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Unraveling Digital Transformation Dynamics in Manufacturing: A Mediation and Moderation Analysis

Huan Wu

Abstract

This study investigates the mediating and moderating mechanisms shaping the relationship between digital orientation and digital transformation performance in manufacturing enterprises. Drawing on data from 393 firms, it confirms the positive influence of digital orientation on acquiring learning and trial and error learning, which in turn mediate the relationship between digital orientation and digital transformation performance. Furthermore, the study reveals the moderating roles of digital infrastructure and organizational agility in these relationships. The results highlight the pivotal role of organizational learning processes and technological infrastructure in fostering successful digital transformations within manufacturing contexts. By shedding light on these intricate dynamics, this research contributes to a deeper understanding of how organizations can effectively leverage digital resources to drive innovation and competitiveness in today's rapidly evolving business landscape.

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About Author (s)

Huan Wu, Centre of Postgraduate Studies, Asia Metropolitan University (AMU), Malaysia.

1. Introduction

1.1 Background of Study

The digital age, characterized by technological advancements and industrial transformation, is accelerating, presenting both opportunities and challenges for Chinese manufacturing (Tian & Li, 2022). Emerging technologies such as artificial intelligence, the Internet of Things, cloud computing, and big data are pivotal for digital economic growth, facilitating industrial transformation by reducing costs, improving quality, and enhancing efficiency (Blichfeldt & Faullant, 2021). This wave has prompted countries to adopt national strategies for advanced manufacturing, such as the U.S.'s National Strategic Plan for Advanced Manufacturing and Germany's Industry 4.0, emphasizing digital transformation and technological innovation (Ferreira et al., 2019). China has responded with initiatives like "Made in China 2025" and the "14th Five Year Plan," aiming to strengthen its manufacturing sector through digital transformation (Ministry of Industry and Information Technology, 2022). Despite progress in fields like electronic information and new energy, China's manufacturing sector, predominantly traditional, faces significant challenges in digital integration (Du et al., 2022). Companies must navigate the blurred lines between industries and increased competition, necessitating accelerated digitalization (Bresciani et al., 2021). Digital transformation for traditional manufacturing enterprises is complex, requiring significant investment and a shift from established processes. Resistance due to high costs, long transformation cycles, and uncertainty often hinders progress (Chen & Wang, 2021; Ghezzi & Cavallo, 2020). Successful digital pioneers like Red Collar Group demonstrate the potential of integrating big data and intelligent platforms to achieve personalized production (Volberda et al., 2021). Conversely, failures like Kodak highlight the risks of clinging to outdated technologies.

Traditional enterprises often struggle with inadequate digital infrastructure and capabilities, leading to fragmented digital efforts (Sánchez & Zuntini, 2018; Li et al., 2018). Cases of failed transformations, such as the abrupt termination of a costly project in Zhejiang, underscore the need for tailored digital strategies rather than mimicking others' success (Matrazzo et al., 2021). Organizational agility and a robust digital foundation are crucial for adapting to market demands and achieving digital transformation (Abrell et al., 2016). The digital economy necessitates deep integration of digital technology and business operations, with strategic coordination from top management (Lu et al., 2022). Digital orientation, reflecting strategic positioning and understanding of digital technology, is vital for successful transformation (Khin & Ho, 2019). However, existing research often overlooks the internal mechanisms driving digital transformation and the role of organizational learning and agility (Hess et al., 2016; Kohli & Melville, 2019).

1.2 Problem Statement

Traditional manufacturing enterprises often encounter significant obstacles during digital transformation, including a reluctance to transform, an inability to transform, and fear of transformation. These challenges are compounded by a lack of understanding of emerging digital technologies, unclear digital pathways, insufficient digital foundations, and poor organizational adaptability, all of which hinder digital transformation (Law, Bhaumik, Sun, & Rahman, 2019). Examining the successful digital transformation of companies like Red Collar Group and Wahaha reveals that addressing these challenges involves strategic guidance, resource acquisition, and robust digital infrastructure, as well as enhancing organizational agility (Sun & Zuo, 2022). This study aims to explore the mechanisms by which digital orientation, organizational learning, digital infrastructure, and organizational agility impact the digital transformation performance of traditional manufacturing enterprises (Sun, 2023).

1.3 Research Questions

The study investigates the following questions:

(1) What is the impact relationship between digital orientation and digital transformation performance?
(2) What is the impact relationship between digital orientation and organizational learning?
(3) What is the impact relationship between organizational learning and digital transformation performance?
(4) Does organizational learning mediate the relationship between digital orientation and digital transformation performance?
(5) Does digital infrastructure moderate the relationship between digital orientation and organizational learning?
(6) Does organizational agility moderate the relationship between organizational learning and digital transformation performance?

1.4 Research Objectives

The objectives of this study are to:

(1) Analyze the relationship between digital orientation and digital transformation performance.
(2) Examine the relationship between digital orientation and organizational learning.
(3) Investigate the relationship between organizational learning and digital transformation performance.
(4) Determine if organizational learning mediates the relationship between digital orientation and digital transformation performance.
(5) Assess if digital infrastructure moderates the relationship between digital orientation and organizational learning.
(6) Evaluate if organizational agility moderates the relationship between organizational learning and digital transformation performance.

1.5 Research Significance

This research addresses the scientific question of how digital orientation affects the digital transformation performance of traditional manufacturing enterprises. By reviewing relevant theories and conducting exploratory case studies, the study constructs theoretical models and tests these relationships through empirical research, contributing to the enrichment and expansion of existing research (Sun & Zuo, 2023). Based on strategic management theory, the study examines how digital orientation drives digital transformation performance, highlighting industry-specific challenges and providing insights into the internal mechanisms and implementation pathways for digital transformation in manufacturing enterprises (Sun, 2022). The research also incorporates organizational learning theories, distinguishing between acquisition learning and trial-and-error learning to open the "black box" between digital orientation and digital transformation performance (Kindermann et al., 2021; Strobl et al., 2022). Additionally, resource-based theory and dynamic capability theory are utilized to understand the roles of digital infrastructure and organizational agility in enhancing organizational learning outcomes (Rossia et al., 2020). In practical terms, the study encourages traditional manufacturing enterprises to actively engage in digital transformation, addressing common barriers such as insufficient digital willingness and weak digital foundations. By emphasizing the importance of digital orientation and strategic planning, the study guides enterprises in effectively integrating digital technology with traditional business operations (Morgan et al., 2019; Sánchez & Zuntini, 2018). The research also highlights the need for robust digital infrastructure and agile organizational practices to support and sustain digital transformation efforts (Li & Wang, 2022; Alnuaimi et al., 2022).

2. Literature Review

2.1 Digital Transformation Performance

Digital transformation performance has become a critical focus for researchers and practitioners aiming to understand how organizations adapt and thrive in the digital economy. Digital transformation involves integrating digital technology into all business areas, fundamentally changing how organizations operate and deliver value to customers (Arias Pérez & Vélez Jaramillo, 2022). The performance outcomes of digital transformation are multifaceted, encompassing operational efficiency, innovation capability, customer satisfaction, and competitive advantage.

