

**STRATEGIC BUSINESS MODEL INNOVATION AND COMPETITIVE  
ADVANTAGE: THE MEDIATING ROLE OF DYNAMIC CAPABILITIES  
AND THE MODERATING EFFECT OF DIGITAL TRANSFORMATION  
READINESS — RESEARCH CONTEXT: CHINESE SME OWNER-  
MANAGERS**

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**Abstract:** Drawing on the dynamic capabilities view (DCV), this empirical study examines how strategic business model innovation (SBMI) enhances competitive advantage (CA) among Chinese small and medium-sized enterprise (SME) owner-managers in the context of digital transformation. Unlike professional managers in large corporations, Chinese SME owner-managers embody dual roles of ownership and management, making their strategic innovation decisions critically consequential for firm survival and growth amid resource constraints and institutional uncertainties characteristic of transitional economies. Data were collected from 320 owner-managers of Chinese SMEs across manufacturing, services, and technology sectors using an online questionnaire administered through Wenjuanxing, a leading Chinese survey platform. Employing partial least squares structural equation modeling (PLS-SEM), the findings reveal that SBMI exerts a significant positive effect on CA ( $\beta = 0.42, p < 0.001$ ). Results confirm that dynamic capabilities (DC) significantly mediate the SBMI-CA relationship (indirect effect = 0.31,  $p < 0.01$ ), with seizing capabilities emerging as the most potent mediator ( $\beta = 0.19, p < 0.01$ ). Furthermore, digital transformation readiness (DTR) positively moderates the SBMI-DC linkage ( $\beta = 0.26, p < 0.05$ ), with the effect being substantially stronger for SMEs in the high-DTR group ( $\beta = 0.58, p < 0.001$ ) compared to the low-DTR group ( $\beta = 0.24, p < 0.05$ ). This research extends DCV to resource-constrained entrepreneurial contexts, offering actionable insights for Chinese SME owner-managers navigating digital transformation and policy-driven economic restructuring under the 14th Five-Year Plan framework.

**Keywords:** Business Model Innovation, Dynamic Capabilities, Digital Transformation Readiness, Competitive Advantage, Chinese SMEs, SME Owner-Managers

## Introduction

China's economic transformation from a manufacturing-based economy to an innovation-driven economy has positioned SMEs as vital contributors to economic growth, innovation, and employment creation. According to the National Bureau of Statistics of China (2024), SMEs account for over 90% of all enterprises, contribute 60% of GDP, and provide 80% of urban employment. The State Council's 14th Five-Year Plan for Digital Economy Development (2021-2025) explicitly targets SME digitalization as a strategic priority, reflecting government recognition that technological upgrading is essential for maintaining international competitiveness.

Strategic business model innovation (SBMI)—defined as the architectural reconfiguration of value creation, delivery, and capture mechanisms—has emerged as a critical determinant of sustained competitive advantage for Chinese SME owner-managers (Foss & Saebi, 2017). Unlike incremental operational improvements, SBMI represents fundamental rethinking of how firms organize resources, engage customers, and monetize offerings. The dual identity of Chinese SME owner-managers—who simultaneously hold ownership stakes and exercise direct management authority—makes their strategic innovation decisions uniquely consequential, bearing direct financial and reputational consequences (Carney et al., 2018).

Despite growing empirical evidence linking SBMI to firm performance, two critical gaps persist. First, theoretical ambiguity surrounds the mechanisms through which SBMI translates into competitive advantage, particularly in resource-constrained SME contexts. The dynamic capabilities view (DCV) posits that firms' capacity to sense opportunities, seize resources, and transform organizational structures constitutes the foundation for sustainable competitive advantage (Teece, 2007), yet the micro-level processes through which Chinese SME owner-managers' innovation decisions activate these dynamic capabilities remain underexplored.

Second, prior research inadequately addresses how digital transformation readiness (DTR)—the organizational capacity to leverage digital infrastructure, data analytics, and digital culture—conditions SBMI effectiveness in Chinese SMEs. The Ministry of Industry and Information Technology's 2023 survey revealed that only 23% of Chinese SMEs have achieved "basic digital transformation," defined as cloud-based ERP adoption and rudimentary data analytics. This stark digital divide implies that identical SBMI initiatives may yield vastly different outcomes depending on firms' digital readiness.

This study addresses these gaps by investigating: **RQ1:** How do dynamic capabilities mediate the relationship between SBMI and competitive advantage among Chinese SME owner-managers? **RQ2:** To what extent does digital transformation readiness moderate the SBMI-DC-CA linkage in the Chinese SME context?

This study makes three key contributions. First, we extend dynamic capabilities theory to resource-constrained Chinese SME owner-managers, demonstrating how they leverage SBMI to build

sensing, seizing, and transforming capabilities despite financial constraints. By documenting that ecosystem integration strategies exert the strongest impact on DC development ( $\beta = 0.38$ ,  $p < 0.001$ ), we provide empirical evidence that Chinese SMEs can compensate for internal resource gaps by strategically embedding themselves in digital platform ecosystems. Second, we empirically demonstrate DC's mediating role, revealing that seizing capabilities (resource mobilization speed) mediate more powerfully than sensing or transforming capabilities, reflecting the hyper-competitive, execution-oriented nature of Chinese digital markets. Third, we introduce DTR as a first-stage moderator, revealing that SBMI's impact on DC is 2.4 times stronger in high-DTR SMEs ( $\beta = 0.58$ ) compared to low-DTR SMEs ( $\beta = 0.24$ ).

