Digital Transformation and Organizational Performance in Chinese Retail SMEs: Unpacking the Mediating Role of Organizational Resilience

Tao Mei., Sidah Idris

Faculty Business, Economic and Accountancy, University of Business and Technology

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ABSTRACT

Purpose: Retail SMEs in China operate in a highly volatile digital commerce ecosystem with rapidly shifting consumer demand, intense platform-based competition, and frequent technological and regulatory changes. This study examines how digital transformation (DT) improves firm performance by strengthening organizational resilience (OR) and whether environmental dynamism (ED) moderates the resilience–performance relationship.

Design/methodology/approach: A quantitative survey was conducted with retail SMEs, and the conceptual model was tested using PLS-SEM to assess measurement properties and estimate direct, mediating, and moderating effects.

Findings: The results show that DT directly improves firm performance and significantly enhances OR, indicating that digital initiatives in retail SMEs create value by boosting efficiency, market responsiveness, and the ability to withstand shocks and adapt quickly. OR partially mediates the DT–performance link, showing that resilience is a key capability through which DT yields superior business outcomes. ED positively moderates the OR–performance relationship, meaning that the performance benefits of organizational resilience increase under high market and technological volatility.

Research limitations/implications: This study uses cross-sectional, self-reported data, limiting causal inference and potentially introducing common method bias. Future research should apply longitudinal or multi-source designs and examine additional mechanisms (e.g., organizational agility, innovation capability) and contextual contingencies (e.g., competitive intensity, regulatory turbulence).

Practical implications: For managers of Chinese retail SMEs, the findings highlight the need to prioritize DT initiatives that improve real-time environmental sensing, speed up data-driven decisions, and enable rapid operational reconfiguration—dynamic capabilities that underpin resilience in highly volatile retail settings. Policymakers can strengthen these SMEs' competitiveness by offering targeted capability-building programs (e.g., digital literacy, data analytics training, resilience-focused technology upgrades) and by enhancing digital infrastructure and governance to reduce excessive environmental uncertainty for small retailers.

Originality/value: This study extends understanding of DT in retail SMEs by explaining when and how DT improves performance: it identifies OR as a central capability mechanism and ED as a key boundary condition in a dynamic, platform-mediated retail context.

Keywords: Digital transformation, Organizational resilience, Small and medium-sized retail enterprises, Environmental dynamism, Firm performance

INTRODUCTION

China's retail small and medium-sized enterprises (SMEs) operate in an increasingly volatile market marked by rapid, unpredictable shifts in consumer demand, intensifying digital competition from platform-based models, and rising cost and delivery uncertainty from recurrent supply-chain disruptions. These conditions create frequent shocks in customer acquisition, order fulfillment, inventory management, cost control, and cash-flow. With limited resources, retail SMEs are more vulnerable to these external shocks, which can quickly trigger operational failures, liquidity pressures, and customer loss, threatening their continuity, competitiveness, and long-term growth.

In this context,Digital transformation (DT) has become a strategic imperative for retail SMEs. It is increasingly seen not just as adopting new digital tools, but as a systemic reconfiguration of processes, resource allocation, and value creation (Pani & Pramanik, 2020; Vial, 2021). For resource-constrained SMEs, DT usually starts with an operations-first focus—such as inventory visibility, order allocation, labor scheduling, and last-mile orchestration—to improve efficiency and cut costs(Etienne Fabian et al., 2024; Mandviwalla & Flanagan, 2021). Over time, this operational digitalization can drive broader organizational and strategic change, as digital workflows reshape internal coordination and market and customer interfaces. Thus, DT is not a one-off technology project but a capability-building process that shapes how quickly SMEs sense environmental change, respond to shocks, and reconfigure routines—capabilities that are especially vital in China's volatile retail ecosystem.

Despite this practical importance, the academic evidence on the DT–performance relationship remains uneven. While many studies report positive associations between DT and firm outcomes, performance returns vary substantially across contexts, industries, and measurement choices(Oduro et al., 2023), suggesting that DT does not automatically translate into superior performance. Recent meta-analytic work points to systematic heterogeneity in DT's performance effects and emphasizes that contextual factors and complementary capabilities shape whether DT yields performance benefits (Orero-Blat et al., 2025; Volz et al., 2025). A major reason for these mixed findings is that under-theorize the organizational capability mechanisms that convert digital investments into sustained performance improvements (Vial, 2021). Consequently, the field increasingly calls for research that opens the "black box" between DT and performance by identifying the capability pathways and boundary conditions that explain why some SMEs benefit more than others.

To address this gap, we theorize organizational resilience (OR) as a central mechanism linking DT to performance in retail SMEs. OR is a firm's capacity to anticipate, absorb, adapt to, and recover from disruptions while sustaining essential operations. In turbulent retail contexts, resilience is not limited to rare large-scale crises but is continually required to manage ongoing volatility, such as rapid demand swings, promotion-driven shocks, supplier delays, and distribution disruptions. From a dynamic capability perspective, resilience is especially critical for SMEs, which face resource constraints and thus rely on speed, flexibility, and cross-functional coordination to buffer and respond to shocks. Emerging evidence indicates that DT enhances resilience by improving information processing and organizational learning, thereby strengthening adaptive capacity(Awad & Martín-Rojas, 2024). Related research shows that digitally enabled capabilities—such as IT resources and organizational ambidexterity—bolster resilience and, in turn, improve business outcomes, positioning resilience as a plausible mediator through which digitalization generates performance gains (Trieu et al., 2023). Nevertheless, the mediating role of resilience in the DT–performance relationship remains under-theorized and under-examined in retail SMEs, particularly in high-velocity, platform-dominated markets such as China.

Furthermore, We argue that the performance effects of resilience depend on environmental dynamism (ED). The Dynamic Capabilities View (DCV) holds that the value of adaptive capabilities is conditional on environmental conditions: under rapid, unpredictable change, firms benefit more from capabilities that enable sensing, seizing, and reconfiguring(Teece, 2007; Teece et al., 1997). Thus, at higher levels of dynamism, resilience should have stronger performance effects because resilient firms can better sustain service continuity, recover faster from disruptions, and reconfigure resources as conditions evolve. This contingency logic aligns with DCV arguments that capabilities create more value when matched to the degree of environmental change(Eisenhardt & Martin, 2017; Teece, 2007). Yet this proposition remains largely untested among Chinese retail SMEs.

Accordingly, this study develops an integrated conceptual framework that specifies both direct and indirect effects of digital transformation (DT) on firm performance (FP) via organizational resilience (OR) and incorporates environmental dynamism (ED) as a moderating variable that conditions the OR–FP relationship. We empirically test the hypothesized relationships using survey data collected from retail small and medium-sized enterprises (SMEs) and apply partial least squares structural equation modeling (PLS-SEM), a method particularly appropriate for predicting key outcome variables and estimating complex mediation and moderation effects in capability-based models. In doing so, we address two core research questions: (1) whether DT enhances the performance of retail SMEs by reinforcing organizational resilience, and (2) whether environmental dynamism intensifies the performance returns associated with resilience.