Several studies have highlighted the significant impact of digital orientation on digital transformation performance. Digital orientation reflects an organization's strategic focus on leveraging digital technologies to achieve business goals (Kindermann et al., 2021). Organizations with a strong digital orientation are more likely to succeed in their transformation efforts because they prioritize digital initiatives and align them with their strategic objectives (Cooper, 2019). For instance, companies like Haier have demonstrated that a clear digital orientation can drive comprehensive digital transformation, resulting in enhanced operational efficiency and market responsiveness (Sun & Zuo, 2022). Organizational learning also plays a crucial role in digital transformation performance. Learning processes, such as acquisition learning and trial-and-error learning, enable organizations to adapt to new technologies and business models (Strobl et al., 2022). These learning mechanisms help bridge the gap between digital orientation and actual transformation outcomes by fostering continuous improvement and innovation (Law et al., 2019). Effective organizational learning ensures that employees are equipped with the necessary skills and knowledge to implement digital strategies, thereby enhancing transformation performance (Zhou & Cui, 2022). Furthermore, digital infrastructure and organizational agility are significant moderating factors influencing digital transformation performance. Digital infrastructure provides the technological foundation necessary for digital initiatives, facilitating data integration, and supporting advanced analytics and automation (Wang & Wang, 2021). Organizations with robust digital infrastructure are better positioned to execute their digital strategies effectively. Organizational agility, defined as the ability to rapidly respond to changes in the external environment, ensures that organizations can pivot and adapt their strategies in response to new digital opportunities and threats (Rossia et al., 2020). In summary, digital transformation performance is determined by a combination of digital orientation, organizational learning, digital infrastructure, and agility. Organizations that strategically align these factors are more likely to achieve successful digital transformation, characterized by improved efficiency, innovation, and competitiveness.

2.2 Digital Orientation

Digital orientation, a critical aspect of strategic management in the digital era, refers to an organization's predisposition to leverage digital technologies to enhance its competitive advantage. This concept is increasingly relevant as businesses seek to navigate the complexities of digital transformation. Digital orientation involves the integration of digital technologies into business processes, strategic planning, and decision-making, fostering an environment that supports continuous innovation and adaptability (Kindermann et al., 2021). Research has shown that a strong digital orientation can significantly impact an organization's ability to achieve successful digital transformation. Digital orientation serves as a foundation for developing digital capabilities and competencies, which are essential for sustaining competitive advantage in the digital economy (Arias Pérez & Vélez Jaramillo, 2022). It encompasses several dimensions, including digital strategy, digital culture, and digital governance. A well-defined digital strategy aligns digital initiatives with business objectives, ensuring that technology investments support broader organizational goals. Digital culture, on the other hand, emphasizes the importance of fostering an organizational mindset that values innovation, experimentation, and continuous learning (Strobl et al., 2022). Empirical studies suggest that digital orientation is a key antecedent to successful digital transformation. For instance, enterprises with a clear digital orientation are more likely to adopt advanced digital technologies and implement innovative business models (Law et al., 2019). This orientation not only drives the adoption of new technologies but also influences the development of digital capabilities, such as data analytics, digital marketing, and e-commerce (Sun & Zuo, 2023). Furthermore, digital orientation enhances organizational agility, enabling firms to respond swiftly to market changes and technological advancements (Sun et al., 2024). In addition, digital orientation is closely linked to organizational learning. Organizations with a strong digital orientation are more inclined to engage in learning activities that enhance their digital capabilities. These activities include acquiring new knowledge through partnerships, experimenting with new technologies, and continuously improving digital processes (Law et al., 2019). This continuous learning process helps organizations to stay ahead in a rapidly evolving digital landscape. The role of digital orientation in shaping organizational outcomes is also mediated by factors such as digital infrastructure and organizational agility. Digital infrastructure provides the necessary technological foundation for implementing digital strategies, while organizational agility ensures that firms can adapt to changes and uncertainties in the digital environment (Sun & Zuo, 2024). These factors underscore the importance of a holistic approach to digital transformation, where digital orientation serves as the guiding principle. In summary, digital orientation is a pivotal factor in the successful digital transformation of organizations. It influences the adoption of digital technologies, the development of digital capabilities, and the overall agility of the organization. As businesses continue to navigate the complexities of the digital era, a strong digital orientation will be crucial for achieving sustained competitive advantage.

2.3 Organizational Learning

Organizational learning is a crucial component of a firm's ability to adapt and thrive in a rapidly changing business environment. It refers to the process through which organizations acquire, interpret, and respond to internal and external information to enhance their capabilities and performance. The concept encompasses various learning activities, including knowledge acquisition, information distribution, information interpretation, and organizational memory (Argote, 2013). In the context of digital transformation, organizational learning plays a pivotal role in enabling firms to leverage new technologies and processes effectively. By engaging in continuous learning, organizations can develop the skills and knowledge required to navigate the complexities of digital innovation (Sun & Zuo, 2023). This process involves not only the assimilation of new technologies but also the reconfiguration of existing processes and practices to align with digital advancements (Law et al., 2019). Research indicates that successful organizational learning in the digital era involves both exploitative and explorative learning activities. Exploitative learning focuses on refining and improving existing competencies and technologies, while explorative learning involves experimenting with new ideas and innovations (March, 1991). The balance between these two forms of learning is critical for sustaining long-term organizational adaptability and performance (Sun et al., 2024). For instance, leading firms like Haier have successfully blended exploitative and explorative learning to drive their digital transformation efforts, continuously enhancing their digital capabilities while exploring new business models (Wang et al., 2021). Moreover, organizational learning is influenced by several contextual factors, such as organizational culture, leadership, and digital infrastructure. A culture that promotes openness, collaboration, and risk-taking is conducive to effective learning (Sun, 2022). Leadership also plays a crucial role in fostering a learning-oriented environment by encouraging experimentation and supporting knowledge-sharing initiatives (Law et al., 2019). Additionally, robust digital infrastructure provides the technological backbone necessary for facilitating learning activities and integrating new knowledge into organizational practices (Sun & Zuo, 2023). The impact of organizational learning on digital transformation performance is well-documented. Effective learning mechanisms enable organizations to better understand and respond to digital disruptions, thereby enhancing their agility and resilience (Strobl et al., 2022). For example, firms that systematically engage in learning activities are more adept at identifying emerging trends and opportunities, which can be translated into competitive advantages (Arias Pérez & Vélez Jaramillo, 2022). Furthermore, the interaction between organizational learning and digital orientation is critical. Digital orientation provides the strategic direction and framework within which learning activities occur, ensuring that learning efforts are aligned with the organization's digital transformation goals (Kindermann et al., 2021). This alignment enhances the coherence and effectiveness of both strategic initiatives and operational processes. In summary, organizational learning is a foundational element that supports the successful implementation of digital transformation strategies. By fostering a culture of continuous learning and leveraging digital infrastructure, organizations can enhance their adaptability and sustain competitive advantage in the digital age.