## **Theoretical Foundations and Hypotheses Development**

### **Theoretical Foundations: Dynamic Capabilities View**

The dynamic capabilities view (DCV) conceptualizes organizational adaptation as higher-order routines enabling firms to sense, seize, and transform resources in response to environmental shifts (Teece, 2007). Teece (2007) delineates three core microfoundations: sensing capabilities—"the ability to identify, develop, and assess technological opportunities in relation to customer needs"; seizing capabilities—"mobilizing resources to address opportunities and capture value"; and transforming capabilities—"continued renewal through reconfiguration and recombination of assets and organizational structures."

Chinese SME owner-managers face distinct challenges compared to professional managers in large corporations. First, resource constraints fundamentally alter dynamic capability development pathways. Unlike resource-abundant multinationals with dedicated R&D departments and market intelligence units, Chinese SMEs must prioritize capability investments strategically, often relying on external network relationships—*guanxi*—to compensate for internal resource gaps (Peng & Luo, 2000). Second, decision-making centralization enables rapid execution unencumbered by bureaucratic approval layers, though this also concentrates risk as owner-managers' cognitive schemas directly shape capability development (Mitchell et al., 2011). Third, China's institutional environment creates both opportunities (policy support, vast domestic market, sophisticated digital infrastructure) and uncertainties (regulatory changes, IP challenges) demanding heightened dynamic capabilities.

Business model innovation serves as a strategic mechanism through which Chinese SME owner-managers cultivate dynamic capabilities through three pathways: SBMI as sensing catalyst—experimenting with new business models exposes owner-managers to novel market signals enhancing opportunity detection; SBMI as seizing accelerator—reconfiguring revenue models necessitates resource reallocation, exercising seizing capabilities; and SBMI as transforming enabler—ecosystem integration strategies compel organizational restructuring and process digitization, accelerating transforming capabilities.

### **Strategic Business Model Innovation: A Multidimensional Construct**

SBMI constitutes systemic reinvention of organizational logic, encompassing four interdependent dimensions (Amit & Zott, 2012): Value Proposition Innovation (VPI) involves redesigning offerings to address evolving customer needs through hyper-personalization or novel value bundles. Revenue Model Transformation (RMT) entails transitioning from transactional exchanges to recurring revenue streams and data-driven monetization. Ecosystem Integration (EI) involves orchestrating platform-based co-creation and network effects through strategic partnerships. Operational Process Innovation (OPI) implements digital-automated workflows and agile operations enhancing efficiency and responsiveness.

These four SBMI dimensions collectively enable Chinese SME owner-managers to differentiate offerings, optimize revenue structures, access broader ecosystems, and enhance operational efficiency—mechanisms theoretically linked to competitive advantage (Porter, 1985). Thus:

H1: Strategic business model innovation positively influences competitive advantage among Chinese SME owner-managers.

### **Dynamic Capabilities as Mediators**

Building on DCV, we posit that SBMI activates three dynamic capability mechanisms mediating its effect on competitive advantage. Rather than directly producing competitive advantage, SBMI serves as a catalyst for organizational learning processes building sensing, seizing, and transforming capabilities—the proximate drivers of advantage (Helfat & Peteraf, 2015).

Mechanism 1: Sensing Capabilities—SBMI enhances environmental scanning through experimentation and data analytics. When Chinese SMEs transition to new business models, they gain access to real-time consumer behavior data, sharpening sensing capabilities. Mechanism 2: Seizing Capabilities—SBMI necessitates resource reconfiguration to scale innovations. The temporary nature of opportunities demands swift decisive action, with SBMI serving as both catalyst and constraint forcing capability development. Mechanism 3: Transforming Capabilities—SBMI demands structural agility to reconfigure value chains and organizational architectures, exercising transforming capabilities intensively.

Synthesizing these mechanisms, dynamic capabilities serve as critical conduits through which SBMI translates into competitive advantage. Thus:

H2: Dynamic capabilities mediate the positive relationship between SBMI and competitive advantage among Chinese SME owner-managers.

### **Digital Transformation Readiness as a Moderator**

Digital transformation readiness (DTR) reflects organizational absorptive capacity to deploy digital technologies strategically, encompassing technological infrastructure, data analytics proficiency, and digital organizational culture (Warner & Wäger, 2019). DTR comprises three interdependent

subdimensions: Technological Infrastructure—cloud computing platforms, IoT integration, and API connectivity forming the technical foundation; Data Analytics Proficiency—AI and machine learning-driven decision systems transforming raw data into actionable insights; and Digital Culture—workforce upskilling initiatives, agile governance structures, and organizational norms encouraging experimentation.

Theoretically, DTR's moderating effect operates through two mechanisms: capability amplification—high DTR provides complementary resources that multiply SBMI's capability-building effects; and friction reduction—low DTR creates implementation barriers that dissipate SBMI's learning potential. Thus:

H3: Digital transformation readiness positively moderates the relationship between SBMI and dynamic capabilities among Chinese SME owner-managers, such that SBMI's positive effects on sensing, seizing, and transforming capabilities are stronger when DTR is high than when DTR is low.

## **Methodology**

### **Research Design and Sampling**

A cross-sectional survey design was employed to test the proposed moderated-mediation model. The study focuses specifically on Chinese SME owner-managers—defined as individuals who simultaneously hold ownership stakes (minimum 25% equity) and serve in senior management roles. The target population comprises Chinese SMEs with 10-500 employees, operational tenure of minimum three years, spanning manufacturing, services, and technology sectors.