LITERATURE REVIEW

Digital Transformation (DT) in SME Retail

In retail SMEs, DT is often observable in the reconfiguration of day-to-day operating routines—such as integrating POS and online order streams, synchronizing inventory across channels, and digitizing service and customer engagement—rather than in a single strategic redesign (Mandviwalla & Flanagan, 2021).

Importantly, DT trajectories differ by firm size and resource endowment. Large firms often pursue top-down, strategy-led transformation programs that are later translated into operational routines and coordination mechanisms. By contrast, SMEs commonly adopt an operations-first pathway because of resource constraints and managerial bandwidth limitations: transformation efforts are initiated to resolve immediate bottlenecks (e.g., limited inventory visibility, inefficient order allocation, inconsistent labor scheduling, or fragmented last-mile coordination) and to generate near-term efficiency and control (Etienne Fabian et al., 2024; Mandviwalla & Flanagan, 2021). Over time, however, these paths tend to converge. Strategy-led DT must ultimately be operationalized through workflows and governance arrangements, while operations-led DT often escalates into strategic reorientation and business model renewal as digital routines reshape market interfaces and competitive positioning (Garzoni et al., 2020). This convergence implies that DT in retail SMEs should be understood as a multidimensional capability-building process spanning both back-end operational redesign and front-end market-facing transformation.

Consistent with this logic, this study conceptualizes DT as a multidimensional construct comprising complementary facets that capture how retail SMEs mobilize and deploy digital resources to reconfigure operations and market engagement. Specifically, we adopt the multidimensional DT instrument by Kao et al.(2024), which treats DT as a higher-order construct spanning six domains: input resources (IR) that support capability development (e.g., data governance, digital skills); digital technologies (DDT) as technological infrastructure (e.g., cloud computing, IoT, AI, analytics); organizational operations (OO) as digitally enabled routines and coordination mechanisms; process optimization (PO) through analytics- and automation-driven process redesign; customer experience (CE) via digital touchpoints and personalization; and business model innovation (BMI) through reconfigured value propositions and revenue logic. This operationalization aligns with the view of DT as an integrated process of organizational reconfiguration (Vial, 2021).

Dynamic Capabilities View

To explain why DT may generate performance gains under turbulence, this study draws on the Dynamic Capabilities View (DCV), which argues that firms achieve sustained advantage in changing environments by developing the abilities to sense opportunities and threats, seize them through timely strategic and operational commitments, and reconfigure resources and routines accordingly(Teece, 2007; Teece et al., 1997). Unlike resource-based explanations that emphasize the possession of valuable assets, DCV focuses on the managerial and organizational processes that enable adaptation when markets and technologies evolve rapidly (Eisenhardt & Martin, 2017). This lens is especially appropriate for retail SMEs because their competitive context is shaped by frequent demand shifts, intense imitation, and fast-moving digital commerce practices, making continuous reconfiguration more critical than static efficiency.

From a DCV perspective, DT can be theorized as an enabling infrastructure that strengthens the microfoundations of dynamic capabilities. First, DT supports sensing by enhancing environmental visibility through data generation and analytics (Feroz et al., 2023; Xia et al., 2022). In retail contexts, such real-time visibility improves the firm's capacity to notice weak signals and respond before disruptions translate into stockouts, lost sales, or reputational damage. Second, DT facilitates seizing by accelerating decision cycles and enabling coordinated action across functions and channels (Ellström et al., 2022; Sestino et al., 2025). When order management, inventory allocation, pricing, and promotions are connected through digital systems, SMEs can deploy resources more quickly and align frontline execution with managerial intent. Third, DT strengthens reconfiguring by enabling modular redesign of workflows and more flexible recombination of resources (Ellström et al., 2022; Schneider et al., 2024). platformization and modular architectures limit the spread of failures across system components and support rapid adaptation and recovery (Fang, 2025; Guo et al., 2022). Overall, the DCV implies that the performance value of DT should depend on whether digital investments become embedded in routines that enhance sensing, seizing, and reconfiguring—capabilities that are particularly vital for retail SMEs facing volatile demand and operational disruptions.

Digital Transformation and SMEs' Performance

Consistent with the dynamic capabilities view (DCV), DT embeds data, systems integration, and modularity into the firm's activity system, structurally reshaping how resources are coordinated, configured, and redeployed (Ciasullo et al., 2022; Orero-Blat et al., 2025). Thereby, this enables firms to develop higher-order capabilities while also achieving immediate gains in operational efficiency and customer experience (Hanelt et al., 2021; Vial, 2019). In resource-constrained SME retail settings, these direct effects are especially strong: incremental digitization of workflows and customer touchpoints can increase throughput, reduce outcome variability, and stabilize the customer journey even before deeper organizational transformation occurs(Karanasios et al., 2025; Zhao et al., 2025). DT also improves customer-facing outcomes by protecting service reliability and enabling personalized, consistent experiences across touchpoints. Systematic digital data capture and analysis help firms anticipate service failures (e.g., stock-outs, delivery delays) and implement proactive remedies. Front-stage value propositions (e.g., dynamic delivery windows, product substitutions) can be aligned with back-stage capacities via integrated information and process management systems (Akter et al., 2020; Delana et al., 2021). Collectively, these mechanisms reduce variance in customer experience and are associated with higher customer satisfaction, repeat purchase, and advocacy, leading to the following hypotheses:

H2. Digital transformation (DT) exerts a positive influence on the firm performance (FP) of SMEs.

Digital Transformation (DT) and Organizational Resilience (OR)

Grounded in the dynamic capabilities view (DCV), we argue that multi-faceted digital transformation (DT) equips SME retailers with both preparedness and enactment routines that together constitute organizational resilience (OR). First, DT embeds data-driven sensing mechanisms that enhance anticipatory capacity. Investments in data acquisition, integration, and analytics expand environmental scanning and strengthen early-warning capabilities (Sahoo et al., 2023). Firms that systematically integrate high-quality data with advanced analytics better detect abrupt changes in demand, marketing effectiveness, and operations, and more effectively design and implement timely corrective or adaptive responses(Mikalef et al., 2020; Sáenz et al., 2022). Second, DT promotes modular, platform-based architectures that support rapid self-adaptation and absorptive capacity. Digitally enabled operations and process optimization reduce system coupling and recombination costs, allowing managers to reconfigure workflows, roles, and integrated product–service offerings quickly in response to shocks (Li et al., 2022; Mikalef et al., 2020). Third, DT strengthens boundary-spanning absorptive capacity and organizational learning that accelerate adaptation and recovery. Digital communication channels and enterprise platforms enhance knowledge flows with customers and partners and support systematic internalization of external information (Browder et al., 2024). These mechanisms help balance exploration and exploitation and codify experiential insights into formal standard operating procedures. Accordingly, we formulate the following hypothesis:

H1. Digital transformation (DT) exerts a positive influence on organizational resilience (OR).

