Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 10, 517-540
2025
Publisher: Learning Gate
DOI: 10.55214/2576-8484.v9i10.10463

Resolving the technology–performance paradox: A capability–technology–performance model of SME digital transformation

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Abstract: In the rapidly evolving digital economy, digital transformation has become critical for small and medium-sized manufacturing enterprises (SMEs) seeking to sustain competitiveness. Yet, technology investment alone does not guarantee performance gains, and the interplay between organizational capabilities and technology application remains underexplored. This study investigates how learning capability and channel integration capability shape the application of digital technologies and, in turn, organizational performance. Using survey data from 476 SMEs in Kunming, China, we construct and empirically validate a structural equation model grounded in the resource-based view and organizational learning theory. The findings show that both capabilities exert significant direct effects on performance and also enhance it indirectly via digital technology application. Importantly, technology application plays a partial mediating role, indicating that internal capabilities not only drive outcomes directly but also magnify the value of digital tools. This research advances digital transformation theory by articulating a "capability–technology–performance" pathway and integrating resource-based and organizational learning perspectives. Practically, it offers SME managers a dual-path framework to convert digital investments into measurable results and provides insights for policy support in capability development.

Keywords: *Channel integration Capability, Digital technology application, Digital transformation, Firm performance, Learning capability.*

1. Introduction

In the lead-up to the 2022 holiday shopping season, U.S. retail giant Target faced a "digital trust crisis": customer pickup reservations were frequently lost, inventory levels failed to match actual deliveries, and the much-anticipated intelligent order system became a focal point of consumer complaints. Despite an investment of over $1 billion in smart store upgrades within two years, Target reported a decline in operational efficiency and a 12% drop in customer satisfaction in its digital segment that quarter, with system utilization falling below 30%. Similar cases have emerged globally. Traditional retailers such as Marks & Spencer in the UK and Metro Group in Germany have also encountered comparable challenges during digital transformation, while technologies were deployed, performance gains failed to materialize. This paradox of "technology without output" has increasingly become a common hurdle for SMEs in the digital era. According to a McKinsey and Company [1] report, over 60% of digital investments by mid-sized enterprises worldwide have not translated into tangible performance improvements. Business leaders widely agree that the issue lies not in the technology itself, but in whether firms possess the foundational capabilities to convert technology into value.

China faces a similar reality. Take Kunming, one of China's pilot cities for SME digitalization, as an example. In 2024, the city's total retail sales reached CNY 363.4 billion, with SMEs contributing over 65%, and online sales accounting for 43%. However, a local government survey revealed that only 34% of enterprises effectively utilize the digital tools they adopt. Nearly half reported insufficient employee

History: Received: 5 August 2025; Revised: 22 September 2025; Accepted: 25 September 2025; Published: 10 October 2025
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digital skills and difficulty integrating channels, with some even experiencing customer attrition and declining repeat purchases following system implementation. The core issue lies in the absence of an integrated capability system for learning, integration, and application; technologies are present but fail to take root. As one business owner aptly put it: "We bought the boat, but never taught our staff how to row." This practical tension raises a critical research question: under the constraints and dynamism that characterize the SME context, how do organizational capabilities influence the effective application of digital technologies and, ultimately, performance improvement?

In recent years, digital transformation has become a central theme in organizational studies, strategic management, and information systems research. Existing literature has extensively explored the adoption, implementation, and outcomes of digital technologies. Dominant theoretical models include the Technology Acceptance Model (TAM), the Technology–Organization–Environment (TOE) framework, and the Unified Theory of Acceptance and Use of Technology (UTAUT) [2]. These models illuminate how technological features, organizational structures, and environmental factors affect adoption behavior and partly explain the drivers of digital transformation.

In the context of small and medium-sized enterprises (SMEs), scholars have further identified limiting factors such as resource scarcity, technological complexity, and organizational culture [3] while also exploring how digital technologies can enhance process efficiency, customer experience, and strategic agility [4]. However, three major limitations can be observed in the current literature:

First, an overemphasis on technology adoption and a lack of focus on capability support. Most studies view digital transformation as a matter of whether technologies are adopted, with limited systematic explanation of how internal organizational capabilities enable effective technology use. For resource-constrained SMEs, capability limitations may be a more fundamental barrier than technology supply [5].

Second, a lack of theoretical fit and fragmented explanations. Much of the literature is based on large enterprise settings, focusing on platform construction and complex system integration, making them ill-suited for SMEs, which typically face lower operational flexibility and weaker capability bases.

Third, insufficient performance orientation and neglect of transformation chains. Most research centers on adoption intention rather than tracing how digital value is triggered and realized through capabilities. As such, the intermediary mechanisms between capabilities, technology use, and performance remain under-theorized, limiting our understanding of why high investment frequently yields low returns.

To address these gaps, this study adopts a capability–technology synergy perspective and focuses on the performance improvement mechanisms in SME digital transformation. Drawing on the Resource-Based View (RBV) and Organizational Learning Theory, we develop a structural equation model (SEM) that incorporates four key constructs: learning capability, channel integration capability, digital technology application, and firm performance. This research seeks to answer the following question:

How do learning capability and channel integration capability influence firm performance through digital technology application in SME digital transformation? Does a significant mediating pathway exist?

To enhance contextual relevance and practical insight, we conduct an empirical study based on firsthand data collected from retail SMEs in Kunming, a national pilot city for SME digitalization in China. We also incorporate real-world cases to strengthen the applied value and interpretive power of our model.

Compared with existing literature, this study advances digital transformation research in three key ways. First, it moves beyond traditional technology adoption models (e.g., TAM, TOE) by conceptualizing a capability–technology–performance chain, clarifying how internal organizational capabilities activate the value of digital tools. Second, it empirically tests a partial mediation model in which technology application serves as a process-based transmission mechanism between learning/integration capabilities and firm performance, thereby addressing a theoretical blind spot in the SME transformation literature. Third, by integrating RBV and organizational learning theory (OLT), this study not only uses these perspectives but extends their logic: it operationalizes learning capability as a dynamic enabler of digital integration, and reframes technology as a contingent resource whose value depends on capability configuration. These contributions offer new directions for theory and practice in digitally constrained SME contexts.

2. Theoretical Foundation and Research Model

2.1. Integrated Theoretical Perspective: Resource-Based View and Organizational Learning Theory

In a rapidly evolving digital environment, the key to converting technological investment into performance returns lies in a firm's internal capability structure and resource integration mechanisms. To explain how SMEs achieve value creation from technology through internal capabilities, this study integrates RBV and OLT as the theoretical foundation. These two theories are complementary in focus and logic and together support the proposed "capability–technology–performance" mechanism model.

(1) Resource-Based View: Structural Logic of Resource-to-Value Conversion. The RBV posits that sustainable competitive advantage originates from internal firm resources rather than external market conditions [6, 7]. Resources that are rare, heterogeneous, inimitable, and organizationally embedded, such as information systems, channel integration capability, and technological processes, are considered the foundation of firm performance differentials.

In the context of digital transformation, although firms invest heavily in technology, performance improvements depend on the depth of integration between technological resources and organizational capabilities [8, 9]. RBV emphasizes that technology does not inherently create value; its performance potential is only realized when it is embedded in organizational routines and supported by appropriate coordination capabilities. Thus, resource orchestration and capability alignment are the critical pathways through which value is unlocked.

(2) Organizational Learning Theory: Unveiling the dynamic activation of resources. OLT, grounded in the dynamic capabilities perspective, emphasizes that organizations must continuously acquire, absorb, and institutionalize new knowledge to remain adaptive and resilient amid environmental turbulence [10, 11]. Learning is not merely a process of knowledge accumulation but serves as a bridge that transforms external inputs (e.g., digital technologies) into organizational actions and redesigned processes.

This study integrates RBV and OLT to construct an explanatory framework for digital transformation in SMEs, as shown in Table 1. While RBV emphasizes the strategic value of internal resources, it under-specifies the activation mechanisms. OLT offers a dynamic lens on how organizations acquire and exploit knowledge, but often lacks clarity on resource-based conditions. We argue that learning capability, as a dynamic process rooted in OLT, is the key enabler that activates the value of digital resources as proposed by RBV. This perspective transitions from a resource possession logic to a resource activation logic, thereby explaining the paradox of technology investment failing to yield performance in SMEs. It bridges the static and dynamic theoretical domains to account for performance heterogeneity in digital transformation.

Table 1.
Theoretical Logic

Theoretical Lens	Core Focus	Theoretical Logic Path	Role in the Research Model
RBV	What strategic resources does the firm own	Structural logic: resource uniqueness and coordination	Dominant theory: explains how capabilities and technology jointly affect performance.
OLT	How firms activate and apply resources	Evolutionary logic: learning, absorption, institutionalization	Supporting theory: explains how learning capability enables effective technology use.

