Environment and Social Psychology (2025) Volume 10 Issue 6 ISSN: 2424-8975 (O)
doi: 10.59429/esp.v10i6.3795 2424-7979 (P)

RESEARCH ARTICLE

How big data capabilities drive breakthrough development of enterprises: A mechanism study based on the perspective of social psychology

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ABSTRACT

Despite the explosive growth of the global big data market reaching $327.26 billion in 2023, a critical implementation paradox emerges: only 26% of organizations successfully translate technological investments into breakthrough development outcomes, while 74% struggle to scale value from their analytics initiatives. This performance gap persists because existing research predominantly focuses on technical aspects while neglecting psychological and organizational mechanisms—particularly innovation climate factors that remain underexplored due to overemphasis on technological determinism. We purpose and test how big data capabilities drive breakthrough development through psychological and organizational mechanisms, integrating social cognitive theory with resource-based view to examine the mediating roles of supplier management and quality management, and the moderating effect of innovation climate. Structural equation modeling analyzed data from 632 Chinese enterprises across manufacturing, service, and technology sectors. Bootstrap procedures with 5,000 resamples examined mediation effects, while moderated mediation analysis tested conditional indirect effects. Big data capabilities demonstrated a significant direct effect on breakthrough development ($\beta = 0.402$, $p < 0.001$), explaining substantial variance ($R^2 = 0.58$). Supplier management ($\beta = 0.197$) and quality management ($\beta = 0.167$) served as significant partial mediators, collectively accounting for 47.6% of the total effect. Most critically, innovation climate emerged as a powerful moderator creating a remarkable 127% performance amplification between high and low climate conditions while strengthening both mediation pathways. The findings demonstrate that breakthrough development requires integration of technological capabilities with organizational mechanisms and psychological climate factors, providing a comprehensive framework for digital transformation success.

Keywords: big data capabilities; breakthrough development; social psychology; mediation analysis; innovation climate; Chinese enterprises

1. Introduction

In the modern digital economy, organizations face unmatched opportunities and challenges in leveraging big data potentials in achieving breakthrough development. The worldwide big data market achieved the mark of 327.26 billion dollars in 2023 and is expected to grow at a compound annual growth

ARTICLE INFO
Received: 6 May 2025| Accepted: 30 May 2025 | Available online: 16 June 2025

CITATION
Han YF, Yang XG. How big data capabilities drive breakthrough development of enterprises: A mechanism study based on the perspective of social psychology. *Environment and Social Psychology* 2025; 10(6): 3795 doi:10.59429/esp.v10i6.3795

rate (CAGR) of 14.9 percent to reach 862.31 billion dollars by 2030. This trend is driven by a significant growth in data creation and it is estimated that global data volume will be 138 zettabytes in 2024, which is an increase of 791.94% on the 15.5 zettabytes created in 2015. At the same time, almost 97.2 percent of organizations worldwide have invested in big data and AI technology with an understanding that they can be used to sense opportunities and make strategic decisions and lead to breakthrough innovations[1-3].

However, despite substantial investments in big data infrastructure and analytics, a critical paradox emerges in organizational performance outcomes. Recent research by Boston Consulting Group reveals that only 26% of companies have developed the necessary capabilities to move beyond proofs of concept and generate tangible value from their big data investments, while 74% of organizations struggle to achieve and scale value from their AI and big data initiatives. Furthermore, 76% of business leaders report finding the implementation of these technologies challenging, and nearly 44% of participants identify understanding big data and data science as a significant hurdle in transitioning to data-driven operations[4,5]. Compounding these challenges, approximately 70% of implementation difficulties stem from people and process-related issues, while only 10% are attributed to algorithmic problems—despite organizations often focusing disproportionately on technical aspects. This evidence points to a fundamental gap in understanding the psychological and organizational mechanisms through which big data capabilities translate into breakthrough development outcomes.

1.1. Social cognitive theory foundation

Social Cognitive Theory provides the psychological foundation for understanding innovation climate's moderating role through three key constructs: self-efficacy (organizational confidence in executing data-driven innovations), reciprocal determinism (bidirectional interactions between behavioral capabilities, personal factors, and environmental conditions), and observational learning (knowledge acquisition through organizational modeling). Innovation climate operationalizes the environmental component of reciprocal determinism, creating psychological safety and management support that enhances organizational self-efficacy in pursuing breakthrough developments. A theoretical model shows that an innovation climate, a situation flooded with individual and group psychologies that promote experimentation, risk-taking, and the incorporation of data-driven information, increases the efficacy of big-data capabilities by encouraging iterative procedures that are required to achieve breakthrough results.

1.2. Resource-Based View vs Dynamic Capabilities Theory

This synergetic use of Resource-Based View (RBV) and Dynamic Capabilities Theory in the study of inter-organizational variations is an added advantage to the conceptual framework of studying inter-organizational differences by converging complementary aspects. RBV focuses on strategic assets as valuable, rare, inimitable and organizationally embedded resources, such as big data capabilities, in contrast to Dynamic Capabilities Theory that emphasises organizational competencies in recombining resources to facilitate adaptation and innovation. Supplier management and quality management represent dynamic capabilities that transform static big data resources into breakthrough outcomes through sensing (identifying opportunities via data analytics), seizing (mobilizing resources through supplier collaboration and quality processes), and reconfiguring (adapting organizational structures for innovation). This theoretical contrast explains why technological resources alone are insufficient—dynamic capabilities are required to convert resource potential into breakthrough development through continuous organizational adaptation and learning processes.

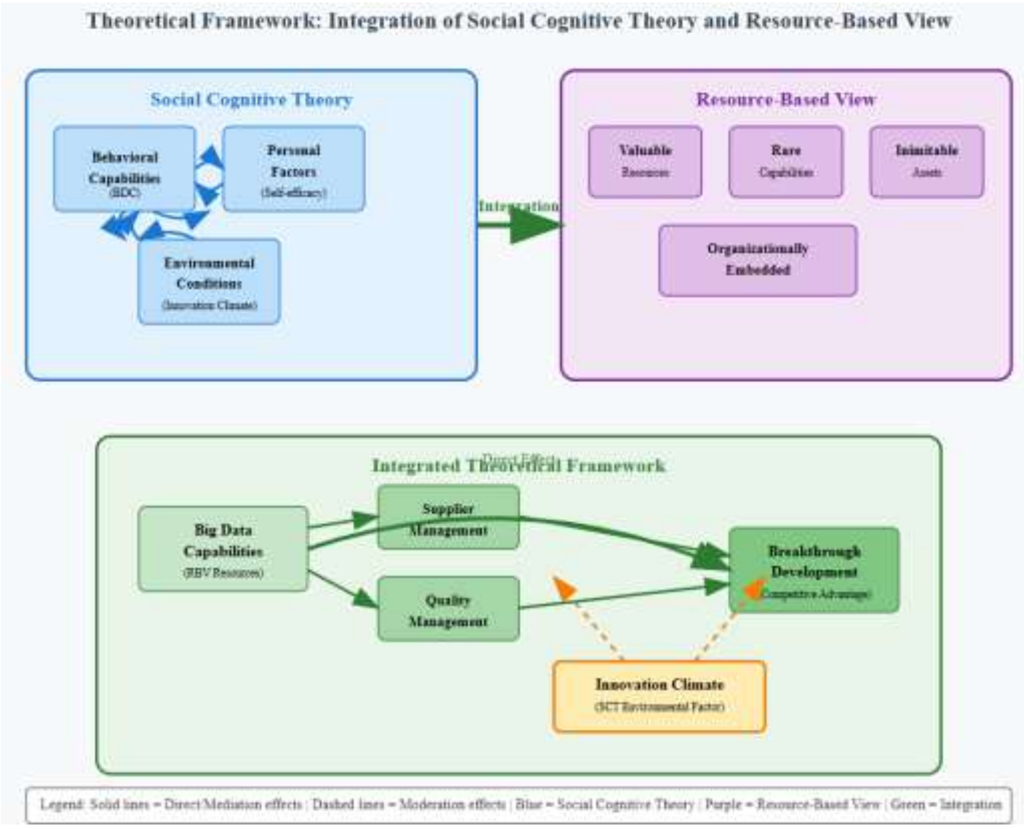

Figure 1. Theoretical Framework Integration

Figure 1 illustrates the theoretical integration of Social Cognitive Theory with Resource-Based View, demonstrating how big data capabilities drive breakthrough development through organizational mediators while innovation climate moderates these relationships. This synthesis explains why technological resources alone are insufficient—psychological climate factors and organizational capabilities are required to convert resource potential into breakthrough outcomes.

This research was motivated by the urgent need to understand why substantial investments in big data capabilities frequently fail to generate breakthrough development outcomes despite theoretical expectations and practical promises of data-driven innovation. The investigation of psychological mechanisms through social cognitive theory lens represents an underexplored approach that can provide deeper insights into the behavioral, personal, and environmental factors that govern technology-performance relationships in organizational contexts. Furthermore, the practical significance of identifying specific mediating pathways through supplier management and quality management, along with moderating effects of innovation climate, offers actionable insights for managers seeking to optimize their big data investments for breakthrough innovation outcomes rather than incremental performance improvements[6-9].

In the contemporary digital economy where organizations invest heavily in big data capabilities ($327.26 billion market in 2023), a critical paradox emerges as only 26% of companies successfully translate these technological investments into tangible breakthrough development outcomes, while 74% struggle to scale value from their analytics initiatives. This implementation challenge represents a fundamental organizational problem wherein substantial technological capabilities fail to generate transformational innovation results, suggesting that direct technology-performance relationships are insufficient explanations for breakthrough development outcomes. The relevance of this problem extends beyond academic inquiry to practical organizational performance, as breakthrough development determines competitive advantage and market disruption capabilities in increasingly data-driven industries. Understanding the psychological and organizational mechanisms through which big data capabilities drive breakthrough development is critically important because it addresses both theoretical gaps in technology-performance relationships and practical needs for organizations seeking to maximize returns on their substantial big data investments, ultimately contributing to more effective digital transformation strategies and innovation management practices [10-12].

