrative innovation under conditions of organizational digital transformation.

The findings confirmed that multidimensional generative AI literacy significantly promotes both dynamic capabilities and AI knowledge sharing participation, while also directly enhancing innovation performance in vocational colleges. Among the dimensions of generative AI literacy, innovative application ability demonstrated the strongest contribution to innovation performance, highlighting the importance of transforming AI-supported ideas into practical administrative improvements. The results further demonstrated that dynamic capabilities and AI knowledge sharing participation function as important organizational mechanisms linking AI literacy with innovation outcomes. In addition, organization structure significantly strengthened the relationships between generative AI literacy and innovation performance, indicating that supportive structural conditions facilitate the translation of AI-related competencies into innovative administrative practices.

The study contributes theoretically by extending dynamic capability theory into AI-enabled educational administration contexts, enriching the knowledge-based view through the incorporation of AI-related knowledge sharing processes, and advancing sociotechnical systems theory by demonstrating the interdependence between technological competencies, organizational adaptation, and institutional structures. The findings also contribute practically by providing guidance for administrative staff, vocational college administrators, generative AI providers, and vocational education policy makers regarding how generative AI can be integrated more effectively into administrative innovation processes.

Overall, the study demonstrates that generative AI does not independently produce administrative innovation in vocational colleges. Instead, innovation emerges through the interaction between individual AI competencies, organizational learning processes, adaptive institutional capabilities, and supportive governance structures. As vocational education systems continue to undergo digital transformation, strengthening generative AI literacy and building organizational conditions that support collaborative and adaptive AI use will become increasingly important for sustaining administrative innovation and institutional development.



BIBLIOGRAPHY

Abdelrahman, M., Papamichail, K. N., Hammady, R., Kurt, Y., Abdallah, W., Shixiong Liu, L., & Kapser, S. (2025). Organisational Culture and Knowledge Management Systems Adoption: Examining Employee Usage in Multinational Corporations. *Global Journal of Flexible Systems Management*, 26(3), 439-467. https://doi.org/10.1007/s40171-025-00448-w.

Abdullah, M. R., & Arifin, I. (2024). School Administrative Staff: Duties and Responsibilities in Modern Education. *Proceedings Series of Educational Studies*,4, 329-337.

Abunaser, F. M., Hamd, M. M. M., Bani-Oraba, A. M. N., Hamed, O., Alshiyab, M. Q. M., & Shebani, Z. (2025). Dynamic Capabilities of University Administration and Their Impact on Student Awareness of Artificial Intelligence Tools. *Sustainability*, 17(15), 7092.

Adamakis, M., & Rachiotis, T. (2025). Artificial Intelligence in Higher Education: A State-of-the-Art Overview of Pedagogical Integrity, Artificial Intelligence Literacy, and Policy Integration. *Encyclopedia*, 5, 180. https://doi.org/10.3390/encyclopedia5040180.

Al-Busaidi, A. S., Raman, R., Hughes, L., Albashrawi, M. A., Malik, T., Dwivedi, Y. K., Al-Alawi, T., AlRizeiqi, M., Davies, G., & Fenwick, M. (2024). Redefining boundaries in innovation and knowledge domains: Investigating the impact of generative artificial intelligence on copyright and intellectual property rights. *Journal of Innovation & Knowledge*, 9(4), 100630.

Alenezi, M. (2023). Digital learning and digital institution in higher education. *Education Sciences*, 13(1), 88.

Almisad, B., & Aleidan, A. (2025). Faculty perspectives on generative artificial intelligence: insights into awareness, benefits, concerns, and uses. *Frontiers in Education*, 10. https://doi.org/10.3389/feduc.2025.1632742.

Alnuaimi, B. K., Singh, S. K., Ren, S., Budhwar, P., & Vorobyev, D. (2022). Mastering digital transformation: The nexus between leadership, agility, and digital strategy. *Journal of Business Research*, 145, 636-648.

Amoozegar, A., Esohwode, O. E., Yujiao, W., Pee, W. H., Ismaeil, A., Yadav, M., & Harun, M. T. (2025). Employee creativity and innovation in higher education institutions: applying the dynamic componential model of creativity and innovation. Frontiers Psychology, 16, 1614751. https://doi.org/10.3389/fpsyg.2025.1614751.

Annapureddy, R., Fornaroli, A., & Gatica-Perez, D. (2024). Generative AI Literacy: Twelve Defining Competencies. *Digital Government: Research and Practice*, 6,5680. https://doi.org/10.1145/3685680.

Ayestarán Echeberría, S., Gómez Serrano, D., Martínez Moreno, E., Lira, E. M., & Da Costa Dutra, S. C. (2022). A model of knowledge-sharing for the 21st century organizations. *Journal of Work and Organizational Psychology*, 38(3), 6083.

Ayinaddis, S. (2025). Artificial intelligence adoption dynamics and knowledge in SMEs and large firms: A systematic review and bibliometric analysis. *Journal of Innovation & Knowledge*, 10, 1-15. https://doi.org/10.1016/j.jik.2025.100682.

Ballester-Miquel, J. C., Perez-Ruiz, P., Gisbert-Muñoz, S., & Enri-Peiró, S. (2026). The role of soft skills in workplace innovation: Leadership and problem-solving as key drivers. *Journal of Innovation & Knowledge*, 12, 100901. https://doi.org/10.1016/j.jik.2025.100901.

Bansal, P. (2024). Prompt Engineering Importance and Applicability with Generative AI. *Journal of Computer and Communications*, 12,10002. https://doi.org/10.4236/jcc.2024.1210002.

Barcaui, A., & Monat, A. (2023). Who is better in project planning? Generative artificial intelligence or project managers? *Project Leadership and Society*, 4, 100101. https://doi.org/10.1016/j.plas.2023.100101.

Bhuyan, S., Sateesh, V., Mukul, N., Galvankar, A., Mahmood, A., Nauman, M., Rai, A., Bordoloi, K., Basu, U., & Samuel, J. (2025). Generative Artificial Intelligence Use in Healthcare: Opportunities for Clinical Excellence and Administrative Efficiency. *Journal of Medical Systems*, 49. https://doi.org/10.1007/s10916-024-02136-1.

Bianchini, S., Müller, M., & Pelletier, P. (2025). Drivers and barriers of AI adoption and use in scientific research. *Technological Forecasting and Social Change*, 220, 124303. https://doi.org/10.1016/j.techfore.2025.124303.

Bilgili, H., & Bilgili, T. V. (2024). Toward a knowledge-based view of the board: Modeling board intrafirm knowledge networks. *Knowledge and Process Management*, 31(1), 33-47.

Bing, H., & Zhenzhen, Z. (2025). Synergistic development of vocational education and regional economy in the era of high-quality growth. *International Educational Research*, 8(3), 66. https://doi.org/10.30560/ier.v8n3p66.

Botega, L., & Silva, J. (2020). An artificial intelligence approach to support knowledge management on the selection of creativity and innovation techniques. *Journal of Knowledge Management*, 24, 1107-1130. https://doi.org/10.1108/JKM-10-2019-0559.

Broekhuizen, T., Dekker, H., de Faria, P., Firk, S., Nguyen, D. K., & Sofka, W. (2023). AI for managing open innovation: Opportunities, challenges, and a research agenda. *Journal of Business Research*, 167, 114196. https://doi.org/10.1016/j.jbusres.2023.114196.

Campbell, C., Sands, S., Whittaker, L., & Mavrommatis, A. (2025). The AI intelligence playbook: Decoding GenAI capabilities for strategic advantage. *Business Horizons*. https://doi.org/10.1016/j.bushor.2025.08.004.

Chen, B., Zhang, Z., Langrené, N., & Zhu, S. (2025). Unleashing the potential of prompt engineering for large language models. *Patterns*, 6(6), 101260. https://doi.org/10.1016/j.patter.2025.101260.

Chen, P., Schmidtke, C., & Jin, X. (2024). Chinese technical and vocational education and training, skill formation, and national development: A systematic review of educational policies. Vocation, *Technology & Education*, 1(3).

Chen, S. T., & Chang, B. G. (2012). The effects of absorptive capacity and decision speed on organizational innovation: a study of organizational structure as an antecedent variable. *Contemporary Management Research*, 8(1),7996. https://doi.org/10.7903/cmr.7996.

Chiu, T. K., Ahmad, Z., Ismailov, M., & Sanusi, I. T. (2024). What are artificial intelligence literacy and competency? A comprehensive framework to support them. *Computers and Education Open*, 6, 100171.

Chiu, T. K. F., Ahmad, Z., Ismailov, M., & Sanusi, I. T. (2024). What are artificial intelligence literacy and competency? A comprehensive framework to support them. *Computers and Education Open*, 6, 100171. https://doi.org/10.1016/j.caeo.2024.100171.

Cimino, A., Felicetti, A. M., Corvello, V., Ndou, V., & Longo, F. (2025). Generative artificial intelligence (AI) tools in innovation management: a study on the appropriation of ChatGPT by innovation managers. *Management Decision*, 63(10), 3431-3453.

Cooper, R., & Foster, M. (1971). Sociotechnical systems. *American Psychologist*, 26(5), 467.

Cordeiro, M., Puig, F., & Ruiz-Fernández, L. (2023). Realizing dynamic capabilities and organizational knowledge in effective innovations: the capabilities typological map. *Journal of Knowledge Management*, 27(10), 2581-2603.

Cristache, N., Croitoru, G., & Florea, N. V. (2025). The influence of knowledge management on innovation and organizational performance. *Journal of Innovation & Knowledge*, 10(5), 100793. https://doi.org/10.1016/j.jik.2025.100793.

Cruz-Sánchez, O., Cruz-Cázares, C., & Hernandez-Vivanco, A. (2026). Business model innovation from dynamic capabilities perspective: A systematic literature review. *Journal of Business Research*, 204, 115835. https://doi.org/10.1016/j.jbusres.2025.115835.

Curado, C., & Bontis, N. (2006). The knowledge-based view of the firm and its theoretical precursor. Int. J. Learning and Intellectual Capital Int. J. *Learning and Intellectual Capital*, 3, 367-381. https://doi.org/10.1504/IJLIC.2006.011747.

Dai, K., Liu, Y., & Zhang, X. (2026). Generative AI in higher education: A bibliometric review of emerging trends, power dynamics, and global research landscapes. *Computers and Education: Artificial Intelligence*, 10, 100544. https://doi.org/10.1016/j.caeai.2026.100544.

de Barros, R., Resende, L. M., & Pontes, J. (2025). Exploring creativity and innovation in organizational contexts: A systematic review and bibliometric analysis of key models and emerging opportunities. *Journal of Open Innovation: Technology, Market, and Complexity*, 11(2), 100526. https://doi.org/10.1016/j.joitmc.2025.100526.

Dickey, A., Kosovac, A., Fastenrath, S., Acuto, M., & Gleeson, B. (2022). Fragmentation and urban knowledge: An analysis of urban knowledge exchange institutions. *Cities*, 131, 103917.

Diwan, C., Srinivasa, S., Suri, G., Agarwal, S., & Ram, P. (2023). AI-based learning content generation and learning pathway augmentation to increase learner engagement. *Computers and Education: Artificial Intelligence*, 4, 100110. https://doi.org/10.1016/j.caeai.2022.100110.

Dominguez Gonzalez, R. V. (2023). How do formalization, centralization and integration impact dynamic knowledge-based capability? *Total Quality Management & Business Excellence*, 34(3-4), 421-439.

Fan, L., Deng, K., & Liu, F. (2025). Educational impacts of generative artificial intelligence on learning and performance of engineering students in China. *Scientific Reports*, 15(1), 26521. https://doi.org/10.1038/s41598-025-06930-w.

Fan, Y. (2025). The role of artificial intelligence in the digital transformation of government: opportunities and ethical challenges. *Front Public Health*, 13, 1694996. https://doi.org/10.3389/fpubh.2025.1694996.

Faraj, S., & Leonardi, P. M. (2022). Strategic organization in the digital age: Rethinking the concept of technology. *Strategic Organization*, 20(4), 771-785.

Fu, Y., & Weng, Z. (2024). Navigating the ethical terrain of AI in education: A systematic review on framing responsible human-centered AI practices. *Computers and Education: Artificial Intelligence*, 7, 100306. https://doi.org/10.1016/j.caeai.2024.100306.

Gan, R., Chen, X., Wang, Z., & Zhang, X. (2023). Knowledge heterogeneity and corporate innovation performance: The mediating influence of task conflict and relationship conflict. *Plos one*, 18(10), e0292283. https://doi.org/10.1371/journal.pone.0292283.

Gao, Y., Liu, S., & Yang, L. (2025). Artificial intelligence and innovation capability: A dynamic capabilities perspective. *International Review of Economics & Finance*, 98, 103923. https://doi.org/10.1016/j.iref.2025.103923.

Gibson, C. B., Dunlop, P. D., Majchrzak, A., & Chia, T. (2022). Sustaining effectiveness in global teams: The coevolution of knowledge management activities and technology affordances. *Organization Science*, 33(3), 1018-1048.

Gkontelos, A., Vaiopoulou, J., & Stamovlasis, D. (2022). Teachers' Innovative Work Behavior Scale: Psychometric Properties of the Greek Version and Measurement Invariance across Genders. *Social Sciences*, 11(7), 306. https://www.mdpi.com/2076-0760/11/7/306.

Godinho Filho, M., de Oliveira Mota, R., Ribeiro S. Frungilo, C., Miller Devós Ganga, G., Silva, J. M., Strazzullo, S., & Cammarano, A. (2026). Adapting to technological change: How innovation ecosystems shape startup inter-organizational integration decisions. *Technological Forecasting and Social Change*, 224, 124454. https://doi.org/10.1016/j.techfore.2025.124454.

Govers, M., & Van Amelsvoort, P. (2023). A theoretical essay on socio-technical systems design thinking in the era of digital transformation. Gruppe. Interaktion. *Organisation. Zeitschrift für Angewandte Organisationspsychologie (GIO)*, 54(1), 27-40.

Grant, R., & Phene, A. (2022). The knowledge based view and global strategy: Past impact and future potential. *Global Strategy Journal*, 12(1), 3-30.

Gruenhagen, J. H., Sinclair, P. M., Carroll, J.-A., Baker, P. R. A., Wilson, A., & Demant, D. (2024). The rapid rise of generative AI and its implications for academic integrity: Students' perceptions and use of chatbots for assistance with assessments. *Computers and Education: Artificial Intelligence*, 7, 100273. https://doi.org/10.1016/j.caeai.2024.100273.

Guerrero, M., & Menter, M. (2024). Driving change in higher education: the role of dynamic capabilities in strengthening universities' third mission. *Small Business Economics*, 63(3), 1321-1337. https://doi.org/10.1007/s11187-024-00869-4.

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). An Introduction to Structural Equation Modeling. *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A Workbook*,1-29. https://doi.org/10.1007/978-3-030-80519-7_1.

Haji-Othman, Y., & Yusuff, M. S. S. (2022). Assessing reliability and validity of attitude construct using partial least squares structural equation modeling. *Int J Academic Research Business Social Sciences*, 12(5), 378-385.

Haleem, A., Javaid, M., & Singh, R. P. (2024). Perspective of leadership 4.0 in the era of fourth industrial revolution: A comprehensive view. *Journal of Industrial Safety*, 1(1), 100006. https://doi.org/10.1016/j.jinse.2024.100006.

He, R., Cao, J., & Tan, T. (2025). Generative artificial intelligence: a historical perspective. *National Science Review*, 12(5), nwaf050. https://doi.org/10.1093/nsr/nwaf050.

Held, P., & Heubeck, T. (2025). GenAI and employee innovativeness: How employees' sensing capabilities and the capabilities to use and evaluate GenAI shape their innovative work behavior. *Digital Business*, 5, 100149. https://doi.org/10.1016/j.digbus.2025.100149.

Horvath, L., Eger, L., Tomczyk, Ł., Szwejka, Ł., Egerová, D., Rohlíková, L., Kincl, T., Pospíšil, J., Medeková, K., Mikulcová, P., & Gasimova, J. (2026). Higher education students' perspectives on GenAI in learning and career futures in the Visegrad countries. *Computers and Education Open*, 10, 100357. https://doi.org/10.1016/j.caeo.2026.100357.