Organizational Resilience and SMEs' Performance

From the perspective of the dynamic capabilities framework, organizational resilience augments the flexibility and responsiveness of operational systems by strengthening the capabilities for sensing environmental changes, seizing emergent opportunities, and reconfiguring resources. (Ortiz-de-Mandojana & Bansal, 2016; Teece, 2007). Such capabilities enable firms to respond more effectively to demand volatility, optimize production processes, and re-establish normal operations more rapidly following disruptions, thereby enhancing overall operational efficiency and quality performance (Branicki et al., 2018). Moreover, resilient organizations typically cultivate a shared crisis response culture and promote cross-functional collaboration, thereby reinforcing employees' implementation capabilities and interdepartmental process coordination, which in turn contributes to superior operational performance.(Annarelli & Nonino, 2016)).

OR further improves customer-facing performance by preserving service reliability and reducing variability in the customer experience across touchpoints under disruptive conditions. Anticipatory planning mitigates both the incidence and the duration of service failures (e.g., stock-outs, delivery delays)(Gallego-García et al., 2021); adjustment aligns front-stage promises with back-stage capabilities (e.g., dynamic delivery windows, substitution rules)(Cui et al., 2020; Ulmer et al., 2022); and restoration deploys effective service recovery routines (refunds, replacements, proactive communication) that mitigate dissatisfaction and rebuild trust (Tahir, 2021). In summary, organizations exhibiting high levels of resilience are more capable of maintaining customers' perceptions of reliability and procedural as well as distributive fairness under adverse conditions, which in turn is associated with increased levels of customer satisfaction.

Accordingly, we propose the following hypothesis:

H3. Organizational resilience (OR) has a positive effect on SMEs' performance (FP).

Organizational Resilience (OR) as Mediator

Prior empirical evidence indicates that the performance implications of digital transformation (DT) for small and medium-sized enterprise (SME) outcomes frequently unfold through intermediate organizational capabilities rather than via a single, linear causal pathway. For instance, Bhatt (2025) demonstrate that DT significantly enhances organizational resilience (OR) in Nepalese SMEs and that this mediating mechanism is only partial, as entrepreneurial orientation only partially mediates the DT–OR linkage. Awad & Martín-Rojas (2024) demonstrated that digital technologies enhance SMEs' learning and innovation, augmenting resilience and adaptability. Omoush et al. (2023) confirmed that digital business transformation significantly impacts SMEs' resilience (214 SMEs). Extending this reasoning to performance outcomes, (Trieu et al. (2023) find that IT competencies and organizational ambidexterity reinforce resilience and, in turn, improve business performance, thereby supporting the notion that resilience-related capabilities are performance-enhancing in SMEs. However, patterns of mediation appear to be context-contingent, (Őri et al.(2024) provide evidence that OR may exert predominantly indirect rather than direct effects in the context of digitalization, highlighting that resilience can operate as an intervening mechanism whose influence materializes through broader organizational processes. Accordingly, we propose:

H4. Organizational resilience (OR) mediates the relationship between digital transformation (DT) and SMEs' performance (FP).

Environmental Dynamism (ED) as Moderator

Dynamic Capabilities Theory (DCT) posits that organizations must continuously adapt, renew, and reconfigure their internal capabilities to align with rapidly changing external environments (Teece, 2018). Within such dynamic contexts, resilience-related capabilities—such as adaptability, problem-solving competence, and flexible resource deployment—constitute critical mechanisms that enable firms to absorb exogenous shocks and capitalize on emerging opportunities, thereby enhancing organizational performance (Duchek, 2020). Resilient organizations are better positioned to navigate turbulent business environments because they possess the capacity to anticipate change, absorb disturbances, and reorganize operations without incurring substantial loss of functionality (Linnenluecke, 2017). Consistent with this view, prior research has argued that in highly dynamic sectors, resilient firms are more likely to outperform competitors, as they are able to balance stability and innovation in their decision-making processes (Ortiz-de-Mandojana & Bansal, 2016). On this basis, the following hypotheses are proposed:

H5. The higher the environmental dynamism (ED), the greater the impact of organization resilience (OR) on SMEs performance (FP).

To achieve our research objectives, we develop a conceptual model, as shown in Fig. 1:

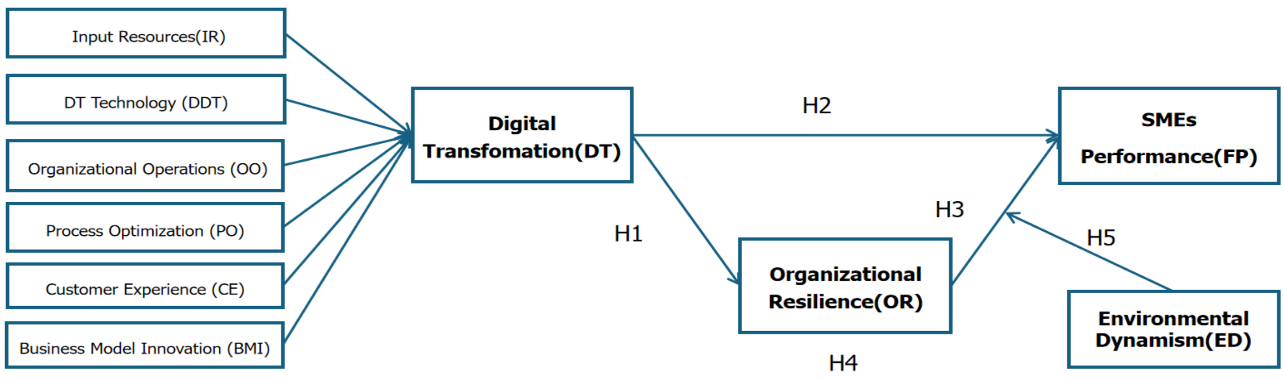

Figure 1 Conceptual Model

Source: Authors own work

METHODS

Sample and Data Collection

G*Power was employed tocalculate the minimum sample size needed forachieving statistical power(Faul et al., 2009). An a priori power analysis in G*Power with three predictors, medium effect size ($f^2 = 0.15$), $\alpha = 0.05$, and power = 0.95 indicated a minimum of N = 119. The final usable sample of 302 firms thus exceeds this requirement, providing sufficient power for estimating path coefficients and testing mediation in the model.

A multi-source sampling frame was constructed by integrating (i) provincial and municipal commerce and market-regulator directories, (ii) membership lists of Guangdong-based retail and SME associations and chambers of commerce, and (iii) curated listings of local merchants on major e-commerce platforms (e.g., certified Guangdong sellers). To enhance the validity of the findings, purposive sampling was employed to identify independent B2C retail SMEs operating in Guangdong Province. Key informants were managers directly responsible for digital/IT, operations/supply chain, or marketing/service functions within these firms.

To increase coverage while maintaining manageable heterogeneity, purposive sampling was combined with snowball sampling. Seed firms were recruited initially, after which each respondent was invited to nominate up to two to three additional eligible firms from different retail formats or cities. All nominations were de-duplicated and monitored against pre-specified quotas for format, channel structure, city tier, and firm size. Participation was fully anonymous, and data protection and privacy assurances were presented on the first page of the questionnaire.

