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Deconstructing Supply Chain Resilience under Big Data Analytics Capability: Exploring the Mediating and Moderating Roles of Agility and Top Management Participation

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ABSTRACT

Although big data analytics capability is widely recognized as significantly impacting supply chain resilience, its internal mechanisms remain unclear. This paper explores three key dimensions of big data analytics capability: tangible resources, human skills, and intangible resources, and examines their relationships with supply chain resilience. It investigates the mediating role of agility and the moderating role of top management participation. The findings demonstrate that agility mediates the relationship between tangible resources, human skills, and intangible resources with supply chain resilience. Meanwhile, top management participation moderates only the impact of intangible resources on supply chain resilience.

Keywords: Big data analytics capabilities, supply chain resilience, agility, top management participation.

INTRODUCTION

In today's interconnected and dynamic business environment, the resilience of supply chains has emerged as a critical factor in determining companies' overall success and sustainability (Hohenstein et al., 2015). Supply Chain Resilience (SCRE) refers to the capability of a supply chain to prepare for unexpected disruptions, respond adaptively, and recover quickly to restore normal operations (Hohenstein et al., 2015). Walmart, a successful case study, exemplifies how a data-driven culture and advanced infrastructure can optimize decision-making and foster employee development, thus enhancing supply chain resilience (Olaniyi et al., 2023). However, despite these advancements, the current application of Big Data Analytics Capability (BDAC) still faces limitations in fully preventing supply chain disruptions. BDAC empowers companies to effectively gather, process, and utilize large data sets, giving them the insights to make informed decisions quickly (Gupta & George, 2016; Han et al., 2020). While data analytics has undoubtedly revolutionized the way companies approach supply chain management, challenges still arise when confronted with unprecedented events. Despite having outstanding digital systems, IKEA, a globally renowned retailer, faced significant challenges during the coronavirus epidemic. Such special events severely disrupted its supply chain, temporarily closing its operations in China (Walker, 2020). This example highlights the need to continually evolve and enhance BDAC to ensure that companies are well-prepared to mitigate the impact of unexpected disruptions. Despite the recognized importance of BDAC in enhancing SCRE, the full potential of BDAC remains underutilized in mitigating supply chain disruptions.

Prior research has demonstrated the critical role of BDAC in improving resource allocation and operational efficiency and enabling effective demand forecasting (Ashrafi et al., 2019). However, studies have reported mixed outcomes concerning the impact of BDAC on firm performance, suggesting that the benefits of BDAC might be mediated by other factors or influenced by how BDAC is conceptualized and implemented within different organizational contexts (Akter et al., 2016; Mandal, 2019). Considering the Dynamic Capabilities Theory (DCT), this research proposes that agility, a higher-order capability, mediates the relationship between BDAC and SCRE, enhancing the firm's ability to respond to market changes swiftly (Winter, 2003). Moreover, this study examines the moderating role of Top Management Participation (TMP) in this mediated relationship, hypothesizing that effective implementation of BDAC, and consequently, SCRE, heavily relies on the active involvement of senior executives (Gopalakrishna-Remani et al., 2019). To empirically test these theoretical propositions, we surveyed executives of listed companies via WeChat, analyzing the data with moderated mediation analysis tools to explore the interactions among BDAC dimensions, agility, and TMP in enhancing SCRE. This approach addresses the identified research gaps and provides a comprehensive framework for understanding the multifaceted impacts of BDAC on supply chain resilience.

This study makes three significant contributions to the field. First, it employs empirical methods to validate the impact of BDAC on SCRE. By breaking down BDAC into three dimensions, the study tests the relationships between these dimensions and SCRE and provides a deeper insight into how BDAC enhances SCRE. Second, the study elucidates the mechanism of BDAC's impact on SCRE, specifically confirming the mediating role of agility. This extends both the depth and breadth of current academic research. Finally, the research highlights the critical moderating role of TMP, underlining the importance of moderating variables in deciphering influence dynamics. Overall, this research delivers a comprehensive understanding of how managers can strategically leverage BDAC to improve SCRE.