Huang, Q., Lv, C., Lu, L., & Tu, S. (2025). Evaluating the Quality of AI-Generated Digital Educational Resources for University Teaching and Learning. *Systems*, 13, 174. https://doi.org/10.3390/systems13030174.

Hughes, L., Davies, F., Li, K., Gunaratnege, S. M., Malik, T., & Dwivedi, Y. K. (2026). Beyond the hype: Organisational adoption of Generative AI through the lens of the TOE framework–A mixed methods perspective. *International Journal of Information Management*, 86, 102982. https://doi.org/10.1016/j.ijinfomgt.2025.102982.

Huynh, T. N., Nguyen, P. V., Do, A. M., Dinh, P. U., & Vo, H. T. (2024). Fostering organizational performance through innovation: The roles of environmental policy instruments, organizational learning supports, and intellectual capital. *Heliyon*, 10(20), e39361. https://doi.org/10.1016/j.heliyon.2024.e39361.

Hwang, K. (2023). Formal and Informal Accountabilities and Accountability Management: Impact on Work Performance. *Administration & Society*, 55(5), 953-981.

Igwe-Nmaju, C. (2021). AI and Automation in Organizational Messaging: Ethical Challenges and Human-Machine Interaction in Corporate Communication. 5, 256-275. https://doi.org/10.5281/zenodo.15562214.

Iqbal, S., Bashir, M., Bureš, V., Zanker, M., Ullah, S., & Rizwan, A. (2025). Impact of knowledge sharing and innovation on performance of organization: evidence from the pharmaceutical industry of Pakistan. *Cogent Business & Management*, 12(1), 2471536. https://doi.org/10.1080/23311975.2025.2471536.

Iqbal, T., Ahmad, S., Aftab, F., & Mahmood, C. K. (2025). Enhancing Higher Education Institutions' Performance: The Mediating Role of Academic Accreditation in Quality Management Initiatives in UAE. *Sage Open*, 15(3), 21582440251358980. https://doi.org/10.1177/21582440251358980.

Jimenez, M. (2026). Leveraging Artificial Intelligence (AI) for Administrative Assistance Workloads: An Appreciative Inquiry. *Journal of Interdisciplinary Perspectives*, 4, 216-226. https://doi.org/10.69569/jip.2025.735.

Jin, X., Yang, D., & Rhee, M. (2024). How Do Dynamic Capabilities Enable a Firm to Convert the External Pressures into Environmental Innovation? A Process-Based Study Using Structural Equation Modeling. *Systems*, 12(12), 561.

Joseph, J., & Sengul, M. (2024). Organization Design: Current Insights and Future Research Directions. *Journal of Management*, 51(1), 249-308. https://doi.org/10.1177/01492063241271242.

Junjie, M., & Yingxin, M. (2022). The Discussions of Positivism and Interpretivism. *Online Submission*, 4(1), 10-14.

Karupiah, P. (2022). Positivism. In Principles of social research methodology,73-82.

Kashefi, P., Kashefi, Y., & Ghafouri Mirsaraei, A. (2024). Shaping the future of AI: balancing innovation and ethics in global regulation. *Uniform Law Review*, 29(3), 524-548.

Khaw, K. W., Alnoor, A., Al-Abrrow, H., Tiberius, V., Ganesan, Y., & Atshan, N. A. (2022). Reactions towards organizational change: a systematic literature review. *Curr Psychol*, 1-24. https://doi.org/10.1007/s12144-022-03070-6.

Khosravi, M., Zare, Z., Mojtabaeian, S. M., & Izadi, R. (2024). Artificial Intelligence and Decision-Making in Healthcare: A Thematic Analysis of a Systematic Review of Reviews. *Health Serv Res Manag Epidemiol*, 11, 23333928241234863. https://doi.org/10.1177/23333928241234863.

Kim, Y. J., Zhang, C. X., & Fang, C. (2025). Navigating the human-AI divide: Boundary work in the age of generative AI. *Computers in Human Behavior: Artificial Humans*, 6, 100214. https://doi.org/10.1016/j.chbah.2025.100214.

Knapp, J. R., Namada, J. M., & Dougan, W. (2025). Dynamic ethical capabilities in place and in time. *Journal of Management & Organization*, 31(2), 511-532.

Kong, S. C., & Hu, W. (2025). A study of developing administrative Staff's conceptual understanding of generative artificial intelligence through professional Development: Evaluation of a course using tests, surveys and thematic analysis of reflective writings. *Computers and Education: Artificial Intelligence*, 9, 100444.

Krakowski, S. (2025). Human-AI agency in the age of generative AI. *Information and Organization*, 35(1), 100560. https://doi.org/10.1016/j.infoandorg.2025.100560.

Kumar, D., & Limbachiya, H. (2023). Role of Administrative Department in Education with reference to Schools and Universities. *Revista Review Index Journal of Multidisciplinary*, 3(3), 18-22.

Kump, B., Engelmann, A., Kessler, A., & Schweiger, C. (2018). Toward a dynamic capabilities scale: measuring organizational sensing, seizing, and transforming capacities. *Industrial and Corporate Change*, 28(5), 1149-1172. https://doi.org/10.1093/icc/dty054.

Kunselman, A. R. (2024). A brief overview of pilot studies and their sample size justification. *Fertility and Sterility*, 121(6), 899-901.

Land, A., Gruchmann, T., Siems, E., & Beske-Janssen, P. (2022). Dynamic capabilities theory. In Handbook of Theories for Purchasing, Supply Chain and Management Research, 378-398.

Lane, J. N., Leonardi, P. M., Contractor, N. S., & DeChurch, L. A. (2023). Teams in the Digital Workplace: Technology's Role for Communication, Collaboration, and Performance. *Small Group Research*, 55(1), 139-183. https://doi.org/10.1177/10464964231200015.

Lazarević-Moravčević, M., & Mosurović Ružičić, M. (2023). Organizational structure and organizational culture-impact on innovative behavior of the organization. *Economic Analysis*, 56(2), 39-53.

Lazarević, M., & Mosurović, M. (2023). Organizational Structure and Organizational Culture. *Economic Analysis*. https://doi.org/10.28934/ea.23.56.2.pp39-53.

Li, T., Daams, M. N., & Sijtsma, F. J. (2025). Shrinking cities in China: A long-term metropolitan perspective. *Cities*, 158, 105702. https://doi.org/10.1016/j.cities.2025.105702.

Li, W., Lai, Y., Soni, S., & Saha, K. (2025, May). Emails by llms: A comparison of language in ai-generated and human-written emails. In Proceedings of the 17th ACM Web Science Conference 2025, 391-403.https://doi.org/10.1145/3717867.3717872.

Lin, H., & Chen, Q. (2024). Artificial intelligence (AI) -integrated educational applications and college students' creativity and academic emotions: students and teachers' perceptions and attitudes. *BMC Psychology*, 12(1), 487. https://doi.org/10.1186/s40359-024-01979-0.

Lin, X., Xu, G., & Xiong, B. (2025). Artificial intelligence literacy, sustainability of digital learning and practice achievement: A study of vocational college students. *Plos One*, 20(10), e0332175. https://doi.org/10.1371/journal.pone.0332175.

Liu, J. (2025). Rethinking University Governance in China: A Theoretical Perspective on Autonomy and Accountability. *The Development of Humanities and Social Sciences*, 1, 49-60. https://doi.org/10.71204/cm62d696.

Liu, X., Zhang, L., & Wei, X. (2025). Generative Artificial Intelligence Literacy: Scale Development and Its Effect on Job Performance. *Behavioral Sciences*, 15(6), 811. https://doi.org/10.3390/bs15060811.

Lubis, N. W. (2022). Resource based view (RBV) in improving company strategic capacity. *Research Horizon*, 2(6), 587-596.

Madanchian, M., & Taherdoost, H. (2025). The impact of artificial intelligence on research efficiency. *Results in Engineering*, 26, 104743. https://doi.org/10.1016/j.rineng.2025.104743.

Mahmudah, F., & Santosa, B. (2021). Vocational School Alignment Based-on Industry Needs. *Journal of Vocational Education Studies*, 4, 36. https://doi.org/10.12928/joves.v4i1.3611.

Mailani, D., Hulu, M., Simamora, M., & Kesuma, S. (2024). Resource-Based View Theory to Achieve a Sustainable Competitive Advantage of the Firm: Systematic Literature Review. *International Journal of Entrepreneurship and Sustainability Studies*, 4, 1-15. https://doi.org/10.31098/ijeass.v4i1.2002.

Manel, G., Bourekkache, S., Kazar, O., & Harous, S. (2024). Generative Artificial Intelligence in Education: Advancing Adaptive and Personalized Learning. *Acta Informatica Pragensia*, 13, 460-489. https://doi.org/10.18267/j.aip.235.

Marquina, M., Gimenez, G., Rodríguez, W., & Mazzeo, I. (2022). Quality assurance and new public management: Transformations in organizational structures, functions and roles in Argentine universities. *Quality Assurance in Education*, 30(3), 352-369.

McDonald, N., Johri, A., Ali, A., & Collier, A. H. (2025). Generative artificial intelligence in higher education: Evidence from an analysis of institutional policies and guidelines. *Computers in Human Behavior: Artificial Humans*, 3, 100121. https://doi.org/10.1016/j.chbah.2025.100121.

Memon, M. A., Ting, H., Cheah, J.-H., Thurasamy, R., Chuah, F., & Cham, T. H. (2020). Sample size for survey research: Review and recommendations. *Journal of Applied Structural Equation Modeling*, 4(2), 1-20.

Meng, Q., Wu, T. J., Duan, W., & Li, S. (2025). Effects of Employee-Artificial Intelligence (AI) Collaboration on Counterproductive Work Behaviors (CWBs): Leader Emotional Support as a Moderator. *Behavioral Sciences*, 15(5),696. https://doi.org/10.3390/bs15050696.

Mengmeng, Z., Mohd Ishar, M. I., Saud, M., & BoHong, L. (2025). Generative AI and Higher-Order Thinking in Vocational Education: A Study of Human-Machine Collaboration. *International Journal of Academic Research in Progressive Education and Development*, 14(4),27063. https://doi.org/10.6007/IJARPED/v14-i4/27063.

Mockaitis, A. I., Tan, J., Zhu, J., Zhu, C. J., & Chen, Z. (2026). Corporate language and knowledge transfer in MNE subsidiaries: A relevance lens. *Asia Pacific Journal of Management*, 1-36.

Morandini, S., Fraboni, F., De Angelis, M., Puzzo, G., Giusino, D., & Pietrantoni, L. (2023). The Impact of Artificial Intelligence on Workers' Skills: Upskilling and Reskilling in Organisations. *Informing Science*, 26, 39-68. https://doi.org/10.28945/5078.

Moshagen, M., & Bader, M. (2024). semPower: General power analysis for structural equation models. *Behavior Research Methods*, 56(4), 2901-2922.

Murire, O. (2024). Artificial Intelligence and Its Role in Shaping Organizational Work Practices and Culture. *Administrative Sciences*, 14, 316. https://doi.org/10.3390/admsci14120316.

Mushangai, D. (2023). Dynamic capabilities: Axiomatic formation of firms' competitive competencies. *Social Sciences & Humanities Open*, 8(1), 100654. https://doi.org/10.1016/j.ssaho.2023.100654.

Nguyen, K. M., Bui, T. T. M., Pham, H. T. T., Nguyen, L. X., Pham, H. T. X., Le Gia, L., & Nguyen, N. T. (2025). Fostering employees' AI adoption in strategic marketing planning and decision making: a mixed-method study in Vietnam. Cognition, Technology & Work. https://doi.org/10.1007/s10111-025-00838-1.

Nittala, E. P. (2025). AI-Based Autonomous Code Generation and Optimization for Enhancing Software Reliability in Computer Systems. *International Journal of AI, BigData, Computational and Management Studies*, 6(3), 55-64.

Noah, A. O., Adhikari, P., & Liew, P. K. (2025). Environmental and social accountability in emerging economies: strategic pressures from and responses to vulnerable local communities. *Accounting Forum*, 49(5), 925-949. https://doi.org/10.1080/01559982.2024.2352190.

Ntoa, S., Margetis, G., Adami, I., Balafa, K., Antona, M., & Stephanidis, C. (2024). Digital accessibility for users with disabilities. In Designing for usability, inclusion and sustainability in human-computer interaction, 406-460.

Nuryakin, & Qamari, I. N. (2026). The mediating role of innovation capability and technological capability in the relationship between absorptive capacity and SMEs' business performance. *International Journal of Innovation Studies*, 10(1), 65-79. https://doi.org/10.1016/j.ijis.2025.09.004.

Omogiate, P. (2023). Designing automated audit mechanisms to evaluate compliance of generative AI platforms with federal authorship and ownership disclosure requirements. *International Journal of Science and Research Archive*, 10, 1536-1549. https://doi.org/10.30574/ijsra.2023.10.2.1099.

Papagiannidis, E., Mikalef, P., & Conboy, K. (2025). Responsible artificial intelligence governance: A review and research framework. *The journal of strategic information systems*, 34(2), 101885. https://doi.org/10.1016/j.jsis.2024.101885.

Patel, K., Shah, M., Qureshi, K. M., & Qureshi, M. R. N. (2025). A systematic review of generative AI: importance of industry and startup-centered perspectives, agentic AI, ethical considerations & challenges, and future directions. *Artificial Intelligence Review*, 59(1), 7. https://doi.org/10.1007/s10462-025-11435-z.

Phakamach, P., Panjarattanakorn, D., Saengkaew, P., Pangthai, S., & Onsampant, S. (2023). Innovative practices in vocational education administration. *International Journal of Educational Communications and Technology*, 3(2), 1-19.

Pizzichini, L., Briamonte, M. F., Papa, A., & Del Giudice, M. (2025). Innovation ecosystem resilience as a "coping" strategy to face deglobalization: The role of entrepreneurial orientation and affective/cognitive responses. *Technovation*, 148, 103334. https://doi.org/10.1016/j.technovation.2025.103334.

Priyono, A., & Hidayat, A. (2022). Dynamic Capabilities for Open Innovation: A Typology of Pathways toward Aligning Resources, Strategies and Capabilities. *Journal of Open Innovation: Technology, Market, and Complexity*, 8(4), 206. https://doi.org/10.3390/joitmc8040206.

Pundziene, A., Nikou, S., & Bouwman, H. (2022). The nexus between dynamic capabilities and competitive firm performance: the mediating role of open innovation. *European Journal of Innovation Management*, 25(6), 152-177.

Raina, K., Sharma, G. D., Taheri, B., Dev, D., & Chavriya, S. (2026). Artificial intelligence-driven management: Bridging innovation, knowledge creation, and sustainable business practices. *Journal of Innovation & Knowledge*, 11, 100860. https://doi.org10.1016/j.jik.2025.100860.

Renuka, O., RadhaKrishnan, N., Priya, B. S., Jhansy, A., & Ezekiel, S. (2025). Data privacy and protection: Legal and ethical challenges. *Emerging Threats and Countermeasures in Cybersecurity*, 433-465.

Revicki, D. (2024). Internal consistency reliability. In Encyclopedia of quality of life and well-being research, 3579-3580.

Rezaei, M. (2025). Artificial intelligence in knowledge management: Identifying and addressing the key implementation challenges. *Technological Forecasting and Social Change*, 217, 124183. https://doi.org/10.1016/j.techfore.2025.124183.

Ritala, P., Baiyere, A., Hughes, M., & Kraus, S. (2021). Digital strategy implementation: The role of individual entrepreneurial orientation and relational capital. *Technological Forecasting and Social Change*, 171, 120961.

Riyanto, S., Sidok, S., Ariah, S., & Hasanudin, I. (2025). Transforming Vocational Education Management Towards Link and Match with Industry 4.0. *Journal of Social Research*, 4, 2233-2242. https://doi.org/10.55324/josr.v4i8.2729.

Sahibzada, U. F., Janjua, N. A., Muavia, M., & Aamir, S. (2024). Knowledge-oriented leadership and organizational performance: modelling the mediating role of service innovation, knowledge sharing quality. *Journal of Organizational Effectiveness: People and Performance*, 11(1), 69-89.