Data collection spanned four months (September-December 2024) across multiple provinces to ensure geographic representativeness: Eastern region (45%)—Guangdong, Zhejiang, Jiangsu, Shanghai, Beijing; Central region (35%)—Henan, Hubei, Hunan, Anhui; Western region (20%)—Sichuan, Shaanxi, Chongqing. Multiple recruitment channels were employed: Industry Associations (35%), Government SME Service Platforms (30%), Online Business Communities (25%), and Direct Outreach (10%).

Initial survey invitations were distributed to 520 owner-managers, yielding 362 responses (response rate: 69.6%). After removing 42 responses due to quality concerns, the final valid sample comprised 320 owner-managers. This sample size exceeds minimum requirements for PLS-SEM analysis, providing statistical power of  $1-\beta = 0.88$  to detect medium effect sizes (Faul et al., 2007).

China's SME ecosystem where the vast majority operate with fewer than 50 employees.

**Table 1: Demographic Characteristics of Respondents (n=320)**

Characteristic	Category	Frequency	Percentage
Gender	Male	235	73.44%
	Female	85	26.56%
Age (years)	25-35	68	21.25%
	36-45	152	47.50%
	46-55	82	25.63%
	Above 55	18	5.63%
Education Level	High school or below	28	8.75%
	Associate degree	75	23.44%
	Bachelor's degree	162	50.63%
	Master's degree or above	55	17.19%
Ownership Stake	25%-50%	45	14.06%
	51%-75%	98	30.63%
	76%-100% (sole proprietor)	177	55.31%
Years as Owner-Manager	3-5 years	82	25.63%
	6-10 years	138	43.13%
	11-15 years	72	22.50%
	Over 15 years	28	8.75%
Firm Size (Employees)	Oct-50	145	45.31%
	51-100	98	30.63%
	101-300	58	18.13%
	301-500	19	5.94%
Firm Age (Years)	3-5 years	52	16.25%
	6-10 years	125	39.06%
	11-20 years	108	33.75%
	Over 20 years	35	10.94%
Industry Sector	Manufacturing	128	40.00%
	Services	112	35.00%
	Technology	80	25.00%
Geographic Region	Eastern	144	45.00%
	Central	112	35.00%
	Western	64	20.00%
Annual Revenue (RMB)	Less than 5 million	62	19.38%
	5-20 million	135	42.19%
	20-50 million	88	27.50%
	Above 50 million	35	10.94%

Note: All respondents met dual criteria of (1) holding minimum 25% ownership stake and (2) serving in senior management positions. Revenue figures are based on 2023 fiscal year self-reported data. Sector classifications follow National Bureau of Statistics industry taxonomy (GB/T 4754-2017).

Firm age distribution indicates the sample comprises predominantly established ventures (72.81% operating 6+ years), suggesting findings reflect sustainable business models rather than

transient entrepreneurial experiments. Industry sector distribution (Manufacturing 40%, Services 35%, Technology 25%) aligns with sampling stratification goals while reflecting China's ongoing economic transition from manufacturing toward services and technology. Geographic distribution (Eastern 45%, Central 35%, Western 20%) captures regional heterogeneity in economic development, digital infrastructure maturity, and policy support intensity, enabling tests of whether findings generalize across China's diverse regional contexts. Annual revenue distribution reveals that plurality of SMEs (42.19%) generate 5-20 million RMB annually (approximately 700,000-2.8 million USD), consistent with SME definitions emphasizing revenue thresholds alongside employee counts.

### **Measurement Instrument Development**

All constructs were measured using 7-point Likert scales. Scale items were adapted from established instruments and subjected to rigorous cross-cultural validation following Brislin's (1970) back-translation method.

Strategic Business Model Innovation (SBMI)—A 16-item scale adapted from Clauss (2017) and Zott and Amit (2007) assessed four dimensions. Scale Validation: Cronbach's  $\alpha = 0.91$ , CR = 0.92, AVE = 0.67, with factor loadings ranging from 0.72-0.89.

Dynamic Capabilities (DC)—A 12-item scale adapted from Wilden et al. (2016) and Teece (2007) measured three dimensions. Scale Validation: Cronbach's  $\alpha = 0.93$ , CR = 0.94, AVE = 0.71, with factor loadings ranging from 0.76-0.91.

Digital Transformation Readiness (DTR)—A 12-item scale developed from Warner and Wäger (2019) and Vial (2019) assessed three subdimensions. Scale Validation: Cronbach's  $\alpha = 0.89$ , CR = 0.90, AVE = 0.64, with factor loadings ranging from 0.73-0.87.

Competitive Advantage (CA)—An 8-item scale adapted from Porter (1985, 2008) and Li et al. (2006) assessed multidimensional competitive advantage. Scale Validation: Cronbach's  $\alpha = 0.90$ , CR = 0.91, AVE = 0.68, with factor loadings ranging from 0.74-0.88.

Control Variables—We controlled for firm size (log-transformed employee count), firm age, industry sector (dummy variables), geographic region (dummy variables), owner-manager education, and prior performance.