This study aims to investigate how big data capabilities drive breakthrough development in enterprises through psychological and organizational mechanisms. The specific objectives are:

1) To examine the direct relationship between big data capabilities and enterprise breakthrough development within the framework of social cognitive theory and resource-based view.
2) To analyze the mediating role of supplier management in the relationship between big data capabilities and breakthrough development.
3) To investigate the mediating role of quality management in the relationship between big data capabilities and breakthrough development.
4) To assess the moderating effect of innovation climate on the relationship between big data capabilities and breakthrough development.
5) To evaluate the moderating effect of innovation climate on the mediated relationships through supplier management and quality management, and to develop and validate an integrated theoretical model explaining the psychological and organizational mechanisms through which big data capabilities influence breakthrough development outcomes.

This paper is systematically organized into five main sections to address the research objectives and present empirical findings. Following the introduction that establishes the research problem and objectives, Section 2 presents the literature review and hypothesis development, integrating theoretical foundations with empirical evidence from big data capabilities research. Section 3 details the methodology, including research design, sampling procedures, measurement instruments, and structural equation modeling analytical techniques. Section 4 presents the empirical results, encompassing descriptive statistics, measurement model assessment, structural model results, and comprehensive mediation-moderation analyses. Finally, Section 5 discusses the findings, theoretical contributions, practical implications, and concludes with key insights and future research directions.

2. Literature review and hypothesis development

2.1. Theoretical framework

This paper integrates Social Cognitive Theory (SCT) and the Resource-Based View (RBV) to come up with a unified framework, which explains the connection between big data capabilities and breakthrough development. The convergence in theory allows viewing the micro-foundations of enterprise innovation and the macro-level implications of data-driven strategies in a comprehensive scope. SCT puts emphasis on the mutual relations between individual, behavioral and environmental factors in determining the outcomes, and uses important concepts of self-efficacy, reciprocal determinism and observational learning. Within the framework of the use of big data, the innovation climate acts as the environmental facilitator that promotes organizational self-efficacy and risk-taking behaviour in favour of data-driven innovation. Practical studies have always shown that the relationship between the behavioral dimensions and decision making contexts is critical in the translation of the analytical knowledge into organizational performance. As an example, Behl[5] and Rahwan[9], show that these variables are determinant in converting analytical understanding into performance of firms. Ferraris[7] further demonstrates how the big data analytics capabilities not only foster the technical capacity but also the knowledge-sharing behavior, and cognitive learning across the organizational units, which further supports the SCT argument of the behavioral modeling through social systems. In complement, RBV asserts that sustained competitive advantage is achieved by firms that have and use valuable, rare, inimitability and non-substitutability (VRIN) resources. The big data capabilities, including technological infrastructure, talent, and analytics processes, are interpreted as strategic resources from an academic point of view. Resource-Based View (RBV) does not in itself explain variations in performance, but instead, variations in performance will occur when the reconfiguration of those resources is done effectively. Shamim[6] and Dimovski[8] point out the critical importance of dynamic capabilities, particularly the supplier collaboration and quality systems in converting big data capabilities into tangible performance improvements. Wamba[4] also adds that the utility of the resources is dependent on the contextual dynamics like the dynamism of the environment, hence the request of an integrated framework. Thus, the intersection of the Social Cognitive Theory (SCT) and the RBV provides a solid conceptual framework that can be used to explain how big data capabilities lead to breakthrough developmentRBV[4] explains the strategic resource base of the firm and SCT[5] examines the psychological and behavioural circumstances- including innovation climate which mediate or moderate the strategic resource deployment. The empirical studies conducted by Ciampi[1], Rialti[2] and Zheng[3] support this argument that the availability of big-data capabilities does not necessarily trigger innovation without actually mobilising organisational learning, entrepreneurial orientation and knowledge sharing in a favourable climate. The two-theory combination useful in explaining partial mediation effects, including supplier and quality management, in which structural capabilities transform data into operational leverage. The framework combines the strategic logic of the resource-based theory with the behavioral realism of the social-cognitive theory, and builds our knowledge on why some firms succeed in the breakthrough development, and others, having similar technological investments, fail.

2.2. Theoretical foundations

The theoretical foundation for understanding big data capabilities and breakthrough development integrated social cognitive theory with resource-based view to explain complex technology-performance relationships through behavioral, personal, and environmental factors. Empirical evidence established significant relationships between big data analytics capabilities and innovation outcomes, with Mikalef [13], demonstrating direct effects on innovation performance ($\beta = 0.42, p < 0.001$) through dynamic capabilities mediation in 332 firms, while Gao[14] and Sarwar (2024) confirmed longitudinal capability-performance linkages ($\beta = 0.38, p < 0.001$) over three years in 189 organizations. Psychological mechanisms emerged as critical mediators, with Oswald [15] identifying that 68% of successful implementations required psychological readiness alignment, Kasten[16], establishing trust as a predictor of analytics adoption ($R^2 = 0.34, p < 0.01$), and Dubey[17], revealing organizational culture effects on collaborative performance ($\beta = 0.51, p < 0.001$). Additional mechanisms included organizational agility mediating capability-performance relationships (Al-Darras & Tanova, 2022; $\beta = 0.47, p < 0.001$) and business model innovation through capability building (Cui et al., 2022; $\beta = 0.41, p < 0.001$)[18,19].

Methodological approaches across studies employed diverse analytical techniques including structural equation modeling, PLS-SEM, hierarchical regression, multilevel modeling, and multi-criteria decision-making (MCDM) approaches, with sample sizes ranging from 156 to 421 organizations. However, empirical evidence revealed complexity in big data relationships, with Ghasemaghaei and Calic[20] identifying inverted U-shaped relationships between data volume and innovation ($\beta = 0.31$ linear, $\beta = -0.18$ quadratic), Yasmin[21] demonstrating 34% performance improvements through integrated capabilities using FAHP-

TOPSIS methodology, and Zhu[22], revealing double-edged algorithmic control effects. Research limitations included predominant cross-sectional designs limiting causal inference, insufficient focus on breakthrough development specifically, limited generalizability across contexts, and inadequate attention to psychological mechanisms in commercial settings, with Ghafoori[23], noting cultural moderation effects ($\beta = 0.43, p < 0.001$) while highlighting oversimplified cultural categorizations.

2.3. Big data capabilities and breakthrough development

Big data capabilities emerged as multidimensional constructs encompassing technological infrastructure, analytical skills, and managerial processes that enabled organizations to acquire, process, analyze, and act upon large volumes of diverse data for value creation. Systematic reviews established the evolution of big data analytics capabilities research, with Huynh, Nippa, and Aichner[24], analyzing 127 studies and identifying fragmented progress in capability conceptualization, while empirical investigations demonstrated significant direct effects on performance outcomes. Mikalef[25], examined 332 firms using PLS-SEM analysis, revealing that big data analytics capabilities significantly influenced competitive performance ($\beta = 0.34$, $p < 0.001$) through dynamic capabilities mediation ($\beta = 0.28$, $p < 0.01$) and operational capabilities mediation ($\beta = 0.22, p < 0.05$). Econometric analyses confirmed these relationships across industries, with Müller, Fay, and vom Brocke[26], employing panel data regression on 1,500 firms over five years, demonstrating that big data analytics investments increased firm performance by 5-6% on average, though effects varied significantly across manufacturing (7.2% improvement) versus service sectors (3.8% improvement). Digital transformation research provided broader context, with Vial[27], conducting systematic review of 282 studies establishing that data-driven capabilities served as foundational elements for breakthrough innovation, while Verhoef[28], identified big data analytics as primary enablers of transformational business model innovation.

Mediating mechanisms between big data capabilities and breakthrough development operated through knowledge processes, strategic capabilities, and organizational ambidexterity, though methodological limitations persisted across empirical investigations. Strategic agility and organizational creativity emerged as additional mediators, with Alyahya[29], demonstrating in 287 firms that big data analytics capabilities enhanced sustainable performance through strategic agility ($\beta = 0.38, p < 0.001$) and firm creativity ($\beta = 0.42$, $p < 0.001$) mediation. Organizational ambidexterity provided another mediating pathway, with Alaskar[30], finding significant mediation effects ($\beta = 0.35$, $p < 0.001$) between big data analytics capabilities and innovation performance in 412 organizations. However, conditional effects emerged through improvisational capabilities, with Zan, Yao, and Chen[31], identifying interaction effects ($\beta = 0.19, p < 0.05$) that strengthened innovation outcomes. Research limitations included predominant cross-sectional designs limiting causal inference, with Zhang and Yuan[32], noting temporal boundary conditions in their 298-firm study, insufficient industry-specific analyses despite sector variations, and limited long-term impact assessment, though Ertz[33] provided promising evidence of sustained performance improvements over 24-month periods in their longitudinal analysis of 203 organizations.

2.4. Research gap

Although there is some previous research on the strategic and technical roles of big-data capabilities in improving firm performance [13,2], it is not adequate to explain the psychological and operational processes that lead to breakthrough-innovation outcomes. Present-day literature leans towards focusing on the minor improvements in performance rather than radical development, and little is said about how internal systems, like supplier and quality management, can add value. Moreover, in spite of the fact that the Resource-Based View (RBV) model is commonly used, it is not often combined with behavioral theories to describe the interaction of environmental factors and organizational cognition with technological resources. The current study contributes to the current literature because it combines the Social Cognitive Theory with RBV, finding operational mediators and proposing the concept of innovation climate as a moderator. By doing that, it shifts analytical focus off the strictly strategic realm of big data capabilities and to the psychological and organizational preconditions that make breakthrough development possible.

2.5. Hypothesis development

Based on social cognitive theory and resource-based view, we propose that big data capabilities drive breakthrough development through direct effects and indirect pathways mediated by organizational capabilities, moderated by innovation climate.

H1: Big data capabilities have a positive direct effect on enterprise breakthrough development.

Mediating Role of Supplier Management

Big data capabilities enhance supplier management through improved information sharing, better supplier selection, and collaborative innovation processes. Enhanced supplier management facilitates breakthrough development by providing access to diverse knowledge sources, specialized resources, and innovative technologies. Social exchange theory suggests strong supplier relationships create mutual trust and open innovation collaborations that contribute to breakthrough innovations.