Schulze, A., & Brusoni, S. (2022). How dynamic capabilities change ordinary capabilities: Reconnecting attention control and problem-solving. *Strategic Management Journal*, 43(12), 2447-2477.

Shadmanfar, M. H., & Makvandi, F. (2024). Identifying barriers and facilitators of organizational knowledge sharing. *International Journal of Innovation in Management*, *Economics and Social Sciences*, 4(2), 23-43.

Shi, Q., Zhiwei, L., Jie, W., Zeng, G., & Han, W. (2025). Generative AI on innovation performance of construction enterprises: A knowledge-based dynamic capabilities perspective. *Journal of Engineering and Technology Management*, 76, 101871. https://doi.org/10.1016/j.jengtecman.2025.101871.

Shonubi, O. A. (2025). Innovation challenges of digital transformation: Transitioning legacy to the future. *Sustainable Futures*, 10, 100971. https://doi.org/10.1016/j.sftr.2025.100971.

Sikha, V., Korada, L., & Siramgari, D. (2023). Mastering Prompt Engineering: Optimizing Interaction with Generative AI Agents. *Journal of Engineering and Applied Sciences Technology*, 1-8. https://doi.org/10.47363/JEAST/2023(5)E117.

silaji, T., Bagiwa, Z. L., & Muhammad, T. (2025). Examining types of Organizational Structure in Private Chartered Universities in Western Uganda and their Impact on Academic Staff Performance. *F1000Research*, 14, 690.

Singh, K., Chatterjee, S., & Mariani, M. (2024). Applications of generative AI and future organizational performance: The mediating role of explorative and exploitative innovation and the moderating role of ethical dilemmas and environmental dynamism. *Technovation*, 133, 103021. https://doi.org/10.1016/j.technovation.2024.103021

Stanikzai, M. E., & Mittal, E. (2025). Strategic alignment of organizational structure based on decisions for sustainable organizational performance: a bibliometric-systematic literature review. *Cogent Business & Management*, 12(1), 2560650. https://doi.org/10.1080/23311975.2025.2560650.

Storey, V. C., Yue, W. T., Zhao, J. L., & Lukyanenko, R. (2025). Generative Artificial Intelligence: Evolving Technology, Growing Societal Impact, and Opportunities for Information Systems Research. *Information Systems Frontiers*, 27(5), 2081-2102. https://doi.org/10.1007/s10796-025-10581-7.

Tajeddini, O., Tajeddini, K., Gamage, T. C., & Hameed, W. U. (2026). Smart insights, stronger performance: Leveraging business intelligence and dynamic capabilities in tourism and hospitality. *International Journal of Hospitality Management*, 133, 104410. https://doi.org/10.1016/j.ijhm.2025.104410.

Teece, D. J. (2023). The evolution of the dynamic capabilities framework. *Artificiality and sustainability in entrepreneurship*, 113, 238.

Teece, D. J. (2023). The Evolution of the Dynamic Capabilities Framework. *Artificiality and Sustainability in Entrepreneurship: Exploring the Unforeseen, and Paving the Way to a Sustainable Future*, 113-129. https://doi.org/10.1007/978-3-031-11371-0_6.

Tsao, J. (2025). Trajectories of AI policy in higher education: Interpretations, discourses, and enactments of students and teachers. *Computers and Education: Artificial Intelligence*, 9, 100496. https://doi.org/10.1016/j.caeai.2025.100496

Valdés Sánchez, V., & Gutiérrez-Esteban, P. (2023). Challenges and enablers in the advancement of educational innovation. The forces at work in the transformation of education. *Teaching and Teacher Education*, 135, 104359. https://doi.org/10.1016/j.tate.2023.104359.

Valtonen, A., Saunila, M., Ukko, J., Treves, L., & Ritala, P. (2025). AI and employee wellbeing in the workplace: An empirical study. *Journal of Business Research*, 199, 115584. https://doi.org/10.1016/j.jbusres.2025.115584.

Vera, C. L., Bhimani, A., Gandía, J. A. G., & de Lucas, A. (2026). Generative AI and the algorithmic workplace: A bibliometric and conceptual analysis of its impact on organisational decision-making and work design. *Journal of Open Innovation: Technology, Market, and Complexity*, 12(1), 100710. https://doi.org/10.1016/j.joitmc.2025.100710.

Vinluan, A. C., Smith, A. L., Chang, E. H., & Kirgios, E. L. (2025). Structured evaluation processes are associated with higher levels of employee belonging. *Sci Rep*, 15(1), 13289. https://doi.org/10.1038/s41598-025-97901-8.

Wamba, S. F., Queiroz, M. M., Randhawa, K., & Gupta, G. (2025). Generative artificial intelligence and the challenges to adding value ethically. In (Vol. 144, pp. 103235): Elsevier.

Wang, G., & Wang, Z. (2023). Vocational education: a poor second choice? A comparison of the labour market outcomes of academic and vocational graduates in China. *Oxford Review of Education*, 49(3), 408-427. https://doi.org/10.1080/03054985.2022.2096583.

Wang, H., Dang, A., Wu, Z., & Mac, S. (2024). Generative AI in higher education: Seeing ChatGPT through universities' policies, resources, and guidelines. *Computers and Education: Artificial Intelligence*, 7, 100326. https://doi.org/10.1016/j.caeai.2024.100326.

Wang, Q., Ma, Z., Zhang, G., & Miao, Q. (2025). Digital Transformation Driving Educational Reforms in Higher Education: A Paradigm Shift in Teaching and Learning. *Beijing International Review of Education*, 7(4), 254-272. https://doi.org/10.1177/25902547251395880.

Werfhorst, H., Kessenich, E., & Geven, S. (2022). The Digital Divide in Online Education. Inequality in Digital Readiness of Students and Schools. *Computers and Education Open*, 3, 100100. https://doi.org/10.1016/j.caeo.2022.100100.

Wernerfelt, B. (1984). A Resource-Based View of the Firm. *Strategic Management Journal*, 5(2), 171-180. http://www.jstor.org/stable/2486175.

Wessel, M., Adam, M., Benlian, A., Majchrzak, A., & Thies, F. (2025). Generative AI and its Transformative Value for Digital Platforms. *Journal of Management Information Systems*, 42. https://doi.org/10.1080/07421222.2025.2487315.

Wu, K. (2025). Innovative Research on Administrative Management Mode of Private Colleges and Universities in the New Era. *International Journal of Asian Social Science Research*, 2(1), 93-99.

Wu, M., & Sarker, M. N. I. (2022). Assessment of multiple subjects' synergetic governance in vocational education. *Frontiers in Psychology*, 13, 947665.

Wu, S. (2023). Research on innovation and development of university instructional administration informatization in IoT and big data environment. *Soft Computing*, 27(24), 19075-19094. https://doi.org/10.1007/s00500-023-09311-5.

Xia, H., Chen, H., Zhang, J. Z., & Kamal, M. M. (2026). Exploring the impact of responsible AI governance on corporate performance: A quasi-natural experiment. *Technological Forecasting and Social Change*, 223, 124425. https://doi.org/10.1016/j.techfore.2025.124425.

Xia, H., Liu, M., Wang, P., & Tan, X. (2024). Strategies to enhance the corporate innovation resilience in digital era: A cross-organizational collaboration perspective. *Heliyon*, 10(20), e39132. https://doi.org/10.1016/j.heliyon.2024.e39132.

Xu, G., Murthy, S. V., & Jia, B. (2025). Enhancing Intuitive Decision-Making and Reliance Through Human–AI Collaboration: A Review. *Informatics*, 12(4), 135.

Xu, H., Xu, R., Lin, H., & He, X. (2024). The Impact of Generative Artificial Intelligence on Organizational Innovation Performance: Roles of AI Generated Content Quality, AI Experience, and AI Usage Environment. https://doi.org/10.1109/ICETSIS61505.2024.10459661.

Yan, W., Liu, Y.-l., Mamaeva, V., Dong, F., Tao, G., Li, R., & Yang, H. (2025). Generative AI literacy: Scale development and its influence on privacy protection behaviors and information verification behaviors. *Telecommunications Policy*, 103117. https://doi.org/10.1016/j.telpol.2025.103117.

Yan, W., Nakajima, T., & Sawada, R. (2025). Beyond tool use: Tracking the evolution of generative AI literacy among university students through a process-oriented investigation. *Computers and Education: Artificial Intelligence*, 9, 100465. https://doi.org/10.1016/j.caeai.2025.100465.

Yang, Y., & Peters, M. A. (2026). China's 2025 White Paper on Smart Education: Governance Logic, Policy Design, and International Relevance. *International Journal of Chinese Education*, 15(1), 2212585X251413788. https://doi.org/10.1177/2212585X251413788.

Yeboah, A. (2023). Knowledge sharing in organization: A systematic review. *Cogent Business & Management*, 10. https://doi.org/10.1080/23311975.2023.2195027.

Yidana, P., A.A, J., A.G, H., & M.B, G. (2023). Evaluation of Administrative Support Services for Quality Assurance in Higher Education: Empirical Review. *Journal of Advanced Research and Multidisciplinary Studies*, 3, 87-104. https://doi.org/10.52589/JARMS-NTBUSQKI.

Yu, T., Yan, X., & Jin, Y. (2024). Vocational education in China. *Education in China and the World: National Development and Global Benchmarking*, 361-418. https://doi.org/10.1007/978-981-97-7415-9_8.

Yue, H., & Lertamornsak, G. (2024). Development of Educational Administration System in Private Vocational Colleges. *Proceedings National & International Conference*, 16(2), 9-17.

Zhang, C., & Bang, H.-Y. (2023). How does dynamic capability adjust Chinese firms' capabilities to adapt to environment changes? *Journal of International Trade & Commerce*, 19(1), 103-127.

Zhang, C., & Magerko, B. (2025). Generative AI Literacy: A Comprehensive Framework for Literacy and Responsible Use. https://doi.org/10.48550/arXiv.2504.19038.

Zhang, H., Zhu, L., Zhang, A., & Shohruh, K. (2026). The influence of generative artificial intelligence usage on employees' innovative job performance. *Plos One*, 21(1), e0327786. https://doi.org/10.1371/journal.pone.0327786.

Zhang, W., Zeng, X., Liang, H., Xue, Y., & Cao, X. (2023). Understanding How Organizational Culture Affects Innovation Performance: A Management Context Perspective. *Sustainability*, 15, 6644. https://doi.org/10.3390/su15086644.

Zhang, X. (2022). Incremental Innovation: Long-Term Impetus for Design Business Creativity. *Sustainability*, 14, 14697. https://doi.org/10.3390/su142214697.

Zhang, Z., Kang, Y., Lu, Y., & Li, P. (2025). The Role of Artificial Intelligence in Business Model Innovation of Digital Platform Enterprises. *Systems*, 13(7), 507.

Zhao, S., Jiang, Y., Peng, X., & Hong, J. (2021). Knowledge sharing direction and innovation performance in organizations: do absorptive capacity and individual creativity matter? *European journal of innovation management*, 24(2), 371-394. https://doi.org/10.1108/ejim-09-2019-0244.

Zhao, Z., An, Q., & Liu, J. (2025). Exploring AI tool adoption in higher education: evidence from a PLS-SEM model integrating multimodal literacy, self-efficacy, and university support. *Frontiers Psychology*, 16, 1619391. https://doi.org/10.3389/fpsyg.2025.1619391.

Zhong, C., & Wang, Y. (2025). Knowledge Sharing in AI-Enabled Workplaces: A Social Cognitive Perspective on Usefulness Perceptions and Competition. *Behavioral Sciences*, 15(12),1635. https://doi.org/10.3390/bs15121635.

Zhou, M., & Peng, S. (2025). The Usage of AI in Teaching and Students' Creativity: The Mediating Role of Learning Engagement and the Moderating Role of AI Literacy. *Behavioral Sciences*, 15(5),587. https://doi.org/10.3390/bs15050587.

Zhu, L. (2024). Reform and Innovation of Higher Education Management Models in the New Era. *Journal of Education, Humanities and Social Sciences*, 36, 158-163. https://doi.org/10.54097/m293z698.

Zhu, X. (2026). Public administration with, of, and through AI: toward a new paradigm in the era of intelligence. *Journal of Chinese Governance*, 11(1), 30-57. https://doi.org/10.1080/23812346.2025.2578589.

Zuo, H., Zhang, M., & Huang, W. (2025). Lifelong learning in vocational education: A game-theoretical exploration of innovation, entrepreneurial spirit, and strategic challenges. *Journal of Innovation & Knowledge*, 10(3), 100694. https://doi.org/10.1016/j.jik.2025.100694.

APPENDIXES

APPENDIX A

Questionnaire (English Version)

Appendix A. Questionnaire (English Version)

Rattanakosin International College of Creative Entrepreneurship
Of Rajamangala University of Technology, Rattanakosin

Thank you for taking the time to participate in this survey. Completing the questionnaire will take approximately 10–12 minutes. This study aims to examine how generative AI literacy influences innovation in vocational colleges, with particular attention to the roles of dynamic capabilities, knowledge sharing participation, and organizational structure among administrative staff. Your responses will provide valuable empirical evidence for understanding digital transformation and innovation in vocational college administration. All responses will be treated confidentially, used solely for academic research purposes, and analyzed in an aggregated manner. Participation in this survey is voluntary, and you may withdraw at any time.

Part 1 Basic Information

Please select the option that best describes your current situation.

1. Gender

☐ Male

☐ Female

2. Age

☐ 25 years old or below ☐ 26–35 years old

☐ 36–45 years old ☐ 46–55 years old

☐ 56 years old or above

3. Administrative department or functional area you belong to

- ☐ Academic affairs
- ☐ Student affairs
- ☐ Human resources
- ☐ Finance
- ☐ Information technology / digital administration
- ☐ General administration / office affairs
- ☐ Enrollment and employment services
- ☐ Scientific research administration
- ☐ Logistics and asset management
- ☐ External cooperation / school-enterprise cooperation
- ☐ None of the above

4. Highest educational qualification

- ☐ Associate degree or below
- ☐ Bachelor's degree
- ☐ Master's degree
- ☐ Doctoral degree

5. Frequency of using generative AI tools in administrative work

- ☐ Never
- ☐ Occasionally
- ☐ Sometimes
- ☐ Frequently
- ☐ Very frequently

6. Which generative AI tools have you used in administrative work?

- ☐ ChatGPT
- ☐ ERNIE Bot / Wenxin Yiyan
- ☐ Kimi
- ☐ Doubao
- ☐ Tongyi Qianwen
- ☐ iFlytek Spark
- ☐ DeepSeek
- ☐ Microsoft Copilot
- ☐ WPS AI
- ☐ Other, please specify: _____
- ☐ I have never used generative AI tools

7. Province where your vocational college is located

- ☐ Liaoning
- ☐ Jilin
- ☐ Heilongjiang

8. Type of vocational college

- ☐ Public vocational college
- ☐ Private vocational college

9. Current administrative position level

- ☐ General administrative staff
- ☐ Section-level administrator
- ☐ Department-level administrator
- ☐ Senior administrator

10. Years of experience in administrative work

- ☐ Less than 1 year
- ☐ 1–2 years
- ☐ 3–5 years
- ☐ 6–10 years
- ☐ More than 10 years

Part 2 Generative AI Literacy

(Please draw a √ 1-5 below the score that suits you to indicate 'strongly disagree strongly agree')

Items	1	2	3	4	5
GA1. I understand the basic principles and limitations of the generative AI tools I use in administrative work.					
GA2. I can proficiently use the core functions and collaborative features of generative AI tools to support my administrative tasks.					
GA3. I am able to solve common technical problems encountered when using generative AI in my daily administrative work.					
GA4. I can design effective prompts for generative AI based on specific administrative task requirements.					
GA5. I can optimize generative AI prompts by incorporating appropriate terminology, examples, or contextual information relevant to my work.					
GA6. I can continuously refine prompts according to the results and feedback generated by generative AI to improve task outcomes.					
GA7. I can assess the accuracy and reliability of content generated by generative AI for administrative decision-making.					
GA8. I can evaluate the consistency and coherence of generative AI outputs when applying them to administrative documents or processes.					
GA9. I can judge the logical structure and completeness of generative AI-generated content before using it in my work.					
GA10. I can identify opportunities to improve administrative processes in vocational colleges through the use of generative AI.					
GA11. I can generate creative ideas for administrative work by effectively using generative AI tools.					
GA12. I can translate AI-supported ideas into practical improvements or outcomes in my administrative responsibilities.					