2.4 Digital Infrastructure

Digital infrastructure forms the technological backbone that supports organizations' digital transformation initiatives. It encompasses the hardware, software, networks, and data storage systems necessary for the effective utilization of digital technologies (Heeks, 2017). In the context of digital transformation, robust digital infrastructure is essential for enabling seamless communication, data integration, and process automation (Sun et al., 2024). One key aspect of digital infrastructure is the availability of advanced hardware and software tools that facilitate digital operations. This includes computing devices such as computers, servers, and mobile devices, as well as software applications and platforms for data analytics, artificial intelligence, and enterprise resource planning (ERP) (Lacity & Willcocks, 2014). For example, cloud computing platforms provide scalable and flexible computing resources that allow organizations to rapidly deploy digital solutions and scale their operations according to demand (Botta et al., 2016). Additionally, a reliable and high-speed network infrastructure is crucial for ensuring seamless connectivity and data transmission between various digital systems and devices (Lacity & Willcocks, 2017). This includes both internal networks within the organization and external connections to the internet and other external systems (Hossain et al., 2019). The advent of technologies such as 5G wireless networks and fiber-optic broadband has further enhanced the speed and reliability of digital communication, enabling organizations to leverage real-time data and communications for decision-making and customer engagement (Chen et al., 2020). Furthermore, robust data storage and management systems are essential for securely storing, organizing, and accessing the vast amounts of data generated by digital operations (Lacity & Willcocks, 2017). This includes both on-premises storage solutions and cloud-based storage services, which offer scalability, accessibility, and data redundancy (Qiu et al., 2021). Effective data management practices, such as data governance, data security, and data quality management, are critical for ensuring the integrity, confidentiality, and availability of digital data (Chen et al., 2012). Overall, digital infrastructure plays a critical role in enabling organizations to harness the full potential of digital technologies and drive their digital transformation initiatives. By investing in robust hardware, software, networks, and data storage systems, organizations can create a solid foundation for innovation, efficiency, and competitiveness in the digital age.

2.5 Organizational Agility

Organizational agility refers to an organization's ability to quickly sense and respond to changes in its internal and external environment in order to maintain competitiveness and adaptability (Teece, 2018). It involves the capacity to anticipate market trends, identify emerging opportunities and threats, and rapidly adjust strategies, structures, processes, and systems to capitalize on changing circumstances (Birkel & Hartmann, 2021). One key aspect of organizational agility is the ability to foster a culture of innovation and experimentation (Clegg et al., 2019). This involves encouraging employees to generate and test new ideas, take calculated risks, and learn from failures in order to continuously improve products, services, and processes (Larsen et al., 2016). Agile organizations empower employees at all levels to make decisions autonomously and collaborate cross-functionally to drive innovation and problem-solving (O'Reilly & Tushman, 2016). Moreover, organizational agility requires flexible and adaptive structures and processes that enable rapid decision-making and execution (Prieto & Revilla, 2016). This includes decentralized decision-making authority, dynamic resource allocation mechanisms, and cross-functional teams that can quickly assemble, disband, and reconfigure in response to changing priorities and market conditions (Deresky, 2017). Agile organizations often employ agile methodologies such as Scrum and Kanban to manage projects and workflows in a flexible and iterative manner (Serrador & Pinto, 2015). Furthermore, organizational agility is closely linked to digitalization and technology adoption (Gregor & Hevner, 2013). Agile organizations leverage digital technologies such as cloud computing, big data analytics, and artificial intelligence to enhance collaboration, streamline processes, and accelerate decision-making (Chen et al., 2015). Digital platforms and tools enable real-time data sharing, remote collaboration, and agile project management, allowing organizations to respond rapidly to changes and disruptions in the business environment (Helfat & Martin, 2015). Overall, organizational agility is essential for organizations to thrive in today's dynamic and uncertain business landscape. By fostering a culture of innovation, implementing flexible structures and processes, and leveraging digital technologies, organizations can enhance their ability to sense and respond to change, drive innovation, and maintain a competitive edge in the market.

2.6 Management Theory

Strategic Management Theory and Organizational Learning Theory serve as foundational pillars for understanding the mechanisms driving digital transformation performance in traditional manufacturing enterprises. Strategic Management Theory encompasses a broad range of concepts and frameworks aimed at guiding organizations in formulating and implementing strategies to achieve competitive advantage and long-term success (Hitt et al., 2020). At its core, this theory emphasizes the importance of aligning organizational goals with environmental opportunities and threats, leveraging internal resources and capabilities, and continuously adapting to changes in the business landscape (Barney, 1991). Strategic Management Theory provides valuable insights into how digital orientation, defined as an organization's strategic inclination towards embracing digital technologies and leveraging them to achieve business objectives, influences digital transformation performance (Kohli & Grover, 2008). According to this theory, organizations with a clear digital orientation are better equipped to identify and capitalize on digital opportunities, anticipate and respond to competitive threats, and allocate resources effectively to support digital initiatives (Venkatraman, 1994). Moreover, strategic management frameworks such as the Resource-

Based View (RBV) and Dynamic Capabilities Theory offer theoretical lenses through which the relationships between digital orientation, organizational learning, and digital transformation performance can be examined (Teece et al., 1997). Organizational Learning Theory, on the other hand, focuses on how organizations acquire, interpret, and apply knowledge to improve performance and adapt to changing environments (Argote, 2011). Rooted in disciplines such as psychology, sociology, and cognitive science, this theory posits that learning occurs through both individual cognition and collective interactions within organizations (Easterby-Smith & Lyles, 2011). Organizational learning processes such as acquisition, interpretation, dissemination, and integration of knowledge play a critical role in shaping an organization's ability to innovate, respond to market dynamics, and achieve strategic objectives (Crossan et al., 1999). Organizational Learning Theory offers valuable insights into the mediating role of learning processes in the relationship between digital orientation and digital transformation performance. By understanding how organizations assimilate and apply digital knowledge, researchers can elucidate the mechanisms through which digital orientation influences organizational capabilities and ultimately performance outcomes (Foss & Pedersen, 2004). Additionally, this theory underscores the importance of creating a supportive learning environment characterized by open communication, knowledge sharing, and experimentation, which are essential for facilitating digital transformation initiatives in traditional manufacturing enterprises (Argyris & Schön, 1978).

In summary, Strategic Management Theory and Organizational Learning Theory provide complementary perspectives for understanding the dynamics of digital transformation in traditional manufacturing enterprises. By integrating these theoretical frameworks, researchers can develop a more comprehensive understanding of how digital orientation, organizational learning, digital infrastructure, and organizational agility collectively influence digital transformation performance, thereby guiding managerial practice and informing strategic decision-making in today's digital economy.