THEORETICAL BACKGROUND AND LITERATURE REVIEW

Dynamic Capabilities Theory

The Dynamic Capabilities Theory (DCT) builds on the Resource-Based View (RBV) by exploring how organizations can create and revitalize Valuable, Rare, Inimitable, and Non-substitutable (VRIN) resources in response to changing environments (Ambrosini & Bowman, 2009). This theory underscores the ability of firms to adapt and renew their internal and external competencies as a critical organizational skill (Ambrosini & Bowman, 2009; Teece et al., 2016). DCT highlights that dynamic capabilities involve organizational processes aimed at modifying the resource base and cultivating an optimal foundation for resources (Ambrosini & Bowman, 2009). Moreover, the theory clarifies how organizations can leverage these resources and capabilities to gain competitive advantages (Ambrosini & Bowman, 2009; Teece et al., 2016).

Scholarly consensus holds that dynamic capabilities, which focus on managing change, are distinct from ordinary capabilities, which address immediate operational needs (Winter, 2003). Dynamic capabilities are instrumental in adjusting the pace at which ordinary capabilities evolve, thereby preventing organizational stagnation and promoting innovation (Ambrosini & Bowman, 2009; Winter, 2003). This adaptability is crucial for sustained competitive advantage in dynamic markets (Ambrosini & Bowman, 2009).

DCT categorizes dynamic capabilities into a hierarchical structure of lower and higher orders, each playing distinct organizational roles (Ambrosini & Bowman, 2009; Winter, 2003). Lower-order capabilities focus on dynamic enhancements in operational activities, while higher-order capabilities emphasize ongoing innovation and strategic adaptability, crucial for managing change and developing enterprise strategies (Ambrosini & Bowman, 2009). Within this framework, BDAC is viewed as a lower-order capability that improves decision-making and resource reconfiguration through data analysis, enhancing operational performance (Singh & Singh, 2019). Higher-order capabilities like organizational agility allow firms to quickly recognize and react to market opportunities and challenges, facilitating strategic adjustments (Teece et al., 2016). Agility is not an end but a means to sustain a competitive advantage in volatile markets (Teece et al., 2016). This theoretical foundation suggests that lower-order capabilities like BDAC serve as the basis for developing higher-order capabilities such as agility, enhancing SCRE, contributing to competitive advantage by enabling firms to generate greater economic value and minimize losses during disruptions (Gu et al., 2021).

Furthermore, DCT posits that the influence of lower-order capabilities on higher-order ones can vary based on other factors, such as the top management team's role in nurturing and sustaining dynamic capabilities (Winter, 2003). This research will explore how TMP may moderate the impact of BDAC on SCRE through agility, providing a comprehensive model for understanding dynamic capabilities within organizations.

Supply Chain Resilience

The concept of supply chain resilience is multidisciplinary and generally lacks a universally accepted definition (Han et al., 2020). Hohenstein et al. (2015), after synthesizing a substantial body of literature, assert that supply chain resilience pertains to the supply chain's ability to prepare for unforeseen risks, respond promptly to them, and recover from potential disruptions, which ultimately enables the supply chain to restore its initial state or progress to a more favorable condition, contributing to the overall enhancement of the firm's value. A well-established supply chain resilience can mitigate the adverse impacts of interruptions, enhance overall business performance, and simultaneously improve customer satisfaction while ensuring the continuity of the supply chain (Gu et al., 2021). Furthermore, as a higher-order capability, supply chain resilience is the bridge that connects various dynamic capabilities (Ponomarov & Holcomb, 2009). In the face of uncertainty, the adaptability and coherence of supply chain resilience can enhance the integration of dynamic capabilities, thus aiding in maintaining competitive advantage (Ponomarov & Holcomb, 2009).

Big Data Analytics Capability

In the contemporary digital landscape, Big Data Analytics Capability (BDAC) has emerged as a pivotal asset for organizations seeking a competitive advantage. To harness BDAC effectively, it is imperative to understand the resources that underpin it, drawing on RBV. BDAC can be segmented into three fundamental components: tangible resources, human skills, and intangible resources (Gupta & George, 2016).