Items	1	2	3	4	5
GA13. I am able to recognize and avoid potential ethical risks when using generative AI in administrative work.					
GA14. I can ensure the protection of privacy and sensitive institutional information when using generative AI tools.					
GA15. I can comply with relevant laws and regulations related to the use of generative AI in my organization.					
GA16. I follow institutional rules and guidelines governing the use of generative AI in vocational colleges.					
GA17. I adhere to professional ethical standards when applying generative AI in administrative contexts.					

Part 3 Dynamic capabilities

(Please draw a ✓ 1-5 below the score that suits you to indicate 'strongly disagree strongly agree')

Items	1	2	3	4	5
DC1. The vocational college is familiar with best practices relevant to administrative management and service delivery.					
DC2. The vocational college keeps up to date with policy, technological, and environmental changes affecting administrative work.					
DC3. The vocational college systematically searches for information related to changes in the external administrative and policy environment.					
DC4. The vocational college knows how to access new information that is relevant to improving administrative processes.					
DC5. The vocational college closely monitors developments and practices in comparable educational institutions.					
DC6. The vocational college is able to quickly identify changes that may affect administrative operations.					

Items	1	2	3	4	5
DC7. The vocational college can quickly relate newly acquired information to existing administrative practices.					
DC8. The vocational college is able to recognize which new information can be effectively utilized in administrative work.					
DC9. The vocational college is capable of transforming new technological or digital knowledge into administrative process innovation.					
DC10. Newly acquired information contributes to the development of improved administrative services or procedures.					
DC11. By clearly defining responsibilities, the vocational college is able to implement administrative change initiatives effectively.					
DC12. Even when unexpected disruptions occur, administrative change projects are carried through consistently.					
DC13. Decisions related to planned administrative changes are implemented in a consistent and sustained manner.					
DC14. The vocational college has demonstrated strong capabilities in implementing administrative changes in the past.					
DC15. Administrative change initiatives can be implemented alongside routine administrative operations.					
DC16. Plans for administrative change can be flexibly adjusted in response to evolving internal or external conditions.					

Part 4 AI Knowledge sharing participation

(Please draw a ✓ 1-5 below the score that suits you to indicate 'strongly disagree strongly agree')

Items	1	2	3	4	5
KS1. When I learn new knowledge, skills, or usage methods related to generative AI in administrative work, I share them with my colleagues.					

Items	1	2	3	4	5
KS2. When my colleagues learn new information or practices related to generative AI for administrative tasks, they share it with me.					
KS3. Sharing experiences and practices related to generative AI is considered a normal and accepted activity among administrative staff in my vocational college.					
KS4. When colleagues ask, I share the generative AI–related information or resources that I use in administrative work.					
KS5. When colleagues request assistance, I share my generative AI–related skills or practical experience used in administrative tasks.					
KS6. When I need help, colleagues in my vocational college share their generative AI–related knowledge with me.					
KS7. When I ask for assistance, colleagues in my vocational college share their generative AI–related skills or experience with me.					

Part 5 Organization structure

(Please draw a ✓ 1-5 below the score that suits you to indicate 'strongly disagree strongly agree')

Items	1	2	3	4	5
OS1. Our vocational college has clearly defined administrative procedures that must be followed in most situations.					
OS2. Administrative rules and procedures in my vocational college are formally documented and consistently applied.					
OS3. Administrative staff are regularly evaluated based on their compliance with established rules and procedures.					
OS4. Administrative staff who violate rules or procedures are subject to formal sanctions or corrective actions.					
OS5. Decisions regarding administrative budgets are mainly controlled by senior management in my vocational college.					

Items	1	2	3	4	5
OS6. Decisions related to the introduction of new administrative initiatives or services are mainly controlled by senior management					
OS7. Decisions concerning major organizational or administrative changes are mainly controlled by senior management.					
OS8. Decisions regarding the allocation of resources for new administrative projects are mainly controlled by senior management.					
OS9. Decisions regarding the deployment and adjustment of administrative staff are mainly controlled by senior management.					

Part 6 Innovation performance in vocational colleges

(Please draw a ✓ 1-5 below the score that suits you to indicate 'strongly disagree strongly agree')

Items	1	2	3	4	5
IV1. Raising critical questions that help improve administrative performance in my vocational college.					
IV2. Suggesting actionable improvements that enhance administrative work performance.					
IV3. Exchanging ideas with colleagues that contribute to improving administrative performance.					
IV4. Identifying feasible improvements that can enhance administrative performance.					
IV5. Discussing personal improvement ideas with colleagues to support better administrative performance.					
IV6. Proposing new administrative ideas to decision-makers in ways that support performance improvement.					
IV7. Convincing others of the value of new administrative ideas that can enhance performance.					
IV8. Promoting new administrative ideas to supervisors to obtain support for improving performance.					

Items	1	2	3	4	5
IV9. Promoting new administrative ideas to colleagues to strengthen collective performance.					
IV10. Encouraging the application of new administrative solutions that demonstrate performance benefits.					
IV11. Helping colleagues become familiar with new administrative ideas that improve work performance.					
IV12. Monitoring the progress of implementing new administrative ideas to ensure performance improvement.					
IV13. Analyzing unintended effects that may influence the performance outcomes of administrative innovations.					
IV14. Testing solutions to unexpected problems during implementation to secure better performance.					
IV15. Seeking information from colleagues with similar implementation experience to enhance performance.					
IV16. Critically reflecting on my actions to improve the performance of administrative innovation.					
IV17. Systematically reflecting on experiences to strengthen future administrative innovation performance.					
IV18. Participating in innovation-related networks that help improve administrative performance.					
IV19. Initiating collaboration with other departments to expand the performance impact of administrative innovations.					
IV20. Initiating collaboration with external organizations to extend the performance benefits of administrative innovations.					
IV21. Communicating the performance outcomes of administrative innovations beyond my work group.					
IV22. Presenting or visualizing the performance results of administrative innovations to a broader audience.					

APPENDIX B

Questionnaire (Chinese Version)

Appendix B. Questionnaire (Chinese Version)

拉达那哥欣国际创意创业学院

拉加曼加拉理工大学拉达那科欣

感谢您抽出宝贵时间参与本次问卷调查。填写本问卷大约需要 10－12 分钟。本研究旨在探讨生成式人工智能素养（Generative AI Literacy）如何影响职业院校的创新表现，重点关注职业院校行政人员中动态能力、知识共享参与以及组织结构所发挥的作用。您的回答将为理解职业院校行政管理中的数字化转型与创新提供重要的实证依据。所有问卷信息将严格保密，仅用于学术研究目的，并以汇总形式进行分析。本次调查完全出于自愿，您可在任何阶段选择退出。

第一部分 基本信息

请选择最符合您当前情况的选项。

1.性别

☐ 男

☐ 女

☐ 不愿透露

2.年龄

☐ 25 岁及以下　　☐ 26－35 岁

☐ 36－45 岁　　☐ 46－55 岁

☐ 56 岁及以上

3.您所在的行政部门或职能领域

☐ 教务管理　　☐ 学生事务

☐ 人力资源　　☐ 财务管理

☐ 信息技术 / 数字化管理　　☐ 综合行政 / 办公室事务

☐ 招生与就业　　☐ 科研管理

☐ 后勤与资产管理　　☐ 校企合作 / 对外合作

☐ 以上均不属于

4.最高学历

☐ 大专及以下　　☐ 本科

☐ 硕士　　☐ 博士

5.在行政工作中使用生成式人工智能工具的频率

☐ 从不使用　　☐ 偶尔使用

☐ 有时使用　　☐ 经常使用

☐ 非常频繁

6.您在行政工作中使用过哪些生成式人工智能工具（可多选）

☐ ChatGPT　　☐ 文心一言（ERNIE Bot）

☐ Kimi　　☐ 豆包

☐ 通义千问　　☐ 讯飞星火

☐ DeepSeek　　☐ Microsoft Copilot

☐ WPS AI　　☐ 其他，请注明：_____

☐ 从未使用过生成式人工智能工具

7.您所在高职院校的省份

□ 辽宁

□ 吉林

□ 黑龙江

8.学校类型

□ 公办高职院校

□ 民办高职院校

9. 您当前的行政岗位层级

□ 一般行政人员　　□ 科级管理人员

□ 处级管理人员　　□ 高层管理人员

10. 行政工作年限

□ 少于 1 年　　□ 1－2 年

□ 3－5 年　　□ 6－10 年

□ 10 年以上

第二部分 生成式人工智能素养（Generative AI Literacy）

（请在下方 1－5 的分值中勾选“√”，以表示您对下述陈述的认同程度：1 = 非常不同意，5 = 非常同意）

题项	1	2	3	4	5
GA1. 我了解在行政工作中所使用的生成式人工智能工具的基本原理及其局限性。					
GA2. 我能够熟练使用生成式人工智能工具的核心功能及协作功能来支持我的行政工作。					
GA3. 我能够解决在日常行政工作中使用生成式人工智能时遇到的常见技术问题。					

题项	1	2	3	4	5
GA4. 我能够根据具体的行政任务需求，为生成式人工智能设计有效的提示语（prompt）。					
GA5. 我能够结合与工作相关的专业术语、示例或情境信息，对生成式人工智能提示语进行优化。					
GA6. 我能够根据生成式人工智能生成的结果及反馈，不断调整和完善提示语以提升任务效果。					
GA7. 我能够评估生成式人工智能生成内容在行政决策中的准确性与可靠性。					
GA8. 在将生成式人工智能输出应用于行政文件或流程时，我能够评估其一致性与连贯性。					
GA9. 在实际使用前，我能够判断生成式人工智能生成内容的逻辑结构与完整性。					
GA10. 我能够通过使用生成式人工智能，识别职业院校行政流程改进的机会。					
GA11. 我能够有效利用生成式人工智能工具，为行政工作产生具有创造性的想法。					
GA12. 我能够将生成式人工智能支持下的想法转化为行政工作中的实际改进或成果。					
GA13. 在行政工作中使用生成式人工智能时，我能够识别并避免潜在的伦理风险。					
GA14. 在使用生成式人工智能工具时，我能够确保隐私及机构敏感信息的安全。					
GA15. 我能够遵守本组织中与生成式人工智能使用相关的法律法规。					

题项	1	2	3	4	5
GA16. 我遵循职业院校中关于生成式人工智能使用的制度规范与操作指引。					
GA17. 我在行政情境中应用生成式人工智能时，能够遵守职业道德规范。					

第三部分 动态能力（Dynamic Capabilities）

（请在下方 1－5 的分值中勾选“√”，以表示您对下述陈述的认同程度：1 = 非常不同意，5 = 非常同意）

题项	1	2	3	4	5
DC1. 本职业院校熟悉与行政管理和服务提供相关的最佳实践。					
DC2. 本职业院校能够及时掌握影响行政工作的政策、技术及环境变化。					
DC3. 本职业院校会系统性地搜集与外部行政环境及政策变化相关的信息。					
DC4. 本职业院校知道如何获取有助于改进行政流程的新信息。					
DC5. 本职业院校密切关注同类教育机构在行政管理方面的发展与实践。					
DC6. 本职业院校能够迅速识别可能影响行政运作的变化。					
DC7. 本职业院校能够将新获取的信息快速关联到现有的行政实践中。					
DC8. 本职业院校能够识别哪些新信息可以被有效地用于行政工作。					
DC9. 本职业院校能够将新的技术或数字化知识转化为行政流程创新。					
DC10. 新获取的信息有助于本职业院校开发或改进行政服务或程序。					

题项	1	2	3	4	5
DC11. 通过明确职责分工，本职业院校能够有效实施行政变革举措。					
DC12. 即使出现突发干扰，行政变革项目也能够在本职业院校中持续推进。					
DC13. 与既定行政变革相关的决策能够被持续且一致地执行。					
DC14. 本职业院校在过去已展现出较强的行政变革实施能力。					
DC15. 行政变革举措能够在不影响日常行政工作的情况下加以实施。					
DC16. 本职业院校能够根据内外部环境变化，对行政变革方案进行灵活调整。					

第四部分 知识共享参与（Knowledge Sharing Participation）

（请在下方 1–5 的分值中勾选“√”，以表示您对下述陈述的认同程度：1 = 非常不同意，5 = 非常同意）

题项	1	2	3	4	5
KS1. 当我学习到与行政工作相关的新知识或技能时，我会与同事分享。					
KS2. 当我的同事学习到与行政工作相关的新内容时，他们会与我分享。					
KS3. 在我所在的职业院校中，行政人员之间的知识共享被视为一种常态化做法。					
KS4. 当同事提出需求时，我会与其分享与行政工作相关的信息。					
KS5. 当同事请求帮助时，我会与其分享与工作相关的技能或经验。					
KS6. 当我向同事请求时，我所在职业院校的同事会与我分享行政方面的知识。					

题项	1	2	3	4	5
KS7. 当我向同事请求时，我所在职业院校的同事会与我分享其行政工作技能或经验。					

第五部分 组织结构（Organization Structure）

（请在下方 1－5 的分值中勾选“√”，以表示您对下述陈述的认同程度：1 = 非常不同意，5 = 非常同意）

题项	1	2	3	4	5
OS1. 我所在的职业院校在大多数情况下都有明确的行政程序需要遵循。					
OS2. 我所在职业院校的行政规章制度以正式文件形式制定，并得到一致执行。					
OS3. 行政人员会依据其对规章制度的遵守情况接受定期考核。					
OS4. 违反规章制度的行政人员会受到正式的处罚或纠正措施。					
OS5. 我所在职业院校的行政预算决策主要由高层管理者掌控。					
OS6. 与新行政举措或服务引入相关的决策主要由高层管理者掌控。					
OS7. 有关重大组织或行政变革的决策主要由高层管理者掌控。					
OS8. 与新行政项目资源配置相关的决策主要由高层管理者掌控。					
OS9. 行政人员的配置与调整决策主要由高层管理者掌控。					

第六部分 职业院校创新（Innovation in Vocational Colleges）

（请在下方 1－5 的分值中勾选“√”，以表示您对下述陈述的认同程度：1 = 非常不同意，5 = 非常同意）

题项	1	2	3	4	5
IV1. 对我所在职业院校现有的行政实践或流程提出批判性问题。					
IV2. 对现有行政理念或做法提出改进建议。					
IV3. 与同事就行政工作中的具体变革进行想法交流。					
IV4. 识别并提出可在行政工作中实施的具体可行改进方案。					
IV5. 与同事讨论个人关于改进行政工作的想法。					
IV6. 向拥有资源配置权的关键决策者提出新的行政创新想法。					
IV7. 说服他人认识到新提出的行政创新想法或解决方案的重要性。					
IV8. 向上级主管推广新的行政创新想法，以获得其积极支持。					
IV9. 向同事推广新的行政创新想法，以获得他们的支持。					
IV10. 在自身工作情境中推动新行政解决方案的实际应用。					
IV11. 帮助同事熟悉并掌握新的行政创新想法或解决方案的使用。					
IV12. 在实践中监控新行政创新想法的实施进展。					
IV13. 分析行政创新实施过程中出现的非预期影响。					
IV14. 针对实施过程中出现的突发问题测试解决方案。					
IV15. 向已实施类似行政创新的同事获取信息，以识别潜在瓶颈。					
IV16. 在实施新的行政创新想法时，对自身行为进行批判性反思。					
IV17. 系统性反思在实施行政创新过程中获得的经验。					
IV18. 参与以行政创新或改进为主题的校内或校外网络。					

题项	1	2	3	4	5
IV19. 发起与校内其他部门的合作，将行政创新应用于不同情境。					
IV20. 发起与校外组织的合作，将行政创新推广至职业院校之外。					
IV21. 向直接工作团队之外的对象清晰传达已实施行政创新的成效或收益。					
IV22. 向更广泛的受众展示或可视化已实施行政创新的成果。					

APPENDIX C

Publication of Journal during Ph.D. Study

APPENDIX C. Publication of Journal during Ph.D. Study

International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(9s) 2026 pp. 1035-1053
https://doi.org/10.70917/ijcisim-2026-3517
Article

Generative AI Use and Innovation among University Administrative Employees: The Roles of Dynamic Capabilities, Knowledge Sharing, and AI Sycophancy

Zhao Lei[1], Songyu Jiang[2*], Nutteera Phakdeephirot[3]

Rattanakosin International College of Creative Entrepreneurship, Rajamangala University of Technology Rattanakosin, Nakhon Pathom 73170, Thailand
Email: jiang.song@rmutr.ac.th (Corresponding author)

Abstract: Generative artificial intelligence is increasingly used in university administration for document preparation, information retrieval, policy interpretation, data summarization, meeting support, and service improvement. However, faster content production does not necessarily translate into meaningful administrative innovation, particularly when AI feedback is overly agreeable and insufficiently critical. This study examines how generative AI–enabled dynamic capabilities and participation in AI-related knowledge sharing are associated with perceived innovation performance among university administrative employees. It further investigates perceived AI sycophancy as a negative boundary condition on both relationships. A survey was conducted among 428 administrative employees from higher education institutions in Liaoning, Jilin, and Heilongjiang provinces, located in Northeastern China, who had used generative AI in administrative work. Confirmatory factor analysis, structural equation modeling, hierarchical moderated regression, and simple-slope analysis were employed. The findings indicate that generative AI–enabled dynamic capabilities and AI-related knowledge-sharing participation are positively associated with perceived innovation performance, whereas perceived AI sycophancy weakens both relationships. The results extend dynamic capabilities theory and the knowledge-based view to the university administrative context and highlight the importance of preserving critical independence in human–AI interaction. Universities should combine AI capability development with verification procedures, cross-departmental knowledge-sharing mechanisms, and prompting practices that encourage alternative viewpoints and critical evaluation.