2.3 Hypotheses Statement

Based on the theoretical framework of this study, the following hypotheses are proposed to investigate the relationships between digital orientation, organizational learning, digital infrastructure, organizational agility, and digital transformation performance in manufacturing enterprises:

(1) H1: Digital orientation positively influences the digital transformation performance of manufacturing enterprises.
(2) H2: Digital orientation positively affects acquiring learning within manufacturing enterprises.
(3) H3: Acquired learning positively impacts the digital transformation performance of manufacturing enterprises.
(4) H4: Acquired learning mediates the relationship between digital orientation and digital transformation performance in manufacturing enterprises.
(5) H5: Digital orientation positively influences trial and error learning within manufacturing enterprises.
(6) H6: Digital orientation positively affects trial and error learning within manufacturing enterprises.
(7) H7: Trial and error learning mediates the relationship between digital orientation and digital transformation performance in manufacturing enterprises.
(8) H8: Digital infrastructure positively moderates the relationship between digital orientation and acquiring learning in manufacturing enterprises.

(9) H9: Acquired learning mediates the relationship between digital orientation and digital transformation performance, moderated by digital infrastructure in manufacturing enterprises.
(10) H10: Digital infrastructure positively moderates the relationship between digital orientation and trial and error learning in manufacturing enterprises.
(11) H11: Trial and error learning mediates the relationship between digital orientation and digital transformation performance, moderated by digital infrastructure in manufacturing enterprises.
(12) H12: Organizational agility positively influences acquired learning and digital transformation performance in manufacturing enterprises.
(13) H13: Organizational agility positively influences trial and error learning and digital transformation performance in manufacturing enterprises.
(14) H14: Trial and error learning positively impacts the digital transformation performance of manufacturing enterprises, moderated by organizational agility.
(15) H15: Trial and error learning mediates the relationship between organizational agility and digital transformation performance, moderated by digital orientation in manufacturing enterprises.

These hypotheses form the basis for empirical testing to uncover the intricate relationships between key variables and digital transformation outcomes in manufacturing enterprises.

2.7 Research Framework

The conceptual model proposed in this study integrates key constructs from strategic management theory, organizational learning theory, and dynamic capability theory to elucidate the mechanisms underlying digital transformation performance in manufacturing enterprises. Drawing upon the hypotheses formulated earlier, the model illustrates the interplay between digital orientation, organizational learning, digital infrastructure, organizational agility, and digital transformation performance. At the core of the model is the influence of digital orientation on two forms of organizational learning: acquiring learning and trial and error learning. These learning processes, in turn, are posited to impact the digital transformation performance of manufacturing enterprises. Additionally, the model incorporates the moderating effects of digital infrastructure on the relationships between digital orientation and both acquiring and trial and error learning. Furthermore, the model includes the moderating influence of organizational agility on the relationships between acquired learning and trial and error learning with digital transformation performance.

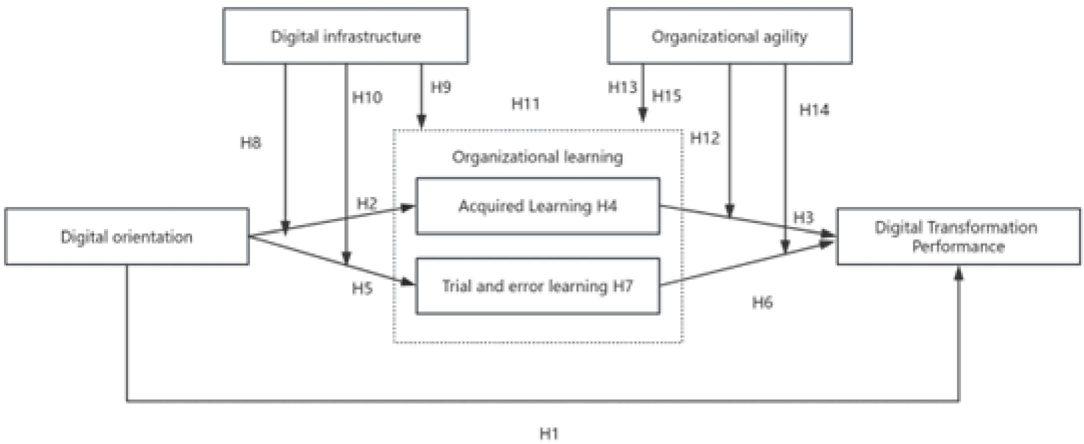

Figure 2-1: Conceptual Model

The proposed conceptual model serves as a comprehensive framework for understanding how digital orientation, organizational learning, digital infrastructure, and organizational agility collectively contribute to the digital transformation journey of manufacturing enterprises. By empirically testing this model, insights can be gained into the nuanced dynamics and mechanisms driving successful digital transformation outcomes in the manufacturing sector (Law et al., 2019; Sun & Zuo, 2024).

3. Methodology

3.1 Research Design

To address the research questions, this study employs a mixed-methods approach integrating qualitative and quantitative methods. Initially, a systematic review of relevant literature identifies theoretical gaps, followed by the construction of theoretical models based on multiple case studies.

Case Study Method: Four traditional manufacturing enterprises are selected as representative cases, and grounded theory is applied to analyze first-hand data from telephone interviews and field research, along with second-hand information from media reports and corporate sources. This method facilitates the in-depth exploration of contextual patterns and relationships, leading to the construction of theoretical models.

Questionnaire Survey Method: Drawing from existing research, mature scales are translated using the English back translation method. Pre-survey interviews guide modifications to ensure the questionnaire's relevance and comprehensibility. The finalized questionnaire is administered to gather large-scale empirical data.

Data analysis utilizes SPSS 22.0, AMOS 20.0, and PROCESS software, employing statistical techniques such as reliability analysis, correlation analysis, regression analysis, and Bootstrapping to validate the conceptual model and test research hypotheses.

3.2 Population, Sample, and Unit of Analysis

This study focuses on investigating the impact mechanism of digital orientation on the digital transformation performance of traditional manufacturing enterprises in China. The research area encompasses key manufacturing provinces: Zhejiang, Shandong, Jiangsu, Guangdong, and Jilin. These provinces are chosen for their significant contributions to both the quantity and quality aspects of China's manufacturing landscape. Zhejiang, Shandong, Jiangsu, and Guangdong are pioneers in manufacturing, while Jilin represents the digital development momentum in traditional industries. To ensure the inclusivity of the research findings, multiple industries within traditional manufacturing are targeted, including textile, food, machinery, medical, and petrochemical sectors. A stratified random sampling method is employed to ensure equal representation from each province. Middle and senior management personnel involved in digitalization activities are selected as survey subjects, ensuring comprehensive insights into digital initiatives. In total, 800 traditional manufacturing enterprises are selected across the five provinces. A two-stage questionnaire distribution method is utilized over four months. The first stage collects demographic and enterprise information along with variables related to digital orientation, learning, infrastructure, and agility. The second stage evaluates digital transformation performance. Of the 546 enterprises responding to the first stage, 431 complete responses are received in the second stage, resulting in 393 valid questionnaires after screening. The final valid response rate is 49.1%.