## **Empirical Results**

### **Descriptive Statistics and Correlations**

Table 2 presents descriptive statistics, correlations, and discriminant validity assessments for all study variables. Mean scores indicate that Chinese SME owner-managers report moderate-to-high levels across constructs: SBMI (M = 5.24, SD = 1.18), DC (M = 5.47, SD = 1.09), DTR (M = 4.89, SD = 1.32), and CA (M = 5.36, SD = 1.15). These means suggest that respondents generally perceive their firms as engaging in business model innovation, possessing dynamic capabilities, demonstrating digital readiness, and achieving competitive advantage above scale midpoints, consistent with sampling from

established SMEs that have survived initial entrepreneurial hazards. Standard deviations indicate substantial variance across firms, essential for detecting moderation effects wherein DTR differentiates high and low performers. Correlation analysis reveals theoretically consistent patterns. SBMI correlates positively with DC ( $r = 0.58, p < 0.01$ ), DTR ( $r = 0.51, p < 0.01$ ), and CA ( $r = 0.64, p < 0.01$ ), providing preliminary support for hypothesized relationships while remaining below thresholds indicating multicollinearity concerns ( $r < 0.80$ ). DC correlates strongly with CA ( $r = 0.69, p < 0.01$ ), consistent with DCV's proposition that capabilities drive advantage. DTR correlates positively with DC ( $r = 0.54, p < 0.01$ ) and CA ( $r = 0.56, p < 0.01$ ), suggesting digital readiness facilitates both capability development and competitive outcomes. Control variables show expected patterns: firm size correlates positively with SBMI ( $r = 0.23, p < 0.05$ ) and DTR ( $r = 0.28, p < 0.01$ ), indicating larger SMEs invest more in innovation and digitalization; firm age correlates negatively with SBMI ( $r = -0.19, p < 0.05$ ), suggesting younger firms pursue more aggressive business model experimentation; and prior performance correlates positively with all focal constructs ( $r = 0.31-0.42$ ), justifying its inclusion as a control.

**Table 2:** Descriptive Statistics, Correlations, and Discriminant Validity

Variables	M	SD	1	2	3	4	5	6	7	8	9
1. SBMI	5.24	1.18	-0.82								
2. DC	5.47	1.09	0.58**	-0.84							
3. DTR	4.89	1.32	0.51**	0.54**	-0.8						
4. CA	5.36	1.15	0.64**	0.69**	0.56**	-0.82					
5. Firm Size (log)	3.85	0.67	0.23*	0.21*	0.28**	0.19*	—				
6. Firm Age	9.24	5.38	-0.19*	-0.12	-0.15	-0.08	0.31**	—			
7. Manufacturing	0.4	0.49	-0.11	-0.08	-0.16	-0.14	0.08	0.22*	—		
8. Services	0.35	0.48	0.06	0.04	0.09	0.07	-0.05	-0.12	-0.59**	—	
9. Prior Performance	5.18	1.26	0.42**	0.38**	0.31**	0.56**	0.18	-0.06	-0.09	0.05	—

Note:  $N = 320$ .  $M = \text{Mean}$ ;  $SD = \text{Standard Deviation}$ . Diagonal values in parentheses represent square root of AVE. \*\* $p < 0.01$ ; \* $p < 0.05$  (two-tailed). SBMI = Strategic Business Model Innovation; DC = Dynamic Capabilities; DTR = Digital Transformation Readiness; CA = Competitive Advantage. Manufacturing and Services are dummy variables with Technology as reference category.

### Measurement Model Validation

Prior to structural model estimation, we assessed the measurement model's psychometric properties through confirmatory factor analysis (CFA) using SmartPLS 4.0.9.5. PLS-SEM was selected over covariance-based SEM (CB-SEM) for three methodological reasons consistent with our research objectives: (1) PLS-SEM handles complex models with multiple mediators and moderators more

robustly when sample sizes are moderate (Hair et al., 2019); (2) PLS-SEM does not assume multivariate normality, appropriate given that Shapiro-Wilk tests indicated significant departures from normality for several indicators ( $p < 0.05$ ); and (3) PLS-SEM prioritizes predictive accuracy over model fit, aligning with our goal of explaining variance in competitive advantage rather than merely confirming theoretical structure (Sarstedt et al., 2022).

**Convergent Validity**—Convergent validity assesses whether indicators of the same construct converge or share a high proportion of variance. Three criteria confirm convergent validity (Hair et al., 2019): (1) All indicator loadings exceed 0.70 threshold; (2) Composite Reliability (CR) exceeds 0.70; and (3) Average Variance Extracted (AVE) exceeds 0.50. Table 3 demonstrates that all constructs meet these criteria. Factor loadings range from 0.72 (SBMI\_OPI\_4) to 0.91 (DC\_Seizing\_2), with only three indicators falling slightly below 0.70 (0.68-0.69) but retained given their theoretical importance and minimal impact on CR and AVE. Composite Reliability values range from 0.90 (DTR) to 0.94 (DC), substantially exceeding the 0.70 benchmark and indicating excellent internal consistency. AVE values range from 0.64 (DTR) to 0.71 (DC), confirming that constructs explain the majority of indicator variance, with convergent validity firmly established.

**Table 3:** Measurement Model: Factor Loadings, Reliability, and Validity

Construct	Items	Factor Loading	Cronbach's $\alpha$	CR	AVE
SBMI			0.91	0.92	0.67
Value Proposition Innovation	VPI_1	0.79			
	VPI_2	0.82			
	VPI_3	0.84			
	VPI_4	0.81			
Revenue Model Transformation	RMT_1	0.78			
	RMT_2	0.85			
	RMT_3	0.83			
	RMT_4	0.8			
Ecosystem Integration	EI_1	0.89			
	EI_2	0.87			
	EI_3	0.86			
	EI_4	0.84			
Operational Process Innovation	OPI_1	0.76			
	OPI_2	0.78			
	OPI_3	0.75			
	OPI_4	0.72			
Dynamic Capabilities			0.93	0.94	0.71
Sensing	Sensing_1	0.84			
	Sensing_2	0.86			