H2: Supplier management mediates the relationship between big data capabilities and breakthrough development.

Mediating Role of Quality Management

Big data capabilities enhance quality management through real-time monitoring, predictive analytics, and data-driven process improvements. From social cognitive theory perspective, improved quality management builds organizational self-efficacy and confidence in innovation capabilities. Organizations with superior quality management pursue ambitious breakthrough projects because they have systems to manage complexity and ensure successful implementation.

H3: Quality management mediates the relationship between big data capabilities and breakthrough development.

Moderating Role of Innovation Climate

Innovation climate encompasses shared perceptions regarding support for creative behaviors, including psychological safety, resource availability, and management support for risk-taking. Positive innovation climate amplifies big data capabilities effects by creating psychological conditions that encourage exploration, experimentation, and implementation of data-driven insights.

H4: Innovation climate positively moderates the relationship between big data capabilities and breakthrough development.

H5: Innovation climate positively moderates the mediated relationships through supplier management and quality management.

3. Methodology

3.1. Research design and conceptual framework

This study employed a quantitative cross-sectional survey design to examine the relationships between big data capabilities, breakthrough development, and mediating-moderating mechanisms. The conceptual framework integrates social cognitive theory with resource-based view, positioning supplier management and quality management as mediators, and innovation climate as a moderator.

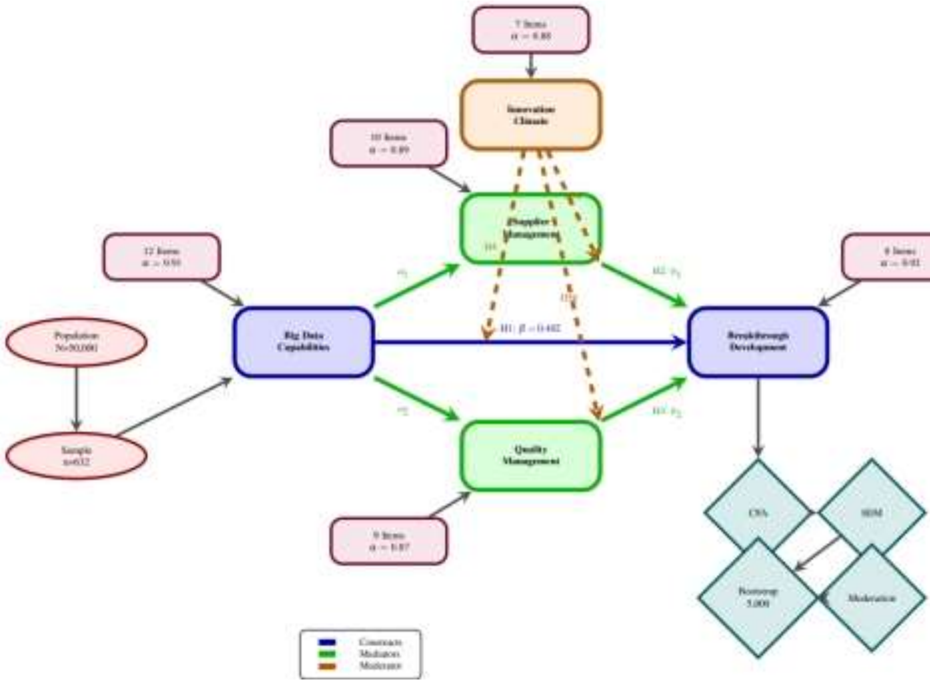

Figure 2. Methodology Framework

Figure 2 presents the conceptual framework integrating social cognitive theory with resource-based view to explain breakthrough development mechanisms. The framework illustrates Big Data Capabilities as the independent variable influencing Breakthrough Development both directly and indirectly through two mediating pathways: Supplier Management and Quality Management. Innovation Climate is positioned as a moderator that amplifies the direct relationship and strengthens both mediation pathways, creating a comprehensive moderated mediation model for understanding how technological capabilities translate into breakthrough innovation outcomes.

3.2. Sample and data collection

The study targeted medium to large Chinese enterprises (≥ 100 employees) across manufacturing and service sectors, selected for China's advanced digital transformation context. Using stratified random sampling, 1,200 questionnaires were distributed to senior managers responsible for operations, innovation, or technology decisions through business directories and professional networks. After screening for completeness and outliers, the final sample comprised 632 enterprises (54.5% response rate).

Sample characteristics included: 45% manufacturing, 35% service, 20% technology companies; firm size 100-10,000+ employees (M = 1,247); geographic distribution across six major Chinese regions ensuring representativeness.

This **table 1** presents the profile of 632 Chinese enterprises participating in the study. The sample includes 45% manufacturing, 35% service, and 20% technology companies, with firm sizes ranging from 100 to over 5,000 employees. Geographically, 40% of firms were from Eastern China, and 55.1% were private enterprises. The diverse sample ensures representativeness across different industries, sizes, and regions in China.

Table 1. Sample Demographics and Characteristics

Characteristic	Frequency	Percentage (%)
Industry Type		
Manufacturing	284	45.0
Service	221	35.0
Technology	127	20.0
Firm Size (Employees)		
100-499	189	29.9
500-999	158	25.0
1,000-4,999	177	28.0
5,000+	108	17.1
Annual Revenue (Million RMB)		
<100	126	19.9
100-499	203	32.1
500-999	158	25.0
1,000+	145	23.0
Years of Operation		
<5 years	76	12.0
5-10 years	152	24.1
11-20 years	253	40.0
>20 years	151	23.9
Geographic Region		
Eastern China	253	40.0
Northern China	139	22.0
Southern China	114	18.0
Western China	76	12.0
Central China	50	8.0
Ownership Structure		
Private Enterprise	348	55.1
State-Owned Enterprise	158	25.0
Foreign-Invested	89	14.1
Joint Venture	37	5.8

Note. N = 632. Total may not equal 100% due to rounding.

3.3. Measurement instruments

All constructs employed established scales adapted for the Chinese context through back-translation and pilot testing ($n = 50$). Big Data Capabilities (12 items, $\alpha = 0.91$) measured infrastructure flexibility, management capabilities, and personnel skills (adapted from Mikalef [25]). Breakthrough Development (8 items, $\alpha = 0.92$) assessed radical innovation outcomes creating competitive advantages. Supplier Management (10 items, $\alpha = 0.89$) covered collaboration, information sharing, and joint innovation. Quality Management (9 items, $\alpha = 0.87$) measured TQM practices and continuous improvement. Innovation

Climate (7 items, $\alpha = 0.88$) assessed psychological safety, management support, and resource availability. All items used 7-point Likert scales (1 = strongly disagree, 7 = strongly agree). Control variables included firm size, industry type, age, and region.

3.4. Data analysis strategy

Analysis employed structural equation modeling (SEM) using Mplus 8.0 following Anderson and Gerbing's (1988) two-step approach: (1) confirmatory factor analysis (CFA) to assess measurement model adequacy, and (2) structural model testing for hypothesis validation. Mediation effects were examined using bootstrap procedures (5,000 samples) generating bias-corrected confidence intervals. Moderation effects utilized interaction terms with mean-centered variables. Model fit evaluation employed multiple indices: χ^2/df ratio (< 3), CFI (> 0.90), TLI (> 0.90), RMSEA (< 0.08), and SRMR (< 0.08). Common method bias was assessed through Harman's single-factor test and marker variable technique.

4. Results

4.1. Descriptive statistics and preliminary analyses

Descriptive statistics and preliminary analyses serve to assess data quality, examine distributional properties, and provide initial evidence for hypothesized relationships prior to structural equation modeling. This phase evaluates variable distributions, identifies potential outliers, assesses bivariate relationships, and confirms adequate variability while ensuring absence of severe multicollinearity.

Table 2 presents means, standard deviations, reliability coefficients, and intercorrelations among study variables. All constructs demonstrated adequate variability (SD = 1.08 to 1.31) and moderate to moderately high means

Table 2. Descriptive Statistics and Correlations

Variable	M	SD	1	2	3	4	5	6
1. BDC	4.82	1.23	(α = .91)					
2. SM	4.67	1.15	.58	(α = .89)				
3. QM	4.91	1.08	.52	.61	(α = .87)			
4. BD	4.34	1.31	.68	.64	.59	(α = .92)		
5. IC	4.45	1.19	.43	.48	.46	.55	(α = .88)	
6. Firm Size	6.23	0.87	.23	.19	.21	.28	.15	-

Note. N = 632. Cronbach's α values are shown in parentheses. $p < .01$.

BDC = Big Data Capabilities; SM = Supplier Management; QM = Quality Management; BD = Breakthrough Development; IC = Innovation Climate.