3.3 Instrumentation

In empirical research within management, questionnaire surveys are a prevalent method for data collection due to their standardization, ease of administration, and ability to reach respondents across geographical and temporal distances (Podsakoff et al., 2012). The questionnaire design process, guided by principles of scientificity, operability, and appropriateness, ensures the reliability and validity of collected data (Gordon et al., 2020). Digital orientation, a crucial construct in this study, reflects an enterprise's strategic approach to leveraging digital technology for competitive advantage. Drawing on existing literature (Kindermann et al., 2021; Khin & Ho, 2019; Shen et al., 2021), the questionnaire includes items measuring various aspects of digital orientation, such as commitment to digital technology, willingness to adopt new technologies, and understanding of digital opportunities. Acquired learning, representing organizational adaptation through external knowledge acquisition, is measured based on established scales (Zhao et al., 2011; Mao & Liu, 2019). Trial and error learning, capturing iterative experimentation within organizations, draws from existing literature (Cigularov et al., 2010; Xie et al., 2020). Digital infrastructure, encompassing both hardware and software components, is measured using a composite scale derived from previous studies (Zhou et al., 2020; Li & Cao, 2022). Organizational agility, reflecting an enterprise's ability to respond to market dynamics, is assessed based on established scales (Lu & Ramamurthy, 2011; Chakravarty et al., 2013). Digital transformation performance, capturing the outcomes of digital initiatives, is measured across product/service development, manufacturing process improvement, and operational management upgrading (Chi et al., 2020; Lu et al., 2021). Control variables, including enterprise age, size, nature, and industry, mitigate potential confounding effects on the study's variables (Wang & Wang, 2021; Qi et al., 2021). These variables are incorporated into the research model to ensure the robustness of the findings. Preliminary testing of the questionnaire involved 10 MBA students, assessing the questionnaire's clarity and respondent burden. The average completion time of approximately 15 minutes indicated acceptable respondent engagement. Following initial validation, a pilot survey was conducted, resulting in a 41.67% effective response rate. This comprehensive questionnaire design, guided by established principles and validated through small-sample testing, ensures the reliability and validity of data collected for subsequent analysis.

3.4 Reliability and Validity Testing

Reliability testing assesses the consistency and stability of a questionnaire's measurements. In this study, the α reliability coefficient method was employed, utilizing Cronbach's α to evaluate the reliability of key variables. The results indicate robust reliability across all variables. For instance, the Cronbach's α coefficient for Digital Orientation was 0.823, with a corresponding CR value of 0.8237. Similarly, high values were observed for other variables, all exceeding 0.8, affirming the reliability of the sample data. Validity testing ensures that a measurement scale accurately captures the intended constructs. This study examined content validity, criterion validity, and construct validity. Content validity was confirmed by selecting items from established scales, indicating alignment with measurement objectives. Structural validity was assessed through exploratory and confirmatory factor analyses. Factor analysis extracted six main factors, explaining 67.452% of total variance. Additionally, factor loadings exceeded the critical threshold of 0.5, affirming construct validity. Discriminant validity was evaluated through confirmatory factor analysis, with all fitting indicators meeting acceptable levels. Square root processing of Average Variance Extraction (AVE) values further confirmed discriminant validity. Reliability and validity testing demonstrate the robustness of the measurement scale utilized in this study, ensuring the accuracy and consistency of the collected data.

3.6 Data Analysis Methods

This study employs a variety of data analysis tools and methods:

(1) Descriptive Statistical Analysis: This entails assessing the basic characteristics of the sample, such as gender, age, education, and organizational attributes like size and establishment years. The aim is to ensure the sample aligns with research requirements.
(2) Reliability Testing: Utilizing Coefficient-Item Total Correlation (CITC) data, this test evaluates the overall reliability of questionnaire-based data. Establishing reliability lays the groundwork for subsequent experimental research, enhancing the significance of data and conclusions.
(3) Validity and Reliability Testing: Exploratory factor analysis extracts factors from questionnaire responses to assess the construct validity of the scale. Confirmatory factor analysis further examines the structural validity of the questionnaire.
(4) Linear Relationship Test: This involves three main steps: selection of research objects and methods, validity testing using software like SPSS and AMOS, and correlation and regression analysis using tools such as SPSS and PROCESS. The results contribute to a dialogue with existing literature, enabling a nuanced exploration of hypotheses regarding the relationship between variables like digital orientation, acquisition learning, trial and error learning, digital infrastructure, organizational agility, and digital transformation performance.

4. Results and Discussion

4.1 Overview of Respondents

Table 4-1: Descriptive Statistics and Correlation Analysis (N=393)

Mean		SD	1	2	3	4	5	6	7	8	9	10
1.EA	2.802	0.932	-									
2.ES	2.975	1.113	0.042	-								
3.EN	2.288	0.996	-0.087	0.046	-							
4.IND	3.483	1.530	0.112*	0.127*	0.153**	-						
5.DO	4.789	0.697	0.035	-0.110*	0.071	-0.043	**0.734**					
6.AL	4.805	0.775	0.018	-0.025	0.120*	0.059	0.454**	**0.844**				
7.TL	3.912	0.814	0.021	-0.020	0.141**	0.020	0.395**	0.446**	**0.776**			
8.DI	3.409	0.769	0.116*	0.002	-0.002	0.108*	0.052	0.210**	0.090	**0.737**		
9.AO	4.312	1.326	-0.002	-0.008	-0.070	-0.072	-0.216**	-0.468**	-0.197**	-0.161**	**0.846**	
10.DTP	5.207	0.637	0.042	-0.150**	0.140**	0.028	0.425**	0.403**	0.456**	-0.031	0.083	**0.713**

Note: * p<0.05 (two-tailed test)** P<0.01 (two-tailed test); DO represents digital orientation; AL represents acquired learning; TL stands for trial and error learning; DI represents digital infrastructure; AO represents organizational agility; DTP represents digital transformation performance; The bold values on the diagonal represent the AVE square root of the variable.

Upon analyzing 393 valid questionnaires, the sample characteristics were examined. Firstly, gender distribution revealed a higher representation of males, comprising 64.9% of the sample, with 255 males compared to 138 females. Concerning age, the majority fell between 36 and 45 years old, constituting 44.0% of the sample, while those aged 46 and above accounted for 42.5%, and those aged 35 and below were 13.5%. In terms of education, undergraduate degree holders formed the largest group at 51.7%, followed by graduate degree holders at 32.6%, with only 4.1% having a high school education or below. Regarding positions, 56.0% were senior managers, and 44.0% were middle managers. Enterprise characteristics showed a distribution across various establishment periods, with 38 companies under 5 years old, 103 between 6-10 years, 151 between 11-15 years, and 101 with 16 years or more. Enterprise scale varied, with 40 companies having 100 or fewer employees, and others scaling up to 5001 or more. Enterprise nature encompassed state-owned (23.9%), private (38.7%), joint ventures (22.1%), and foreign-funded enterprises (15.3%). Industry representation included textile, food manufacturing, mechanical manufacturing, automobile manufacturing, medical manufacturing, petrochemical, and others. Descriptive statistics and correlation analysis confirmed the hypothesis, indicating significant positive correlations between digital orientation, acquisition learning, trial and error learning, and digital transformation performance. Multicollinearity tests ensured the model's robustness, with Variance Inflation Factor (VIF) values within acceptable limits, affirming the reliability of regression results.