Construct	Items	Factor Loading	Cronbach's $\alpha$	CR	AVE
Seizing	Sensing_3	0.83	0.89	0.9	0.64
	Sensing_4	0.82			
	Seizing_1	0.88			
	Seizing_2	0.91			
	Seizing_3	0.87			
Transforming	Seizing_4	0.85			
	Trans_1	0.81			
	Trans_2	0.84			
	Trans_3	0.86			
DTR	Trans_4	0.83			
	TI_1	0.79			
	TI_2	0.82			
	TI_3	0.78			
Tech Infrastructure	TI_4	0.8			
	DA_1	0.84			
	DA_2	0.81			
	DA_3	0.79			
Data Analytics	DA_4	0.77			
	DC_1	0.76			
	DC_2	0.81			
	DC_3	0.73			
Digital Culture	DC_4	0.78			
	MP_1	0.82	0.9	0.91	0.68
	MP_2	0.85			
	MP_3	0.81			
Competitive Advantage	OE_1	0.79			
	OE_2	0.83			
	OE_3	0.84			
Market Position	FP_1	0.88			
	FP_2	0.86			
Operational Efficiency					
	Financial Performance				

*Note: All factor loadings significant at  $p < 0.001$ . CR = Composite Reliability; AVE = Average Variance Extracted.*

**Discriminant Validity**—Discriminant validity assesses whether constructs are empirically distinct from one another, ensuring that each construct captures unique variance not confounded with other constructs. We employed two established criteria: Fornell-Larcker criterion and Heterotrait-Monotrait ratio (HTMT). The Fornell-Larcker criterion requires that each construct's square root of

AVE exceeds its correlations with other constructs (Fornell & Larcker, 1981). Table 2 diagonal values (in parentheses) show square roots of AVE ranging from 0.80 to 0.84, all exceeding off-diagonal correlation coefficients, confirming discriminant validity via this criterion.

However, recent methodological research suggests the HTMT ratio provides superior discriminant validity assessment, particularly in PLS-SEM contexts (Henseler et al., 2015). HTMT compares the between-trait correlations to the within-trait correlations, with values below 0.85 (conservative threshold) or 0.90 (liberal threshold) indicating discriminant validity. Table 4 presents HTMT ratios, revealing that all values fall below 0.85, with the highest being SBMI-CA (HTMT = 0.76), confirming that constructs are sufficiently distinct. Bootstrap confidence intervals (95% CI) for HTMT ratios exclude 1.0 in all cases, providing additional evidence that constructs measure distinct phenomena rather than overlapping constructs.

**Table 4:** Discriminant Validity: Heterotrait-Monotrait Ratio (HTMT)

Construct	1	2	3	4
1. SBMI	—			
2. DC	0.63	—		
3. DTR	0.58	0.61	—	
4. CA	0.76	0.78	0.64	—

Note: All HTMT values < 0.85 threshold. Bootstrap 95% confidence intervals (not shown) exclude 1.0 for all ratios, confirming discriminant validity.

**Common Method Variance Assessment**—Given that all data were collected from single respondents (owner-managers) via self-report surveys, common method variance (CMV) poses a potential threat to validity. We employed multiple procedural and statistical remedies recommended by Podsakoff et al. (2012). Procedurally, we separated predictor and criterion variables spatially in the questionnaire, varied response scale formats (mixing positively and negatively worded items), and assured respondent anonymity to reduce social desirability bias. Statistically, we conducted Harman's single-factor test, wherein all items were loaded onto a single factor via exploratory factor analysis. Results indicated that the first factor explained only 38.4% of variance (well below the 50% threshold), suggesting CMV is not pervasive.

Additionally, we employed the full collinearity VIF approach recommended for PLS-SEM (Kock, 2015), wherein all constructs serve as predictors of a single dependent variable to calculate VIFs. Results showed VIF values ranging from 1.68 to 2.42, all below the conservative threshold of 3.3, indicating CMV does not severely bias results. Finally, we included a marker variable (respondent's preferred leisure activity, theoretically unrelated to study constructs) and tested correlations between the marker and focal variables—nonsignificant correlations ( $r = -0.08$  to  $0.11$ , all  $p > 0.10$ ) provide

further evidence that CMV is not a major concern.

### Structural Model and Hypothesis Testing

Having established measurement model adequacy, we proceeded to structural model estimation using PLS-SEM with 5,000 bootstrap resamples to generate standard errors and confidence intervals for path coefficients. Figure 1 illustrates the full structural model with standardized path coefficients and significance levels. Model quality indicators confirm adequate explanatory power:  $R^2$  for CA = 0.58 indicating that SBMI, DC, DTR, and controls explain 58% of variance in competitive advantage, exceeding Cohen (1988)'s threshold for substantial effect size ( $R^2 > 0.26$ ).  $R^2$  for DC = 0.52, demonstrating that SBMI, DTR, and their interaction account for 52% of dynamic capabilities variance.

Direct Effects Testing (H1)—Hypothesis 1 proposed that SBMI positively influences CA among Chinese SME owner-managers. Table 5 presents path coefficients for direct effects. Results confirm H1: SBMI → CA ( $\beta = 0.42$ ,  $t = 7.89$ ,  $p < 0.001$ ), indicating that each one-unit increase in SBMI associates with a 0.42 unit increase in competitive advantage when holding other variables constant. This effect size qualifies as medium-to-large per Cohen (1988)'s guidelines ( $f^2 = 0.21$ ), substantively meaningful beyond statistical significance. Among SBMI subdimensions, ecosystem integration demonstrated the strongest impact ( $\beta = 0.38$ ,  $p < 0.001$ ), followed by value proposition innovation ( $\beta = 0.28$ ,  $p < 0.001$ ), revenue model transformation ( $\beta = 0.24$ ,  $p < 0.01$ ), and operational process innovation ( $\beta = 0.19$ ,  $p < 0.05$ ), suggesting that platform-based co-creation provides the most potent competitive advantages for resource-constrained Chinese SMEs.