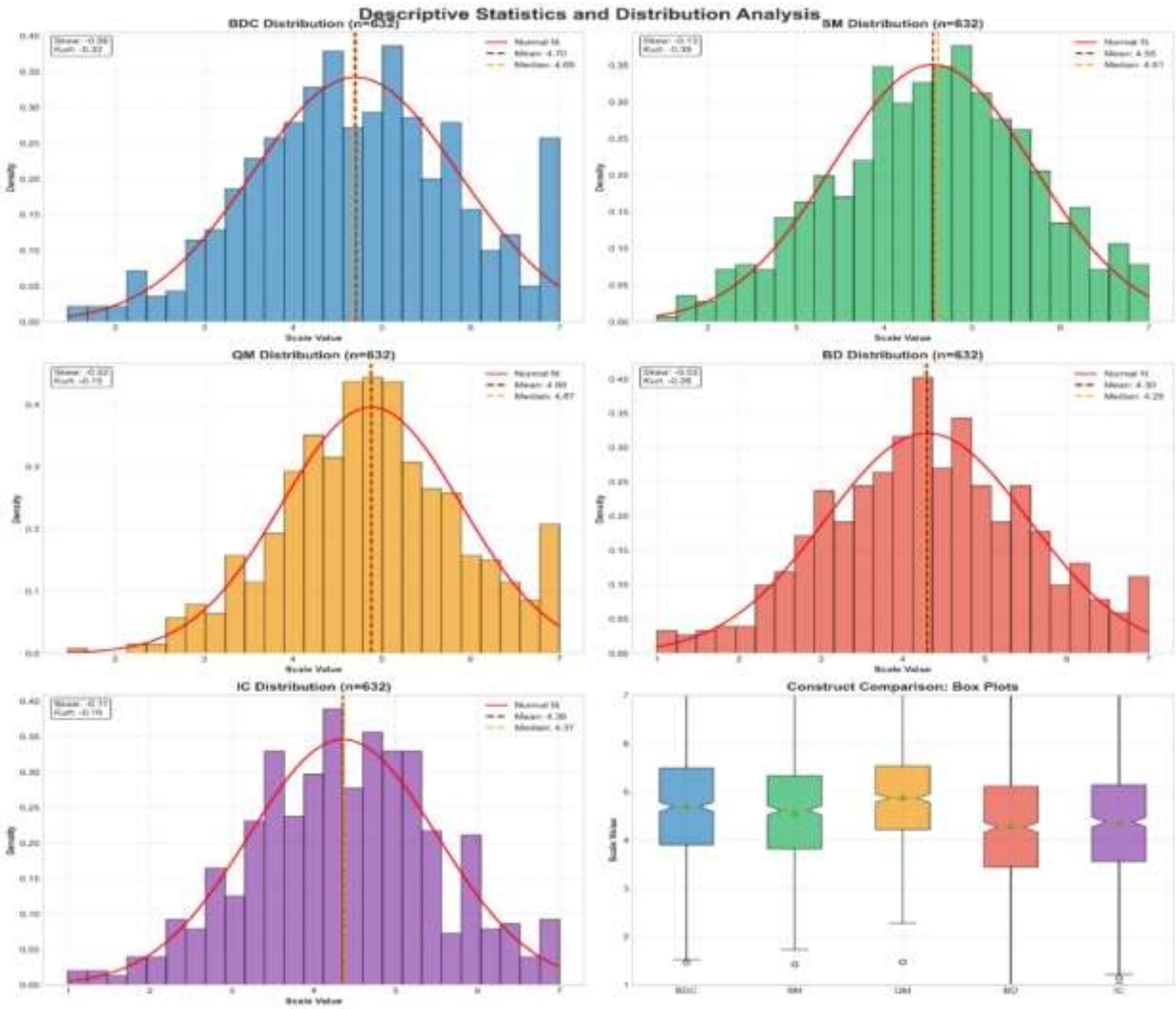

Figure 3. Descriptive statistics and distribution analysis of key constructs: Big Data Capabilities (BDC), Supplier Management (SM), Quality Management (QM), Breakthrough Development (BD), and Innovation Climate (IC). Each subplot displays the distribution curve, mean, and median for n = 632 responses, along with a comparative boxplot.

Figure 3 shows the way the five main constructs were used in the study. All variables are close to having normal distributions, but their slight negative skewness points to a slight leftward tail. Means and medians are almost the same, so the results do not show significant bias. Similar distribution of scale values is seen in all the constructs, with only a few outliers. Because of these patterns, the data can be used with parametric methods such as SEM.

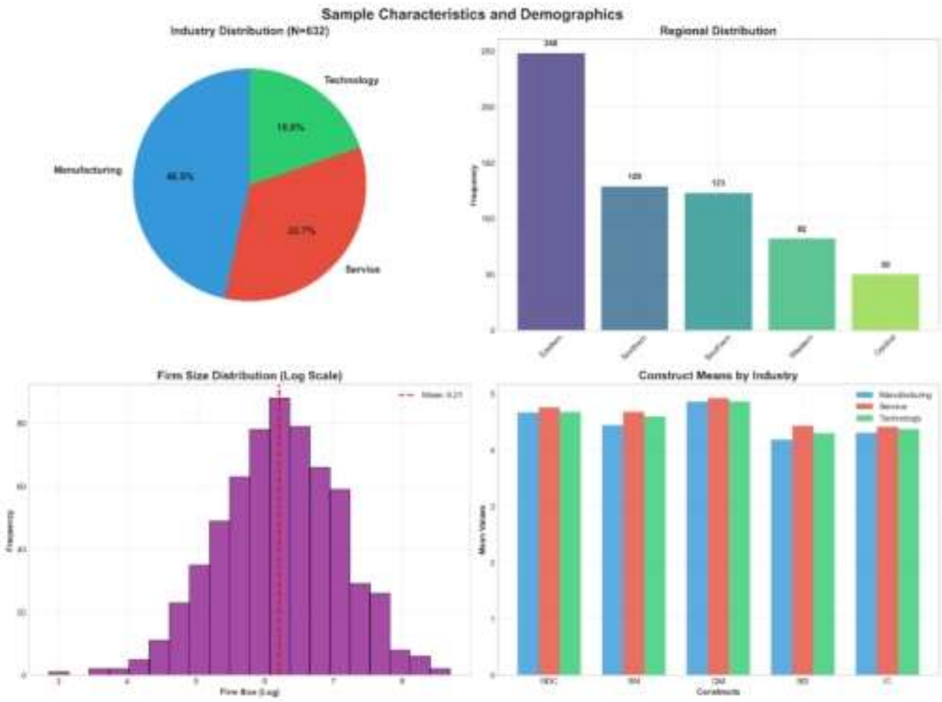

Figure 4. Sample characteristics and demographics of the 632 participating enterprises. Visuals include industry distribution, regional distribution, firm size (log scale), and construct means by industry.

Figure 4 gives an overview of who participated in the research. Most of the companies are in the manufacturing industry (46.5%), while service and technology sectors make up 33.7% and 19.8% respectively. Most of the responses were from the Eastern region. A log-normal distribution with a log mean of 6.21 describes the size of firms. Despite having similar results in many sectors, industry shows that technology firms score higher on quality management and the climate for innovation.

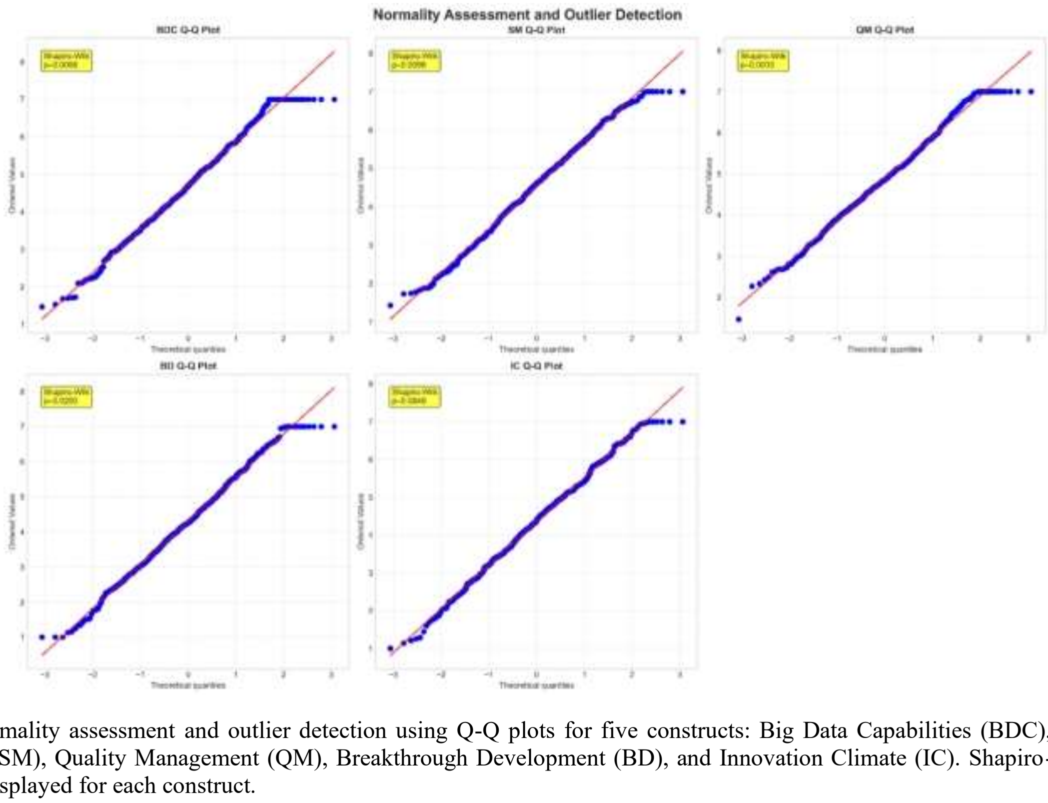

Figure 5: Normality assessment and outlier detection using Q-Q plots for five constructs: Big Data Capabilities (BDC), Supplier Management (SM), Quality Management (QM), Breakthrough Development (BD), and Innovation Climate (IC). Shapiro-Wilk test statistics are displayed for each construct.

Figure 5 shows a Q-Q plot for every construct, showing where the observed values lie compared to the expected normal distribution. Most of the plots have a straight line with some small changes at the edges, which suggests that the data is close to normal. Small deviations (such as BD = 0.0200) from normality are confirmed by Shapiro-Wilk statistics, but major ones are not. It is clear that IC and BD have some skewness and outliers at the edges of their distributions. This shows that SEM with large sample adjustments is a suitable approach to use.