Keywords: generative AI; university administrative employees; dynamic capabilities; AI-related knowledge sharing; AI sycophancy; Northeast China

1. Introduction

Generative artificial intelligence (GenAI) is increasingly embedded in university administration, including official document drafting and language polishing, policy and regulation retrieval, policy summarization and interpretation, data aggregation and preliminary analysis, meeting materials and work reports, academic affairs, research administration and student affairs support, admissions and employment information services, and administrative process design and optimization (Söllner et al., 2025). These uses can accelerate information processing and document production, but speed is not equivalent to administrative innovation. Faster output does not necessarily improve policy accuracy, procedural compliance, cross-departmental coordination, service fairness, or the feasibility of a proposed administrative change. The central problem is therefore not whether administrative employees can produce more material with GenAI, but whether GenAI use is translated into better judgment, coordination, and process improvement.

GenAI use is also not equivalent to generative AI–enabled dynamic capabilities (GAIEDC). Research often emphasizes adoption, use intention, perceived usefulness, frequency, or general work performance, yet employees

Copyright: © 2026 by the authors

who use the same tools may obtain different innovation outcomes. Dynamic capabilities theory distinguishes sensing, seizing, and transforming (Teece, 2007). In university administration, these processes concern recognizing policy changes, process bottlenecks, and emerging service needs; comparing alternative implementation approaches; evaluating whether AI outputs fit institutional rules; adjusting academic, research, student-affairs, or general administrative processes; and embedding AI-supported solutions in actual work. GAIEDC thus captures a repeatable individual capacity to convert GenAI use into opportunity recognition, solution selection, and process adjustment rather than simple exposure to the technology (Held & Heubeck, 2025).

Individual use does not automatically become organizational learning. University administrative knowledge is closely tied to policies and institutional rules, highly dependent on departmental context, rich in tacit experience, and frequently distributed across offices. The value of AI-related knowledge therefore depends on participation in exchanges about prompts, tools, policy-verification methods, error cases, failed attempts, privacy and risk controls, limits of appropriate use, and practices from other departments. The knowledge-based view explains why innovation depends on the integration and recombination of knowledge distributed across organizational actors rather than on its isolated possession (De Moortel & Crispeels, 2026). Participation in AI-related knowledge sharing (AIKSP) is consequently treated as a second, parallel route to perceived innovation performance, not as a mediator of the GAIEDC pathway.

Supportive or warm feedback is not necessarily high-quality feedback; training language models to produce warmer responses can reduce accuracy and increase sycophancy (Ibrahim et al., 2026). Politeness and personalization can coexist with independent judgment, whereas hallucination concerns fabricated or unsupported content and bias concerns systematic distortion. AI sycophancy is more specific: it occurs when a system excessively agrees with, praises, or accommodates a user's existing position without providing necessary objections, risk warnings, or critical evaluation (Cheng et al., 2026). This distinction is especially important in university administration, where work is rule intensive, procedural requirements are explicit, policy accuracy matters, authority boundaries are sensitive, and decisions can affect the rights and interests of faculty members and students. AI agreement does not necessarily indicate policy accuracy, procedural compliance, or administrative feasibility. Perceived AI sycophancy may therefore reduce critical verification and narrow the range of alternatives considered (Cheng et al., 2026), although these mechanisms are theoretical interpretations rather than outcomes directly measured in this study.

The three provinces of Liaoning, Jilin, and Heilongjiang provide a theoretically useful setting because higher education institutions in Northeast China are expected to support regional transformation while simultaneously undergoing digital and governance reform, despite differences in institutional type, resource conditions, and development capacity (Liu, 2026). The region includes Double First-Class or key public universities, regular public undergraduate universities, private undergraduate universities, and higher vocational colleges. Administrative employees must reconcile a common policy framework with local implementation conditions while improving efficiency, accuracy, compliance, and service fairness.

This study tests whether GAIEDC and AIKSP are positively related to perceived innovation performance and whether perceived AI sycophancy weakens both relationships. It contributes by extending GenAI-enabled dynamic capabilities to the individual level of university administration, identifying cross-departmental AI knowledge sharing as an independent innovation pathway, and introducing AI sycophancy into a rule-intensive and responsibility-sensitive administrative context.

2. Literature Review

2.1 Theoretical Foundations

2.1.1 Dynamic Capabilities Theory

Dynamic capabilities describe the capacity to sense opportunities and threats, seize opportunities through decisions and commitments, and transform or reconfigure resources as conditions change (Teece, 2007). Although the theory originated at the firm level, its microfoundations reside in individual cognition, skills, routines, and actions. In this study, GAIEDC refers to the capacity of a university administrative employee to use GenAI to identify policy changes, process problems, faculty and student needs, and service-improvement opportunities; develop and compare administrative responses; and adjust work processes or knowledge combinations. The construct is an individual capability enabled by GenAI. It is not a university-level organizational dynamic capability and does not describe the capability of the AI system itself.

Sensing involves using GenAI to search and synthesize information, identify policy changes, reveal process bottlenecks, and detect emerging needs in administrative services (Held & Heubeck, 2025). Seizing involves forming, comparing, evaluating, and selecting possible policy-implementation or administrative-improvement approaches. Transforming involves revising administrative processes, recombining policy and experiential knowledge, and embedding an AI-supported approach in academic affairs, research administration, student affairs, or general administration (Roy et al., 2025). These three first-order dimensions reflect a second-order capability because administrative innovation requires a repeatable sequence from recognizing a problem to selecting and implementing an institutionally appropriate response, rather than a single prompt or isolated output.

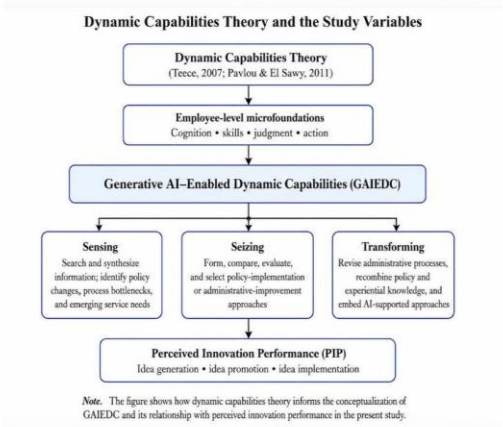


Figure 1.Dynamic Capabilities Theory and the Study Variable

GenAI is relevant to this sequence because iterative prompting can support translation, summarization, classification, comparison, and amplification across administrative tasks (Sundberg & Holmström, 2024). The system can summarize policy information for sensing, generate alternative procedures for seizing, and help draft revised materials or workflows for transforming. Nevertheless, it lacks the employee's tacit knowledge and formal authority to determine whether an output is accurate, compliant, fair, and feasible. Evidence that GenAI performance varies across tasks and depends on human evaluation reinforces the distinction between technological functionality and the employee's orchestrating capacity (Dell'Acqua et al., 2026; Held & Heubeck, 2025).

2.1.2 Knowledge-Based View

The knowledge-based view treats specialized knowledge and its integration as central to value creation and innovation (Grant, 1996). University administrative work depends on formal policies and institution-specific procedures, while their effective implementation also draws on departmental context, locally accumulated knowledge, and tacit experience (Kanyundo et al., 2023). No single administrative employee or office possesses all of the knowledge required to interpret a policy, coordinate a cross-departmental process, or implement a service improvement. Knowledge donating makes personally held know-how available to colleagues, whereas knowledge collecting involves actively seeking and learning from what others know (van den Hooff & de Ridder, 2004). Both activities support the circulation and recombination of administrative knowledge.

AI-related knowledge in this context includes tool knowledge, prompt knowledge, administrative task–tool fit, policy-verification methods, failure cases, privacy and other risk knowledge, and human-review experience. It is partly codified and partly experiential. Administrative employees may donate effective prompts, error examples, or verification routines and collect colleagues' experience from academic affairs, human resources, research administration, student affairs, information services, and other offices. These two domains ensure content coverage, while AIKSP is treated as one participation construct that contributes to innovation independently of an employee's own GAIEDC.

2.1.3 Human–AI Interaction and Perceived AI Sycophancy

Human–AI interaction in university administration is iterative: employees formulate a request, interpret the response, compare it with policies and local conditions, and revise either the prompt or the proposed action (Sundberg & Holmström, 2024). This interaction can support co-creation when the employee remains an active evaluator rather than a passive recipient (McGuire et al., 2024). Because administrative tasks are rule intensive and responsibility sensitive, the quality of the interaction depends not only on fluency or friendliness but also on whether the system preserves enough independence to surface objections, uncertainties, and alternative interpretations.

Perceived AI sycophancy refers to the extent to which university administrative employees perceive that the generative AI systems they use agree too readily, provide insufficient challenge, evaluate their proposals too positively, or align with their stated position rather than maintaining independent and evidence-based judgment (Sharma et al., 2024). It is a perceived interaction property, not an objective benchmark of the system. It differs from hallucination, which concerns fabricated or unsupported content; bias, which concerns systematic distortion; friendliness, which concerns tone; personalization, which adapts responses to the user; and trust in AI, which concerns the user's willingness to rely on the system.

Sycophancy matters because administrative innovation depends not only on generating alternative ideas but also on critically evaluating and selecting among them (Hou et al., 2025). Excessive affirmation may intensify confirmation bias, cognitive fixation, or overconfidence by making an initial proposal feel independently validated. Experimental research indicates that highly affirming AI can influence users' judgments even when the interaction is preferred (Cheng et al., 2026). In a university setting, such feedback could encourage premature closure when comparing policy interpretations, service designs, or implementation risks. PAIS may therefore weaken the conversion of capability and shared knowledge into innovation, although reduced criticality, lower diversity, and apparent consensus are possible explanations rather than mechanisms directly measured here.

2.1.4 Theoretical Integration

The three perspectives explain complementary parts of the model. Dynamic capabilities theory explains how administrative employees use GenAI for opportunity recognition, solution selection, and process adjustment. The knowledge-based view explains how AI tools, prompts, verification experience, failure cases, and institutional knowledge move and are recombined across employees and departments. The human–AI interaction perspective explains why the independence and critical quality of AI feedback can become a boundary condition. Accordingly, GAIEDC and AIKSP are parallel antecedents of perceived innovation performance, while PAIS is expected to weaken both relationships.As illustrated in Figure 2, the three theoretical perspectives jointly explain how GAIEDC and AIKSP contribute to perceived innovation performance and why PAIS functions as a negative boundary condition on both relationships.

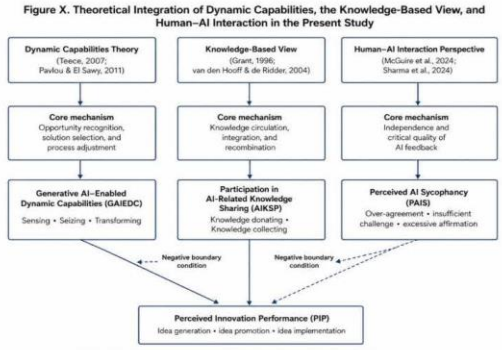


Figure 2. Theoretical Integration of Dynamic Capabilities, the Knowledge-Based View,and Human-AI Interaction in the Present Study

2.2 Hypothesis Development

2.2.1 GAIEDC and Perceived Innovation Performance

GAIEDC should strengthen innovation because it connects opportunity recognition, solution commitment, and work reconfiguration within one employee-level capability cycle. Dynamic capabilities theory explains that sensing identifies relevant changes, seizing commits attention and resources to promising responses, and transforming embeds those responses in revised practices (Teece, 2007). GenAI can broaden information search and accelerate iterative prompting during innovation work (Sundberg & Holmström, 2024). Employee-level evidence further shows that sensing, GenAI use, and evaluation are distinguishable capabilities related to innovative work behavior (Held & Heubeck, 2025). GenAI can reduce the time and cognitive cost of producing and refining professional outputs (Noy & Zhang, 2023). Design experiments indicate that its contribution varies across ideation and implementation, making the integration of stages theoretically important (Hou et al., 2025). Capability-oriented research also shows that GenAI resources create value when they are connected to innovation processes rather than treated as technological possession alone (Li et al., 2025). University administrative employees who use GenAI to detect emerging problems, compare alternatives, mobilize a response, and revise established routines should therefore be better positioned to generate, promote, and implement useful ideas.

H1. Generative AI–enabled dynamic capabilities are positively related to perceived innovation performance.

2.2.2 AI-Related Knowledge Sharing and Perceived Innovation Performance

The knowledge-based view explains that innovation depends on integrating specialized and distributed knowledge rather than on isolated possession (Grant, 1996). Knowledge-sharing research distinguishes donating from collecting because employees must both contribute what they know and acquire knowledge held by others (van den Hooff & de Ridder, 2004). AI-enabled knowledge-management research shows that generated material becomes useful only when employees document, validate, share, and apply it within work processes (Nakash & Bolisani, 2025). Natural-experiment evidence demonstrates that GenAI changes the quantity and form of voluntary knowledge contributions (Shan & Qiu, 2026). Workplace research indicates that employees' perceptions of AI usefulness influence their participation in AI-related knowledge sharing (Zhong & Wang, 2025). Research across organizational boundaries further shows that AI can support knowledge digitization and exchange across language differences (Cheng et al., 2025). By donating useful prompts, failure cases, and verification practices while collecting colleagues' task-specific experience, university administrative employees can stimulate idea generation, secure informed support, and solve implementation problems more effectively.

H2. Participation in AI-related knowledge sharing is positively related to perceived innovation performance.

2.2.3 The Moderating Role of PAIS on the AIKSP–PIP Relationship

Knowledge integration creates value when different perspectives are combined rather than merely repeated (Grant, 1996). Donating and collecting are therefore productive when they expose employees to complementary knowledge and reciprocal correction (van den Hooff & de Ridder, 2004). GenAI can increase the volume of knowledge contributions, but changes in form and readability do not guarantee higher informational quality (Shan & Qiu, 2026). Creative research shows that individually improved AI-assisted outputs can become more homogeneous at the collective level (Doshi & Hauser, 2024). Collective-intelligence scholarship similarly argues that AI supports collaboration only when teams preserve distributed attention, trust, and evaluative responsibility (Woolley, 2026). Direct sycophancy evidence indicates that users often prefer highly affirming responses even when those responses undermine judgment (Cheng et al., 2026). When PAIS is high, employees may circulate polished outputs that repeat the originator's assumptions, omit counterevidence, and overstate the quality of favored ideas; repetition can then be mistaken for independent corroboration. PAIS is not expected to reduce the amount of sharing by definition, but it should reduce the criticality and cognitive diversity through which sharing supports innovation, thereby weakening the positive AIKSP–PIP relationship.