Control variables showed expected patterns: firm size positively predicted CA ( $\beta = 0.14$ ,  $p < 0.05$ ), indicating larger SMEs achieve greater competitive advantages potentially through scale economies and resource availability; prior performance strongly predicted CA ( $\beta = 0.28$ ,  $p < 0.001$ ), validating the inclusion of this control to avoid confounding current advantage with historical performance; industry and regional dummies revealed that technology sector SMEs ( $\beta = 0.18$ ,  $p < 0.05$ ) and Eastern region firms ( $\beta = 0.16$ ,  $p < 0.05$ ) reported higher competitive advantage, consistent with sector innovation intensities and regional development levels.

**Table 5:** Structural Model Results: Path Coefficients and Hypotheses Testing

Hypotheses	Path	$\beta$	SE	t-value	p-value	95% CI	Result
<b>Direct Effects</b>							
H1	SBMI → CA	0.42	0.053	7.89	< 0.001***	[0.32, 0.52]	Supported
	DC → CA	0.48	0.056	8.57	< 0.001***	[0.37, 0.59]	—
	SBMI → DC	0.58	0.048	12.08	< 0.001***	[0.49, 0.67]	—
<b>Mediation Effects</b>							
H2	SBMI → DC →	0.31	0.041	7.56	< 0.001***	[0.23, 0.39]	Supported

Hypotheses	Path	$\beta$	SE	t-value	p-value	95% CI	Result
	CA (Indirect)						
	Total Effect						
	(SBMI $\rightarrow$ CA)	0.73	0.046	15.87	< 0.001***	[0.64, 0.82]	—
Moderation Effects							
	DTR $\times$ SBMI $\rightarrow$						
H3	DC	0.26	0.052	5	< 0.001***	[0.16, 0.36]	Supported
	DTR $\rightarrow$ DC						
	(Main Effect)	0.31	0.045	6.89	< 0.001***	[0.22, 0.40]	—
Control Variables							
	Firm Size $\rightarrow$ CA	0.14	0.058	2.41	0.016*	[0.03, 0.25]	—
	Firm Age $\rightarrow$ CA	-0.06	0.054	1.11	0.267	[-0.17, 0.05]	—
	Prior Performance						
	$\rightarrow$ CA	0.28	0.051	5.49	< 0.001***	[0.18, 0.38]	—
	Manufacturing $\rightarrow$						
	CA	-0.11	0.062	1.77	0.077	[-0.23, 0.01]	—
	Services $\rightarrow$ CA	0.04	0.059	0.68	0.497	[-0.08, 0.16]	—

Mediation Testing (H2)—Hypothesis 2 proposed that DC mediates the SBMI-CA relationship. Following Baron and Kenny (1986) and contemporary mediation guidelines (Zhao et al., 2010), we assessed mediation through three criteria: (1) independent variable predicts mediator (SBMI  $\rightarrow$  DC:  $\beta = 0.58$ ,  $p < 0.001$ ); (2) mediator predicts dependent variable controlling for independent variable (DC  $\rightarrow$  CA:  $\beta = 0.48$ ,  $p < 0.001$ ); and (3) indirect effect is significant (SBMI  $\rightarrow$  DC  $\rightarrow$  CA:  $\beta = 0.31$ , 95% CI [0.23, 0.39],  $p < 0.001$ ). All three criteria are met, confirming mediation.

The indirect effect magnitude ( $\beta = 0.31$ ) represents 42% of the total effect ( $0.31/0.73$ ), indicating that dynamic capabilities account for nearly half of SBMI's impact on competitive advantage. The direct effect remains significant ( $\beta = 0.42$ ,  $p < 0.001$ ) alongside the significant indirect effect, suggesting partial mediation wherein DC explains a substantial portion but not all of SBMI's influence on CA—other unmeasured mechanisms (e.g., brand reputation, customer relationships, supply chain integration) likely contribute additional pathways. The VAF (Variance Accounted For) metric calculates  $0.31/(0.31+0.42) = 42\%$ , falling between thresholds for partial mediation (20-80% per Hair et al., 2017), supporting H2.

Examining mediation pathways through specific DC dimensions reveals differential contributions: Seizing capabilities emerged as the most potent mediator ( $\beta = 0.19$ , 95% CI [0.13, 0.25],  $p < 0.001$ ), accounting for 26% of total variance in CA; Sensing capabilities contributed moderately ( $\beta = 0.15$ , 95% CI [0.09, 0.21],  $p < 0.001$ ); while Transforming capabilities showed the smallest but still

significant mediation ( $\beta = 0.13$ , 95% CI [0.08, 0.18],  $p < 0.01$ ). These differential effects suggest that Chinese SMEs' ability to mobilize resources rapidly (seizing) provides more immediate competitive advantages than opportunity detection (sensing) or structural reconfiguration (transforming), possibly reflecting the fast-paced, execution-oriented nature of Chinese digital markets where first-mover advantages erode quickly and implementation speed determines success.

**Moderation Testing (H3)**—Hypothesis 3 proposed that DTR positively moderates the SBMI-DC relationship, such that SBMI's effects on dynamic capabilities are stronger when digital readiness is high. We tested moderation by including an interaction term (DTR  $\times$  SBMI) predicting DC, following standard PLS-SEM procedures (Hair et al., 2019). Results strongly support H3: the interaction term is positive and significant ( $\beta = 0.26$ ,  $t = 5.00$ ,  $p < 0.001$ ), indicating that DTR amplifies SBMI's capability-building effects. The interaction explains an additional  $\Delta R^2 = 0.08$  beyond main effects ( $p < 0.001$ ), representing a small-to-medium effect size ( $f^2 = 0.09$ ) but substantively meaningful given the practical implications for investment sequencing.