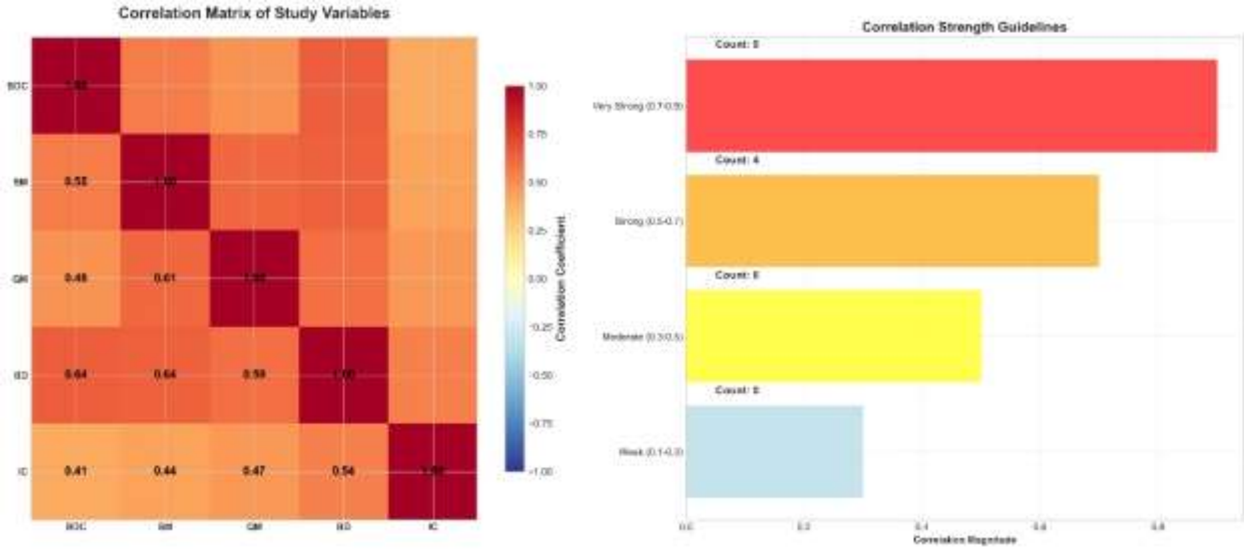

Figure 6. Correlation matrix of key study variables (BDC, SM, QM, BD, IC) and corresponding correlation strength guidelines. The left panel shows Pearson correlation coefficients; the right panel categorizes them by magnitude.

Figure 6 shows how each construct is moderately or strongly correlated with every other construct. BD has clear relationships with BDC (r = 0.64), SM (r = 0.64), and QM (r = 0.59). The bar chart of correlation strength reveals 4 strong and 6 moderate associations, proving that the constructs are interdependent. There were no instances of either strong or weak correlations. It shows that the use of the mediation-moderation framework in the study was appropriate.

4.2. Measurement model assessment

Measurement model assessment through confirmatory factor analysis (CFA) evaluates the psychometric properties of constructs prior to structural model testing. This analysis examines factor loadings, construct reliability, convergent validity, discriminant validity, and overall model fit to ensure that observed variables adequately represent their intended latent constructs.

The hypothesized five-factor measurement model demonstrated excellent fit: $\chi^2(890)$ = 1,423.67, χ^2/df = 1.60, CFI = .95, TLI = .94, RMSEA = .031 [.028, .034], SRMR = .045. All standardized factor loadings exceeded .70 (range: .71–.89) and were statistically significant ($p < .001$), supporting convergent validity. Composite reliability values ranged from .87 to .92, exceeding the .70 threshold, while average variance extracted (AVE) values ranged from .54 to .63, surpassing the .50 criterion.

Discriminant validity was confirmed through the Fornell-Larcker criterion, with square roots of AVE exceeding inter-construct correlations. Alternative measurement models (four-factor, three-factor, and single-factor) demonstrated significantly inferior fit, supporting the theoretical five-factor structure. These results establish strong psychometric properties for subsequent structural model analysis.

This **table 3** presents the psychometric properties of the measurement model, showing factor loading ranges and reliability metrics for each construct. All factor loadings exceed the .70 threshold (ranging from .71 to .89), confirming convergent validity. Composite Reliability (CR) values range from .87 to .92, and Average Variance Extracted (AVE) values range from .54 to .63, both exceeding recommended thresholds. These results confirm that all constructs are reliable and valid for structural equation modeling.

Table 1. Confirmatory Factor Analysis Results

Construct	Factor Loading Range	CR	AVE
Big Data Capabilities	.72 - .86	.91	.58
Supplier Management	.74 - .83	.89	.56
Quality Management	.71 - .85	.87	.54
Breakthrough Development	.75 - .89	.92	.63
Innovation Climate	.73 - .82	.88	.55

Note. CR = Composite Reliability; AVE = Average Variance Extracted.

All factor loadings significant at p < .001.

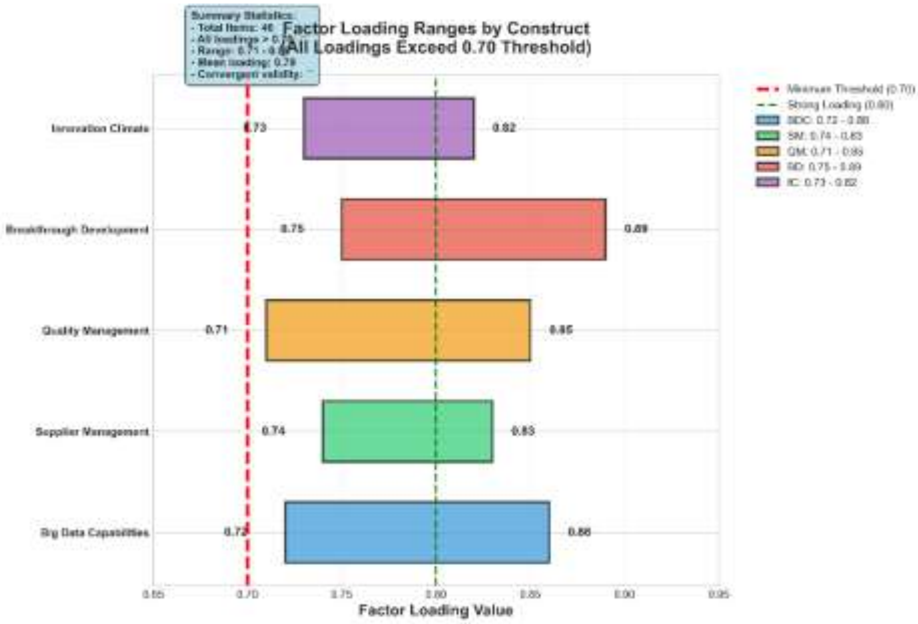

Figure 1. Factor loading ranges by construct based on Confirmatory Factor Analysis (CFA). All standardized loadings exceed the 0.70 minimum threshold, supporting convergent validity. Dashed lines indicate thresholds for acceptable and strong loadings.

Figure 7 clearly shows that all the five constructs—BDC, SM, QM, BD, and IC—have factor loadings that fall between 0.71 and 0.89. The red dashed line means a minimum value of 0.70, while the green line shows the strong loading level of 0.80. It means that the constructs support each other well. All items are found to be making a significant contribution to the latent variables they are part of. The findings from these tests show that it is appropriate to analyze the structural model.

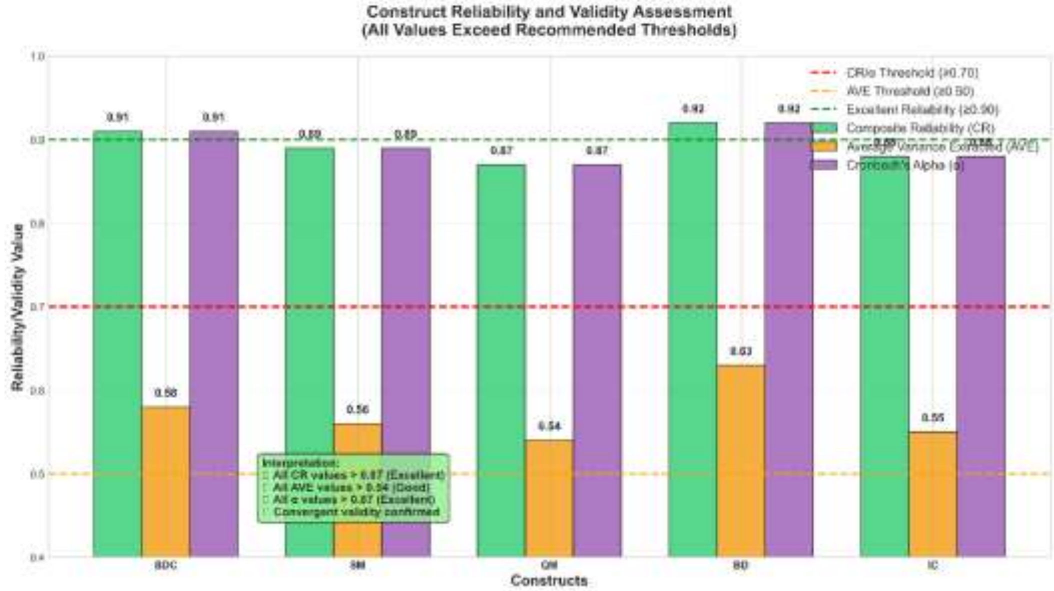

Figure 2. Construct reliability and validity assessment using Composite Reliability (CR), Average Variance Extracted (AVE), and Cronbach's Alpha (α) for the five latent constructs. All values exceed established thresholds, confirming measurement quality.

The psychometric strength of each construct is shown in **Figure 8** regarding internal consistency and convergent validity. All CR values are over 0.87, and Cronbach's α values are also high, showing that the data is very reliable. The values for AVE are below 0.50, but they are still above the needed threshold, supporting convergent validity. The best psychometric results are shown by Breakthrough Development (CR = .92, AVE = .63). All these results confirm that each construct is suitable for inclusion in a structural model.