2.2. Research Hypotheses

2.2.1. Learning Capability and Firm Performance

According to OLT, learning capability is a dynamic capability that enables firms to continuously acquire, assimilate, and apply new knowledge in uncertain and fast-evolving environments [12, 13]. It enhances external knowledge absorption and promotes internal institutionalization and process embedding.

Prior studies indicate that firms with strong learning capabilities can better identify the value of technology, accelerate employee adaptation, and more effectively convert knowledge into performance [14]. For resource-constrained SMEs, this capability is particularly critical.

$H_{1:}$ Learning capability is positively associated with firm performance.

2.2.2. Channel Integration Capability and Firm Performance

Under the RBV, channel integration capability is considered a structural resource embedded in organizational routines. It is rare, inimitable, and sustainable qualities that underpin a differentiated competitive advantage [15, 16]. This capability enables firms to coordinate multi-channel resources, ensuring information consistency, marketing coherence, and process synergy.

Empirical evidence suggests that high channel integration enhances customer experience, brand consistency, and cost efficiency [17]. For SMEs, it also helps mitigate management challenges associated with weak IT infrastructure.

$H_{2:}$ Channel integration capability is positively associated with firm performance.

2.2.3. Technology Application and Firm Performance

Within the RBV framework, technology resources yield performance gains only when effectively integrated with internal capabilities [18, 19]. Technology application entails more than system deployment; it includes process integration, employee proficiency, and data-driven decision-making.

Prior research shows that deep use of ERP, CRM, and related systems can significantly enhance decision support, process optimization, and customer service [20]. For SMEs prone to "deployment without use," the depth of technology application is a decisive factor in performance outcomes.

$H_{3:}$ The level of technology application is positively associated with firm performance.

2.2.4. The Mediating Role of Technology Application in the Learning–Performance Link

Drawing on OLT and Absorptive Capacity Theory, learning capability is a prerequisite for understanding, absorbing, and redeploying new technologies [21, 22]. Firms with strong learning capabilities can more effectively integrate digital systems into their workflows, improving application depth.

Research confirms that learning-oriented firms are more proactive in training, process adaptation, and continuous system refinement, thereby improving alignment between technology and business objectives [23]. This mechanism is especially salient in SMEs.

$H_{4:}$ Learning capability indirectly enhances firm performance through technology application.

2.2.5. The Mediating Role of Technology Application in the Channel–Performance Link

According to the RBV's resource orchestration logic, channel integration capability serves as a foundational enabler of system deployment by providing process infrastructure and data flow [24, 25]. Strong channel integration alleviates issues such as data silos and redundancy, facilitating system embedding.

Studies have shown that in highly integrated environments, digital systems generate greater synergistic value, enabling closed-loop data flow and process coordination, which enhances technological efficiency and ultimately improves performance [26].

H_5: Channel integration capability indirectly enhances firm performance through technology application.

2.3. Model Construction

This study's research model aims to address a critical practical dilemma in SME digital transformation: despite increasing investment in digital technologies, performance returns often fall short of expectations, which we term the "technology non-performance paradox." To explain this gap, we construct a multi-layered mediation model guided by the RBV as the dominant theory and OLT as the supporting theory. This model conceptualizes performance generation along the "resource–capability–performance" chain.

RBV asserts that sustainable competitive advantage stems from rare, inimitable, and strategically organized internal resources. In digital transformation, although technological resources are widely available, their value realization hinges on the firm's complementary capabilities. We define technology application capability as a strategic resource, with its performance effects depending on the configuration of internal capabilities.

OLT, from a dynamic capability's standpoint, explains how firms respond to external change by acquiring and institutionalizing new knowledge. It provides the process logic for why digital technologies often fail to generate value, namely, a lack of effective learning capability impedes absorption and application.

Accordingly, this study selects learning capability and channel integration capability as key enabling resources:

- Learning capability represents cognitive capability: it involves employees' and organizations' ability to understand, absorb, and reconfigure digital technologies.
- Channel integration capability represents a structural capability: it ensures that digital systems are effectively embedded in operational processes across multi-channel platforms.

2.3.1. Path Logic of the Model

- Learning and channel integration capabilities exert direct effects on performance.
- These capabilities also have indirect effects through enhanced technology application.
- Firm performance is conceptualized as a composite of customer satisfaction, operational efficiency, and cost reduction, reflecting the tangible outcomes of digital transformation.

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 10: 517-540, 2025
DOI: 10.55214/2576-8484.v9i10.10463

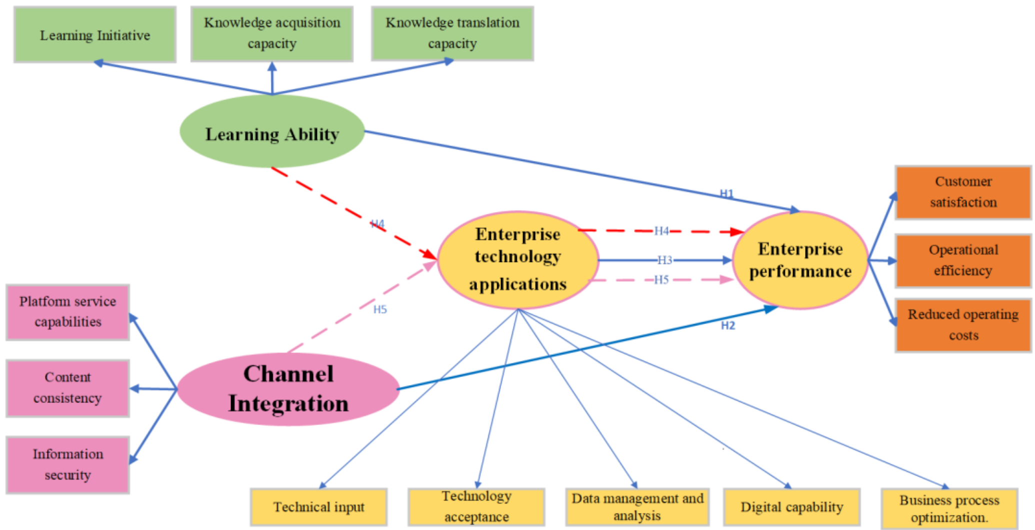

Figure 1.
Capability Mechanism Model for SME Digital Transformation.

Figure 1 presents the theoretical framework of this study. Learning capability includes dimensions such as learning proactiveness, knowledge acquisition, and knowledge transformation. Channel integration capability comprises platform service capability, content consistency, and information security. Technology application involves technological investment, user acceptance, data management and analytics, digital capability, and process optimization. Firm performance is reflected in customer satisfaction, operational efficiency, and cost control.

By integrating RBV and OLT, the model underscores the activation role of internal capabilities in digital value realization, contributing to a deeper theoretical understanding of performance mechanisms in SME digital transformation. This study advances the literature on SME digital transformation by integrating RBV and OLT into a unified explanatory framework. While prior research often isolates resources or capabilities, our model conceptualizes digital performance generation as a resource–capability–application–performance chain. Specifically, we distinguish between cognitive capability (learning capability) and structural capability (channel integration capability), and demonstrate how these underpin the depth of technology application as a mediating mechanism. By theorizing technology application not merely as system deployment but as a process of integration, adaptation, and refinement, we provide a nuanced explanation for the "technology non-performance paradox" in SMEs. This dual-theory integration contributes to RBV by extending its structural logic to digital contexts and enriches OLT by revealing how learning capabilities activate technological resources for sustained performance.

3. Research Design

3.1. Research Context and Data Collection

This study focuses on SMEs in Kunming, China, for the following reasons. First, Kunming was selected as one of China's first pilot cities for SME digital transformation, granting it strong regional representativeness and policy significance. Second, SMEs in this region commonly face challenges such as limited resources, weak internal capabilities, and stagnant performance improvement conditions that align well with the theoretical and practical focus of this research.

Data were collected through a structured questionnaire survey. Respondents included senior executives and core functional department managers to ensure a comprehensive understanding of the firms' digital strategies, capability development, and performance outcomes. The questionnaire was distributed via both online and offline channels. Online dissemination occurred through industry associations and corporate WeChat groups, while offline distribution was conducted during chamber of commerce meetings and professional networking events.

To enhance measurement validity and reliability, a pilot study (n=30) was conducted prior to the full-scale survey to refine the phrasing, structure, and comprehension of questionnaire items. In the formal survey, 356 questionnaires were distributed, and after excluding responses with over 20% missing data or evident invalid entries, 328 valid responses were retained, resulting in a response rate of 92.1%. These data provided a solid foundation for subsequent empirical analyses.