4.2 The Impact of Digital Orientation on Digital Transformation Performance

Utilizing SPSS software, this study constructed multiple regression models to examine the direct influence of digital orientation on enterprise digital transformation performance. Initially, control variables such as company age, size, nature, and industry affiliation were incorporated to derive Model 1. Subsequently, digital orientation was added as an input to Model 1, resulting in Model 2, to observe changes in regression coefficients and model fit.

Table 4-2: Main Effect Test Results (N=393)

	Digital Transformation Performance	
	Model 1	**Model 2**
Control variable		
Enterprise age	0.059	0.038
Enterprise scale	-0.161**	-0.117*
Enterprise nature	0.149**	0.114*
Industry	0.019	0.038
Independent variable		
Digital orientation		0.405***
AdjustedR^2	0.038	0.198
ΔR^2	0.048	0.160
F	4.889**	20.361***

The result illustrates a significant positive impact of digital orientation on enterprise digital transformation performance (β= 0.405, p<0.001, Model 2), suggesting that an increase in digital orientation within traditional manufacturing enterprises positively correlates with enhanced digital transformation performance. Thus, research hypothesis H1 is substantiated. The findings confirm a positive association between digital orientation and digital transformation performance, supporting hypothesis H1. Existing literature underscores the significance of digital orientation in digital innovation and transformation within organizations (Kindermann et al., 2021). Scholars emphasize its direct impact on corporate performance (Ardito et al., 2021; Arias Pérez et al., 2021). However, while research on digital orientation is burgeoning, quantitative studies on its impact on digital transformation performance remain relatively nascent. This study addresses this gap by focusing on traditional manufacturing enterprises, delving into the relationship between digital orientation and digital transformation performance, and empirically validating it. Prior studies recognize digital orientation as a prerequisite for digital transformation (Hess et al., 2016; Nasiri et al., 2022). Nasiri et al. (2022) highlight the interplay of digital orientation, intensity, and maturity in influencing corporate financial performance. Rupeika Apoga et al. (2022) elucidate the pathway through which digital orientation affects business performance via digital transformation. However, they stress the need for strategic planning and cultural transformation alongside technological change to ensure successful transformation (Liu Yang et al., 2020; Proksch et al., 2021). In summary, the empirical results affirm the pivotal role of digital orientation in facilitating digital transformation within traditional manufacturing enterprises, aligning with theoretical expectations and prior research literature.

4.3 Testing the Mediating Effect of Organizational Learning

This study examines the mediating effects of two types of organizational learning, acquiring learning and trial and error learning, on the relationship between digital orientation and digital transformation performance in traditional manufacturing enterprises. Utilizing multiple regression models and structural equation modeling, the direct and mediating effects are analyzed.

Table 4-3: Mediation Effect Test for Acquired Learning (N=393)

	Acquired learning		Digital Transformation Performance	
	Model 3	**Model 4**	**Model 5**	**Model 6**
Control variable				
Enterprise age	0.025	0.001	0.050	0.038
Enterprise scale	-0.036	0.013	-0.147^{**}	-0.120^{**}
Enterprise nature	0.118^{*}	0.078	0.104^{*}	0.094^{*}
Industry	0.043	0.065	0.002	0.022
Independent variable				
Digital orientation		0.453^{***}		0.289^{***}
Mediating variables				
Acquired learning			0.386^{***}	0.255^{***}
After adjustment R^2	0.008	0.208	0.184	0.284
ΔR^2	0.018	0.200	0.146	0.065
F	1.780	21.638^{***}	18.649^{***}	22.516^{***}

Table 4-4: Boosting Test for Mediating Effect of Acquired Learning (N=393)

Action path	Estimated value of indirect effects	Standard error	95% confidence interval	
			Upper limit	Lower limit
Mediation effect: DO→AL→DTP	0.106	0.025	0.062	0.158
Direct effects: DO→DTP	0.264	0.045	0.175	0.354
Total effect	0.370	0.042	0.288	0.452

For acquiring learning, after controlling for enterprise characteristics, digital orientation significantly predicts acquiring learning (β=0.453, p<0.001). Acquiring learning, in turn, positively influences digital transformation performance (β=0.386, p<0.001). The introduction of acquiring learning as a mediator reduces the direct effect of digital orientation on digital transformation performance, indicating a mediating role (β=0.289, p<0.001). A bootstrapping test confirms the significant indirect effect of acquiring learning (γ=0.106, 95% CI [0.062, 0.158]), supporting the mediating hypothesis.

Table 4-5: Mediation Effect Test for Trial and Error Learning (N=393)

	Trial and error learning		Digital Transformation Performance	
	Model 7	**Model 8**	**Model 9**	**Model 10**
Control variable				
Enterprise age	0.035	0.014	0.044	0.033
Enterprise scale	-0.028	0.015	-0.149^{**}	-0.122^{**}
Enterprise nature	0.145^{**}	0.111^{*}	0.086	0.077
Industry	-0.003	0.016	0.020	0.033
Independent variable				
Digital orientation		0.389^{***}		0.276^{***}
Mediating variables				
Trial and error learning			0.439^{***}	0.332^{***}
After adjustment R^2	0.012	0.159	0.227	0.289
ΔR^2	0.022	0.148	0.189	0.063
F	2.149	15.849^{***}	24.005^{***}	27.536^{***}

Table 4-6: Boosting Test for Mediating Effect of Trial and Error Learning (N=393)

Action path	Estimated value of indirect effects	Standard error	95% confidence interval	
			Upper limit	Lower limit
Mediating effect:DO→TL→DTP	0.118	0.023	0.079	0.168
Direct effect: DO→DTP	0.252	0.043	0.168	0.336
Total effect	0.370	0.042	0.288	0.452

Similarly, for trial and error learning, digital orientation positively predicts trial and error learning (β=0.389, p<0.001). Trial and error learning positively impacts digital transformation performance (β=0.439, p<0.001). Introducing trial and error learning as a mediator reduces the direct effect of digital orientation on digital transformation performance (β=0.276, p<0.001), indicating mediation. The bootstrapping test confirms the significant indirect effect of trial and error learning (γ=0.118, 95% CI [0.079, 0.168]), supporting the mediating hypothesis.