Tangible resources constitute the core of BDAC, comprising data, technology, and foundational resources (Gupta & George, 2016). Data acts as the cornerstone, underpinning all analytics initiatives. With digital advancements, especially in social media, the diversity and volume of data accessible to organizations have surged, presenting both opportunities and challenges. This data, often described by its volume, velocity, variety, veracity, and value, necessitates robust storage, analysis, and visualization solutions (Akter et al., 2016). Technology plays a crucial role in navigating these challenges, enabling the processing of large datasets to derive actionable insights. Additionally, essential resources like time and financial commitments are vital for acquiring and updating technological infrastructures (Gupta & George, 2016). Human skills enhance the utility of tangible resources, providing the expertise required to effectively leverage big data. Technical skills, such as data mining and analytics proficiency, are essential for extracting insights, while managerial skills are crucial for translating these insights into strategic business decisions (Akter et al., 2016; Gupta & George, 2016). This skill set is integral in bridging the divide between data specialists and executive management, ensuring that insights inform broader business strategies. Intangible resources round out the BDAC framework, embedding a data-driven ethos within the organizational culture. This culture prioritizes data over intuition in decision-making processes, promoting an analytical mindset across all organizational tiers (Gupta & George, 2016). The degree of organizational learning reflects the organization's commitment to continual knowledge acquisition and adaptation, a necessity in a rapidly evolving technological landscape (Gupta & George, 2016).

The synergy among tangible, human, and intangible resources forms the foundation of BDAC. Collectively, these resources empower organizations to manage, analyze, and leverage extensive datasets to maintain a competitive edge (Akter et al., 2016). However, the mere possession of these resources isn't sufficient; their strategic integration and application are what truly enable organizations to generate substantial value through BDAC.

Agility

Agility is a critical capability that allows organizations to promptly identify and respond to changing market demands. An agile supply chain is characterized by market sensitivity, virtuality, process integration, and network-based operations, emphasizing customer responsiveness and collaborative awareness (Christopher, 2000). As a higher-order capability, agility enables organizations to continuously adapt their business models and strategies to changing circumstances, ultimately creating value (Teece et al., 2016).

Previous studies highlight the importance of agility in helping companies navigate competitive markets. Faster market response increases market share and strengthens industry position (Han et al., 2020). The role of agility in supply chain management has also gained recognition, enabling organizations to reconfigure supply chains based on market demands and enhance ambidexterity (Aslam et al., 2018). Companies must uncover new opportunities in today's turbulent markets and flexibly adapt to maintain competitiveness. Agility enables supply chains to adapt to unpredictable markets (Christopher, 2000). However, limited empirical research explores the relationship between agility and SCRE.

To foster agility, organizations need an environment conducive to informed decision-making. BDAC is crucial in enhancing decision-making quality and facilitating rapid responses through data integration and analysis (Gupta & George, 2016; Han et al., 2020). Harnessing the full potential of BDAC is essential for leveraging agility and aligning with DCT. While BDAC positively impacts firm performance, the relationship between BDAC and agility remains unclear (Aslam et al., 2018). This paper proposes that agility mediates BDAC's positive impact on SCRE, transforming data analytics capabilities into enhanced supply chain resilience.

HYPOTHESES DEVELOPMENT

Big Data Analytics Capability, Agility, and Supply Chain Resilience

Drawing upon the DCT's hierarchical structure, we propose that the development of BDAC can serve as a foundation for cultivating higher-order capabilities, specifically agility, which elevates SCRE. To foster agility, companies require a supportive environment that encourages informed decision-making, and BDAC plays a pivotal role in creating such a data-driven decision-making environment. This capability enables organizations to adjust quickly to unknown changes (Han et al., 2020).

Tangible resources, such as access to high-quality data, advanced technologies, and sufficient financial and temporal resources, are crucial for effective BDAC. High-quality data forms the backbone for informed decision-making, while leveraging technologies like cloud computing aids in identifying shifts in competitors and customer preferences and facilitates information sharing across the supply chain, enhancing decision-making quality (Ashrafi et al., 2019; Christopher, 2000). Human skills, specifically data-specific technical and managerial expertise, further augment agility. Technical analytics utilizing these skills extract valuable insights from data, assisting managers in making data-driven decisions, such as forecasting market demand and devising contingency plans (Ashrafi et al., 2019; Cetindamar et al., 2021). Intangible resources, including a data-driven culture and organizational learning, are fundamental for exploiting and sustaining the advantages brought by data analysis. A data-driven culture elevates the significance of data in decision-making, a prerequisite for leveraging its full potential. Meanwhile, organizational learning fosters a proactive attitude toward external changes and enables organizations to detect and integrate these changes into organizational strategies (Cetindamar et al., 2021).

Improved agility, in turn, catalyzes the development of SCRE. An agile supply chain network enables organizations to respond swiftly to market shifts, and the speed of response largely determines a company's SCRE (Ponomarov & Holcomb, 2009). With agility, firms can detect and alert to market changes, allowing them to be aware of potential challenges and promptly adjust routines and strategies, thereby implementing remedial measures before risks materialize. In this way, agility enhances SCRE by detecting and averting shocks caused by market changes.