3.2. Methodology

This study employs SEM for empirical analysis. As a multivariate statistical technique that integrates path analysis with measurement error control, SEM is well-suited for examining complex mediating mechanisms involving latent variables. The analytical procedure includes reliability and validity assessments, model fit evaluation, and hypothesis testing. Data processing was conducted using SPSS 26.0 and AMOS 24.0 software.

3.3. Variable Definitions and Scale Development

In this study, five key constructs were measured to capture the mechanisms underpinning digital transformation in SMEs. Learning capability, grounded in OLT, is conceptualized as a dynamic capability that enables firms to acquire, absorb, integrate, and apply internal and external knowledge resources. It encompasses processes such as knowledge acquisition, dissemination, sharing, and application [8]. Following Shirokova et al. [27], learning capability is operationalized through four dimensions: learning commitment, shared vision, open-mindedness, and knowledge sharing, measured on a 5-point Likert scale. Channel integration capability refers to a firm's ability to coordinate information, services, and processes across online and offline channels to ensure a seamless and consistent customer experience at multiple touchpoints [28]. Drawing on Wu et al. [29], this construct is captured through three dimensions: information consistency, service consistency, and operational coordination, each adapted to the SME retail context and measured on a 5-point Likert scale. Enterprise technology application emphasizes the depth and breadth of digital system utilization (e.g., ERP, CRM, data analytics platforms, and mini-program storefronts), focusing on process integration, functional usage, and value realization rather than mere adoption intention [30]. Based on Oke et al. [31], it is operationalized through operational proficiency, functional breadth, and process embeddedness, using 5-point Likert items refined with insights from Kunming's SME development bureau and local firm interviews. Enterprise performance is conceptualized as the aggregate of financial, operational, and market outcomes, in line with the Balanced Scorecard [32] and subjective performance evaluation approaches. Specifically, it comprises financial performance (e.g., sales growth, net profit margin), operational performance (e.g., inventory turnover, order fulfillment efficiency), and market performance (e.g., customer satisfaction, repurchase rate). All performance measures are relative, with respondents benchmarking their firms against industry peers to minimize inter-industry variation, and are rated on a 5-point Likert scale. Finally, control variables including firm size, years of establishment, industry type, and ownership nature (state-owned vs. privately owned) are incorporated to enhance model robustness. Prior evidence highlights their significant association with firm performance [33], justifying their inclusion in the structural model.

3.4. Scale Design

To ensure theoretical rigor and contextual fit, this study adopts measurement scales that have been widely validated in prior domestic and international research, adapting them to the digital transformation context of SMEs to enhance structural validity and contextual relevance, as shown in Table 2. All items are rated on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree), allowing for standardized quantification of respondents' perceptions and improving data interpretability.

Specifically, learning capability is measured based on the organizational learning constructs proposed by Berndt et al. [34], comprising four dimensions: learning commitment, shared vision, open-mindedness, and knowledge sharing that reflect a firm's ability to internalize and institutionalize knowledge. Channel integration capability draws from Li et al. [35], focusing on omnichannel retail coordination, including information consistency, service consistency, and operational coordination, to capture the efficiency of resource alignment across platforms. Enterprise technology application builds on IT capability measurement frameworks developed by Chen et al. [36], emphasizing the depth and breadth of system use across operational proficiency, functional utilization, and process embedding. Finally, enterprise performance is assessed subjectively using a relative performance method, guided by the Balanced Scorecard approach [37], and is disaggregated into financial, operational, and market performance, thereby offering a holistic view of digital transformation outcomes.

Table 2.
Research Variables.

Construct	Dimension	Sample Measurement Item	Source
Learning Capability (LC)	Learning Commitment	The company encourages employees to continuously acquire new knowledge and skills.	Berndt et al. [34]
	Shared Vision	All employees share a common understanding of the firm's strategic goals and direction.	
	Open-Mindedness	Employees are encouraged to question existing practices and propose improvements.	
	Knowledge Sharing	Knowledge and experience flow smoothly across departments.	
Channel Integration Capability (CIC)	Information Consistency	Channels provide consistent information on pricing, promotions, and product details.	Li et al. [35]
	Service Consistency	Customers receive consistent service experiences across different channels.	
	Operational Coordination	Online and offline processes, including inventory management, are closely coordinated.	
Enterprise Technology Application (ETA)	Operational Proficiency	Employees are proficient in using the core functions of information systems.	Chen et al. [36]
	Functional Usage	The firm fully utilizes various system functions, not limited to specific modules.	
	Process Embeddedness	Information systems are deeply integrated into daily business processes.	
Enterprise Performance (EP)	Financial Performance	The firm's sales growth rate exceeds the industry average.	Oubrahim and Sefiani [37]
	Operational Performance	Inventory turnover and order processing efficiency outperform major competitors.	
	Market Performance	Customer satisfaction and repurchase rates continue to improve.	

3.5. Reliability and Validity Testing

To ensure the reliability and validity of the measurement instruments and enhance both the statistical robustness and the theoretical explanatory power of the SEM, this study conducted a comprehensive assessment of the psychometric properties of all scales prior to model estimation. As shown in Table 3, the evaluation covered internal consistency reliability, construct validity, convergent validity, and discriminant validity. First, internal consistency reliability was tested using Cronbach's alpha (α). All coefficients exceeded the recommended threshold of 0.70 [38], indicating strong reliability: learning capability (α = 0.912), channel integration capability (α = 0.895), enterprise technology application (α = 0.924), and enterprise performance (α = 0.837). Second, construct validity was supported by a Kaiser-Meyer-Olkin (KMO) value of 0.927, well above the 0.80 benchmark, and

ISSN: 2576-8484
Vol. 9, No. 10: 517-540, 2025
DOI: 10.55214/2576-8484.v9i10.10463

Bartlett's test of sphericity was significant ($\chi^2 = 4286.731$, df = 276, $p < 0.001$), confirming sampling adequacy and suitability for factor analysis. Third, convergent validity was evaluated through confirmatory factor analysis (CFA). Results showed that all standardized factor loadings ranged from 0.703 to 0.882, composite reliability (CR) values ranged from 0.882 to 0.932, and average variance extracted (AVE) values ranged from 0.605 to 0.737, all meeting or surpassing recommended thresholds [39], indicating that observed indicators effectively represented their corresponding latent constructs. Finally, discriminant validity was established by comparing the square root of AVE for each construct with inter-construct correlations, where each construct's AVE square root was consistently greater than its correlations with other constructs, confirming construct independence. Overall, these results demonstrate that the measurement model exhibits high reliability, strong convergent and discriminant validity, and robust psychometric properties, providing a solid foundation for subsequent SEM analysis and hypothesis testing.

Table 3
Reliability and Validity Assessment of the Measurement Model.

Variable	Cronbach's α	CR	AVE	Standardized factor loading range
Learning ability	0.912	0.921	0.682	0.721–0.865
Channel integration ability	0.895	0.905	0.605	0.703–0.854
Enterprise technology application	0.924	0.932	0.737	0.743–0.882
Enterprise performance	0.837	0.882	0.612	0.715–0.826

4. Quantitative Analysis Results

4.1. Sample Characteristics

To evaluate the representativeness and contextual validity of the dataset, this study conducted a descriptive analysis of firm-level characteristics (please refer to Table 1 in the Appendix). Among the 500 questionnaires distributed via online platforms such as WeChat, QQ, and industry forums, 476 valid responses were collected, yielding a high response rate of 95.2%. The sample reflects substantial heterogeneity across sectors, with retail (35.29%), manufacturing (25.00%), healthcare (14.50%), and other industries (25.21%) all well represented. In terms of scale and financial capacity, 67.44% of firms employ fewer than 30 staff, and 75.84% report annual revenues below CNY 2 million, highlighting the resource limitations typical of Chinese SMEs. Firm maturity is similarly balanced, with 28.57% in operation for less than two years, 34.66% for 2–5 years, and 36.77% for more than five years. Regarding digitalization, 71.64% of firms reported some form of online activity, yet most had invested less than CNY 50,000 annually in digital technologies, and half provided fewer than seven days of employee training, underscoring limited digital capacity-building. Respondents were primarily business owners (43.70%) and middle managers (46.85%), ensuring insights from individuals with decision-making authority. Digital adoption trends show a strong customer-facing orientation, with online sales platforms (50.21%) being the most common, followed by internal office systems (20.59%) and supply chain platforms (15.97%). Collectively, the sample offers a contextually grounded and diverse portrayal of SMEs undergoing digital transformation under resource-constrained conditions.

4.2. Reliability Analysis

To evaluate the internal consistency of the measurement constructs, this study employed Cronbach's alpha (α) as the primary reliability coefficient. Cronbach's α is widely regarded as a robust indicator of scale reliability, with values closer to 1.0 denoting greater homogeneity among the items

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ISSN: 2576-8484
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measuring a latent construct. According to conventional thresholds, α values above 0.80 are considered highly reliable, values between 0.70 and 0.80 are acceptable, while those below 0.70 may indicate insufficient internal consistency.