The survey instrument consisted of three sections: (1) screening items and firm profile, used for eligibility verification and contextual information; (2) focal constructs, organized in randomized item blocks to reduce evaluation apprehension; and (3) demographics and control variables, positioned at the end of the questionnaire to minimize response burden and potential respondent stress.

Measurements

All multi-item constructs used five-point Likert scales (1 = strongly disagree; 5 = strongly agree). Measurement items were translated into Chinese, back-translated into English, and refined using cognitive pretests with Guangdong B2C retail managers to ensure semantic equivalence and content validity. Reflective constructs were assessed for indicator reliability (standardized loadings≥0.70), internal consistency (composite reliability,

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CR≥0.70), and convergent validity (average variance extracted, AVE≥0.50) (Hair et al., 2021). Discriminant validity was evaluated using the heterotrait–monotrait ratio (HTMT<0.85) with bootstrapped confidence intervals (Ab Hamid et al., 2017).

Digital transformation (DT) is operationalized using the multidimensional measurement instrument developed by Kao et al.(2024)Kao et al. (2024), modeled as a formative higher-order construct and estimated through a disjoint two-stage procedure. All indicators were adapted to the business-to-consumer (B2C) retail context. Indicator loadings were assessed at both stages of the estimation procedure, and the second-stage DT composite score was subsequently employed as an exogenous predictor in the structural model. Organizational resilience (OR) is operationalized using the validated measurement scale developed by Verreynne et al. (2023). Following expert review and a preliminary pilot test, eight items were selected for inclusion in the final measurement instrument. To benchmark outcomes at the firm level, we employ the relative performance scale developed by Vorhies & Morgan (2005) Vorhies and Morgan (2005) to assess both operational performance and customer performance, thereby capturing process reliability and efficiency, as well as customer-oriented outcomes.

Data analysis

We conducted the statistical analyses in SmartPLS 4.1.2 using variance-based partial least squares structural equation modeling (PLS-SEM). PLS-SEM is appropriate because our focus is prediction rather than strict theory testing, the structural model is highly complex, and the survey data likely deviate from multivariate normality (Hair & Alamer, 2022). It maximizes explained variance in endogenous latent variables (e.g., R^2, Q^2), supports hierarchical component models via the disjoint two-stage approach, and allows bootstrap-based inference for indirect effects, making it well suited to this research context (Hair & Alamer, 2022).

Sample profile

We collected 349 firm-level questionnaires and, after data quality checks, handling missing values, and removing outliers, retained 302 valid observations (effective response rate: 86.5%). As shown in Table 1, the sample covers the main B2C retail formats in Guangdong within a shared institutional environment. Single-channel firms account for 176 cases (58.28%) and omnichannel firms for 126 cases (41.72%), indicating substantial but not universal omnichannel adoption among SMEs. All sampled firms are small and medium-sized enterprises (≤ 300 employees) and relatively young, with only 10% operating for more than 10 years. Respondents hold decision-relevant positions and have relatively high educational attainment: 228 (75.50%) have at least a bachelor’s degree. This profile supports using these key informants to assess digital transformation, organizational resilience, and firm performance.

Table 1. Sample profile (firm and respondent characteristics, N =302)

Demographic	Frequency (n=302)	Percentage (%)
Gender		
Male	187	61.92
Female	115	38.08
Age		
Below 30 years	43	14.24
30-39 years	70	23.18
40-49 years	98	32.45
50-59 years	45	14.9

Above 60 years	46	15.23
Education		
Primary school or below	0	0
Junior high school	11	3.64
Senior high school or vocational school	63	20.86
College diploma or bachelor’s degree	192	63.58
Postgraduate degree or above	36	11.92
Position / Job Title		
Business Owner / Founder	39	12.91
Senior Management	84	27.81
Middle Management	118	30.07
Supervisor	61	20.2
Other	0	0
Years in Operation		
Less than 1 year	0	0
1–3 years	64	21.19
4–6 years	115	38.08
7–10 years	77	25.5
More than 10 years	46	15.23
Employee Size		
Fewer than 10 employees	19	6.29
10–49 employees	57	18.87
50–99 employees	104	34.44
100–249 employees	79	26.16
250 employees or more	43	14.24
Retail Format		
Brick-and-mortar retail	80	26.49
E-commerce	51	16.89
Omnichannel retail (online + offline)	126	41.72
Social commerce	30	9.93
Other	15	4.97

Level of Digitalization		
Initial stage	69	22.85
Partially digitalized	85	28.15
Mostly digitalized	98	32.45
Fully digitalized	50	16.56

Common method bias

To address potential common method bias from using a single data collection procedure, we applied Harman's single-factor test (Kock, 2020). The first unrotated factor explained 34.59% of the total variance (< 50%), indicating no single dominant latent factor. Following Kock (2020), we also calculated full collinearity VIFs for all latent constructs. All values were below the conservative threshold of 3.3 (maximum outer VIF = 2.777; maximum inner VIF = 1.785), indicating no problematic common variance, including method variance.

Measurement model analysis

Specifying higher-order factors reduces model complexity and enables a more coherent theoretical interpretation, supporting robust statistical inference (Hair & Alamer, 2022; Sarstedt et al., 2019). Accordingly, and following PLS-SEM guidelines, the first-order reflective measurement model was evaluated for indicator reliability, internal consistency reliability, convergent validity, and discriminant validity (Hair & Alamer, 2022), as shown in Table 2.

Indicator reliability was evaluated using standardized factor loadings, which ranged from 0.789 to 0.880, exceeding the recommended 0.70 threshold and indicating that each item adequately represents its latent construct (Hair & Alamer, 2022). Internal consistency reliability, assessed via Cronbach's alpha and composite reliability (CR), showed alpha values from 0.821 to 0.936 and CR values from 0.822 to 0.937, all above the 0.70 benchmark(Hair & Alamer, 2022; Peterson & Kim, 2013). Convergent validity, measured by average variance extracted (AVE), ranged from 0.667 to 0.761, surpassing the 0.50 criterion and indicating that each construct explains more than 50% of the variance in its indicators (Fornell & Larcker, 1981; Hair & Alamer, 2022). Discriminant validity assessed using the heterotrait–monotrait ratio of correlations (HTMT), showed values between 0.344 and 0.548 (Table 3), well below the conservative cut-off of 0.85 (and the liberal 0.90), confirming that the constructs are empirically distinct (Henseler et al., 2015).