Moreover, agility fosters collaboration among supply chain members, increasing visibility and ultimately improving SCRE (Scholten et al., 2019). As a higher-order capability, agility facilitates information dissemination among supply chain entities, enabling internal and external process integration and improving information transparency (Scholten et al., 2019). This allows supply chain partners to leverage their respective strengths and utilize the collaborative network to mitigate disruptions. Therefore, we propose the following hypotheses:

H1a. Agility mediates the relationship between tangible resources and SCRE.

H1b. Agility mediates the relationship between human skills and SCRE.

H1c. Agility mediates the relationship between intangible resources and SCRE.

Moderation Role of Top Management Participation

According to DCT, TMP is a crucial contingent factor influencing the relationship between BDAC and SCRE, with agility as a mediating variable. TMP encompasses the strategic and proactive behaviors undertaken by top management to implement strategic decisions, suggesting that their direct involvement is essential for guiding the successful integration of BDAC within organizational processes (Gopalakrishna-Remani et al., 2019). TMP significantly bolsters the impact of tangible resources on agility. Higher levels of management engagement ensure that critical resources are adequately allocated to support activities that enhance agility (Gopalakrishna-Remani et al., 2019; Hu et al., 2012). This active involvement prioritizes the allocation of essential resources and minimizes the hurdles associated with establishing new information technology systems, ensuring comprehensive support and successful implementation of agility-focused initiatives.

Furthermore, top management's role extends to leading transformative efforts and strategically steering the company. This leadership fosters collaboration and enhances the development of human skills, essential for leveraging data technologies and expertise across the organization (Liang et al., 2007). Top managers also play a critical role in fostering synergies between IT teams and other departments, facilitating a unified approach towards corporate digital transformation and promoting consensus (Gopalakrishna-Remani et al., 2019). Their involvement is crucial in coordinating internal data management and encouraging information sharing across the supply chain, significantly contributing to enhanced agility (Gopalakrishna-Remani et al., 2019).

Moreover, TMP creates a conducive environment for adopting new technologies, thus enhancing the role of intangible resources. By legitimizing the use of BDAC, top management builds employee confidence in the benefits of new systems, fostering a culture that embraces technological innovations and continuous learning (Gopalakrishna-Remani et al., 2019). This shift enables employees to utilize data analytics more effectively, optimizing business strategies and operations, and allowing for rapid adaptation to market changes.

In conclusion, we argue that higher levels of TMP enable companies to fully leverage the benefits of BDAC to increase agility and, consequently, enhance SCRE. Given the mediating role of agility in this dynamic, we propose that TMP will positively moderate the mediating effect of agility on the relationships between tangible resources, human skills, and intangible resources with SCRE. Accordingly, we articulate the following hypotheses:

H2a. TMP positively moderates the meditation effect of agility on the relationship between tangible resources and SCRE.

H2b. TMP positively moderates the meditation effect of agility on the relationship between human skills and SCRE.

H2c. TMP positively moderates the meditation effect of agility on the relationship between intangible resources and SCRE.

METHODOLOGY

Research Design

This study employed the questionnaire-based survey method for data collection due to its efficiency in addressing sensitive topics. The constructs and corresponding items in this questionnaire were derived from previously published latent variables, bolstered by established psychometric properties attesting to their validity in academic research. All the constructs and corresponding items were conducted using a 5-point Likert scale ranging from (1) “strongly disagree” to (5) “strongly agree”.

To test our research model, we collaborated with a reputable media company known for listing disclosure. We conducted a survey targeting executives of companies partnered with the media firm through WeChat, with 200 participants. The data collection process lasted approximately one month, with respondents averaging 10 minutes to complete the survey. The final sample comprises 149 responses. Given our focus on publicly listed companies, we excluded incomplete and non-listed company responses, making 114 questionnaires available for analysis.

The survey responses were received from companies with diverse industry backgrounds. The largest proportion was from manufacturing and real estate (31.58%), followed by service and consumption (26.32%) and finance and healthcare (19.30%). Additionally, a significant portion of responses came from other sectors (22.80%). Most participating companies were privately owned, accounting for 61.40% of the sample.