As reported in Table 4, all 13 latent dimensions in this study demonstrated Cronbach's α values ranging from 0.836 to 0.858. Specifically, the highest reliability was observed for both platform service capabilities and operational efficiency (α = 0.858), while the lowest, though still strong, was noted for data management and analysis (α = 0.836). Other dimensions, such as learning initiative (α = 0.847), knowledge acquisition capacity (α = 0.851), digital capability (α = 0.842), and customer satisfaction (α = 0.844), also exhibited excellent internal consistency, each exceeding the 0.80 benchmark.

Collectively, these results confirm that all measurement scales exhibit high internal reliability, thereby providing a statistically sound foundation for subsequent empirical analyses, including SEM modeling and hypothesis testing.

Table 4.
Cronbach's reliability analysis

Dimension	Cronbach's α Coefficient	Number of Items
Learning Initiative	0.847	5
Knowledge acquisition capacity	0.851	5
Knowledge translation capacity	0.847	5
Platform service capabilities	0.858	5
Content consistency	0.854	5
Information security	0.850	5
Technical input	0.841	5
Technology acceptance	0.844	5
Data management and analysis	0.836	5
Digital capability	0.842	5
Business process optimization	0.841	5
Customer satisfaction	0.844	5
Operational efficiency	0.858	5

4.3. Exploratory Factor Analysis

To evaluate the construct validity of the measurement scales, we conducted Exploratory Factor Analysis (EFA) using SPSS 27. Prior to factor extraction, data adequacy was verified. As shown in Table 5, the KMO values for all four constructs (Learning Capability, Platform Service Capability, Digital Capability, and Enterprise Performance) exceeded 0.90, and Bartlett's tests were all highly significant ($p < 0.001$), indicating excellent suitability for factor analysis.

Table 5.
KMO and Bartlett's Test.

Construct	KMO	Bartlett χ^2	df	p-value
Learning Capability	0.909	3022.074	105	0
Platform Service Capability	0.981	3160.796	105	0
Digital Capability	0.938	3160.796	300	0
Enterprise Performance	0.917	3145.926	105	0

To further assess the construct validity of the measurement scales, Principal Component Analysis (PCA) with Varimax rotation was conducted to extract latent factors for each construct. As summarized in Table 6, all constructs exhibited well-defined multidimensional structures with satisfactory statistical properties. Specifically, Learning Capability yielded three factors with eigenvalues of 5.897, 1.824, and 1.649, cumulatively explaining 62.46% of the total variance. Factor loadings ranged from 0.688 to 0.790. Platform Service Capability also produced three factors (eigenvalues = 6.102, 1.788, 1.623), accounting for 63.41% of the total variance, with loadings between 0.719 and 0.790. For Digital Capability, five distinct factors were extracted (eigenvalues = 9.117, 1.916, 1.697, 1.520, 1.166), explaining 61.67% of the variance, with loadings ranging from 0.644 to 0.766. Finally, Enterprise Performance yielded three factors (eigenvalues = 6.059, 1.813, 1.600), explaining 63.14% of the variance, with loadings between 0.703 and 0.828.

All factor loadings exceeded the commonly accepted threshold of 0.60, and all item communalities were above 0.55, indicating strong convergent validity and well-differentiated factor structures. These findings confirm that the measurement items effectively capture their respective latent constructs, thereby providing a psychometrically robust foundation for subsequent Confirmatory Factor Analysis (CFA) and SEM.

Table 6.
Factor loading coefficients after rotation.

Construct	Number of Factors	Eigenvalues	Cumulative Variance Explained (%)	Factor Loading Range
Learning Capability	3	5.897, 1.824, 1.649	62.46	0.688–0.790
Platform Service Capability	3	6.102, 1.788, 1.623	63.413	0.719–0.790
Digital Capability	5	9.117, 1.916, 1.697, 1.520, 1.166	61.665	0.644–0.766
Enterprise Performance	3	6.059, 1.813, 1.600	63.144	0.703–0.828

4.4. Confirmatory Factor Analysis

To further validate the measurement model, Confirmatory Factor Analysis (CFA) was conducted on the four constructs: learning capability, channel integration capability, technology application, and enterprise performance.

As reported in **Table 7**, all models demonstrate excellent overall fit. Specifically, the CMIN/DF values range from 1.115 to 1.466, far below the recommended upper limit of 3, while RMSEA values remain between 0.016 and 0.031, well under the 0.08 threshold. Moreover, all goodness-of-fit indices (GFI=0.95–0.974, CFI=0.986–0.997, NFI=0.939–0.97, IFI=0.986–0.997) exceed the 0.9 benchmark, confirming that the four models exhibit strong explanatory power and theoretical consistency.

Table 7.
Model fitting indicators.

Model	CMIN	DF	CMIN/DF	GFI	RMSEA	CFI	NFI	IFI
Learning Capability	127.542	87	1.466	0.966	0.031	0.986	0.958	0.986
Channel Integration	97.019	87	1.115	0.974	0.016	0.997	0.97	0.997
Tech Application	331.499	265	1.251	0.95	0.023	0.987	0.939	0.987
Enterprise Performance	118.983	87	1.368	0.967	0.028	0.99	0.963	0.99

At the indicator level, Appendix Table 2 shows that all standardized factor loadings are above 0.65 (e.g., A1 = 0.743, H5 = 0.764, O1 = 0.864), and all paths are statistically significant ($p < 0.001$). This demonstrates that each observed variable strongly explains its corresponding latent construct. The critical ratios (z-values) for all items are well above 13, further supporting the robustness of the measurement structure.

Table 8.
Model AVE and CR index results.

Construct	Factor	AVE	CR
Learning Capability	Learning Initiative	0.527	0.848
	Knowledge Acquisition Capacity	0.533	0.851
	Knowledge Translation Capacity	0.526	0.847
Channel Integration	Platform Service Capability	0.55	0.859
	Internal Consistency	0.54	0.854
	Information Security	0.534	0.851
Technology Application	Technology Input	0.517	0.842
	Technology Acceptance	0.522	0.845
	Data Management and Analysis	0.507	0.837
	Digital Capability	0.517	0.842
	Business Process Optimization	0.516	0.842
Enterprise Performance	Customer Satisfaction	0.523	0.846
	Operational Efficiency	0.548	0.858
	Reduce Operating Costs	0.54	0.853

In terms of convergent validity, Table 8 indicates that the Composite Reliability (CR) values for all dimensions range from 0.837 to 0.859, significantly higher than the minimum threshold of 0.7. The Average Variance Extracted (AVE) values also exceed the 0.5 benchmark across all factors (e.g., learning initiative = 0.527, technology acceptance = 0.522, operational efficiency = 0.548), confirming that the majority of the variance in measurement items is explained by their corresponding latent constructs. These results establish both internal consistency and convergent validity of the measurement scales.

Finally, discriminant validity is confirmed in Appendix Table 3 using the Fornell–Larcker criterion. The square roots of AVE (e.g., learning initiative = 0.726, platform service capability = 0.742, customer satisfaction = 0.723) are consistently greater than their corresponding inter-construct correlations (e.g., learning initiative–knowledge acquisition = 0.521; operational efficiency–reduced costs = 0.501). This indicates that each construct explains its own items better than those of other constructs, thereby demonstrating strong discriminant validity across the four models.

Taken together, the CFA results provide robust evidence of reliability, convergent validity, and discriminant validity for all measurement models, laying a solid foundation for subsequent SEM modeling.

4.5. Descriptive Statistics

Descriptive statistics were employed to analyze the fundamental statistical characteristics of the variables, providing insights into the distribution and internal structure of the data. As shown in Table 9, the sample size for each variable is 476. The range of values for each variable falls within reasonable limits, with no outliers detected. For Learning Ability, the mean value is 3.482, with a standard deviation of 0.620, and the skewness and kurtosis values are 0.049 and -0.396, respectively, indicating a nearly symmetric distribution. Channel Integration has a mean value of 3.338 and a standard deviation of 0.604, with skewness of 0.271 and kurtosis of -0.189, suggesting that the data distribution is slightly positively skewed but still close to normal. The variable Enterprise Technology Application has a mean of 3.468, a standard deviation of 0.555, and skewness and kurtosis values of -0.143 and -0.659, respectively, indicating a slight negative skew and a platykurtic distribution. Finally, Enterprise Performance shows a mean of 3.342, a standard deviation of 0.586, with skewness and kurtosis of -0.069 and -0.395, respectively, suggesting a near-normal distribution.