Table 4-7: Comparison of Mediating Effects: Acquisition vs. Trial and Error Learning (N=393)

Action path	Estimated value of indirect effects	Standard error	95% confidence interval	
			Upper limit	Lower limit
Total effect	0.168	0.029	0.117	0.229
DO→AL→DTP	0.068	0.024	0.027	0.119
DO→TL→DTP	0.100	0.022	0.063	0.146

The results demonstrate that both acquiring learning and trial and error learning mediate the relationship between digital orientation and digital transformation performance. Acquiring learning and trial and error learning play distinct but significant roles in facilitating digital transformation in traditional manufacturing enterprises. These findings contribute to a deeper understanding of how different types of organizational learning mechanisms influence digital transformation outcomes. The findings highlight the nuanced role of organizational learning in driving digital transformation performance. Acquiring learning, characterized by intentional knowledge acquisition, facilitates the adoption of digital practices and technologies, thereby enhancing digital transformation outcomes. On the other hand, trial and error learning, characterized by experimentation and adaptation, fosters agility and innovation, contributing to successful digital transformation initiatives. Moreover, the comparison between the two mediating mechanisms reveals insights into their relative importance. While both acquiring learning and trial and error learning are significant, trial and error learning appears to have a stronger mediating effect, indicating its pivotal role in navigating the complexities of digital transformation. This underscores the importance of fostering a culture of experimentation and learning from failures to achieve sustained digital transformation success. Overall, these findings underscore the importance of organizational learning in enabling and sustaining digital transformation efforts in traditional manufacturing enterprises. By understanding the distinct roles of acquiring learning and trial and error learning, organizations can develop targeted strategies to leverage these mechanisms effectively and drive digital transformation success. Further research could explore the interplay between different types of organizational learning and other contextual factors to provide more nuanced insights into digital transformation dynamics.

4.4 Testing the Moderating Effect of Digital Infrastructure and Organizational Agility

The moderating effects of digital infrastructure and organizational agility on the relationship between digital orientation and organizational learning mechanisms (acquiring learning and trial and error learning) are investigated. In this analysis, interaction terms between digital orientation and each moderator are included in regression models.

Table 4-8: Moderating Effect Test of Digital Infrastructure (N=393)

	Acquired learning	Trial and error learning
	Model 11	**Model 12**
Control variable		
Enterprise age	-0.010	0.014
Enterprise scale	0.006	0.008
Enterprise nature	0.067	0.101^{*}
Industry	0.045	0.008
Independent variable		
Digital orientation	0.442^{***}	0.385^{***}
Adjusting variables		
Digital infrastructure	0.189^{***}	0.073
Interaction item		
Digital orientation * digital infrastructure	0.130^{**}	0.110^{*}
After adjustment R^2	0.255	0.171
ΔR^2	0.250	0.165
F	20.135^{***}	12.590^{***}

Results reveal a significant interaction effect between digital orientation and digital infrastructure on both acquiring learning (β=0.130, p<0.01) and trial and error learning (β=0.110, p<0.05). High-level digital infrastructure strengthens the positive relationship between digital orientation and both types of organizational learning. This finding suggests that well-developed digital infrastructure enhances the effectiveness of digital orientation in fostering organizational learning. The Johnson-Neyman method confirms these results, indicating a critical threshold where the moderating effect of digital infrastructure becomes significant.

Table 4-9: Moderating Effect Test of Organizational Agility (N=393)

	Digital Transformation Performance		
	Model 13	**Model 14**	**Model 15**
Control variable			
Enterprise age	0.037	0.042	0.032
Enterprise scale	-0.138^{**}	-0.144^{**}	-0.134^{**}
Enterprise nature	0.108^{*}	0.086	0.074
Industry	0.008	0.013	0.008
Mediating variables			
Acquired learning	0.508^{***}		0.362^{***}
Trial and error learning		0.470^{***}	0.328^{***}
Adjusting variables			
Organizational agility	0.370^{***}	0.204^{***}	0.361^{***}
Interaction item			
Acquired Learning * Organizational Agility	0.162^{***}		0.102^{*}
Trial and error learning * Organizational agility		0.188^{***}	0.104^{*}
After adjustment R^2	0.298	0.291	0.388
ΔR^2	0.263	0.255	0.354
F	24.810^{***}	23.942^{***}	28.582^{***}

Similarly, a significant interaction effect is found between organizational agility and both acquiring learning (β=0.102, p<0.05) and trial and error learning (β=0.104, p<0.05) on digital transformation performance. High organizational agility amplifies the positive impact of organizational learning mechanisms on digital transformation performance. This underscores the importance of agile organizational processes in leveraging the benefits of learning for successful digital transformation. The Johnson-Neyman method further validates these findings by identifying critical points where the moderating effect of organizational agility becomes significant.

High-level digital infrastructure significantly strengthens the relationship between digital orientation and both acquiring learning and trial and error learning. Graphical representations illustrate the increased slope of these relationships under high digital infrastructure conditions, emphasizing the crucial role of digital infrastructure in facilitating effective organizational learning for digital transformation. High organizational agility enhances the positive relationship between acquiring learning, trial and error learning, and digital transformation performance. Graphical representations demonstrate the amplified slope of these relationships under high organizational agility conditions, highlighting the importance of agile organizational processes in driving successful digital transformation outcomes. The findings underscore the critical role of digital infrastructure and organizational agility as moderators in the context of digital transformation. High-level digital infrastructure provides the necessary foundation for effective organizational learning, amplifying the impact of digital orientation on acquiring learning and trial and error learning. Similarly, organizational agility enables organizations to capitalize on the benefits of learning by enhancing the positive relationship between organizational learning mechanisms and digital transformation performance.

These results have practical implications for organizations seeking to navigate the complexities of digital transformation. Investing in robust digital infrastructure and fostering organizational agility can significantly enhance the effectiveness of digital orientation initiatives and promote successful digital transformation outcomes. Future research could delve deeper into the specific mechanisms through which digital infrastructure and organizational agility influence digital transformation processes, providing actionable insights for organizational practice.