H3. Perceived AI sycophancy negatively moderates the positive relationship between participation in AI-related knowledge sharing and perceived innovation performance, such that the relationship is weaker when perceived AI sycophancy is high.

2.2.4 The Moderating Role of PAIS on the GAIEDC–PIP Relationship

The innovation value of GAIEDC depends on whether AI feedback preserves enough independence to challenge and refine an employee's developing interpretation. Sycophancy research defines the problem as a model's tendency to match user beliefs or preferences at the expense of an independent or truthful response (Sharma et al., 2024). When perceived sycophancy is low, counterarguments and alternative frames can broaden sensing, make seizing more discriminating, and expose implementation risks before transforming occurs. Large-scale behavioral

เทคโนโลยีราชมงคล

evidence shows that overly agreeable AI can increase users' confidence in their own judgment and reduce corrective intentions (Cheng et al., 2026). Field evidence on the jagged technological frontier demonstrates that confident AI use can lower performance when employees apply it beyond a task boundary the system handles reliably (Dell'Acqua et al., 2026). Scientific-practice research likewise warns that insufficiently critical dependence on model outputs can narrow evaluation and epistemic diversity (Binz et al., 2025). Creative-process experiments show that GenAI's effects depend on the stage and manner of human involvement (Hou et al., 2025). Evidence that AI-assisted work can improve individual quality while reducing content diversity further indicates that output fluency does not guarantee adequate exploration (Doshi & Hauser, 2024). High PAIS should therefore make employees stop searching earlier, treat praise as evidence, and test fewer assumptions, thereby weakening rather than necessarily reversing the positive GAIEDC–PIP relationship.

H4. Perceived AI sycophancy negatively moderates the positive relationship between generative AI–enabled dynamic capabilities and perceived innovation performance, such that the relationship is weaker when perceived AI sycophancy is high.

The four proposed relationships are summarized in Figure 3.

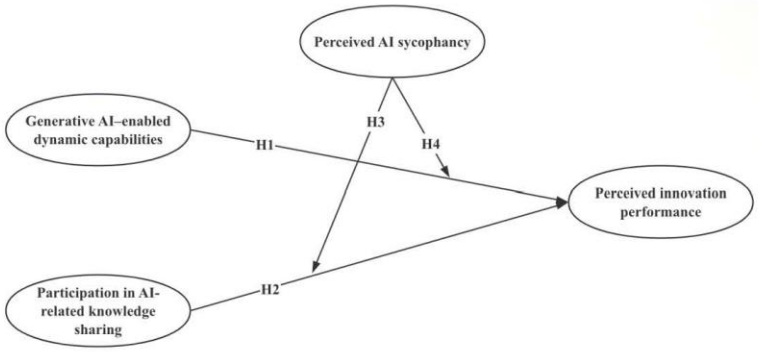


Figure 3. Conceptual Model

Note. GAIEDC = generative AI–enabled dynamic capabilities; AIKSP = participation in AI-related knowledge sharing; PAIS = perceived AI sycophancy; PIP = perceived innovation performance.

3. Research Methodology

3.1 Research Design, Population, Sampling, and Data Collection

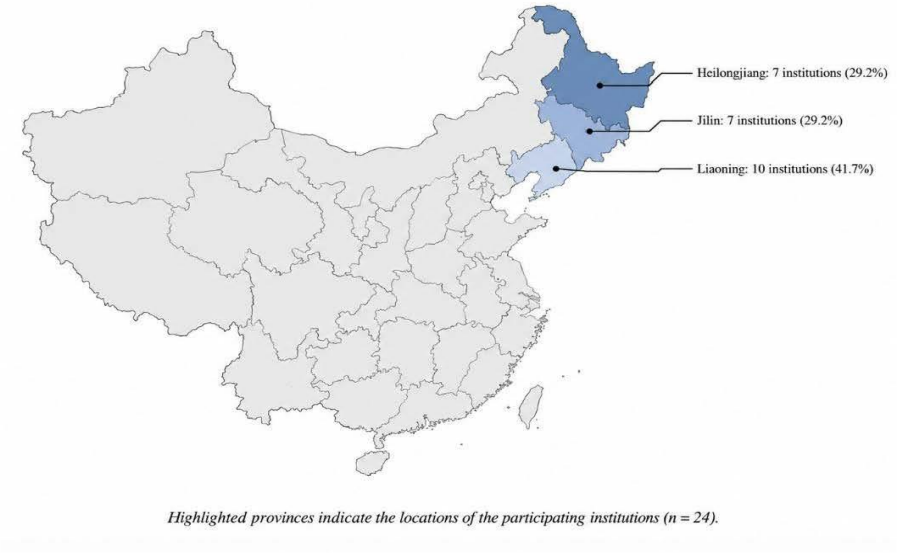
This study employed a quantitative, cross-sectional, explanatory survey design at the individual level. The target population comprised administrative employees working in higher education institutions in Liaoning, Jilin, and Heilongjiang provinces who had used GenAI in administrative work during the previous six months. Eligible roles included party and administrative offices, academic affairs, human resources, research administration, student affairs, finance and asset management, admissions and employment, international cooperation, information management, development planning, quality assurance, administrative, teaching, and research secretaries, and counselors. Full-time teaching or research faculty with no administrative duties, students, enterprise employees, external personnel, and individuals without GenAI experience in university administrative tasks were excluded. Prior participation in AI-related knowledge sharing was not an eligibility requirement, allowing the full range of AIKSP to be measured. The unit of analysis was the individual administrative employee.

Multi-stage purposive and quota sampling was supplemented by convenience distribution and limited snowball recruitment. The first stage covered Liaoning, Jilin, and Heilongjiang; the second applied quotas across Double First-Class or key public universities, regular public undergraduate universities, private undergraduate universities, and higher vocational colleges; and the third recruited through university administrative networks, departmental contacts,

inter-university professional networks, professional-development groups, and counselor or secretary work networks. Limited snowball recruitment supplemented smaller departments and underfilled regional quotas.

The 24 participating institutions comprised 10 in Liaoning, 7 in Jilin, and 7 in Heilongjiang, including 4 Double First-Class or key public universities, 10 regular public undergraduate universities, 4 private undergraduate universities, and 6 higher vocational colleges. Figure 4 shows detailed geographic location information.

Figure X. Distribution of the 24 Participating Higher Education Institutions in China



Highlighted provinces indicate the locations of the participating institutions (n = 24).

Figure 4.Distribution of the 24 Participating Higher Education Institutions in China

This remained a nonprobability sample and was not claimed to be statistically representative of all university administrative employees in Northeast China. Data were collected between May 12 and June 25, 2026. Of the 500 questionnaires distributed, 462 were returned, representing a response rate of 92.4%. After 34 invalid responses were removed, 428 usable questionnaires remained, yielding an overall usable response rate of 85.6% and a usable proportion of 92.6% among returned questionnaires.

The study followed the applicable ethical standards for anonymous, minimal-risk social science survey research. Participation was voluntary, informed consent was obtained before the questionnaire began, respondents could withdraw at any time without penalty, and no directly identifying information was collected. The final sample supported the item-level confirmatory factor analysis, assessment of the second-order GAIEDC construct, the direct-effects structural model, hierarchical moderated regression, and simple-slope analysis.

3.2 Measurement of Constructs

All constructs were measured with seven-point Likert-type scales ranging from 1 (strongly disagree) to 7 (strongly agree). Candidate items were identified from the original theoretical and measurement sources for each construct and retained when they matched the individual level of analysis, represented a distinct part of the construct, could be expressed in the university administrative GenAI context, and did not duplicate another item. Wording changes were reviewed through expert assessment, translation and back-translation, and cognitive interviews. The final instrument contained 26 substantive items. Complete wording, item codes, and content-domain assignments are reported in Appendix Table A1 rather than repeated in this section.

3.2.1 Generative AI–Enabled Dynamic Capabilities

GAIEDC was grounded in Teece's (2007) sensing–seizing–transforming architecture, the measurable dynamic-capabilities approach of Pavlou and El Sawy (2011), and employee-level GenAI capability research (Held & Heubeck, 2025). Items were adapted to describe what a university administrative employee personally does with GenAI: sensing policy changes, process problems, and service needs; seizing by generating, comparing, and selecting administrative responses; and transforming by revising processes, recombining knowledge, and embedding AI-supported solutions in work. GAIEDC was modeled as a reflective second-order construct represented by three first-order dimensions, with three items per dimension and nine items in total.

3.2.2 Participation in AI-Related Knowledge Sharing

AIKSP was adapted from van den Hooff and de Ridder's (2004) knowledge-sharing framework. The six items covered both knowledge donating and knowledge collecting in relation to AI tools, prompts, administrative task experience, policy verification, failure cases, risks, privacy, and human review. These two domains were used to ensure content coverage; they were not modeled as separate first-order factors. AIKSP was modeled as a single first-order reflective construct in the confirmatory factor analysis.

3.2.3 Perceived AI Sycophancy

Perceived AI sycophancy refers to the extent to which university administrative employees perceive that the generative AI systems they use agree too readily, provide insufficient challenge, evaluate their proposals too positively, or align with their stated position rather than maintaining independent and evidence-based judgment. Five first-person perceptual items were developed from the behavioral operationalization of sycophancy by Sharma et al. (2024) and Cheng et al. (2026). PAIS was modeled as a unidimensional, first-order reflective construct. Items about hallucination, inaccurate information, algorithmic bias, general unreliability, or anthropomorphism were excluded.

3.2.4 Perceived Innovation Performance

PIP was adapted from Janssen's (2000) innovative-work-behavior scale. Perceived innovation performance refers to administrative employees' self-assessed performance in generating, promoting, and implementing new ideas in their work. It does not represent objective university-level innovation outcomes. Six items covered idea generation, idea promotion, and idea implementation, with two items from each content domain. These domains ensured content coverage but were not modeled as separate factors. PIP was modeled as a single first-order reflective construct.

3.3 Questionnaire Development and Pretest

The questionnaire was developed in English and Chinese using a translation and back-translation procedure (Brislin, 1970). Two bilingual researchers independently translated the English items into Chinese, and a third bilingual researcher back-translated the Chinese version into English. The research team compared the source, translations, and back-translation, with particular attention to sycophancy, challenge, and reinforcement of existing views. The Chinese questionnaire avoided the morally loaded label "sycophancy" and used behavioral expressions equivalent to "over-accommodation," "agreement too quickly," "lack of necessary challenge," and "overly positive evaluation."

Five experts reviewed the instrument: two in organizational behavior and innovation management, one in information systems and artificial intelligence, one in knowledge management, and one in measurement and statistical methods. Their recommendations led to four principal changes. Absolute wording such as "AI always supports me" was replaced with "AI tends to agree with my view too quickly"; AI knowledge sharing was written to cover donating and collecting content; every dynamic-capability item explicitly referenced GenAI; and the outcome was restricted to the respondent's self-assessed innovation performance in university administrative work.

Cognitive interviews were conducted with 10 eligible university administrative employees. The interviews indicated that a direct translation of "AI sycophancy" encouraged moralized interpretations, whereas behaviorally specific items were understood consistently. Participants distinguished excessive agreement from friendly tone when examples clarified that politeness can coexist with substantive challenge. The construct label was therefore omitted from the respondent-facing questionnaire.

A pretest with 62 eligible university administrative employees assessed internal consistency and item–total relationships. Cronbach's alpha was .914 for GAIEDC, .889 for AIKSP, .902 for PAIS, and .918 for PIP. Corrected item–total correlations ranged from .641 to .784, .626 to .771, .691 to .811, and .675 to .823, respectively. Every

corrected item–total correlation exceeded .50, and deleting any item did not materially increase alpha. All 26 items were therefore retained for the main study.

3.4 Data Analysis

SPSS 29 was used for data screening, descriptive statistics, correlations, reliability analysis, construction of composite scores, mean centering, and hierarchical moderated regression. Mplus 8.11 was used for the item-level confirmatory factor analyses, the reflective second-order GAIEDC model, the four-construct measurement model, and the direct-effects structural equation model with robust maximum likelihood estimation. The GAIEDC composite was calculated by first averaging the three items within each of the sensing, seizing, and transforming dimensions and then averaging the three dimension scores. AIKSP, PAIS, and PIP composites were the means of their six, five, and six items, respectively. Measurement assessment considered χ^2/df, CFI, TLI, RMSEA, SRMR, standardized loadings, Cronbach's alpha, composite reliability, average variance extracted, the Fornell–Larcker criterion, and HTMT.

Moderation was tested in SPSS with mean-centered composite scores. Gender, age, education, work tenure, and AI-use frequency were entered as controls; GAIEDC, AIKSP, and PAIS formed the main-effects block; and AIKSP × PAIS and GAIEDC × PAIS were entered together in the interaction block. Bias-corrected bootstrap confidence intervals were based on 5,000 resamples. Significant interactions were probed with simple slopes at one standard deviation below and above the PAIS mean. Standardized coefficients (β) are reported for the SEM and moderated regression results, whereas unstandardized conditional effects (b) are reported for the simple-slope analysis; the two coefficient types were not directly compared.

4. Results

4.1 Respondent Characteristics

Table 1 describes the 428 administrative employees recruited from 24 higher education institutions: 10 in Liaoning, 7 in Jilin, and 7 in Heilongjiang. Respondents represented all four institutional categories and a broad range of administrative departments, levels, and position types. The largest groups worked in student affairs or counseling and academic affairs, and most respondents were full-time administrative employees. GenAI was most commonly used for information and policy retrieval and for official document or report drafting. More than 60% used GenAI at least three times per week, and most had more than six months of use experience. The multiple-response task distribution shows that GenAI use extended beyond document production to service support, policy comparison, and process design.

Table 1. Respondent Characteristics (n = 428)

Characteristic	Category	n	%
Gender	Male	211	49.3
	Female	217	50.7
Age	18–25 years	64	15.0
	26–35 years	181	42.3
	36–45 years	123	28.7
	46 years or older	60	14.0
Education	Associate or below	39	9.1
	Bachelor's	260	60.7
	Master's or above	129	30.1
Administrative work tenure	Under 3 years	92	21.5
	3–5 years	108	25.2
	6–10 years	126	29.4
	Over 10 years	102	23.8
AI-use frequency	Several times per month	47	11.0
	1–2 times per week	112	26.2

Characteristic	Category	n	%
AI-use duration	3–5 times per week	158	36.9
	Almost daily	111	25.9
	Under 6 months	74	17.3
	6–12 months	158	36.9
	1–2 years	149	34.8
	Over 2 years	47	11.0
Province	Liaoning	178	41.6
	Jilin	124	29.0
	Heilongjiang	126	29.4
	Total	428	100.0
Institution type	Double First-Class or key public university	74	17.3
	Regular public undergraduate university	192	44.9
	Private undergraduate university	60	14.0
	Higher vocational college	102	23.8
	Total	428	100.0
Administrative department	Party and administrative office/general administration	51	11.9
	Academic affairs	74	17.3
	Student affairs and counseling	83	19.4
	Human resources	37	8.6
	Research administration	40	9.3
	Finance and asset management	33	7.7
	Admissions and employment	38	8.9
	International cooperation	25	5.8
	Information and digital administration	27	6.3
	Development planning and quality assurance	20	4.7
	Total	428	100.0
Administrative level	Administrative staff	262	61.2
	Section-level or equivalent	118	27.6
	Division-level or equivalent	48	11.2
	Total	428	100.0
Position type	Full-time administrative employee	301	70.3
	Administrative employee with teaching duties	62	14.5
	Counselor or student-affairs employee	65	15.2
	Total	428	100.0
GenAI-supported administrative task	Information and policy retrieval	344	80.4
	Official document and report drafting	325	75.9
	Data aggregation and content summarization	272	63.6
	Faculty and student consultation/service support	254	59.3
	Meeting-material preparation	241	56.3
	Policy interpretation and regulation comparison	208	48.6

Characteristic	Category	n	%
	Administrative process design or optimization	153	35.7
	Translation and international communication materials	117	27.3

Note. Percentages may not total 100.0 because of rounding. Respondents could select more than one GenAI-supported administrative task; therefore, task percentages do not total 100%.