Overall, all variables exhibit skewness and kurtosis values within acceptable ranges (i.e., absolute values below 1), confirming that the data closely follow a normal distribution. These results provide a solid foundation for further statistical analysis, including subsequent factor and SEM modeling.

Table 9.
Descriptive statistics.

	Sample Size	Minimum Value	Maximum Value	Mean Value	Standard Deviation	Skewness	Kurtosis
Learning Ability	476	2	5	3.482	0.620	0.049	-0.396
Channel Integration	476	2	5	3.338	0.604	0.271	-0.189
Enterprise Technology Application	476	2.080	4.640	3.468	0.555	-0.143	-0.659
Enterprise Performance	476	1.800	4.933	3.342	0.586	-0.069	-0.395

4.6. Correlation Analysis

Correlation analysis was conducted to examine the linear relationships among the four core constructs: learning ability, channel integration, enterprise technology application, and enterprise performance. As shown in Table 10, all Pearson correlation coefficients are positive and statistically significant at the 0.01 level (two-tailed), indicating stable and meaningful associations between variables.

Specifically, learning ability is positively correlated with channel integration ($r = 0.276$, $p < 0.01$), enterprise technology application ($r = 0.422$, $p < 0.01$), and enterprise performance ($r = 0.435$, $p < 0.01$), suggesting that firms with stronger learning capabilities are more likely to adopt integrated channels, implement technological solutions, and achieve better performance. Channel integration is also significantly associated with both enterprise technology application ($r = 0.381$, $p < 0.01$) and enterprise performance ($r = 0.434$, $p < 0.01$), implying that more integrated channels may facilitate both technological deployment and business outcomes.

Notably, enterprise technology applications demonstrate the strongest correlation with enterprise performance ($r = 0.617$, $p < 0.01$), underscoring the critical role of technology in enhancing firm-level outcomes. These results collectively support the hypothesized positive interrelationships among the constructs and provide a strong empirical basis for subsequent SEM modeling.

Table 10.
Correlation analysis results of various variables (N=476).

	1	2	3	4
Learning Ability	1			
Channel Integration	0.276**	1		
Enterprise Technology Application	0.422**	0.381**	1	
Enterprise Performance	0.435**	0.434**	0.617**	1

Note: **. The correlation is significant at the 0.01 level (two-tailed). *. The correlation is significant at the 0.05 level (two-tailed).

4.7. Structural Equation Modeling

In this study, Amos 26.0 software was employed to construct the SEM, conduct model fit tests, and analyze path coefficients. The statistical model established is shown in Figure 2.

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 10: 517-540, 2025
DOI: 10.55214/2576-8484.v9i10.10463

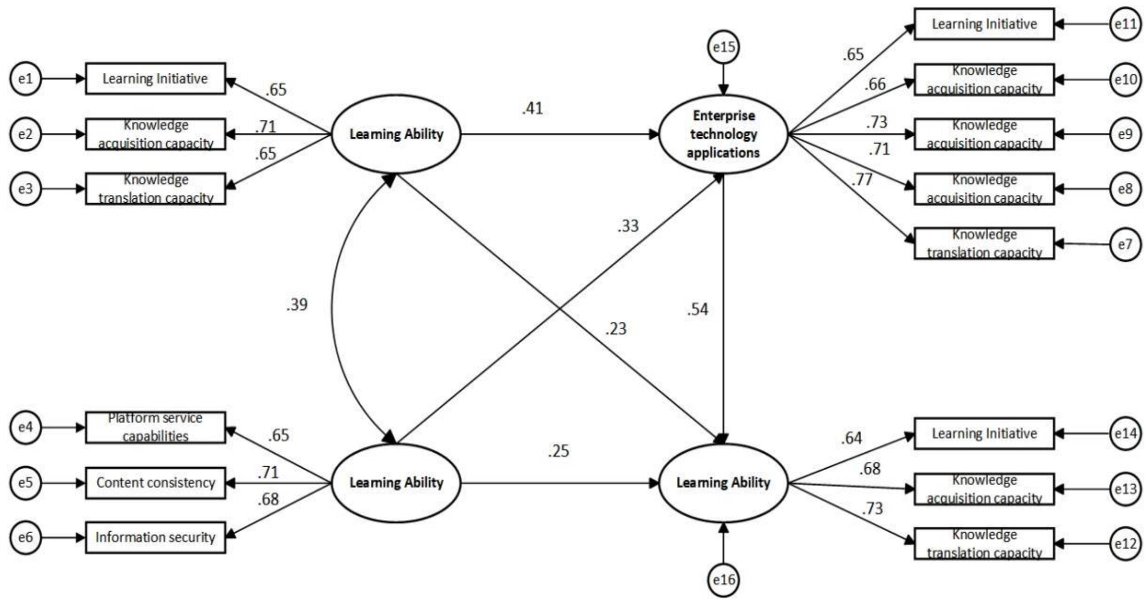

Figure 2.
SEM model.

1. Model Fit and Overall Assessment. Empirically test the hypothesized relationships among learning capability, channel integration, technology application, and enterprise performance; SEM was conducted. The global fit indices indicate that the proposed model achieves an excellent fit to the data (see Table 11). The ratio of chi-square to degrees of freedom (χ^2/df = 1.275) is well below the recommended cutoff of 3.0, suggesting a parsimonious model fit. The Root Mean Square Error of Approximation (RMSEA = 0.024) is substantially lower than the threshold of 0.05, reflecting a close fit of the model to the population covariance structure. In addition, the incremental fit indices, including the Goodness-of-Fit Index (GFI = 0.975), Comparative Fit Index (CFI = 0.991), and Incremental Fit Index (IFI = 0.991), all exceed the stringent benchmark of 0.95, while the Normed Fit Index (NFI = 0.958) surpasses the minimum requirement of 0.90. These results collectively exceed the conventional thresholds, thereby demonstrating both the robustness and theoretical soundness of the model.

Table 11.
Model Fit Indicators

Indicator	CMIN	DF	CMIN/DF	GFI	RMSEA	CFI	NFI	IFI
Ideal Value	-	-	<3	>0.9	<0.08	>0.9	>0.9	>0.9
Compliance Value	-	-	<5	>0.8	<0.10	>0.8	>0.8	>0.8
Fitted Value	90.546	71	1.275	0.975	0.024	0.991	0.958	0.991

2. Direct Effects Analysis. The results of the SEM path analysis (Table 12) confirm five significant direct effects, aligning with the hypothesized structural relationships (H1–H3). First, learning capability → technology application is positive and significant ($\beta = 0.411$, $p < 0.001$), indicating that firms with strong knowledge acquisition and assimilation capabilities are more likely to embed and utilize digital technologies effectively. Similarly, channel integration → technology application is positive and significant ($\beta = 0.331$, $p < 0.001$), suggesting that seamless cross-channel coordination facilitates the adoption and deep use of enterprise technologies. Together, these two capability-based antecedents explain approximately 23.7% of the variance in technology application ($R^2 = 0.237$), underscoring the role of organizational capabilities as enablers of digital technology utilization.

Second, when predicting performance outcomes, learning capability → enterprise performance ($\beta = 0.232$, $p < 0.001$) and channel integration → enterprise performance ($\beta = 0.248$, $p < 0.001$) both remain positive and significant, confirming that organizational capabilities exert a direct influence on firm outcomes independent of technology use. Most importantly, technology application → enterprise performance exhibits the strongest direct effect ($\beta = 0.538$, $p < 0.001$), suggesting that deep and effective utilization of digital systems (e.g., ERP, CRM, and data analytics platforms) is the dominant driver of enterprise performance improvement.

Collectively, the three predictors account for 37.7% of the variance in enterprise performance ($R^2 = 0.377$), indicating substantial explanatory power. These results highlight a dual pathway: organizational capabilities not only directly enhance firm performance but also act indirectly by enabling more effective technology application. The findings provide strong empirical support for the dynamic capabilities view, emphasizing that learning and integration capabilities constitute foundational resources, while technology application represents the proximal mechanism that translates these resources into superior performance outcomes.

Table 12.
Model coefficients.

Independent Variable	Dependent Variable	Unstandardized Path Coefficient	Standardized Path Coefficient	Standard Error	z (C.R.)	p
Learning Ability	Enterprise Technology Application	0.47	0.411	0.076	6.174	***
Channel Integration	Enterprise Technology Application	0.371	0.331	0.071	5.207	***
Learning Ability	Enterprise Performance	0.248	0.232	0.069	3.586	***
Channel Integration	Enterprise Performance	0.261	0.248	0.064	4.055	***
Enterprise Technology Application	Enterprise Performance	0.504	0.538	0.065	7.773	***

3. Mediation Effects. To further validate the hypothesized mediation mechanisms, we employed the non-parametric bootstrapping method with 5000 resamples to test the indirect effects of learning capability and channel integration on enterprise performance through technology application. Bootstrapping is widely recognized as a robust approach for mediation analysis because it does not rely on the assumption of normality of the indirect effect distribution [40].