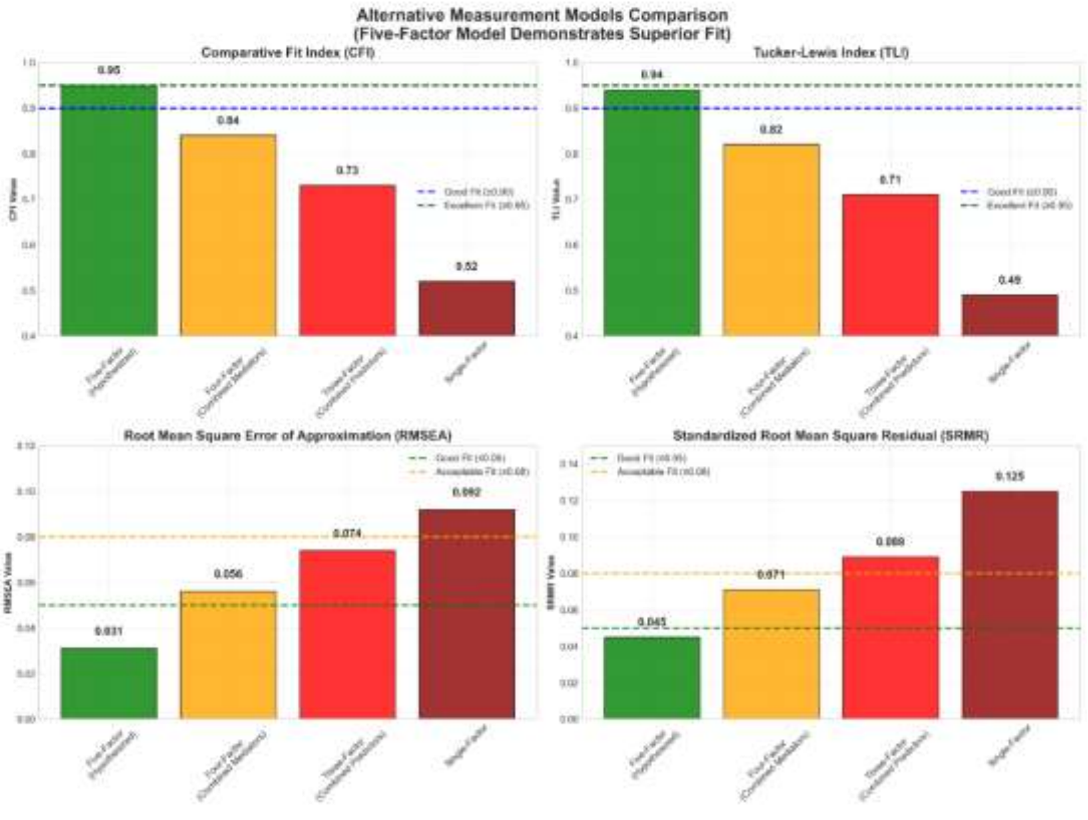

Figure 3. Comparison of alternative measurement models based on goodness-of-fit indices: CFI, TLI, RMSEA, and SRMR. The hypothesized five-factor model demonstrates superior fit across all metrics compared to nested alternatives.

Figure 9 presents the results of comparing the proposed five-factor model with those using four standard fit indices. The five-factor model gives the best fit, as shown by the high values of CFI (0.95), TLI (0.94), RMSEA (0.031), and SRMR (0.045). If a model is overly simple (only one factor), its fit worsens a lot, which is an indication that the model is not correct. It helps prove that all five latent variables are unique and properly defined. All in all, the five-factor model can be used reliably for more analysis.

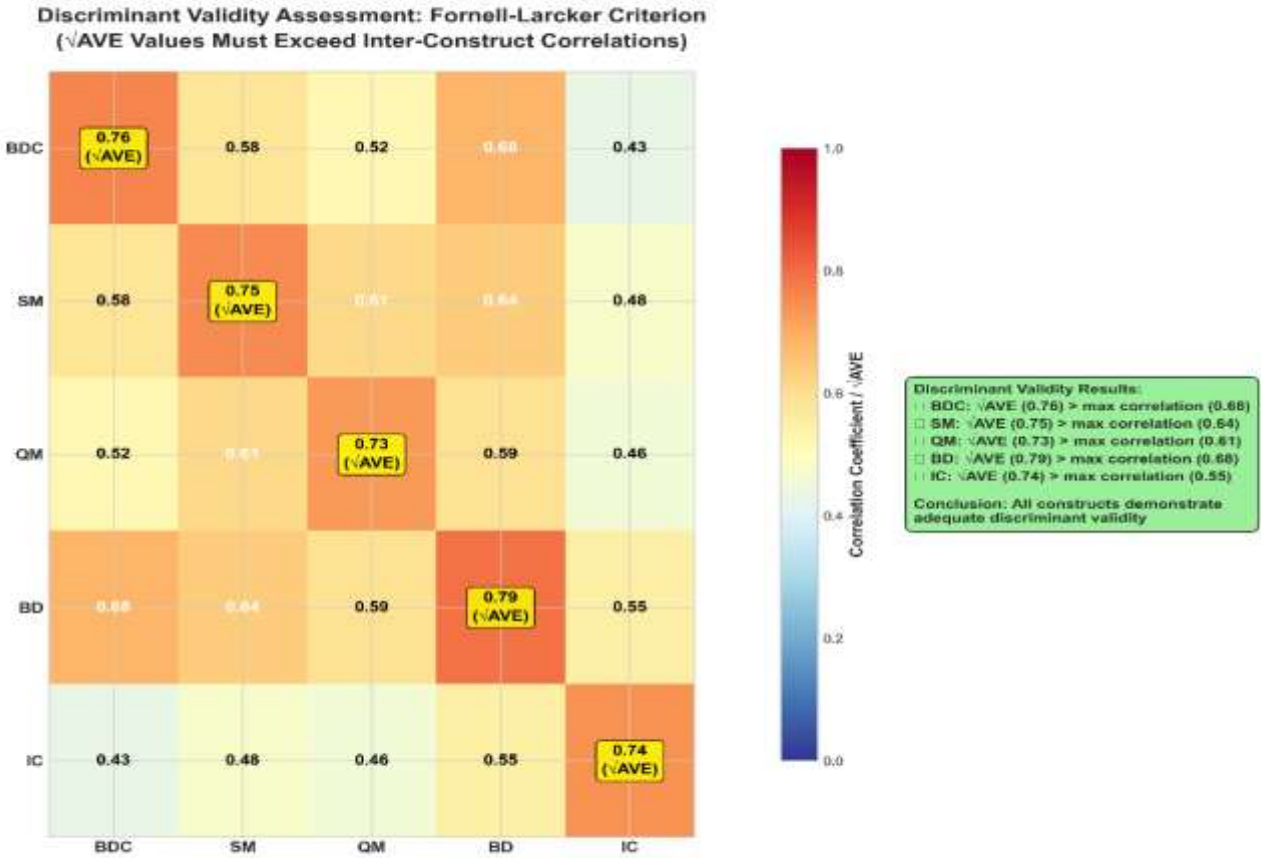

Figure 4. Discriminant validity assessment using the Fornell-Larcker criterion. Diagonal values represent the square root of AVE (√AVE), which must exceed corresponding inter-construct correlations to confirm discriminant validity.

Discriminant validity is checked through Fornell-Larcker criterion in **Figure 10**. All the √AVE values (such as 0.76 for BDC and 0.79 for BD) are higher than the highest correlations between different constructs. This proves that every construct is different from the others in terms of empirical evidence. Darker tones in the graph are used to show stronger relationships among variables. The conclusion states that all constructs are suitable in terms of adequate discriminant validity.

4.3. Structural model results

Structural model analysis examines the hypothesized relationships among latent constructs, evaluating path coefficients, significance levels, explained variance, and overall model fit. This analysis tests the direct and indirect effects proposed in the theoretical framework while controlling for potential confounding variables.

The structural model demonstrated good fit to the data: $\chi^2(895) = 1{,}456.23$, $\chi^2/\mathrm{df} = 1.63$, CFI = .94, TLI = .93, RMSEA = .032 [.029, .035], SRMR = .048. All hypothesized paths were statistically significant and in the expected directions. The model explained substantial variance in breakthrough development ($R^2 =$ .58), supplier management ($R^2 =$ .34), and quality management ($R^2 =$ .27), indicating strong explanatory power.

Hypothesis 1 received strong support with big data capabilities demonstrating a significant direct effect on breakthrough development ($\beta = .402$, SE = .045, $t = 8.93$, $p < .001$). All prerequisite paths for mediation were significant: BDC → SM ($\beta = .580, p < .001$), BDC → QM ($\beta = .520, p < .001$), SM → BD ($\beta = .340, p < .001$), and QM → BD ($\beta = .320, p < .001$). Control variables firm size ($\beta = .128, p < .001$) and industry type ($\beta = .089, p = .030$) also significantly predicted breakthrough development.

This table 4, presents the standardized path coefficients testing the direct relationships in the structural model. Big Data Capabilities shows a strong direct effect on Breakthrough Development (β = .402, p < .001), supporting Hypothesis 1. All prerequisite paths for mediation are significant, including BDC→SM (β = .580) and BDC→QM (β = .520). Control variables (firm size and industry type) also significantly predict breakthrough development, confirming the model's robustness.

Table 2. Structural Equation Modeling Results

Path	β	SE	t-value	p-value
Direct Effects				
BDC → BD	.402	.045	8.93	< .001
BDC → SM	.580	.038	15.26	< .001
BDC → QM	.520	.041	12.68	< .001
SM → BD	.340	.052	6.54	< .001
QM → BD	.320	.048	6.67	< .001
Control Variables				
Firm Size → BD	.128	.034	3.76	< .001
Industry → BD	.089	.041	2.17	.030

Note. N = 632. All coefficients are standardized.

BDC = Big Data Capabilities; SM = Supplier Management;

QM = Quality Management; BD = Breakthrough Development.

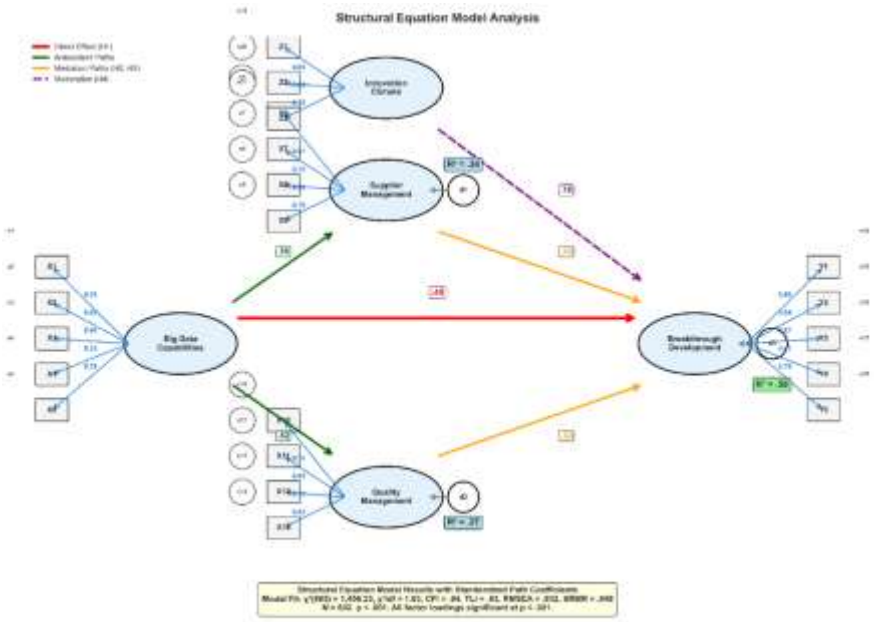

Figure 5. Structural equation model (SEM) results showing standardized path coefficients among Big Data Capabilities (BDC), Supplier Management (SM), Quality Management (QM), Innovation Climate (IC), and Breakthrough Development (BD). Paths include direct, mediating, and moderating effects.