Table 2. Construct reliability and convergent validity (first-order reflective constructs)

Constructs and Items	**Factor Loading**	**Cronbach's α**	**CR**	**AVE**
1.Input Resources (IR)		0.821	0.822	0.737
IR1 Our company already has a certain proportion of dedicated digital professionals.	0.865			
IR2 We plan to increase our investment in digital areas in the future.	0.862			
IR3 We provide regular training for employees on data analysis or system operation.	0.849			
2.DT Technology (DDT)		0.906	0.906	0.68
DDT1 We have a complete information system (such as ERP, CRM).	0.825			

DDT2 The various systems within the enterprise have achieved good integration.	0.807			
DDT3 We actively apply various digital technologies in our daily operations.	0.835			
DDT4 The enterprise has a strong data collection capability.	0.820			
DDT5 The enterprise has a strong data analysis capability.	0.828			
DDT6 The enterprise can effectively apply the analysis results to business decisions.	0.832			
3.Organizational Operations (OO)		0.908	0.91	0.686
OO1 Top management has a transformative vision for the company's digital future.	0.814			
OO2 Senior and middle management have a clear consensus on digital transformation.	0.829			
OO3 Everyone in the company has the potential to participate in the conversation around digital transformation.	0.843			
OO4 Our company is driving the cultural change required for digital transformation.	0.835			
OO5 Our company's digital initiatives can be coordinated across siories-such as functions or geographies.	0.854			
OO6 Our company clearly defines the roles and responsibilities for managing digital initiatives.	0.793			
4.Process Optimization (PO)		0.929	0.929	0.668
PO1 The enterprise has optimized the order processing procedure.	0.826			
PO2 The procurement process has been standardized and digitized.	0.821			
PO3 The warehousing and logistics operations are highly efficient.	0.831			
PO4 The collaboration process among departments is smooth and responsive.	0.801			
PO5 Data collaboration and sharing have been achieved with suppliers.	0.789			
PO6 A large number of steps in the sales process have been digitized.	0.823			
PO7 Marketing promotion mainly relies on digital channels.	0.814			
PO8 The customer service process (such as after-sales and consultation) has been online or automated.	0.831			
5.Customer Experience (CE)		0.829	0.832	0.745

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CE1 We can accurately grasp the preferences and behaviours of customers through their data.	0.86			
CE2 We can accurately identify customer needs and optimize service content and delivery methods through data.	0.856			
CE3 We can promptly respond to customer feedback through digital platforms and optimize services.	0.873			
6.Business Model Innovation (BMI)		0.843	0.843	0.761
BMI1 We have developed new products or services to adapt to the digital trend.	0.873			
BMI2 We have expanded new sales channels or markets	0.880			
BMI3 We are trying to establish or restructure new business models based on digital technology.	0.863			
7.Organizational Resilience (OR)		0.936	0.937	0.69
OR1 When facing new challenges, we can quickly develop feasible solutions using existing resources.	0.825			
OR2 We dynamically adjust and communicate priorities based on environmental changes.	0.839			
OR3 We have backup equipment/facilities/capacity to meet unexpected demands.	0.836			
OR4 We are capable of resolving novel or unexpected problems collaboratively.	0.825			
OR5 Our internal processes can be quickly adjusted when needed.	0.821			
OR6 We maintain close internal communication across departments.	0.831			
OR7 We continuously learn from past disruptions to improve future responses.	0.837			
OR8 We regularly update strategies in response to changing environments.	0.831			
8.Firm Performance (FP)		0.9	0.901	0.667
FP1 Customers always tend to seek out new products and services.	0.827			
FP2 Customers' preferences for products and services change rapidly over time.	0.811			
FP3 Almost every day, people hear about new competitors from either the direct or adjacent industries.	0.820			
FP4 Technological change offers huge opportunities for our industry.	0.817			

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FP5 The technology in our industry is changing rapidly.	0.806			
FP6 In our major markets, competitors' actions change quite fast.	0.819			
9.Environmental Dynamism (ED)		0.909	0.914	0.687
ED1 Higher customer satisfaction	0.847			
ED2 Providing more value to customers	0.818			
ED3 Better meeting customer needs Market performance	0.832			
ED4 Increased sales revenue	0.854			
ED5 Acquiring more new customers	0.813			
ED6 Increased sales to existing customers financial performance	0.809			

Table 3 Discriminant validity of the measurement model.

	IR	DDT	OO	PO	CE	BMI	FP	OR	ED
Input Resources (IR)	0.699								
DT Technology (DDT)	0.458	0.809							
Organizational Operations (OO)	0.428	0.453	0.817						
Process Optimization (PO)	0.419	0.486	0.497	0.874					
Customer Experience (CE)	0.535	0.501	0.554	0.540	0.798				
Business Model Innovation (BMI)	0.462	0.518	0.474	0.474	0.502	0.635			
Firm Performance (FP)	0.435	0.486	0.445	0.344	0.483	0.444	0.557		
Organizational Resilience (OR)	0.504	0.542	0.462	0.429	0.548	0.534	0.481	0.634	
Environmental Dynamism (ED)	0.485	0.499	0.472	0.423	0.505	0.530	0.480	0.507	0.612

Digital transformation (DT) was operationalized as a reflective–formative hierarchical component model using the two-stage approach. In this specification, the first-order dimensions were modeled as formative indicators of the second-order DT construct. Because DT is conceptualized as formative at the higher-order level, traditional internal consistency reliability indices (e.g., Cronbach's alpha, composite reliability [CR], average variance extracted [AVE]) are not applicable or informative (Hair & Alamer, 2022; MacKenzie, 2003).

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To assess potential collinearity among the formative indicators, variance inflation factors (VIFs) were examined and found to be well below established critical values (VIF range = 1.395–1.642), indicating no evidence of multicollinearity. The relative and unique contribution of each dimension to the formation of DT, while controlling for the other dimensions, was evaluated through bootstrapped outer weights (Cenfetelli & Bassellier, 2009; Hair & Alamer, 2022). The outer weights for BMI, DDT, IR, and OO were statistically significant, indicating that these dimensions contribute meaningfully to the higher-order DT construct.

In contrast, process optimization (PO) yielded a very small and statistically non-significant outer weight ($w = 0.019$, $t = 0.238$, $p = 0.812$). Nevertheless, its outer loading was significant (loading = 0.602, $t = 9.452$, $p < 0.001$), suggesting that PO is associated with the overall DT construct but adds little incremental explanatory power beyond the other formative dimensions (Hair & Alamer, 2022). Given the non-significant outer weight of PO, a robustness check was performed by re-estimating the model excluding PO to ascertain whether the key structural relationships and substantive conclusions remained stable, in line with best-practice guidelines for formative measurement models (Hair et al., 2021).

Table 4. Formative measurement model assessment for the second-order construct (DT)

Formative indicator → DT	Weight (O)	T -value	P -value	Loading (O)	t-value (loading)	p-value (loading)	VIF
BMI → DT	0.257	3.716	0.000	0.724	15.859	0.000	1.485
CE → DT	0.278	3.557	0.000	0.758	17.301	0.000	1.642
DDT → DT	0.364	5.624	0.000	0.789	18.691	0.000	1.526
IR → DT	0.234	3.507	0.000	0.684	13.174	0.000	1.395
OO → DT	0.208	2.573	0.010	0.694	13.821	0.000	1.533
PO → DT	0.019	0.238	0.812	0.602	9.452	0.000	1.553

Structural model analysis

The structural model was assessed using bootstrapping to test the significance of hypothesized relationships and by examining explanatory power, effect sizes, and out-of-sample predictive performance with PLSpredict, following established PLS-SEM reporting guidelines (Hair & Alamer, 2022; Sarstedt et al., 2019; Shmueli et al., 2019).