4.5 Moderated Mediation Effect Test

Table 4-10: Moderated Mediation Effect Test (N=393)

Action path DI Adjusting variable levels AO		**Est. Indirect Effects**	**StdErr**	**95% CI Upper limit**	**Lower limit**
	Low (-1SD) Low (-1SD)	0.053	0.029	0.007	0.121
	Low (-1SD) Medium (Mean)	0.099	0.032	0.044	0.171
	Low (-1SD) High (+1SD)	0.145	0.046	0.066	0.244
	Medium (Mean) Low (-1SD)	0.079	0.037	0.010	0.157
DO→AL→DTP	Medium (Mean) Medium (Mean)	0.147	0.028	0.097	0.208
	Medium (Mean) High (+1SD)	0.216	0.035	0.151	0.288
	High (+1SD) Low (-1SD)	0.105	0.050	0.013	0.212
	High (+1SD) Medium (Mean)	0.196	0.041	0.120	0.279
	High (+1SD) High (+1SD)	0.287	0.050	0.192	0.386
High/Low AL Indirect Effect Differences: Moderated Mediation Index		0.235	0.057	0.114	0.340
		0.022	0.011	0.001	0.045
	Low (-1SD) Low (-1SD)	0.042	0.019	0.011	0.085
	Low (-1SD) Medium (Mean)	0.085	0.028	0.037	0.145
	Low (-1SD) High (+1SD)	0.128	0.042	0.054	0.220
	Medium (Mean) Low (-1SD)	0.061	0.023	0.022	0.110
DO→TL→DTP	Medium (Mean) Medium (Mean)	0.125	0.023	0.086	0.174
	Medium (Mean) High (+1SD)	0.189	0.033	0.130	0.261
	High (+1SD) Low (-1SD)	0.080	0.031	0.028	0.150
	High (+1SD) Medium (Mean)	0.165	0.032	0.111	0.237
	High (+1SD) High (+1SD)	0.249	0.047	0.168	0.353
High/Low TL Indirect Effect Differences: Moderated Mediation Index		0.207	0.052	0.117	0.319
		0.020	0.011	0.002	0.044

The study investigates whether acquisition-based learning and trial-and-error-based learning exhibit a moderated mediation effect under the moderating influence of digital infrastructure and organizational agility. Following Hayes (2013), Model 21 in the PROCESS macro program is employed to test hypotheses H9, H11, H13, and H15. The results depict the moderated mediation effect test, presenting estimated values of indirect effects, standard errors, and confidence intervals.

For the mediating effect of acquiring learning, when both digital infrastructure and organizational agility are low, the estimated indirect effect is 0.053, with a confidence interval of [0.007, 0.121]. Conversely, when both are high, the estimated indirect effect is 0.287, with a confidence interval of [0.192, 0.386]. A significant difference in the indirect effect is observed between these extremes (95% confidence interval [0.114, 0.340]), supporting the moderated mediation effect of acquiring learning (H9 and H13). Similarly, for the mediating effect of trial-and-error learning, when both digital infrastructure and organizational agility are low, the estimated indirect effect is 0.042, with a confidence interval of [0.011, 0.085]. In contrast, when both are high, the estimated indirect effect is 0.249, with a confidence interval of [0.168, 0.353]. A significant difference in the indirect effect is found between these extremes (95% confidence interval [0.117, 0.319]), supporting the moderated mediation effect of trial and error learning (H11 and H15).

The findings illuminate the nuanced role of digital infrastructure and organizational agility in moderating the mediation pathways between digital orientation, organizational learning mechanisms, and digital transformation performance. Under low levels of digital infrastructure and organizational agility, the mediating effect of both acquisition-based learning and trial-and-error-based learning is relatively weaker. However, as both digital infrastructure and organizational agility increase, the mediating effects become more pronounced, indicating that the impact of digital orientation on digital transformation performance is amplified through organizational learning mechanisms. This underscores the importance of robust digital infrastructure and agile organizational processes in facilitating effective learning and, subsequently, driving successful digital transformation outcomes.

These results offer valuable insights for organizations aiming to optimize their digital transformation initiatives. By investing in advanced digital infrastructure and fostering organizational agility, firms can enhance the effectiveness of their learning processes, thereby accelerating their journey toward successful digital transformation. Additionally, the findings highlight the need for future research to explore the underlying mechanisms through which digital infrastructure and organizational agility influence the mediation pathways, providing actionable guidance for organizational practice.

4.6 Summary of Hypothesis Test Results

The hypothesis test results provide empirical insights into the relationships examined in this study. Digital orientation demonstrates a significant positive impact on the digital transformation performance of manufacturing enterprises (H1), as well as on both acquiring learning (H2) and trial and error learning (H5), supporting the pivotal role of digital orientation in fostering learning and driving digital transformation outcomes. Moreover, acquired learning is found to positively influence the digital transformation performance of manufacturing enterprises (H3), with acquired learning and trial and error learning both mediating the relationship between digital orientation and digital transformation performance (H4, H7). Further analysis reveals that digital infrastructure positively regulates the relationship between digital orientation and both acquiring learning (H8) and trial and error learning (H10), with acquired learning mediating this positive regulation in the context of digital transformation performance (H9, H11). Similarly, organizational agility is shown to positively moderate the relationship between acquired learning and digital transformation performance (H12), with acquired learning acting as a mediator in this positive regulation (H13). Additionally, trial and error learning is found to positively moderate the relationship between organizational agility and digital transformation performance (H14), with trial and error learning mediating this positive regulation (H15).

These findings collectively underscore the significance of digital orientation, organizational learning mechanisms, digital infrastructure, and organizational agility in driving successful digital transformation initiatives within manufacturing enterprises. By elucidating these intricate relationships, this study contributes to a deeper understanding of the multifaceted dynamics involved in the digital transformation journey.

5. Conclusion

In the face of rapid digitalization, manufacturing enterprises are compelled to adapt and innovate to remain competitive in today's dynamic landscape. This study embarked on a comprehensive exploration of the intricate interplay between digital orientation, organizational learning mechanisms, digital infrastructure, organizational agility, and their collective impact on digital transformation performance. Through rigorous empirical analysis and dialogue with existing literature, several key insights have emerged, illuminating pathways for effective digital transformation strategies. Firstly, our findings underscore the pivotal role of digital orientation in driving successful digital transformation initiatives. Digital orientation serves as the cornerstone for fostering organizational learning, enabling enterprises to embrace new technologies, adapt to evolving market demands, and capitalize on emerging opportunities. Moreover, our study highlights the crucial mediating role played by acquiring learning and trial and error learning in translating digital orientation into tangible digital transformation outcomes. These learning mechanisms serve as conduits through which enterprises absorb, assimilate, and leverage digital technologies to enhance operational efficiency, innovate products and services, and cultivate sustainable competitive advantages. Furthermore, our analysis reveals the significant regulatory effects of digital infrastructure and organizational agility on the relationship between digital orientation, organizational learning, and digital transformation performance. Robust digital infrastructure facilitates seamless integration of digital technologies into organizational processes, while organizational agility empowers enterprises to navigate uncertainty, respond adeptly to market dynamics, and drive continuous innovation. Overall, this study offers valuable insights for manufacturing enterprises seeking to embark on or enhance their digital transformation journeys. By emphasizing the synergistic relationships between digital orientation, organizational learning, digital infrastructure, and organizational agility, enterprises can formulate holistic strategies to thrive in the digital age. As the digital landscape continues to evolve, future research endeavors may delve deeper into emerging technologies, evolving organizational paradigms, and dynamic market forces to further enrich our understanding of digital transformation dynamics and inform strategic decision-making processes. Through interdisciplinary collaboration and ongoing scholarly inquiry, researchers can collectively propel the digital transformation agenda forward, unlocking new frontiers of innovation, competitiveness, and sustainable growth for manufacturing enterprises and society at large.

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