The results (Table 13) reveal that the indirect effect of learning capability on enterprise performance through technology application is statistically significant ($\beta = 0.133$, 95% CI [0.078, 0.212], $p < 0.001$). Similarly, the indirect effect of channel integration on enterprise performance via technology application is also significant ($\beta = 0.136$, 95% CI [0.085, 0.228], $p < 0.001$). Importantly, both mediating effects are partial rather than full, as the direct paths from learning capability ($\beta = 0.232$, $p < 0.01$) and channel integration ($\beta = 0.248$, $p < 0.01$) to enterprise performance remain significant when technology application is included in the model.

These findings underscore the pivotal mediating role of technology application in the capability–performance chain. Specifically, organizational capabilities in learning and channel integration not only exert direct effects on firm performance but also enhance performance indirectly by deepening the effective use of digital technologies. This aligns with the RBV and dynamic capability theory, which emphasize that the value of organizational resources is realized through their integration with technological applications.

Table 13.
Path analysis test.

Indirect Path	Standardized β	95% CI Lower	95% CI Upper	p-value	Mediation Type
Learning Capability → Technology Application → Enterprise Performance	0.133	0.078	0.212	< 0.001	Partial Mediation
Channel Integration → Technology Application → Enterprise Performance	0.136	0.085	0.228	< 0.001	Partial Mediation

Table 14 presents that all five hypotheses (H1–H5) are empirically supported. The analysis reveals that both learning capability and channel integration capability significantly enhance firm performance, not only directly but also indirectly through the mediating role of technology application. Technology application itself emerges as the strongest determinant of enterprise performance. Importantly, the mediation tests confirm that technology application serves as a partial mediator, thereby reinforcing the "capability–technology–performance" logic. These results jointly underscore that organizational capabilities provide the foundational conditions for digital transformation, while technology application acts as the critical transmission mechanism that amplifies their impact on firm performance.

Table 14.
Summary of assumptions.

Hypothesis	Path relationship	Std. Path Coefficient (β)	z-value	p-value	Conclusion
H1	Learning Capability→Firm Performance	0.232	3.586	***	Supported
H2	Channel Integration Capability → Firm Performance	0.248	4.055	***	Supported
H3	Technology Application → Firm Performance	0.538	7.773	***	Supported
H4	Learning Capability → Technology Application → Firm Performance	0.133 (indirect)	Bootstrap CI [0.078, 0.212]	***	Supported (Partial Mediation)
H5	Channel Integration Capability → Technology Application → Firm Performance	0.136 (indirect)	Bootstrap CI [0.085, 0.228]	***	Supported (Partial Mediation)

5. Discussion

5.1. Theoretical Contributions

This study offers three distinct theoretical contributions to the literature on digital transformation in SMEs.

First, it develops and empirically validates a mechanism-based mediation model that explains how internal capabilities (learning and channel integration) shape performance through technology application. This structure moves beyond existing adoption-centric frameworks (e.g., TAM, TOE), providing a deeper understanding of the process through which digital value is realized in resource-constrained firms.

Second, this study extends the RBV by introducing a dynamic capability lens. Rather than treating digital technologies as static resources, the model shows that their value realization depends on capability-driven orchestration. Learning capability is framed not just as a supportive asset but as a prerequisite mechanism that activates and amplifies the performance effects of technology.

Third, it contributes to OLT by grounding its abstract logic in digital practice. Through empirical modeling, this study shows that knowledge acquisition and integration directly influence both the depth of digital system use and the realization of performance gains. This dual impact offers theoretical clarity on how learning transforms external inputs (technologies) into internal outcomes (efficiency, satisfaction, cost reduction).

5.2. Managerial Implications

The findings of this study not only have theoretical value but also provide actionable insights for managers of SMEs and policymakers, particularly in the following five areas:

(1) Prioritize Capability Building in Digital Strategies. The study finds that both learning capability and channel integration capability have a significant direct impact on performance. This suggests that SMEs can still achieve performance improvements through internal knowledge absorption, sharing, and external resource collaboration, even when technology application is not optimal. Managers should focus on investing in organizational culture, employee training, knowledge management, and cross-channel integration to lay a solid foundation for digital transformation.

(2) Enhance the Depth and Embedding of Technology Application. Performance improvement depends not only on technology adoption but more crucially on the effective integration of information systems into actual business processes. Managers should avoid the misconception that "system implementation equals transformation" and instead focus on process reengineering, institutional coordination, and operational feedback mechanisms. This will enhance the practical value of systems in areas such as procurement, sales, and customer service, creating a closed loop from "system implementation" to "process transformation" to "performance improvement."

(3) Build high consistency in channel integration mechanisms. The study confirms the positive effect of channel integration capability on performance. Enterprises should coordinate their online and offline channel layouts to ensure consistent customer experiences across product information, pricing strategies, promotional activities, and service standards. Moreover, they should integrate data across multiple channels to enhance customer insights and improve responsiveness to market changes.

(4) Optimize the Linkage Between Capabilities and Technology to Unleash Mediating Effects. The results indicate that technology application plays a partial mediating role in the path from learning capability and channel integration capability to performance. This suggests that managers should design organizational mechanisms such as cross-departmental collaboration platforms, technology usage feedback systems, and data-driven decision support systems to enhance the synergistic effects between capabilities and technology. This will create a positive feedback loop, where capabilities empower technology, and technology, in turn, supports performance.

(5) Provide a Reference Path for Digital Transformation of SMEs Globally. Although this study focuses on SMEs in China, the core conclusions have broad implications for SMEs in developing countries at the early stages of digital transformation. In regions like Latin America, Southeast Asia, Africa, and Eastern Europe, SMEs face similar challenges of "easy technology procurement, but difficult value realization." Therefore, the proposed “capabilities-first technology embedding performance release” path provides a universal reference for digital strategies in international contexts, offering a low-cost and high-efficiency approach to digital transformation.

5.3. Research Limitations and Future Research Directions

Despite the contributions made in theory building and empirical testing, this study has several limitations that should be addressed in future research. First, the sample data mainly comes from SMEs in China. While it is representative, the study may suffer from regional bias, limiting the external generalizability of the findings. Future research could introduce multi-country samples to compare the applicability and differences of the capability–technology–performance mechanism in different institutional environments or cultural backgrounds, thus enhancing the cross-cultural applicability of the model.

Second, this study uses cross-sectional data, which, while revealing correlations between variables, offers limited support for causal inferences. Future studies could adopt longitudinal tracking or experimental design methods to more rigorously test the dynamic evolution of the relationships between capabilities, technology application, and performance.

Lastly, the organizational capability dimensions selected in this study focus primarily on learning and channel integration capabilities, without considering other potential factors such as organizational resilience or leadership support. Future research could further enrich the capability system by including these dimensions to provide a more comprehensive explanation of the multiple pathways through which performance is achieved in the context of digital transformation.

6. Conclusion

This study, supported by the RBV and OLT, constructs a "capability–technology–performance" mediation model to systematically explore the performance realization mechanisms of SMEs during digital transformation. The study finds that learning capability and channel integration capability not only have a significant direct impact on firm performance but also indirectly promote performance growth by enhancing technology application. This confirms the foundational role of capability building in the realization of technological value. This finding addresses the gap in previous research regarding the interaction mechanisms between capability and technology, advancing the theoretical understanding of resource integration and technology absorption in the digital context of SMEs.

In terms of theoretical contributions, this study deepens the concept of "capability conversion into value" within the RBV and expands the applicability of the OLT's mediating mechanisms in digital practice, providing a new perspective on how firms transform resource advantages into performance advantages. Practically, the study emphasizes that firms should simultaneously advance capability building and technology deployment, avoiding the structural bias of "emphasizing technology while neglecting capability." This offers realistic strategic recommendations for SMEs' digital transformation. It also provides policy implications, suggesting that in promoting the digital transformation of SMEs, policymakers should strengthen support for capability training, resource integration, and digital literacy improvement to enhance the return on technological investments.

Future research could validate the applicability of this model across a broader range of industries and national contexts, examining the moderating effects of institutional environments, cultural factors, or industry maturity on the capability–technology–performance path. This would further promote the contextual and international development of digital transformation theories for SMEs.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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References

[1] McKinsey and Company, *Rewired to outcompete: A new era of digital transformation*. New York: McKinsey & Company, 2023.