The model shows moderate explanatory power for the endogenous constructs. Digital transformation (DT) explains 40.9% of the variance in organizational resilience (OR) ($R^2 = 0.409$), while DT, OR, and their interaction together explain 35.0% of the variance in firm performance (FP) ($R^2 = 0.350$). In behavioral and management research, these R^2 values are typically considered indicative of moderate explanatory capacity and acceptable in-sample accuracy (Chin, 1998; Hair & Alamer, 2022).

Beyond its explanatory capability, the model also shows out-of-sample predictive relevance. All FP and OR indicators have positive Q^2_predict values (Table 4), indicating smaller prediction errors than a naïve benchmark and thus predictive relevance for these endogenous constructs (Shmueli et al., 2019). Moreover, for every FP and OR indicator, the PLS-SEM RMSE is lower than that of the linear model (LM), confirming superior predictive accuracy. Under the PLSpredict framework, this pattern signals high predictive power and supports the model’s practical predictive utility (Shmueli et al., 2019).

The bootstrapping results (Table 5) indicate that all hypothesized direct effects are statistically supported. First, DT exerts a significant positive influence on FP (H1: $\beta = 0.326$, $t = 4.775$, $p < 0.001$), suggesting that DT directly enhances firm performance. The corresponding effect size is small to moderate ($f^2 = 0.071$), implying that DT

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contributes meaningfully—although not predominantly—to the explanation of FP when accounting for other predictors (Cohen, 2013; Hair & Alamer, 2022). Second, DT is a strong predictor of OR (H2: $\beta = 0.639$, $t = 19.896$, $p < 0.001$) with a large effect size ($f^2 = 0.691$), underscoring DT as a central driver in the development of organizational resilience capabilities. Third, OR positively influences FP (H3: $\beta = 0.145$, $t = 2.291$, $p = 0.022$) with a small effect size ($f^2 = 0.020$), indicating that organizational resilience contributes to performance, albeit with a relatively modest incremental impact beyond the direct effect of DT (Cohen, 2013; Hair & Alamer, 2022).

The moderation hypothesis is also substantiated. The interaction term ED × OR exerts a statistically significant positive effect on FP (H4: $\beta = 0.136$, $t = 2.848$, $p = 0.004$) with a small effect size ($f^2 = 0.023$). This result indicates that environmental dynamism amplifies the positive relationship between organizational resilience and firm performance, meaning that the performance returns to resilience are greater under conditions of heightened environmental dynamism (Hair & Alamer, 2022).

The mediating role of OR is confirmed. The indirect effect of DT on FP via OR is statistically significant (H5: $\beta = 0.093$, $t = 2.226$, $p = 0.026$), indicating that DT enhances firm performance partly by increasing organizational resilience. Because the direct effect of DT on FP remains significant (H1), this reflects partial mediation: DT improves FP both directly and indirectly through OR (Hair & Alamer, 2022).

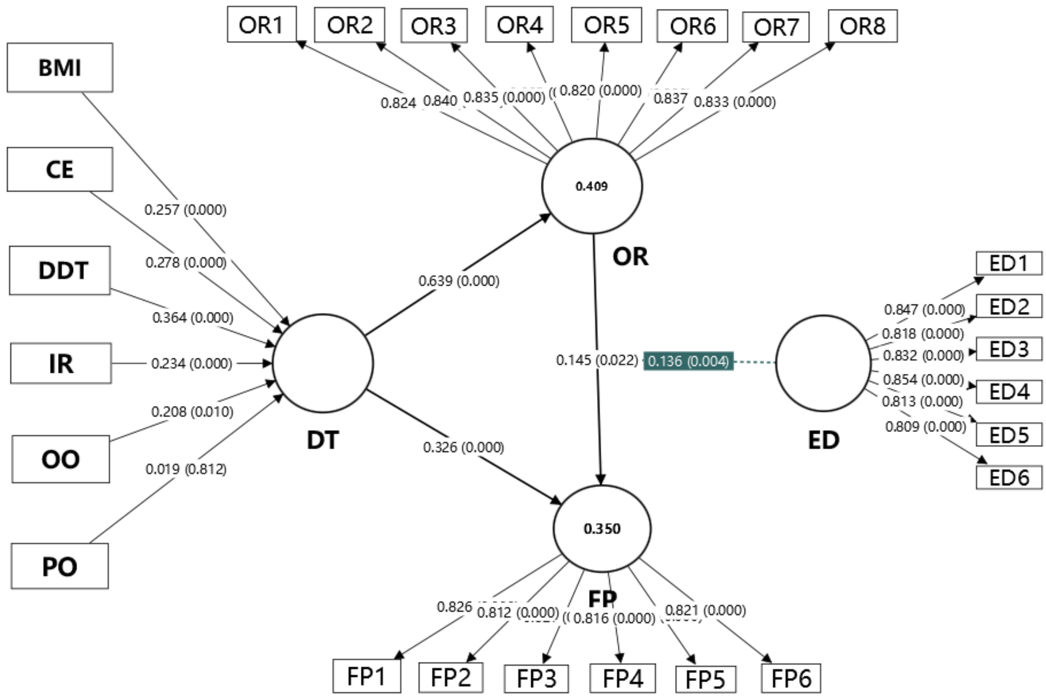

Figure 2 Structural model and analysis.

Source: Authors own work

Table 5 Q2 predict.

	Q^2predict	PLS-SEM_RMSE	LM_RMSE
FP1	0.217	1.037	1.061
FP2	0.233	1.024	1.030
FP3	0.163	1.060	1.082
FP4	0.201	1.032	1.059

FP5	0.218	0.983	1.010
FP6	0.218	1.037	1.062
OR1	0.273	1.054	1.083
OR2	0.281	1.056	1.073
OR3	0.268	1.009	1.043
OR4	0.235	1.039	1.059
OR5	0.287	0.994	1.013
OR6	0.319	0.986	1.015
OR7	0.262	1.019	1.038
OR8	0.251	1.063	1.080

Table 6 Results of hypothesis.

Hypothesis	**Std. Beta**	**Std. Error**	**T values**	**P values**	**F^2**	**PCILL**	**PCIUL**	**Supported**
H1: DT -> FP	0.326	0.068	4.775	0.000	0.071	0.204	0.470	YES
H2: DT -> OR	0.639	0.032	19.896	0.000	0.691	0.578	0.703	YES
H3: OR -> FP	0.145	0.063	2.291	0.022	0.020	0.011	0.257	YES
H4: ED x OR -> FP	0.136	0.048	2.848	0.004	0.023	0.039	0.226	YES
H5: DT -> OR -> FP	0.093	0.042	2.226	0.026		0.007	0.170	YES

Robustness analysis

To evaluate the robustness of the structural inferences with respect to the inclusion of Process Optimization (PO) in the formative second-order DT construct, we compared the baseline model (with DT specified to include PO) to an alternative specification omitting PO. This approach follows established guidelines for estimating and validating hierarchical component models and conducting robustness checks in PLS-SEM (Becker et al., 2012; Hair & Alamer, 2022). The results reveal a very high degree of stability across specifications (see Table 6). All focal relationships preserved their direction and statistical significance, and changes in path coefficients were negligible (maximum $|\Delta\beta|$ = 0.001). Correspondingly, effect sizes (f^2) remained virtually unchanged, indicating that the substantive contribution of the predictor constructs was invariant across model specifications (Cohen, 2013; Hair & Alamer, 2022). With respect to overall model performance, both explanatory power and predictive relevance exhibited slight improvements when PO was excluded (ΔR^2 up to +0.007; ΔQ^2_predict up to +0.003), further corroborating the robustness of the findings as well as the predictive adequacy of the model (Shmueli et al., 2019). Collectively, these results indicate that the central conclusions are not contingent on the inclusion of PO in the formative DT specification. Consequently, PO can be retained when warranted by theoretical domain coverage and content validity considerations, in line with the logic of formative measurement (Hair & Alamer, 2022).