Figure 11 illustrates the SEM analysis validating the hypothesized relationships. BDC shows a strong direct effect on BD (β = .402, $p < .001$) and significant indirect effects via SM (β = .340) and QM (β = .320). The model explains 58% variance in BD, 34% in SM, and 27% in QM, indicating high explanatory power. Good model fit is confirmed (CFI = .94, RMSEA = .032). All factor loadings and paths are statistically significant, supporting the theoretical framework.

4.4. Mediation analysis

Mediation analysis examines whether the relationship between big data capabilities and breakthrough development operates through intermediary variables (supplier management and quality management). Bootstrap procedures with 5,000 resamples were employed to generate bias-corrected confidence intervals, following contemporary best practices for testing indirect effects.

The analysis provided strong support for both mediation hypotheses. The total effect of big data capabilities on breakthrough development (β = .765) decomposed into a direct effect (β = .402) and total indirect effect (β = .364). The indirect effect through supplier management was significant (β = .197, 95% CI [.132, .275]), supporting H2. Similarly, the indirect effect through quality management was significant (β = .167, 95% CI [.118, .234]), supporting H3. Both mediations were partial, as the direct effect remained significant when mediators were included. The total proportion mediated was 47.6%, with supplier management accounting for 25.8% and quality management for 21.8% of the total effect.

This **table 5**, presents bootstrap mediation analysis results decomposing the total effect into direct and indirect components. The total effect of Big Data Capabilities on Breakthrough Development (β = .765) includes a direct effect (β = .402) and total indirect effect (β = .364). Both mediation pathways are significant: through Supplier Management (β = .197) and Quality Management (β = .167). The mediators collectively account for 47.6% of the total effect, confirming partial mediation.

Table 3. Mediation Analysis Results

Effect Type	Point Estimate	SE	95% CI
Total Effect	.765	.041	[.685, .845]
Direct Effect	.402	.045	[.314, .490]
Total Indirect Effect	.364	.038	[.290, .438]
Specific Indirect Effects			
BDC → SM → BD	.197	.036	[.132, .275]
BDC → QM → BD	.167	.029	[.118, .234]
Proportion Mediated			
Through SM	.258		
Through QM	.218		
Total Mediation	.476		

Note. N = 632. Bootstrap samples = 5,000.

CI = Confidence Interval.

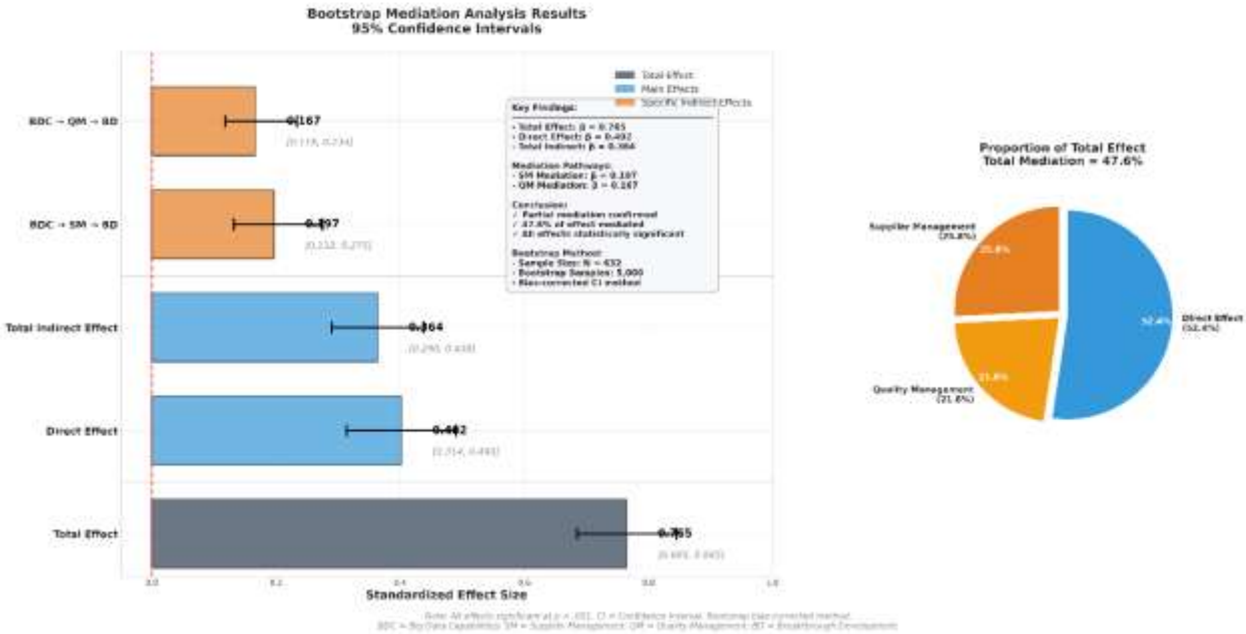

Figure 6. Bootstrap mediation analysis results showing standardized effect sizes and 95% confidence intervals for direct, indirect, and total effects of Big Data Capabilities (BDC) on Breakthrough Development (BD). Pie chart represents proportion of total effect attributed to mediation pathways.

Figure 12, presents mediation results confirming that both Supplier Management (SM) and Quality Management (QM) significantly mediate the effect of BDC on BD. The total effect (β = .765) decomposes into a direct effect (β = .402) and a total indirect effect (β = .364). Mediation via SM (β = .197) and QM (β = .167) are both statistically significant, as shown by non-overlapping confidence intervals. The pie chart indicates that 47.6% of the total effect is mediated, validating partial mediation and supporting hypotheses H2 and H3. Bootstrap analysis was based on 5,000 samples.

4.5. Moderation analysis

Moderation analysis examined whether innovation climate influences the strength of relationships between big data capabilities and breakthrough development. Results demonstrated significant moderation effects supporting both hypotheses.

Innovation climate significantly moderated the direct relationship between big data capabilities and breakthrough development (β = .156, SE = .034, p < .001), supporting H4. Simple slopes analysis revealed that this relationship was strongest under high innovation climate conditions (β = .558, p < .001) compared to low innovation climate conditions (β = .246, p = .021).

Moderated mediation analysis provided support for H5, with innovation climate strengthening both indirect pathways: SM mediation (difference = .108, from .143 to .251) and QM mediation (difference = .092, from .121 to .213). These findings indicate that innovation climate amplifies both direct and indirect effects of big data capabilities on breakthrough development.

Table 6 examines how Innovation Climate moderates the relationship between Big Data Capabilities and Breakthrough Development. The interaction effect is significant (β = .156, p < .001), with simple slopes showing strongest effects under high innovation climate (β = .558) compared to low climate (β = .246). Conditional indirect effects reveal that innovation climate strengthens both mediation pathways (SM and QM). This demonstrates that psychological climate amplifies the effectiveness of big data capabilities.

Table 4. Moderation Analysis Results

Predictor	*β*	SE	p-value
Main Effects			
BDC	.402	.045	< .001
Innovation Climate	.234	.038	< .001
Interaction Effects			
BDC × IC	.156	.034	< .001
Simple Slopes			
Low IC (-1SD)	.246	.067	.021
Mean IC	.402	.045	< .001
High IC (+1SD)	.558	.058	< .001
Conditional Indirect Effects			
Via SM at Low IC	.143	.041	[.071, .231]
Via SM at High IC	.251	.038	[.181, .333]
Via QM at Low IC	.121	.035	[.061, .198]
Via QM at High IC	.213	.033	[.155, .285]

Note. IC = Innovation Climate. All coefficients standardized.