To interpret the moderation pattern, we conducted simple slopes analysis at three DTR levels: high (+1 SD above mean), mean, and low (-1 SD below mean). Figure 2 plots these slopes, revealing that SBMI's effect on DC is substantially stronger at high DTR ( $\beta = 0.74$ ,  $p < 0.001$ ) compared to mean DTR ( $\beta = 0.58$ ,  $p < 0.001$ ) and low DTR ( $\beta = 0.42$ ,  $p < 0.001$ ). The difference between high and low DTR slopes ( $\Delta\beta = 0.32$ ) is statistically significant ( $t = 4.82$ ,  $p < 0.001$ ), confirming that digital readiness serves as a critical boundary condition. Practically, this finding implies that Chinese SMEs with mature digital infrastructure, analytics proficiency, and digital culture extract nearly twice the capability-building value from identical SBMI investments compared to digitally nascent peers.

Among DTR subdimensions, data analytics proficiency exhibited the strongest moderating effect ( $\beta = 0.31$ ,  $p < 0.001$ ), suggesting that the ability to transform experimentation into insights through analytics amplifies SBMI's learning potential most powerfully. Technological infrastructure showed moderate moderation ( $\beta = 0.24$ ,  $p < 0.01$ ), while digital culture demonstrated the weakest but still significant effect ( $\beta = 0.18$ ,  $p < 0.05$ ), indicating that all three DTR facets matter but analytics capabilities provide the most potent amplification.

### **Multi-Group Analysis**

To further explore DTR's moderating role and test model robustness across contexts, we conducted multi-group analysis (MGA) comparing high-DTR (top quartile,  $n = 80$ ) and low-DTR (bottom quartile,  $n = 80$ ) subsamples. This approach complements interaction term analysis by revealing whether structural relationships differ fundamentally across digital readiness levels rather than merely varying in magnitude. Table 6 presents path coefficients for each subgroup alongside permutation-based significance tests of between-group differences.

Results reveal striking heterogeneity across DTR levels. In the high-DTR subsample, SBMI strongly predicts DC ( $\beta = 0.68$ ,  $p < 0.001$ ) and CA ( $\beta = 0.51$ ,  $p < 0.001$ ), with DC fully mediating the

SBMI-CA relationship (indirect effect  $\beta = 0.38$ , direct effect becomes non-significant  $\beta = 0.13$ ,  $p = 0.142$ ). This pattern suggests that digitally mature SMEs translate business model innovations almost entirely through capability development, with limited direct effects—capabilities serve as the primary mechanism. In contrast, the low-DTR subsample shows weaker SBMI  $\rightarrow$  DC linkage ( $\beta = 0.38$ ,  $p < 0.01$ ) and smaller indirect effects ( $\beta = 0.19$ ,  $p < 0.05$ ), with stronger direct SBMI  $\rightarrow$  CA paths ( $\beta = 0.42$ ,  $p < 0.001$ ) indicating that less digitally mature firms achieve competitive advantages through SBMI via alternative pathways bypassing systematic capability development.

**Table 6:** Multi-Group Analysis: High vs. Low Digital Transformation Readiness

Path	High DTR (n=80)	Low DTR(n=80)	Difference	t-value	p-value
SBMI $\rightarrow$ DC	0.68***	0.38**	0.3	3.67	< 0.001
DC $\rightarrow$ CA	0.56***	0.50***	0.06	0.71	0.478
SBMI $\rightarrow$ CA (Direct)	0.13	0.42***	-0.29	2.94	0.003
SBMI $\rightarrow$ DC $\rightarrow$ CA (Indirect)	0.38***	0.19*	0.19	2.58	0.01
Total Effect	0.51***	0.61***	-0.1	1.08	0.28
R <sup>2</sup> (CA)	0.64	0.52	—	—	—
R <sup>2</sup> (DC)	0.61	0.28	—	—	—

Note: Standardized path coefficients reported. \*\*\* $p < 0.001$ ; \*\* $p < 0.01$ ; \* $p < 0.05$ . Difference tests based on permutation procedure with 5,000 iterations. High DTR = top quartile ( $DTR \geq 5.8$ ); Low DTR = bottom quartile ( $DTR \leq 3.9$ ).

Industry-specific MGA revealed additional nuances. Technology sector SMEs ( $n = 80$ ) demonstrated the strongest SBMI-DC-CA linkages ( $\beta = 0.62$ ,  $p < 0.001$ ), likely due to rapid innovation cycles and digital-native business models where capability development is intrinsic to operations. Manufacturing sector SMEs ( $n = 128$ ) showed weaker mediation effects ( $\beta = 0.24$ ,  $p < 0.05$ ), potentially constrained by capital-intensive asset bases and regulatory barriers (environmental compliance, safety certifications) that slow capability development. Services sector SMEs ( $n = 112$ ) exhibited moderate mediation ( $\beta = 0.33$ ,  $p < 0.01$ ), falling between technology and manufacturing extremes.

Regional MGA comparing Eastern ( $n = 144$ ), Central ( $n = 112$ ), and Western ( $n = 64$ ) regions revealed expected patterns: Eastern region SMEs with superior digital infrastructure and talent access showed stronger SBMI-DC linkages ( $\beta = 0.64$ ,  $p < 0.001$ ) compared to Central ( $\beta = 0.54$ ,  $p < 0.001$ ) and Western regions ( $\beta = 0.42$ ,  $p < 0.01$ ), confirming that institutional context conditions capability development opportunities. However, DTR's moderating effect remained significant across all regions (interaction  $\beta = 0.22$ - $0.29$ , all  $p < 0.01$ ), suggesting that firm-level digital readiness matters beyond regional infrastructure endowments.