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Table 7 Structural Relationships Comparison (β / p / f^2)

Hypothesis	Std. Beta	Std. Error	T values	P values	F^2	PCIL L	PCIU L	Supported
H1: DT -> FP	0.326	0.068	4.775	0.000	0.071	0.204	0.470	YES
H2: DT -> OR	0.639	0.032	19.896	0.000	0.691	0.578	0.703	YES
H3: OR -> FP	0.145	0.063	2.291	0.022	0.020	0.011	0.257	YES
H4: ED x OR -> FP	0.136	0.048	2.848	0.004	0.023	0.039	0.226	YES
H5: DT -> OR -> FP	0.093	0.042	2.226	0.026		0.007	0.170	YES

Note: BL= Baseline; Rm=Remove

Table 8 Explanatory and predictive performance Comparison (R^2 / Q^2predict)

Endogenous construct	Bl- R^2	Rm-PO R^2	ΔR^2	Bl- Q^2predict	Rm-PO Q^2predict	ΔQ^2predict
FP	0.344	0.351	0.007	0.315	0.317	0.002
OR	0.402	0.408	0.006	0.391	0.394	0.003

Note: Bl= Baseline; Rm=Remove

DISCUSSION

Building on the Dynamic Capabilities View (DCV), this study elucidates how digital transformation (DT) contributes to performance enhancement in retail SMEs by explicating organizational resilience (OR) as a central mediating mechanism and environmental dynamism (ED) as a critical moderating boundary condition.

Digital transformation

The findings show that DT is positively linked to firm performance, indicating that retail SMEs can convert digital initiatives into measurable outcomes. From a DCV perspective, DT accelerates information flows, strengthens analytical capabilities, and improves coordination across functions and channels, reinforcing the microfoundations of sensing and seizing (Kowalski et al., 2025; Teece, 2018). In retail, this typically appears as better demand forecasting, real-time customer engagement, omni-channel integration, and more adaptive pricing and promotions. (Mrutzek et al., 2020; Venkata Krishna Pradeep Mattegunta, 2025). Such digitally enabled managerial processes augment the firm's capacity to reconfigure product assortments, marketing initiatives, and service delivery mechanisms, thereby facilitating performance enhancements even under conditions of heightened environmental volatility (Amit & Han, 2017; Panichakarn et al., 2024). Notably, our findings align with the tenets of dynamic capabilities theory (DCV), which posit that sustainable competitive advantage seldom derives from technology in isolation, but rather from the extent to which technology is embedded within organizational processes and routines that support timely and effective adaptation(Eisenhardt & Martin, 2017; Teece, 2007).

Organizational resilience as a mediator

A key contribution of this study is showing that organizational resilience (OR) partially mediates the relationship between digital transformation (DT) and firm performance. In dynamic capabilities view (DCV) terms, resilience is an outcome of a firm's resource reconfiguration capability: resilient firms better absorb shocks, sustain core operations, recover quickly, and adapt their operational and strategic routines (Kähkönen et al., 2023). DT strengthens resilience by improving situational awareness (sensing), decision-making speed and coordination (seizing), and the capacity to redesign processes and reallocate resources (reconfiguring). (Rizana et al., 2024; Zhang et al., 2021). For retail SMEs, such mechanisms may encompass the rapid reallocation of inventory across distribution channels, the dynamic rebalancing of supplier portfolios, the modification of order fulfillment configurations, and the preservation of uninterrupted customer service through digital interaction touchpoints.

The observation of partial mediation is theoretically significant. It indicates that DT generates value through multiple mechanisms: one operates via resilience—whereby DT enables firms to withstand and adapt to disruptions—while additional mechanisms plausibly involve efficiency improvements, enhanced customer relationship management, and business model innovation that are not fully encompassed by resilience alone(Gillani et al., 2024; Gouveia et al., 2024). This is consistent with the broader proposition of the DCV that dynamic capabilities influence performance through a portfolio of adaptive mechanisms rather than a single, uniform causal pathway. Methodologically, the mediation result also strengthens causal interpretation by identifying a plausible capability-based process through which DT translates into performance outcomes (He et al., 2022; Trieu et al., 2023).

Environmental dynamism as a moderator

The significant positive moderating effect of ED on the OR–performance relationship indicates that organizational resilience becomes increasingly valuable as environmental turbulence intensifies. This result aligns with contingency-based perspectives in management, which posit that the performance outcomes associated with specific capabilities are contingent on contextual exigencies and competitive conditions (Parast, 2022; Shojaee et al., 2025). In highly dynamic environments—marked by rapid shifts in customer preferences, accelerated technological change, and heightened competitive activity—resilience is recurrently “activated” and therefore more likely to be converted into performance advantages(Bughin, 2024; Shojaee et al., 2025). Retail SMEs operating under such dynamic conditions must continuously adjust their channel configurations, product assortments, and supply chain arrangements; resilient firms are able to implement these adjustments with lower disruption costs and shorter recovery times, thereby achieving superior performance outcomes.

From dynamic capabilities view (DCV), environmental dynamism (ED) amplifies the need for sensing, seizing, and reconfiguring capabilities. In relatively stable environments, the marginal returns to such adaptive capabilities may be limited because established routines remain effective over extended periods. Under conditions of pronounced dynamism, by contrast, these same routines become obsolete more rapidly, rendering reconfiguration capabilities a critical source of performance differentials (Wilhelm et al., 2015). Accordingly, the observed moderation effect offers boundary conditions that support the proposition that the performance contributions of capabilities increase as environmental change becomes more frequent and less predictable.

Additional insight from the multidimensional operationalization of DT

While the main theoretical focus is the DT–OR–performance link and ED’s moderating role, the multidimensional view of DT offers further managerial and conceptual insights. Consistent with formative measurement research, modeling DT as a higher-order construct acknowledges that transformation comprises multiple complementary dimensions rather than interchangeable reflective indicators (Schneider et al., 2024). Crucially, the pattern of relative weights across the dimensions suggests that, in the retail SME context examined here, DT should not be interpreted as a purely “IT-driven project.” Instead, it emerges as a composite organizational capability that integrates technological infrastructure with customer-facing initiatives and strategic renewal processes. The empirical results show that the process optimization (PO) dimension adds little at the higher-order level. In a formative measurement model, a non-significant indicator weight does not mean the indicator lacks theoretical or practical relevance; it simply suggests that, after accounting for the other dimensions, it explains little additional variance(Hair et al., 2021). A likely reason is that PO strongly overlaps with technology capability and operational reconfiguration, as retail SMEs often achieve process improvements through digital technologies and better operational integration. PO may act as a broadly implemented “hygiene factor” that weakly differentiates firms, whereas customer-facing digitalization and business model innovation better capture distinctive transformation efforts. Robustness analyses excluding PO yield virtually unchanged structural results, indicating that the study's main inferences do not depend on including PO and supporting the robustness and stability of the model (Becker et al., 2012; Hair & Alamer, 2022).