[2] J. K. Mensah and Y. Xu, "Adoption of E-commerce technologies among SMEs in Ghana under the influence of integrated UTAUT and TOE frameworks," *Information Development*, p. 02666669251325479, 2025. https://doi.org/10.1177/02666669251325479

[3] A. Dizdarevic, V. van de Vrande, and J. Jansen, "When opposites attract: A review and synthesis of corporate-startup collaboration," *Industry and Innovation*, vol. 31, no. 5, pp. 544-578, 2024. https://doi.org/10.1080/13662716.2023.2271853

[4] H. Zheng, J. Dai, and B. Li, "Exploring the relationship between digital integration and agility: The role of organizational inertia and market information transparency," *International Journal of Operations & Production Management*, vol. 45, no. 8, pp. 1602-1626, 2025. https://doi.org/10.1108/IJOPM-08-2024-0663

[5] R. Agrawal, A. Samadhiya, A. Banaitis, and A. Kumar, "Entrepreneurial barriers in achieving sustainable business and cultivation of innovation: A resource-based view theory perspective," *Management Decision*, vol. 63, no. 4, pp. 1207-1228, 2025. https://doi.org/10.1108/MD-11-2023-2032

[6] S. El Nemar, H. El-Chaarani, I. Dandachi, and S. Castellano, "Resource-based view and sustainable advantage: A framework for SMEs," *Journal of Strategic Marketing*, vol. 33, no. 6, pp. 798-821, 2025. https://doi.org/10.1080/0965254X.2022.2160486

[7] K. P. Gabriel, M. E. Ezerins, C. C. Rosen, A. S. Gabriel, C. Patel, and G. J. Lim, "Socioeconomic status and employee well-being: An intersectional and resource-based view of health inequalities at work," *Journal of Management*, vol. 51, no. 6, p. 01492063241311869, 2025. https://doi.org/10.1177/01492063241311869

[8] G. Secundo, I. De Turi, A. Garzoni, M. Posa, and D. Barile, "Unveiling knowledge practices and microfoundations of knowledge-based dynamic capabilities for digital transformation in SMEs through industry–university perspective," *Journal of Knowledge Management*, 2025. https://doi.org/10.1108/JKM-02-2024-0244

[9] M. Hock-Doepgen, S. Heaton, T. Clauss, and J. Block, "Identifying microfoundations of dynamic managerial capabilities for business model innovation," *Strategic Management Journal*, vol. 46, no. 2, pp. 470-501, 2025. https://doi.org/10.1002/smj.3663

[10] Y. Kyrdoda, M. Balzano, and G. Marzi, "Learn to survive crises: The role of firm resilience, innovation capabilities and environmental dynamism," *Technology in Society*, vol. 74, p. 102285, 2023. https://doi.org/10.1016/j.techsoc.2023.102285

[11] E. Quansah, D. E. Hartz, and P. Salipante, "Adaptive practices in SMEs: leveraging dynamic capabilities for strategic adaptation," *Journal of Small Business and Enterprise Development*, vol. 29, no. 7, pp. 1130-1148, 2022. https://doi.org/10.1108/JSBED-07-2021-0269

[12] S. Douglas and G. Haley, "Connecting organizational learning strategies to organizational resilience," *Development and Learning in Organizations: An International Journal*, vol. 38, no. 1, pp. 12-15, 2024. https://doi.org/10.1108/DLO-01-2023-0018

[13] B. F. Abrantes, M. T. Preto, and N. Antonio, "Unraveling collaborative learning stimuli and effective dynamic capability integration on MNCs: The global capabilities administration model (GCAM)," *Review of International Business and Strategy*, vol. 33, no. 2, pp. 272-300, 2023. https://doi.org/10.1108/RIBS-06-2021-0085

[14] M. Rezaei, "Unlocking knowledge transfer dynamics across borders: Key drivers in international strategic alliances," *Journal of Knowledge Management*, vol. 29, no. 8, pp. 2497-2517, 2025. https://doi.org/10.1108/JKM-12-2023-1188

[15] K. Kaur and S. Kumar, "Resource-based view and SME internationalization: A systematic literature review of resource optimization for global growth," *Management Review Quarterly*, pp. 1-43, 2024. https://doi.org/10.1007/s11301-024-00478-1

[16] A. Razzaque, I. Lee, and G. Mangalaraj, "The effect of entrepreneurial leadership traits on corporate sustainable development and firm performance: a resource-based view," *European Business Review*, vol. 36, no. 2, pp. 177-200, 2024. https://doi.org/10.1108/EBR-03-2023-0076

[17] F. Arkadan, E. K. Macdonald, and H. N. Wilson, "Customer experience orientation: Conceptual model, propositions, and research directions," *Journal of the Academy of Marketing Science*, vol. 52, pp. 1560-1584, 2024. https://doi.org/10.1007/s11747-024-01031-y

[18] C. Larabi, "Linking intangible resources to predict firm performance through technology innovation and strategic flexibility: Leveraging the resource-based view of the manufacturing firms," *Journal of Strategy and Management*, 2025. https://doi.org/10.1108/JSMA-08-2024-0204

[19] M. R. H. Polas, A. Afshar Jahanshahi, M. E. Islam, A. I. Kabir, A. S. M. Sohel-Uz-Zaman, and A. A. Fahad, "A journey from traditional supply chain processes to sustainability-oriented blockchain supply chain: The critical role of organizational capabilities," *Business Strategy and the Environment*, vol. 34, no. 3, pp. 3522-3543, 2025. https://doi.org/10.1002/bse.4159

[20] S. Neiroukh, O. L. Emeagwali, and H. Y. Aljuhmani, "Artificial intelligence capability and organizational performance: Unraveling the mediating mechanisms of decision-making processes," *Management Decision*, 2024. https://doi.org/10.1108/MD-10-2023-1946

[21] G. Hashem, "Adopting Industry 4.0 through absorptive capacity and innovation ambidexterity with the moderation of learning capability," *Business Process Management Journal*, vol. 30, no. 6, pp. 1995-2024, 2024. https://doi.org/10.1108/BPMJ-12-2023-0939

[22] S. Liu, P. Du, and Z. Ling, "A meta-analysis on the relationship between enterprise knowledge search and ambidextrous innovation," *Journal of Knowledge Management*, 2025. https://doi.org/10.1108/JKM-07-2024-0794

[23] S. Rana, J. Wu, A. Waheed, and M. A. Gulzar, "Toward a sustainable future: Enhancing environmental performance through reverse logistics, resource commitment and organizational learning capability for circular business models," *Journal of Organizational Change Management*, 2025. https://doi.org/10.1108/JOCM-01-2025-0075

[24] H. Mao, S. Liu, and Y. Gong, "Balancing structural IT capabilities for organizational agility in digital transformation: A resource orchestration view," *International Journal of Operations & Production Management*, vol. 44, no. 1, pp. 315-344, 2024. https://doi.org/10.1108/IJOPM-09-2022-0595