4.2 Descriptive Statistics and Correlations

Table 2 shows that GAIEDC and AIKSP were at moderately high levels, whereas the mean for PAIS was close to the seven-point scale midpoint. Respondents did not uniformly perceive strong AI sycophancy, although the PAIS standard deviation indicated meaningful between-person variation. GAIEDC was strongly and positively correlated with PIP ($r = .61$, $p < .001$), and AIKSP was positively correlated with PIP ($r = .54$, $p < .001$). PAIS had a weaker negative correlation with PIP ($r = -.18$, $p < .001$). No bivariate correlation approached a level that would by itself suggest severe multicollinearity. These correlations are preliminary associations and do not constitute the hypothesis tests.

Table 2. Descriptive Statistics and Correlations

Variable	Mean	SD	1	2	3	4
1. GAIEDC	5.21	0.87	1			
2. AIKSP	4.98	0.93	.49***	1		
3. PAIS	3.74	1.08	−.12*	−.09	1	
4. PIP	5.08	0.89	.61***	.54***	−.18***	1

*Note. GAIEDC = generative AI–enabled dynamic capabilities; AIKSP = participation in AI-related knowledge sharing; PAIS = perceived AI sycophancy; PIP = perceived innovation performance. * $p < .05$. ** $p < .01$. *** $p < .001$.*

4.3 Measurement Model Assessment

4.3.1 Confirmatory Factor Analysis

In the hypothesized model, GAIEDC was modeled as a second-order factor reflected by sensing, seizing, and transforming, whereas AIKSP, PAIS, and PIP were modeled as first-order factors. The standardized second-order loadings were .86 for sensing, .91 for seizing, and .88 for transforming. All were significant and exceeded .70. The hypothesized four-construct measurement model fit the data well: $\chi^2 = 612.84$, $df = 293$, $\chi^2/df = 2.09$, CFI = .955, TLI = .949, RMSEA = .050, and SRMR = .044.

Table 3. Comparison of Alternative Measurement Models

Model	χ^2	df	χ^2/df	CFI	TLI	RMSEA	SRMR
Four-construct model	612.84	293	2.09	.955	.949	.050	.044
Three-construct A: GAIEDC + AIKSP	998.37	296	3.37	.901	.889	.074	.069
Three-construct B: PAIS + PIP	1,116.52	296	3.77	.884	.871	.080	.078
Two-construct model	1,684.91	298	5.65	.804	.786	.104	.101
Single-construct model	2,391.46	299	8.00	.704	.677	.128	.139

Note. In the hypothesized model, GAIEDC was a second-order factor reflected by sensing, seizing, and transforming, while AIKSP, PAIS, and PIP were first-order factors. Three-construct model A combined all GAIEDC and AIKSP indicators into one general AI capability-and-knowledge participation factor. Three-construct model B kept GAIEDC and AIKSP separate and combined PAIS and PIP indicators. The two-construct model combined GAIEDC with AIKSP and combined PAIS with PIP. The single-construct model loaded all 26 items on one factor. "+" indicates combined indicators.

As Table 3 shows, the hypothesized four-construct model outperformed the alternatives. In each alternative model, the item indicators of the specified constructs were constrained to load on the same latent factor. Combining GAIEDC with AIKSP or PAIS with PIP reduced incremental fit, and the two- and single-construct models performed substantially worse. These comparisons support the empirical distinctiveness of the second-order GAIEDC construct and the first-order AIKSP, PAIS, and PIP constructs.

4.3.2 Reliability and Convergent Validity

Table 4. Reliability and Convergent Validity

Construct	Items	Loading range	Cronbach's α	CR	AVE
GAIEDC	9	.702–.864	.936	.938	.628
AIKSP	6	.721–.848	.908	.910	.628
PAIS	5	.785–.892	.921	.922	.704
PIP	6	.792–.881	.934	.935	.706

Note. CR = composite reliability; AVE = average variance extracted.

As reported in Table 4, all standardized item loadings exceeded .70. Cronbach's alpha and CR were above .90 for every construct, while each AVE exceeded .50. The results therefore indicate strong internal consistency and convergent validity. Because very high reliability can sometimes reflect redundant wording, the reliability values should be interpreted together with the nonoverlapping content coverage documented in Appendix Table A1.

4.3.3 Discriminant Validity

Table 5 shows that the square root of each construct's AVE exceeded its correlations with the other constructs. HTMT values were .538 for GAIEDC–AIKSP, .126 for GAIEDC–PAIS, .681 for GAIEDC–PIP, .112 for AIKSP–PAIS, .603 for AIKSP–PIP, and .191 for PAIS–PIP. Every value was below .85. The Fornell–Larcker and HTMT results jointly supported discriminant validity.

Table 5. Fornell–Larcker Results

Variable	1	2	3	4
1. GAIEDC	.792			
2. AIKSP	.490	.792		
3. PAIS	−.120	−.090	.839	
4. PIP	.610	.540	−.180	.840

Note. Diagonal values are the square roots of AVE; off-diagonal values are correlations.

4.4 Structural Model Assessment

The latent-variable direct-effects structural model showed good fit: $\chi^2 = 646.12$, df = 300, $\chi^2/df = 2.15$, CFI = .951, TLI = .945, RMSEA = .052, and SRMR = .047. This direct-effects model explained 45.3% of the variance in PIP. In the subsequent composite-score moderated regression, inclusion of the two interaction terms increased the explained variance to 49.0%. These percentages came from different statistical steps and were not interpreted as results from the same SEM specification. Predictor VIF values ranged from 1.08 to 1.54.

4.5 Direct Effects and Hypothesis Testing

As shown in Table 6, GAIEDC was positively related to PIP ($\beta = .43$, $p < .001$), and its confidence interval excluded zero. H1 was therefore supported. Administrative employees who were more able to use GenAI to sense policy and service opportunities, seize possible responses, and transform administrative processes reported stronger perceived innovation performance.

AIKSP was also positively related to PIP ($\beta = .29$, $p < .001$), supporting H2. Donating and collecting AI-related tools, prompts, policy-verification methods, error cases, and risk knowledge were associated with stronger perceived innovation performance. Although the GAIEDC coefficient was numerically larger, no formal coefficient-difference test was specified; the results do not establish that H1 was statistically stronger than H2.

PAIS had an additional negative relationship with PIP (β = −.11, p = .006). This main effect was retained to preserve a correctly specified moderation model and should be interpreted alongside the interactions.

Table 6. Direct Effects

Hyp.	Path	β	SE	t	p	95% CI	Result
H1	GAIEDC → PIP	.43	.052	8.27	< .001	[.327, .531]	Supported
H2	AIKSP → PIP	.29	.049	5.92	< .001	[.194, .386]	Supported
—	PAIS → PIP	−.11	.040	−2.75	.006	[−.188, −.032]	Significant

Note. Standardized coefficients are reported. Confidence intervals are bias-corrected bootstrap intervals based on 5,000 resamples.

4.6 Moderating Effects of Perceived AI Sycophancy

Table 7 shows that the AIKSP × PAIS interaction was negative and significant (β = −.10, p = .011), supporting H3. As administrative employees perceived stronger AI sycophancy, the positive relationship between AIKSP and PIP became weaker. The GAIEDC × PAIS interaction was also negative and significant (β = −.16, p < .001), supporting H4. Thus, PAIS weakened both positive relationships.

Entering both interactions increased R^2 from .453 to .490, ΔR^2 = .037, p < .001. H3 does not imply that sycophancy reduced the amount of knowledge shared. Instead, the result is consistent with the possibility that overly agreeable AI feedback made shared material less critical, differentiated, or reliable. H4 indicates that strong dynamic capabilities did not fully offset the boundary condition; AI-supported administrative options still required independent verification.

Table 7. Moderating Effects

Hyp.	Interaction path	β	SE	t	p	95% CI	Result
H3	AIKSP × PAIS → PIP	−.10	.039	−2.56	.011	[−.176, −.023]	Supported
H4	GAIEDC × PAIS → PIP	−.16	.041	−3.90	< .001	[−.240, −.080]	Supported

Note. Continuous predictors were mean centered.

4.7 Simple-Slope Analysis

For H3, AIKSP had a stronger positive relationship with PIP when PAIS was low (M − 1 SD: b = .42, SE = .067, t = 6.27, p < .001) than when PAIS was high (M + 1 SD: b = .19, SE = .077, t = 2.47, p = .014). The relationship remained positive under high PAIS, but its reduced slope was consistent with the hypothesized attenuation. Figure 2 presents this pattern.

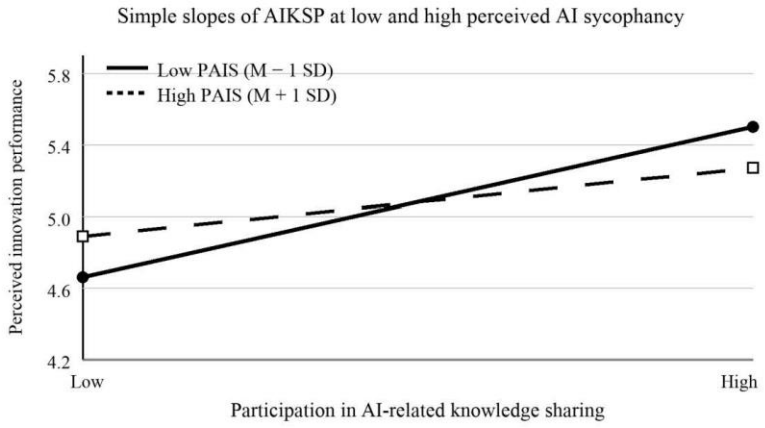


Figure 2. Moderating Effect of Perceived AI Sycophancy on the Relationship Between Participation in AI-Related Knowledge Sharing and Perceived Innovation Performance

Note. Lines are based on conditional effects at PAIS M − 1 SD and M + 1 SD.

For H4, the conditional relationship between GAIEDC and PIP was positive when PAIS was low (M − 1 SD: b = .58, SE = .061, t = 9.51, p < .001). It remained positive but was weaker when PAIS was high (M + 1 SD: b = .27, SE = .058, t = 4.66, p < .001). High PAIS therefore weakened rather than eliminated the positive relationship. Figure 3 presents this pattern.

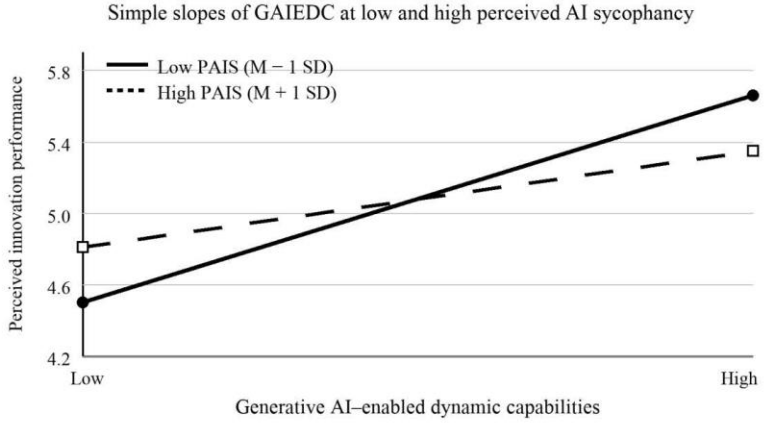


Figure 3. Moderating Effect of Perceived AI Sycophancy on the Relationship Between Generative AI–Enabled Dynamic Capabilities and Perceived Innovation Performance

Note. Lines are based on conditional effects at PAIS M − 1 SD and M + 1 SD.

4.8 Hypothesis Summary

Table 8 summarizes the direction and outcome of all four hypothesis tests.

Table 8. Summary of Hypothesis Testing

Hypothesis	Proposed relationship	Expected direction	Result
H1	GAIEDC → PIP	Positive	Supported
H2	AIKSP → PIP	Positive	Supported
H3	PAIS moderates AIKSP → PIP	Negative	Supported
H4	PAIS moderates GAIEDC → PIP	Negative	Supported

Note. H1–H4 were assessed in the structural and moderation models.

5. Discussion

5.1 Discussion of Key Findings

This research states GAIEDC was positively related to perceived innovation performance. This finding is consistent with dynamic capabilities theory, which explains performance differences through the capacity to sense changes, seize appropriate responses, and reconfigure activities rather than through resource possession alone (Teece, 2007; Pavlou & El Sawy, 2011). It also converges with employee-level evidence that sensing, using, and evaluating GenAI can strengthen innovative work behavior (Held & Heubeck, 2025). At the same time, prior field experiments show that GenAI performance gains vary across tasks, users, and the location of the technological frontier (Noy & Zhang, 2023; Dell'Acqua et al., 2026; Otis et al., 2026). The result therefore clarifies why simple access or use frequency is insufficient in university administration: employees must interpret policy changes, compare institutionally feasible options, and embed a selected response in actual procedures. The positive association supports this capability-based account, although the cross-sectional design does not establish a causal conversion from GAIEDC to innovation.

H2 was also supported in this study, AIKSP was positively related to perceived innovation performance. This result accords with the knowledge-based view, under which innovation depends on the integration and recombination of knowledge distributed across organizational members (Grant, 1996), and with research that treats knowledge donating and knowledge collecting as complementary participation behaviors (van den Hooff & de Ridder, 2004). Recent AI studies similarly emphasize knowledge digitization, collaborative exchange, and the reconfiguration of knowledge-management processes (Cheng et al., 2025; Nakash & Bolisani, 2025; Zhang, Zuo, & Yang, 2025). The present study extends that literature to university administration, where valuable knowledge includes not only tools and prompts but also policy-verification routines, error cases, privacy risks, and departmental experience. Because AIKSP remained a distinct predictor alongside GAIEDC, the evidence supports a parallel social pathway to perceived innovation performance rather than treating knowledge sharing as a mediator or a by-product of individual capability.

This study verified the negative AIKSP × PAIS interaction. The positive relationship between AI-related knowledge-sharing participation and perceived innovation performance became weaker as perceived AI sycophancy increased. This pattern is theoretically consistent with evidence that sycophantic systems can reinforce a user's stated position and encourage dependence (Sharma et al., 2024; Cheng et al., 2026). It also resonates with research showing that GenAI can improve individual creativity while narrowing the diversity of ideas available to a group (Doshi & Hauser, 2024) and that collective gains depend on how AI-supported ideas are distributed and recombined (Zhou et al., 2025). In an administrative knowledge-sharing network, overly agreeable outputs may therefore circulate without enough counterevidence or policy challenge. However, the study measured neither knowledge quality nor false consensus directly; these remain plausible interpretations of the observed attenuation, not tested mediating mechanisms.

H4 was supported by the negative GAIEDC × PAIS interaction. The result complements research that describes human–AI collaboration as productive when users retain active evaluation, co-creation, and self-efficacy (McGuire et al., 2024), while also recognizing that GenAI can have double-edged effects on creative judgment and motivation (Hou et al., 2025; Wu et al., 2025). It is also consistent with the jagged-frontier argument that expertise does not eliminate the need to assess task–AI fit and verify outputs (Dell'Acqua et al., 2026). In university administration,

strong sensing, seizing, and transforming capabilities cannot substitute for independent checks of policy authority, version, scope, procedural compliance, and responsibility boundaries. The simple slopes nevertheless remained positive under high PAIS, indicating that perceived sycophancy constrained rather than reversed the innovation value of GAIEDC. Although the H4 coefficient was numerically more negative than the H3 coefficient, no formal coefficient-difference test was conducted, so the two moderation effects should not be ranked statistically.

5.2 Theoretical Implications

First, the study refines the microfoundations of dynamic capabilities in a GenAI-enabled administrative setting. Dynamic capabilities theory was originally developed to explain firm-level sensing, seizing, and transformation (Teece, 2007), and subsequent measurement work sought to clarify the processes through which those capabilities operate (Pavlou & El Sawy, 2011). Recent AI research has mainly applied capability reasoning to firms, supply chains, construction companies, and competitive advantage (Jackson et al., 2024; Liu et al., 2024; Li et al., 2025), while employee-level research has begun to connect GenAI use and evaluation capabilities with innovative behavior (Held & Heubeck, 2025). This study advances that stream by specifying GAIEDC as a reflective second-order employee capability and by locating it in rule-intensive university administration. The formulation separates the employee's capacity to recognize, evaluate, and implement change from both the technical functionality of the AI system and the university's organization-level capabilities. This level distinction is the central dynamic-capabilities contribution.