### **Robustness Checks and Additional Analyses**

We conducted several robustness checks to validate findings. First, endogeneity concerns regarding reverse causality (successful firms invest more in SBMI) were addressed through Heckman two-stage procedures. Using firm age, industry, and region as instruments (correlated with SBMI but not CA directly), we calculated inverse Mills ratios and included them as controls—SBMI's effect remained significant ( $\beta = 0.39$ ,  $p < 0.001$ ), suggesting reverse causality does not fully explain findings. Second, alternative model specifications were tested, including positioning DTR as a second-stage moderator (moderating  $DC \rightarrow CA$ ) rather than first-stage—results indicated weaker moderation ( $\beta = 0.12$ ,  $p = 0.068$ ), supporting our theoretical specification that DTR conditions capability development rather than capability deployment.

Third, subsample analyses excluding potential outliers (firms with extreme values on DTR or SBMI) yielded consistent results, confirming findings are not driven by extreme cases. Fourth, alternative competitive advantage measures using single-item global assessments ("Overall, our competitive position is stronger than rivals") correlated strongly with our multi-dimensional CA measure ( $r = 0.78$ ,  $p < 0.001$ ), with structural model results remaining substantively unchanged when substituting measures. Finally, temporal stability was assessed through a follow-up survey with 95 respondents six months post-initial data collection—test-retest correlations for focal constructs ranged from  $r = 0.71$  to  $0.82$ , indicating adequate stability.

## **Discussion**

### **Theoretical Contributions**

This research makes four key theoretical contributions. First, we extend DCV to resource-constrained Chinese SME owner-managers, demonstrating how entrepreneurial firms systematically cultivate dynamic capabilities through SBMI despite lacking financial buffers and specialized departments. Our finding that ecosystem integration exerts the strongest impact on DC development ( $\beta = 0.38$ ) provides empirical evidence that resource-constrained SMEs compensate for internal capability gaps through strategic embedding in digital platform ecosystems.

Second, we illuminate the "black box" linking business model innovation to competitive advantage by demonstrating that seizing capabilities mediate most powerfully (26% of total variance), followed by sensing (19%) and transforming capabilities (17%). This contradicts conventional wisdom suggesting opportunity detection precedes and dominates execution, reflecting the hyper-competitive nature of Chinese digital markets.

Third, we introduce DTR as a first-stage moderator, revealing that identical SBMI investments yield vastly heterogeneous outcomes depending on digital maturity. High-DTR SMEs extract 79% more capability-building value ( $\beta = 0.68$  vs.  $0.38$ ) than low-DTR peers, establishing digital readiness as a critical boundary condition.

Fourth, we demonstrate how Chinese institutional contexts shape the effectiveness of Western-derived strategic management theories. Regional multi-group analysis revealed systematic variation across China's Eastern ( $\beta = 0.64$ ), Central ( $\beta = 0.54$ ), and Western ( $\beta = 0.42$ ) regions, while firm-level DTR remained significant across all regions.

### **Managerial Implications**

Owner-managers should: (1) prioritize ecosystem integration over isolated BMI initiatives; (2) sequence digital investments strategically by establishing digital readiness foundations before pursuing ambitious SBMI; (3) focus capability development on seizing speed through financial flexibility and agile decision-making; (4) proactively engage government support programs reducing capability development costs by 40-60%.

Platform orchestrators should design services explicitly supporting SME capability development rather than merely providing transactional marketplaces. Policymakers should balance investments between digital infrastructure (currently 70% of budgets) and capability development (training, consulting, experimentation subsidies).

### **Limitations and Future Research**

Despite contributions, this study has limitations. Our cross-sectional design cannot definitively establish causal directionality. Future research should employ multi-wave panel designs tracking SMEs over three-to-five-year periods. Self-report measures remain vulnerable to social desirability bias—multi-source designs would enhance construct validity. Our exclusive focus on Chinese SMEs constrains generalizability—cross-national replications would clarify boundary conditions. Our partial mediation finding (DC explains 42% of SBMI  $\rightarrow$  CA linkage) indicates additional mechanisms warrant investigation, including organizational learning routines, relational capital, and brand reputation.

### **Conclusion**

This study resolves critical theoretical ambiguities surrounding mechanisms through which strategic business model innovation enhances competitive advantage among Chinese SME owner-managers. Analysis of 320 Chinese SME owner-managers revealed robust support for all hypotheses: SBMI positively influences competitive advantage, dynamic capabilities mediate this relationship, and digital transformation readiness amplifies SBMI's capability-building effects.

Our findings provide actionable guidance for Chinese SME owner-managers navigating digital transformation imperatives under the 14th Five-Year Plan. We recommend prioritizing ecosystem integration, sequencing digital investments strategically, focusing on seizing speed, and engaging government support programs. For policymakers, findings suggest rebalancing digital economy investments from infrastructure-heavy toward capability-building programs.

As China transitions from manufacturing-based growth toward innovation-driven development, the 90+ million SMEs accounting for 60% of GDP must develop dynamic capabilities enabling

continuous adaptation. Our research demonstrates that strategic business model innovation, when coupled with digital readiness and systematically cultivated capabilities, provides a viable pathway for resource-constrained entrepreneurs to achieve sustainable competitive advantage.

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