[25] B. Li, D. J. Teece, A. Baskaran, and V. Chandran, "Dynamic Knowledge Management: A dynamic capabilities approach to knowledge management," *Technovation*, vol. 147, p. 103316, 2025. https://doi.org/10.1016/j.technovation.2025.103316
[26] S. Sahoo and A. Upadhyay, "Improving triple bottom line (TBL) performance: Analyzing impacts of industry 4.0, lean six sigma and circular supply chain management," *Annals of Operations Research*, pp. 1-32, 2024. https://doi.org/10.1007/s10479-024-05945-2
[27] G. Shirokova, K. Khrabust, E. Fedotova, and M. Solesvik, "Proactive learning culture and SME performance in a challenging environment: The mediating role of innovative capability," *International Journal of Entrepreneurial Behavior & Research*, vol. 31, no. 9, pp. 2205–2229, 2025. https://doi.org/10.1108/IJEBR-08-2024-0887
[28] W. Gao, H. Fan, W. Li, and H. Wang, "Crafting the customer experience in omnichannel contexts: The role of channel integration," *Journal of Business Research*, vol. 126, pp. 12-22, 2021. https://doi.org/10.1016/j.jbusres.2020.12.056
[29] X. Wu, Y. Li, and Z. Zhu, "Does online–offline channel integration matter for supply chain resilience? The moderating role of environmental uncertainty," *Industrial Management & Data Systems*, vol. 123, no. 5, pp. 1496-1522, 2023. https://doi.org/10.1108/IMDS-06-2022-0361
[30] Y. Liu, M. Wu, K.-H. Lai, J. Z. Zhang, and J. Wang, "Strategic responses to market uncertainty: Performance value of strategic agility and online-to-offline platform adoption," *Enterprise Information Systems*, vol. 18, no. 1, p. 2292983, 2024. https://doi.org/10.1080/17517575.2023.2292983
[31] A. E. Oke, V. A. Arowoiya, M. Chan, and A. Oyediran, "Digital twin technology (DTT) in a developing construction industry: evaluation of the awareness and usage among professionals in Nigeria," *International Journal of Construction Management*, vol. 25, no. 11, pp. 1313-1323, 2025. https://doi.org/10.1080/15623599.2024.2411885
[32] K. Abrokwah-Larbi, "The nexus between customer value analytics and SME performance in emerging market: A resource-based view perspective," *Journal of Global Entrepreneurship Research*, vol. 14, p. 26, 2024. https://doi.org/10.1007/s40497-024-00396-2
[33] X. Zhao, X. Zhan, and J. Su, "Technological diversification and innovation performance: Ownership structure," *Management Decision*, 2025. https://doi.org/10.1108/MD-03-2024-0437
[34] A. C. Berndt, G. Gomes, and F. M. Borini, "Exploring the antecedents of frugal innovation and operational performance: The role of organizational learning capability and entrepreneurial orientation," *European Journal of Innovation Management*, vol. 27, no. 5, pp. 1704-1722, 2024. https://doi.org/10.1108/EJIM-06-2022-0320
[35] Y. Li, B. Yang, K. Zhang, and X. Hu, "What drives corporate entrepreneurship in omnichannel marketing? The effects of cross-channel integration and e-commerce type," *R&D Management*, 2025. https://doi.org/10.1111/radm.12775
[36] Z.-S. Chen, Z.-R. Wang, X.-J. Wang, M. J. Skibniewski, B. B. Gupta, and M. Deveci, "Leveraging probabilistic optimization for digital transformation maturity evaluation of construction enterprises," *IEEE Transactions on Engineering Management*, vol. 71, pp. 8717-8746, 2024. https://doi.org/10.1109/TEM.2024.3396503
[37] I. Oubrahim and N. Sefiani, "An integrated multi-criteria decision-making approach for sustainable supply chain performance evaluation from a manufacturing perspective," *International Journal of Productivity and Performance Management*, vol. 74, no. 1, pp. 304-339, 2025. https://doi.org/10.1108/IJPPM-09-2023-0464
[38] J. C. Nunnally and I. H. Bernstein, *Psychometric theory*, 3rd ed. New York: McGraw-Hill, 1994.
[39] C. Fornell and D. F. Larcker, "Evaluating structural equation models with unobservable variables and measurement error," *Journal of Marketing Research*, vol. 18, no. 1, pp. 39–50, 1981. https://doi.org/10.1177/002224378101800104
[40] K. J. Preacher and A. F. Hayes, "Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models," *Behavior Research Methods*, vol. 40, no. 3, pp. 879–891, 2008.

Appendix 1.

Table 1.
Sample characteristic statistics.

Name	Category	Frequency	Percentage (%)
Industry	Medical Service Industry	69	14.496
	Etail Industry	168	35.294
	Manufacturing Industry	119	25.000
	Others	120	25.210
Number of Employees	Less than 10 people	138	28.992
	11-30 people	183	38.445
	31-50 people	114	23.950
	More than 50 people	41	8.613
Operating Income	Less than 1 million	141	29.622
	1-2 million	220	46.218
	2-5 million	103	21.639
	More than 5 million	12	2.521
Operating Years	Less than 1 year	43	9.034
	1-2 years	93	19.538
	2-5 years	165	34.664
	More than 5 years	175	36.765
Whether to Operate Online	Yes	341	71.639
	No	135	28.361
Amount of Technical Input	Less than 10,000	188	39.496
	10,000-20,000	140	29.412
	20,000-50,000	101	21.218
	More than 50,000	47	9.874
Technical Training Time	7 days	238	50.000
	15 days	145	30.462
	30 days	74	15.546
	More than 30 days	19	3.992
Position	Store Owner	208	43.697
	Department Manager	120	25.210
	Clerk	45	9.454
	Others	103	21.639
Type of Technical Input	Online Sales Platform	239	50.210
	Department Office Platform	98	20.588
	Goods Supply Platform	76	15.966
	Others	63	13.235

Table 2.
Factor loading coefficient.

Construct	Item	Unstd. Loading	Std. Loading	SE	z (C.R.)	p-value
Learning Initiative	A1	0.991	0.743			
	A2	1.012	0.716	0.068	14.577	***
	A3	0.97	0.73	0.068	14.848	***
	A4	0.968	0.723	0.066	14.707	***
	A5	1	0.716	0.066	14.565	***
Knowledge Translation	B1	1.037	0.704			
	B2	1.037	0.731	0.073	14.255	***
	B3	1.052	0.719	0.072	14.678	***
	B4	1.033	0.737	0.072	14.412	***
	B5	1.01	0.756	0.072	14.047	***
	C1	1	0.756			
	C2	1.044	0.744	0.069	15.028	***
	C3	1.061	0.734	0.071	14.849	***
	C4	1.015	0.73	0.069	14.768	***
	C5	0.944	0.68	0.068	13.792	***
Platform Service	D1	1	0.663			
	D2	1.78	0.774	0.083	14.168	***
	D3	1.15	0.771	0.079	14.119	***
	D4	1.094	0.734	0.08	13.596	***
	D5	1.147	0.762	0.082	13.999	***
Internal Consistency	F1	1	0.675			
	F2	1.149	0.766	0.08	14.272	***
	F3	1.154	0.745	0.083	13.96	***
	F4	1.1	0.735	0.08	13.796	***
	F5	1.121	0.751	0.08	14.042	***
	G1	1	0.729			
	G2	1.013	0.748	0.067	15.091	***
	G3	1.023	0.739	0.069	14.924	***
	G4	0.912	0.658	0.068	13.327	***
	G5	1.067	0.773	0.069	15.555	***
Tech Input	H1	1	0.692			
	H2	1.062	0.747	0.073	14.466	***
	H3	0.992	0.701	0.073	13.67	***
	H4	0.989	0.686	0.074	13.408	***
	H5	1.052	0.764	0.071	14.747	***
Tech Acceptance	I1	1	0.72			
	I2	0.97	0.761	0.064	15.183	***
	I3	0.929	0.733	0.063	14.652	***
	I4	0.952	0.712	0.067	14.286	***
	I5	0.915	0.683	0.067	13.709	***
Data Management	J1	1	0.661			
	J2	1.054	0.718	0.08	13.174	***
	J3	1.064	0.731	0.08	13.36	***
	J4	0.993	0.721	0.075	13.217	***
	J5	1.071	0.727	0.08	13.308	***
Digital Capability	K1	1	0.748			
	K2	0.982	0.718	0.067	14.743	***
	K3	0.981	0.736	0.065	15.102	***
	K4	0.959	0.688	0.068	14.125	***
	K5	0.94	0.703	0.065	14.449	***
Process Optimization	L1	1	0.677			
	L2	1.065	0.718	0.079	13.471	***
	L3	1.183	0.765	0.083	14.183	***
	L4	1.06	0.761	0.075	14.122	***

	L5	0.997	0.666	0.079	12.64	***
Customer Satisfaction	M1	1	0.71			
	M2	0.97	0.72	0.069	14.096	***
	M3	0.982	0.748	0.067	14.389	***
	M4	0.994	0.692	0.073	13.591	***
	M5	1.006	0.744	0.069	14.511	***
Operational Efficiency	N1	1	0.732			
	N2	1.042	0.777	0.066	15.786	***
	N3	0.972	0.723	0.066	14.728	***
	N4	1.002	0.722	0.068	14.718	***
	N5	1.037	0.745	0.068	15.162	***
Reduce Operating Costs	O1	1	0.864			
	O2	0.842	0.742	0.047	17.794	***
	O3	0.739	0.65	0.049	15.02	***
	O4	0.792	0.678	0.05	15.844	***
	O5	0.863	0.721	0.05	17.142	***

Table 3.
Pearson correlation and AVE square root value.

	Learning Initiative	**Knowledge Acquisition**	**Knowledge Translation**	**Platform Service**	**Content Consistency**	**Information Security**	**Tech Input**	**Tech Acceptance**	**Data Mgmt & Analysis**	**Digital Capability**	**Process Optimization**	**Customer Satisfaction**	**Operational Efficiency**	**Reduced Costs**
Learning Initiative	0.726	0.521	0.494											
Knowledge Acquisition	0.521	0.73	0.557											
Knowledge Translation	0.494	0.557	0.725											
Platform Service				0.742	0.527	0.534								
Content Consistency				0.527	0.735	0.566								
Information Security				0.534	0.566	0.73								
Tech Input							0.719	0.64	0.703	0.627	0.63			
Tech Acceptance							0.64	0.722	0.627	0.564	0.563			
Data Mgmt & Analysis							0.703	0.627	0.712	0.554	0.482			
Digital Capability							0.627	0.564	0.554	0.719	0.47			
Process Optimization							0.63	0.563	0.482	0.47	0.719			
Customer Satisfaction												0.723	0.571	0.546
Operational Efficiency												0.571	0.74	0.501
Reduced Costs												0.546	0.501	0.735