Implication

Theoretical contributions

This study contributes to DCV-informed DT literature by situating capability arguments in the context of Chinese retail SMEs. It extends the DCV by showing how DT functions enables resilience in resource-constrained retail SMEs. Although the DCV highlights sensing, seizing, and reconfiguring as sources of competitive advantage (Teece, 2007; Teece et al., 1997), empirical SME research—especially in emerging economies—still offers limited insight into the micro-level mechanisms connecting digital initiatives to adaptive outcomes.

This study shows that DT significantly enhances organizational resilience in Chinese retail SMEs by offsetting structural disadvantages. Digitalization does so by improving real-time market sensing (via platform data and customer analytics), speeding up seizing processes (through shorter decision cycles and better channel coordination), and enabling reconfiguration (via operational flexibility and rapid cross-channel redeployment) (Ellström et al., 2022; Kowalski et al., 2025). It thus helps open the "black box" of DT by empirically identifying resilience as a central capability outcome of digitalization, especially in retail settings with frequent demand fluctuations and intense competitive imitation.

The study shows empirically that environmental dynamism strengthens the positive link between organizational resilience and firm performance, extending the contingency logic of the dynamic capabilities view (DCV) and indicating that resilience is not uniformly beneficial. Its performance payoffs rise under high environmental turbulence, when capabilities must be deployed frequently and iteratively. This contextual contribution suggests that in China's retail ecosystem, resilience should be seen not only as a "crisis-only" attribute, but as an ongoing dynamic capability that systematically turns recurrent disruptions into sustained competitive advantages.

Lastly, by operating DT as a multidimensional construct and showing consistent structural relationships across alternative models, the study supports the DCV view that competitive advantage arises from orchestrating complementary capabilities rather than technology alone (Teece, 2007). The pattern of dimensional contributions further indicates that "DT capability" here is closely tied to market-facing and strategic-renewal dimensions, helping reconcile inconsistent SME DT findings where DT has often been treated as a single index or an IT adoption proxy.

Managerial implications

The findings offer several actionable implications for Chinese retail SMEs, which now operate in platform-mediated, highly turbulent markets with rapid shifts in demand, intense price competition, algorithm-driven traffic, and fast-changing digital formats. First, managers should prioritize digital transformation that strengthens real-time sensing and rapid decision cycles. In China's retail ecosystem, platform traffic, promotional rules, and consumer trends can change within days or hours, making slow information processing especially costly (He et al., 2025). SMEs should therefore invest in integrated dashboards that unify platform analytics, point-of-sale data, customer feedback, and inventory signals to support timely sensing and faster decisions. Beyond adopting digital tools, the key is to embed data into organizational routines. Examples include frequent (e.g., weekly or daily) demand-review meetings, automated alerts for inventory discrepancies and service failures, and structured rapid experiments in content, pricing, and assortment. These practices help institutionalize sensing and seizing capabilities as stable organizational processes rather than ad hoc, individual-driven reactions.

Besides, managers should treat organizational resilience as a strategic, capability-based asset grounded in identifiable, assessable routines, especially under high environmental dynamism. For Chinese retail SMEs, resilience should be operationalized through: (i) multi-sourcing and contingency-oriented procurement to avoid dependence on single suppliers(Mehta et al., 2024), (ii) flexible order-fulfillment and last-mile distribution (e.g., in-store pickup, local delivery, platform-based delivery)(Liao et al., 2025), (iii) modular workforce designs with cross-training and flexible scheduling(Robertson et al., 2022), and (iv) codified shock-response playbooks that standardize responses to demand surges, platform policy shifts, and logistics disruptions(Liu et al., 2022). Together, these routines enable rapid resource and process reconfiguration, reduce downtime and service failures, and stabilize and protect organizational performance.

Third, Because DT is multidimensional and performance gains come mainly from technology infrastructure and market-oriented transformation, firms should jointly upgrade back-end systems and front-end customer-facing digitization, including experimenting with new digital business models. Managers should avoid tool fragmentation from using many non-integrated apps and instead focus on interoperability across the digital ecosystem by linking content acquisition, customer engagement, order management, and fulfillment so that separate digital initiatives form coherent firm-level dynamic capabilities.

Lastly, the limited incremental explanatory power of process optimization suggests a sequencing issue rather than a rejection of process improvement. Many Chinese retail SMEs have already adopted basic digital tools (e.g., standardized ordering, electronic payments), reducing the differentiation potential of further process optimization. Managers should treat process optimization as necessary infrastructure and direct marginal resources to higher-impact areas that strengthen environmental sensing, customer engagement, and business model innovation or renewal.

In addition, policymakers should shift support from equipment subsidies to capability-building. Because digital transformation (DT) strengthens firm performance partly by improving organizational resilience, policies should focus on managerial and organizational capabilities—such as training in data-driven decision-making, designing digital governance structures, and institutionalizing rapid reconfiguration routines—rather than mainly funding hardware and software. Policy design should also reflect the level of environmental dynamism (ED). Since the resilience–performance link is stronger under high ED, policymakers should prioritize SMEs in the most turbulent subsectors (e.g., fast fashion, consumer electronics accessories, emerging lifestyle categories, instant retail) and in regions with intense competitive churn. Tailored instruments may include rapid-response financing, temporary logistics support during disruptions, and digital transformation vouchers tied to specific capability outcomes (e.g., better data integration, shorter recovery time, lower stockout rates), instead of generic subsidies.

Limitations and future research

Notwithstanding its contributions, this study is characterized by several limitations that delineate fruitful avenues for future research. First, the reliance on cross-sectional survey data constrains the robustness of causal inferences; longitudinal research designs or multi-wave data collections would be more suitable for capturing the temporal dynamics through which DT capabilities and resilience emerge, co-evolve, and interact over time (Hair & Alamer, 2022). Second, although ED was conceptualized and empirically examined as a key boundary condition, subsequent investigations could incorporate additional contextual contingencies (e.g., competitive intensity, regulatory turbulence) and explore potential nonlinear relationships to yield more fine-grained boundary conditions and interaction patterns. Third, although OR was theorized as a core mediating mechanism, DT may also exert its effects through alternative capability pathways (e.g., innovation capability, organizational learning, organizational agility). The use of multiple-mediation models would facilitate a comparative assessment of the relative explanatory power of these mechanisms in the context of retail SMEs (Preacher & Hayes, 2008). Advancing these extensions would further enrich DCV-based theorizing by providing a more comprehensive account of how digital transformation generates sustained performance advantages.

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