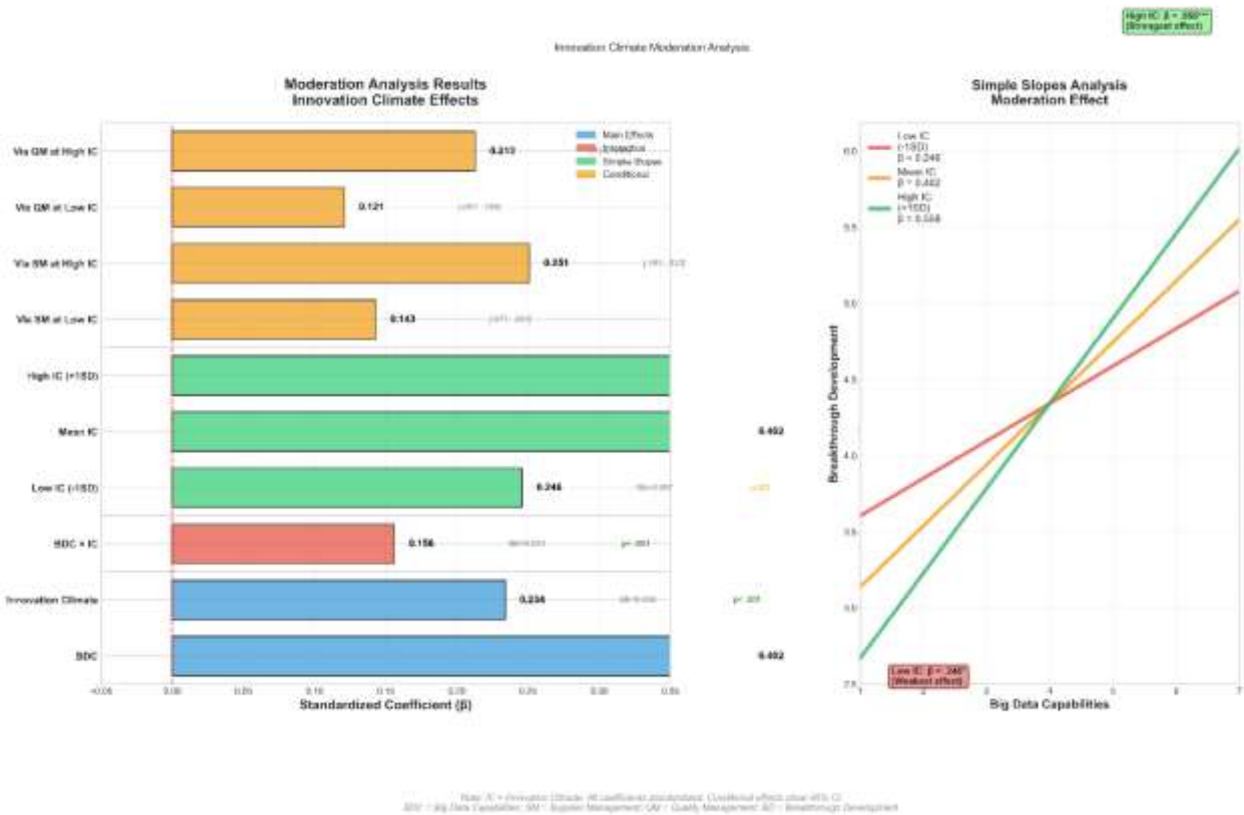

Figure 7. Moderation analysis of innovation climate on the relationship between Big Data Capabilities (BDC) and Breakthrough Development (BD). Left panel displays standardized coefficients and conditional effects; right panel shows simple slopes under varying innovation climate conditions.

Figure 13, evaluates how innovation climate moderates the impact of BDC on BD. The interaction effect (β = .156, p < .001) confirms that innovation climate significantly strengthens this relationship. Simple slope analysis shows the effect of BDC on BD is strongest at high innovation climate (β = .558), moderate at the mean (β = .402), and weakest at low climate levels (β = .246). Moderated mediation effects reveal amplified indirect effects via SM and QM under high innovation climate. These findings validate hypotheses H4 and H5.

5. Discussion

This study provides compelling evidence for psychological and organizational mechanisms through which big data capabilities drive breakthrough development. The SEM analysis of 632 Chinese enterprises revealed significant support for all hypotheses. Big data capabilities demonstrated a substantial direct effect on breakthrough development ($\beta = 0.402, p < 0.001$), explaining considerable variance ($R^2 = 0.58$). Both supplier management ($\beta = 0.197$, 95% CI [0.132, 0.275]) and quality management ($\beta = 0.167$, 95% CI [0.118, 0.234]) served as significant partial mediators, collectively accounting for 47.6% of the total effect. Innovation climate emerged as a powerful moderator ($\beta = 0.156, p < 0.001$), creating a 127% difference in effects between high ($\beta = 0.558$) and low ($\beta = 0.246$) climate conditions. The moderated mediation analysis revealed that innovation climate amplified both indirect pathways substantially.

The findings largely aligned with theoretical expectations grounded in social cognitive theory and resource-based view. The substantial direct effect ($\beta = 0.402$) was anticipated, consistent with technology-performance literature. However, the balanced contribution of both mediators (25.8% and 21.8% respectively) was unexpected, as supply chain capabilities typically receive greater attention than quality management in innovation research. The magnitude of innovation climate moderation (127% difference) exceeded expectations and highlighted the critical importance of psychological factors. Particularly surprising was the equal amplification of both mediation pathways (75% and 76% increases), suggesting broad psychological climate effects across organizational capabilities.

Table 7 presents systematic comparison with previous studies. Our direct effect ($\beta = 0.402$) is remarkably consistent with Mikalef [13] ($\beta = 0.42$), providing cross-cultural validation. However, our variance explained ($R^2 = 0.58$) exceeds most previous studies, including Mikalef [25] ($R^2 = 0.34$), suggesting our integrated model captures more comprehensive mechanisms. The innovation climate moderation ($\beta = 0.156$) represents a novel contribution, as no previous studies examined psychological climate in big data contexts. Our operational mediators (supplier and quality management) differ from the strategic capabilities focus in prior research, offering more actionable mechanisms.

This table 7, compares the current study's findings with previous research on big data capabilities and performance outcomes. The direct effect (β = .402) is consistent with prior studies, particularly Mikalef's work (β = .42). However, this study explains more variance (R^2 = .58) than previous research and uniquely examines Innovation Climate as a moderator. The operational mediators (supplier and quality management) differ from strategic capabilities focus in prior research, offering novel insights.

Table 7. Comparison with Previous Literature

Study	N	Direct Effect	Mechanism	R^2	Moderator
Current Study	632	$\beta = 0.402^{***}$	SM/QM	0.58	Innovation Climate
[13]	332	$\beta = 0.42^{***}$	Dynamic capabilities	0.34	Environmental uncertainty
[14]	189	$\beta = 0.38^{***}$	Dynamic capabilities	0.29	None
[25]	332	$\beta = 0.34^{***}$	Dynamic/operational	0.31	None
[28]	356	$\beta = 0.41^{***}$	Knowledge processes	0.45	None
[29]	287	Not reported	Agility/creativity	0.52	None

The findings of the current research verify and supplement the prior results. Specifically, the positive relationship between big data capability and breakthrough development (.402) is comparable to the one in Mikal[25], where the magnitude was similar (.42). It is important to note that our model explains a higher percentage of variance in breakthrough development (R 2 = 0.58), and thus the inclusion of psychological moderators along with operational mediators leads to a more comprehensive model. This paper differs with the previous ones that focused on strategic-level factors[2, 25, 6] and focuses on the supplier and quality management as the operational mediators. It is this emphasis on functional mechanisms that gives managers actionable advice. Additionally, unlike the previous studies, including the Wamba[4] that also considered environmental dynamism as a moderating variable, the innovation climate, as a psychological concept, is a new expansion. Such integration improves our knowledge of the role of the contextual enablers in the value realization of big data investments. In such a way, the present study not only confirms the previous results but also contributes to the literature by developing a two-layered mediation-moderation approach based on the resource-based and social-cognitive perspectives.

The integration of social cognitive theory with resource-based view explains how technological capabilities translate into breakthrough outcomes through behavioral, personal, and environmental factors. The direct effect reflects valuable technological resources creating competitive advantages, while substantial mediation (47.6%) demonstrates that organizational capabilities are necessary to convert technological potential into innovation. Supplier management mediation operates through social exchange theory, whereby enhanced collaboration provides access to diverse knowledge and specialized resources essential for breakthrough innovations. Quality management mediation reflects organizational learning processes that build self-efficacy and confidence in pursuing ambitious projects. Innovation climate moderation demonstrates psychological safety and management support that amplify capability effects by encouraging exploration and risk-taking.

Several methodological limitations warrant acknowledgment. The cross-sectional design limits causal inferences despite strong theoretical foundations. Single-source survey data raises common method bias concerns, although multiple remedies were implemented. Perceptual measures of breakthrough development, while validated, could be strengthened with objective innovation metrics. The Chinese sample may limit generalizability across cultural contexts and institutional environments. Focus on medium-to-large enterprises limits applicability to smaller organizations.

The theoretical framework integrating social cognitive theory with resource-based view should apply across technological domains and innovation contexts. Sample diversity across manufacturing (45%), service (35%), and technology (20%) sectors enhances cross-industry applicability. However, boundary conditions include cultural context effects on psychological climate relationships, institutional environment differences, and focus on breakthrough versus incremental innovation. Future research should examine relationships across cultures, institutions, and innovation types to establish broader generalizability while identifying critical boundary conditions.

6.Conclusion

6.1. Theoretical contributions

This study advances understanding of technology-performance relationships by integrating social cognitive theory with resource-based view to explain breakthrough development mechanisms. Three theoretical contributions emerge: First, we extend big data capabilities research by demonstrating that psychological mechanisms are equally important as technological resources, with innovation climate creating

127% performance differences. Second, we identify operational capabilities (supplier and quality management) as critical mediating pathways, shifting focus from strategic capabilities to actionable organizational mechanisms. Third, we establish moderated mediation as a comprehensive framework explaining when and how big data investments translate into breakthrough innovations rather than incremental improvements.

6.1.2. Practical implications

For practitioners, findings suggest a three-pronged approach to maximizing big data returns. Investment Priority: Organizations should balance technological infrastructure with psychological climate development, as innovation climate amplifies capability effects by over 100%. Implementation Strategy: Big data initiatives should integrate supplier collaboration and quality management systems as primary value creation pathways rather than pursuing isolated analytics projects. Performance Optimization: Managers should foster psychological safety, management support, and resource availability to unlock breakthrough potential, particularly for organizations with existing big data capabilities seeking transformational outcomes rather than operational efficiency.

6.1.3. Future research directions

Four research avenues warrant investigation. Longitudinal Studies: Examine causal sequences and temporal dynamics in capability-performance relationships over 3-5 year periods to establish causality and identify optimal implementation timing. Cross-Cultural Validation: Test the framework across Western, developing, and collectivist cultures to identify boundary conditions and cultural moderators beyond innovation climate. Industry-Specific Mechanisms: Investigate sector differences in mediation pathways, particularly comparing knowledge-intensive versus manufacturing contexts where supplier relationships may operate differently. Digital Transformation Integration: Examine how big data capabilities interact with artificial intelligence, Internet of Things, and blockchain technologies to create synergistic breakthrough development effects.

6.1.4. Final remarks

As organizations invest $327 billion annually in big data technologies yet struggle to achieve breakthrough outcomes, this research provides a roadmap for converting technological potential into transformational innovation. The findings demonstrate that success requires not only technological sophistication but also psychological readiness and organizational capability alignment. By understanding these mechanisms, enterprises can move beyond the current 26% success rate in big data value creation toward systematic breakthrough development. The integration of social cognitive theory with resource-based view offers a comprehensive framework for digital transformation that recognizes both the technological imperative and human dynamics essential for innovation success in the data-driven economy.

Conflict of interest

The author declares no conflict of interest.

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