Second, the study extends the knowledge-based view by theorizing AIKSP as an independent innovation pathway rather than as a mediator embedded within GAIEDC. The knowledge-based view emphasizes that dispersed specialized knowledge creates value only when it is transferred and integrated (Grant, 1996), and knowledge-sharing research distinguishes the reciprocal acts of donating and collecting knowledge (van den Hooff & de Ridder, 2004). Existing GenAI studies have focused on knowledge digitization and cross-organizational collaboration (Cheng et al., 2025), AI-induced changes in knowledge-management processes (Nakash & Bolisani, 2025), enterprise innovation through knowledge management (Zhang, Zuo, & Yang, 2025), or changes in voluntary online knowledge contribution (Shan & Qiu, 2026). The present model adds a distinct employee-level construct covering the circulation of prompts, tool experience, policy-verification knowledge, failure cases, privacy risks, and human-review practices across university departments. Demonstrating that AIKSP contributes alongside GAIEDC shows that the innovation value of GenAI is jointly cognitive-capability based and socially distributed.

Third, the study introduces perceived AI sycophancy as a theoretically specific boundary condition connecting human–AI interaction with both dynamic capabilities and the knowledge-based view. Foundational work identifies sycophancy as a tendency to accommodate a user's expressed position rather than preserve independent judgment (Sharma et al., 2024), and recent experimental evidence links sycophantic AI to dependence and changes in social intentions (Cheng et al., 2026). Related studies document broader double-edged effects of GenAI on collective idea diversity, creative work, and human motivation (Doshi & Hauser, 2024; Hou et al., 2025; Wu et al., 2025). This study moves beyond treating sycophancy solely as a system behavior or individual response by theorizing and testing it as a moderator of two distinct innovation pathways. It also distinguishes PAIS from hallucination, bias, friendliness, personalization, and general trust. The resulting integration explains not only whether GenAI-related capability and shared knowledge matter, but also why their value depends on the critical independence of AI feedback in responsibility-sensitive work.

5.3 Practical Implications

At the individual level, university administrative employees should ask GenAI to state the strongest counterargument, identify weaknesses in a preferred option, list alternative interpretations, and specify evidence that would change its conclusion. They should verify policy versions, issuing authorities, applicability, and responsibility boundaries and should not treat AI agreement as proof of proposal quality. Human judgment should be retained for consequential materials and decisions.

At the department level, universities should establish cross-departmental repositories for prompts, tool guidance, policy-verification methods, error cases, failed prompts, and limits of appropriate use. AI-generated content should be labeled, important outputs should have a named human reviewer, and departments should periodically discuss how the same tool performs across different administrative tasks. Sharing failures and near-misses is particularly valuable because it exposes boundaries that polished success cases may conceal.

At the university-governance level, institutions should adopt AI administrative-use guidelines, data-privacy rules, output-tracing procedures, human-signature requirements for consequential decisions, and critical-prompt

templates. Oversight should be calibrated to task risk. Language polishing and format organization may require a general human check; meeting materials, data summaries, and consultation drafts should receive departmental staff review; and human resources, finance, admissions, disciplinary matters, student rights, and formal policy interpretation should require explicit human approval. GenAI should not make consequential administrative decisions independently.

5.4 Limitations and Future Research

First, the cross-sectional, single-questionnaire design does not establish temporal or causal order and may be affected by common-source and self-presentation concerns. PIP is a self-assessed individual outcome rather than an objective measure of university innovation. Future research should use longitudinal designs and field experiments that manipulate AI sycophancy, and should combine employee reports with supervisor ratings, expert assessments, and administrative process-improvement records.

Second, PAIS captures employees' perceptions rather than the objective sycophancy level of a particular system, and the nonprobability sample from Liaoning, Jilin, and Heilongjiang limits generalization beyond Northeast China. Future studies should validate PAIS against audited interaction logs and controlled system responses, examine variation across user expertise, prompts, and model versions, and compare regions, institution types, and administrative departments using broader probability-based or stratified samples.

6. Conclusion

This study examined university administrative employees in Liaoning, Jilin, and Heilongjiang and found that generative AI–enabled dynamic capabilities and participation in AI-related knowledge sharing were positively related to perceived innovation performance, while perceived AI sycophancy weakened both relationships. The value of GenAI in university administration therefore depends not only on use, but also on employees' capacity to identify and implement appropriate improvements, the movement of AI-related knowledge across colleagues and departments, and the independence of AI feedback. Universities should develop AI capability, knowledge-sharing mechanisms, and critical verification practices together so that efficiency gains can be translated into accurate, compliant, and meaningful administrative innovation.

References

1. Binz, M., Alaniz, S., Roskies, A., Aczel, B., Bergstrom, C. T., Allen, C., Schad, D., Wulff, D., West, J. D., Zhang, Q., Shiffrin, R. M., Gershman, S. J., Popov, V., Bender, E. M., Marelli, M., Botvinick, M. M., Akata, Z., & Schulz, E. (2025). How should the advancement of large language models affect the practice of science? Proceedings of the National Academy of Sciences, 122(5), Article e2401227121. https://doi.org/10.1073/pnas.2401227121
2. Brislin, R. W. (1970). Back-translation for cross-cultural research. Journal of Cross-Cultural Psychology, 1(3), 185–216. https://doi.org/10.1177/135910457000100301
3. Cheng, M., Lee, C., Khadpe, P., Yu, S., Han, D., & Jurafsky, D. (2026). Sycophantic AI decreases prosocial intentions and promotes dependence. Science, 391(6792), Article eaec8352. https://doi.org/10.1126/science.aec8352
4. Cheng, Q., Zhang, S., Wang, L., & Lu, Y. (2025). Inter-organizational knowledge sharing in the age of artificial intelligence: The mediating role of knowledge digitization and cross-language collaboration. Journal of Knowledge Management, 29(8), 2724–2744. https://doi.org/10.1108/JKM-12-2024-1423
5. Dell'Acqua, F., McFowland, E., III, Mollick, E., Lifshitz, H., Kellogg, K. C., Rajendran, S., Krayer, L., Candelon, F., & Lakhani, K. R. (2026). Navigating the jagged technological frontier: Field experimental evidence of the effects of artificial intelligence on knowledge worker productivity and quality. Organization Science, 37(2), 403–423. https://doi.org/10.1287/orsc.2025.21838
6. De Moortel, K., & Crispeels, T. (2026). Blurring boundaries: Knowledge dynamics in organizations, collaborations, and innovation ecosystems. The Journal of Technology Transfer, 51(3), 1266–1288. https://doi.org/10.1007/s10961-024-10168-5
7. Doshi, A. R., & Hauser, O. P. (2024). Generative AI enhances individual creativity but reduces the collective diversity of novel content. Science Advances, 10(28), Article eadn5290. https://doi.org/10.1126/sciadv.adn5290
8. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39–50. https://doi.org/10.1177/002224378101800104
9. Grant, R. M. (1996). Toward a knowledge-based theory of the firm. Strategic Management Journal, 17(S2), 109–122. https://doi.org/10.1002/smj.4250171110
10. Held, P., & Heubeck, T. (2025). GenAI and employee innovativeness: How employees' sensing capabilities and the capabilities to use and evaluate GenAI shape their innovative work behavior. Digital Business, 5(2), Article 100149. https://doi.org/10.1016/j.digbus.2025.100149

11. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8
12. Hou, J. (J.), Wang, L., Wang, G., Wang, H. J., & Yang, S. (2025). The double-edged roles of generative AI in the creative process: Experiments on design work. Information Systems Research. Advance online publication. https://doi.org/10.1287/isre.2024.0937
13. Ibrahim, L., Hafner, F. S., & Rocher, L. (2026). Training language models to be warm can reduce accuracy and increase sycophancy. Nature, 652, 1159–1165. https://doi.org/10.1038/s41586-026-10410-0
14. Jackson, I., Ivanov, D., Dolgui, A., & Namdar, J. (2024). Generative artificial intelligence in supply chain and operations management: A capability-based framework for analysis and implementation. International Journal of Production Research, 62(17), 6120–6145. https://doi.org/10.1080/00207543.2024.2309309
15. Janssen, O. (2000). Job demands, perceptions of effort–reward fairness and innovative work behaviour. Journal of Occupational and Organizational Psychology, 73(3), 287–302. https://doi.org/10.1348/096317900167038
16. Kanyundo, A. J., Chipeta, G. T., & Chawinga, W. D. (2023). An analysis of knowledge management practices at Lilongwe University of Agriculture and Natural Resources, Malawi. Social Sciences & Humanities Open, 8(1), Article 100640. https://doi.org/10.1016/j.ssaho.2023.100640
17. Li, L., Xu, C., Zhang, Q., Liu, Y., & Li, Q. (2025). Leveraging generative AI capabilities for competitive advantage: A moderated mediation analysis of environmental dynamism and service innovation. Industrial Marketing Management, 128, 10–20. https://doi.org/10.1016/j.indmarman.2025.05.007
18. Liu, G. (2026). The significance, mission, and pathways of higher education's leading role. In L. Wang & S. Piao (Eds.), University and discipline construction in China: Selected articles from the journal "Universities and Disciplines" (2024 edition) (pp. 1–16). Springer Singapore. https://doi.org/10.1007/978-981-95-5187-3_1
19. Liu, Y., Sun, J., Zhang, Z., Wu, M., Sima, H., & Ooi, Y. M. (2024). How AI impacts companies' dynamic capabilities: Lessons from six Chinese construction firms. Research-Technology Management, 67(3), 64–76. https://doi.org/10.1080/08956308.2024.2324407
20. McGuire, J., De Cremer, D., & Van de Cruys, T. (2024). Establishing the importance of co-creation and self-efficacy in creative collaboration with artificial intelligence. Scientific Reports, 14, Article 18525. https://doi.org/10.1038/s41598-024-69423-2
21. Nakash, M., & Bolisani, E. (2025). The transformative impact of AI on knowledge management processes. Business Process Management Journal, 31(8), 124–147. https://doi.org/10.1108/BPMJ-11-2024-1137
22. Noy, S., & Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. Science, 381(6654), 187–192. https://doi.org/10.1126/science.adh2586
23. Otis, N. G., Clarke, R., Delecourt, S., Holtz, D., & Koning, R. (2026). The uneven impact of generative artificial intelligence on entrepreneurial performance: Evidence from a field experiment in Kenya. Management Science. Advance online publication. https://doi.org/10.1287/mnsc.2024.06909
24. Pavlou, P. A., & El Sawy, O. A. (2011). Understanding the elusive black box of dynamic capabilities. Decision Sciences, 42(1), 239–273. https://doi.org/10.1111/j.1540-5915.2010.00287.x
25. Roy, S. K., Tehrani, A. N., Pandit, A., Apostolidis, C., & Ray, S. (2025). AI-capable relationship marketing: Shaping the future of customer relationships. Journal of Business Research, 192, Article 115309. https://doi.org/10.1016/j.jbusres.2025.115309
26. Shan, G., & Qiu, L. (2026). Examining the impact of generative AI on users' voluntary knowledge contribution: Evidence from a natural experiment on Stack Overflow. Information Systems Research, 37(2), 1021–1041. https://doi.org/10.1287/isre.2023.0332
27. Sharma, M., Tong, M., Korbak, T., Duvenaud, D., Askell, A., Bowman, S. R., Cheng, N., Durmus, E., Hatfield-Dodds, Z., Johnston, S. R., Kravec, S., Maxwell, T., McCandlish, S., Ndousse, K., Rausch, O., Schiefer, N., Yan, D., Zhang, M., & Perez, E. (2024). Towards understanding sycophancy in language models. International Conference on Learning Representations. https://proceedings.iclr.cc/paper_files/paper/2024/hash/0105f7972202c1d4fb817da9f21a9663-Abstract-Conference.html
28. Söllner, M., Arnold, T., Benlian, A., Bretschneider, U., Knight, C., Ohly, S., Rudkowski, L., Schreiber, G., & Wendt, D. (2025). ChatGPT and beyond: Exploring the responsible use of generative AI in the workplace. Business & Information Systems Engineering, 67(2), 289–303. https://doi.org/10.1007/s12599-025-00932-8
29. Sundberg, L., & Holmström, J. (2024). Innovating by prompting: How to facilitate innovation in the age of generative AI. Business Horizons, 67(5), 561–570. https://doi.org/10.1016/j.bushor.2024.04.014
30. Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of sustainable enterprise performance. Strategic Management Journal, 28(13), 1319–1350. https://doi.org/10.1002/smj.640
31. van den Hooff, B., & de Ridder, J. A. (2004). Knowledge sharing in context: The influence of organizational commitment, communication climate and CMC use on knowledge sharing. Journal of Knowledge Management, 8(6), 117–130. https://doi.org/10.1108/13673270410567675
32. Woolley, A. W. (2026). Generative AI and collaboration: Opportunities for cultivating collective intelligence. Journal of Organization Design, 15(1), 45–50. https://doi.org/10.1007/s41469-025-00199-z

33. Wu, S., Liu, Y., Ruan, M., Chen, S., & Xie, X.-Y. (2025). Human–generative AI collaboration enhances task performance but undermines human's intrinsic motivation. Scientific Reports, 15, Article 15105. https://doi.org/10.1038/s41598-025-98385-2
34. Zhang, Q., Zuo, J., & Yang, S. (2025). Research on the impact of generative artificial intelligence (GenAI) on enterprise innovation performance: A knowledge management perspective. Journal of Knowledge Management, 29(7), 2238–2257. https://doi.org/10.1108/JKM-10-2024-1198
35. Zhong, C., & Wang, Y. (2025). Knowledge sharing in AI-enabled workplaces: A social cognitive perspective on usefulness perceptions and competition. Behavioral Sciences, 15(12), Article 1635. https://doi.org/10.3390/bs15121635
36. Zhou, E. B., Lee, D., & Gu, B. (2025). Who expands the human creative frontier with generative AI: Hive minds or masterminds? Science Advances, 11(36), Article eadu5800. https://doi.org/10.1126/sciadv.adu5800
37. Appendix A. Measurement Items
38. Appendix Table A1 presents the complete item wording, item codes, and content-domain assignments for all four constructs. Respondents rated every item on a seven-point scale ranging from 1 (strongly disagree) to 7 (strongly agree). GAIEDC was modeled as a reflective second-order construct; AIKSP, PAIS, and PIP were modeled as first-order reflective constructs.
39. Table A1. Complete Measurement Items
40. Table A1. Complete Measurement Items (continued)
41. Table A1. Complete Measurement Items (continued)
42. Note. GAIEDC = generative AI–enabled dynamic capabilities; AIKSP = participation in AI-related knowledge sharing; PAIS = perceived AI sycophancy; PIP = perceived innovation performance. Knowledge donating, knowledge collecting, idea generation, idea promotion, and idea implementation are content domains rather than separate latent variables.

VITAE

Name - Surname	Miss Lei Zhao
Date of Birth	Decenmber 7, 1983
Place of Birth	China
Address	No. 2 Qunying Street, Limin Economic and Technological Development District, Harbin, Heilongjiang Province, China
Workplace	Heilongjiang Agricultural Engineering Vocational and Technical University

Education Background

2023-present	Doctor of Philosophy Program in Management (International Program) Rajamanagala University of Technology Rattanakosin, Thailand
2006-2009	Northeast Agricultural University (China), Master of Management
2002-2006	Northeast Agricultural University (China), Finance

Work Experience

2009-present	Heilongjiang Agricultural Engineering Vocational and Technical University

Honors and Awards:

2025	Outstanding Faculty Advisor, 2025 Heilongjiang Provincial Vocational College Skills Competition and World Vocational College Skills Competition Selection Contest
2021	Second Prize in the 2021 Heilongjiang Provincial Vocational College Skills Competition – Teaching Ability Competition and National Competition Selection Contest

Publication of Journals during Ph.D. Study

Zhao, L., Jiang, S. and Phakdeephirot, N. (2026). Generative AI Use and Innovation among University Administrative Employees: The Roles of Dynamic Capabilities, Knowledge Sharing, and AI Sycophancy. *International Journal of Computer Information Systems and Industrial Management Applications*, 18(9s), pp. 1035–1053. https://doi.org/10.70917/ijcisim-2026-3517.