Most of the executives who participated in the survey have received a solid education, with 100% holding a bachelor's degree or higher. They also have extensive tenure within their respective companies, with an average duration of 8.31 years, indicating a comprehensive understanding of their company's information. Therefore, the data collected in this study is deemed to provide a reliable reflection of the current status of the companies they represent.

Table 1: Descriptive Statistics of the Sample and Respondents

Factors	Sample (N=114)	Proportion(%)
Listing Duration		
1-4 years	15	13.16%
5-9 years	30	26.32%
10-49 years	68	59.65%
50+ years	1	0.88%
Firm Size (Number of Employees)		
<100	3	2.63%
100-500	9	7.89%
500-2000	37	32.46%
2000-5000	29	25.44%
>5000	36	31.58%
Industry		
Manufacturing and Real Estate	36	31.58%
Service and Consumption	30	26.32%
Finance and Healthcare	22	19.30%
Other (Technology and E-commerce, etc.)	26	22.81%
Nature		
Private Enterprise	70	61.40%
State-owned Enterprise	28	24.56%
Wholly Foreign-owned Enterprise	4	3.51%
Sino Foreign Joint Venture/Cooperative Enterprise	5	4.39%
Other	7	6.14%

Measures

The scales for various constructs were developed based on previous literature. Therefore, they have been previously tested in empirical studies. The appendix provides a summary of the scales used, along with their descriptive statistics and supporting references.

According to Gupta and George (2016), big data analytics capability is conceptualized and developed as a third-order formative construct, with its primary components being tangible resources, human skills, and intangible resources, which are further characterized as second-order formative constructs composed of seven first-order constructs. However, since this paper separately analyzes the three components of big data analytics capability, it treats tangible resources, human skills, and intangible resources individually as second-order formative constructs. Previous studies have introduced four categories of higher-order constructs: reflective-reflective, reflective-formative, formative-reflective, and formative-formative (Sarstedt et al., 2019). This study conceptualizes tangible resources as a formative-formative higher-order construct, while human skills and intangible resources are considered reflective-formative higher-order constructs. Respondents assessed their company's big data analytics capability on a 5-point Likert scale.

The questions used to measure agility were adapted from the scale of Liang et al. (2017). Respondents were asked to evaluate their effectiveness in agility using six items on a 5-point Likert scale.

The items employed to assess supply chain resilience were drawn from the metric devised by Ambulkar et al. (2015). Respondents were asked to appraise their proficiency in supply chain resilience by evaluating four items on a 5-point Likert scale.

The scale used to assess TMP in this study is adapted from Gopalakrishna-Remani et al. (2019) and measured using a five-point Likert scale.

We also controlled three typical firm demographic variables that could influence supply chain resilience: listing duration, firm size, and industry. Firm size is measured using the natural logarithm of the number of employees, and firm age is measured using the natural logarithm of the period from the company's initial listing on the securities market to the present. The listing duration and firm size data was sourced from Guosen Golden Sun, a software developed by Guosen Securities to provide comprehensive services, including securities market information, securities trading, account inquiries, interbank transfers, and securities news. We also controlled for industry types, which included three industry dummy variables: manufacturing industry, service industry, and financial industry, with other industries as the baseline. The industry type was gathered based on archival data provided by respondents.

ANALYSIS AND RESULTS

To assess the effectiveness and reliability of the hierarchical research model, we employed the Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis using SmartPLS 4.0 software. A significant advantage of PLS-SEM is that since the PLS-SEM algorithm is based on ordinary least squares regression, it provides the flexibility to freely employ single-item, reflective, or formative measures (Hair Jr et al., 2014). As a result, when the structure involves formative constructs, PLS-SEM is the preferred method (Sarstedt et al., 2016). Additionally, in this study, we used SmartPLS 4.0 software for analysis due to its ability to analyze higher-order models. Specifically, we conceptualized tangible resources, human skills, and intangible resources as second-order variables, and employed a two-stage approach to validate and analyze these higher-order constructs. Meanwhile, to obtain more comprehensive moderation effect data, Stata was utilized for computations in this study.

Measurement Model

Due to the model encompassing formative and reflective constructs, we employed different evaluation criteria to assess each construct. Firstly, for the reflective constructs, we conducted reliability, convergent validity, and discriminant validity tests in each analysis phase. We measured Composite Reliability (CR) and Cronbach's Alpha (CA) for reliability. As the table indicates, both CR and CA coefficients exceeded the threshold values of 0.7. Therefore, the scales utilized in this study demonstrated reliability.

Table 2: Assessment of Reliability, Convergent, and Discriminant Validity of Reflective Constructs

	Measures	Items	Cronbach's Alpha	Composite Reliability	AVE
Phase One	Managerial	3	0.946	0.965	0.902
	Technical	2	0.921	0.962	0.927
	Data-Driven Culture	2	0.711	0.874	0.776
	Organizational Learning	2	0.880	0.943	0.892
Phase Two	Agility	6	0.917	0.936	0.710
	SC/Organization Resilience	4	0.888	0.923	0.749
	Top Management Participation	3	0.923	0.951	0.866

We examined whether the Average Variance Extracted (AVE) exceeded the lower limit of 0.5 to assess convergent validity. The table displays a minimum value of 0.710, significantly surpassing this threshold. For discriminant validity, we employed two methods. Firstly, following Fornell-Larcker's criterion, the AVE of a construct should be greater than the square of its correlation with other constructs. The data in this study all met this requirement. Secondly, the Heterotrait-Monotrait Ratio (HTMT) is a robust method for discriminant validity assessment. It evaluates questionnaire effectiveness by comparing the average correlations between different constructs and within the same construct. Henseler et al. (2015) indicated that an HTMT value exceeding 0.90 suggests poor discriminant validity. In this study, the maximum HTMT value was 0.890, below the specified threshold, affirming the questionnaire's effectiveness.

For formative constructs, we first examined their associated weights and significance with their respective constructs. For first-order constructs, each item exhibited significance. Regarding second-order constructs, each formative construct's weight on its second-order construct was also significant. Additionally, this study investigated the level of collinearity presented by the formative constructs. Upon examination, the Variance Inflation Factor (VIF) values were all below 10, indicating low collinearity.

Table 3: Higher-order Construct Validation

Model Construct	Measures	Outer Loadings	Outer Weights	VIF	t-Value	Significance
Data	DATACA1	0.876	0.233	3.156	13.621	p<0.001
	DATACA2	0.919	0.366	3.617	21.758	p<0.001
	DATACA3	0.942	0.488	3.454	31.690	p<0.001

Technology	DATACA4	0.901	0.335	4.159	18.810	p<0.001
	DATACA5	0.899	0.410	2.755	17.055	p<0.001
	DATACA6	0.931	0.355	3.724	25.426	p<0.001
Basic Resources	DATACA7	0.972	0.557	4.153	65.644	p<0.001
	DATACA8	0.962	0.477	5.183	44.073	p<0.001
Tangible Resources	Data	0.878	0.243	3.024	18.493	p<0.001
	Technology	0.857	0.086	3.302	15.851	p<0.001
	Basic Resources	0.985	0.724	3.556	66.189	p<0.001
Human Skills	Managerial	0.905	0.269	3.247	17.241	p<0.001
	Technical	0.989	0.765	3.247	80.105	p<0.001
Intangible Resources	Data-Driven Culture	0.894	0.664	1.264	11.650	p<0.001
	Organizational Learning	0.807	0.503	1.264	7.799	p<0.001

Finally, before testing the structural model, we assessed its fit. Despite the NFI value being 0.829, which falls below the recommended threshold of 0.90, the SRMR value of 0.054 meets the standard. Therefore, the model can still be deemed to demonstrate a satisfactory fit.

Structural Model

The table below summarizes the structural model analyzed through PLS-SEM, presenting the explained variance (R^2) of endogenous variables and the standardized path coefficients (β). The significance of the estimated values (t-statistics) was obtained through Bootstrapping with 5000 repetitions. As shown in the table, both agility (β=0.531, t=5.639, p<0.001) and tangible resources (β=0.368, t=5.209, p<0.001) have a positive impact on the SCRE. However, human skills (β=-0.038, t=0.395, p>0.05) and intangible resources (β=-0.003, t=0.031, p>0.05) do not impact SCRE. Meanwhile, tangible resources (β=0.266, t=2.311, p<0.05), human skills (β=0.313, t=2.572, p<0.01), and intangible resources (β=0.339, t=2.190, p<0.05) in the company's BDAC all have an impact on agility. The structural model accounts for 63.7% of the variance in agility (R^2=0.637) and 65.3% of the variance in SCRE (R^2=0.653). The model's fit indices both exceed 0.5, indicating a good fit.

Table 4: Regression on Agility and SCRE

	Model 1		Model 2	
	Agility		SC/Organization resilience	
Regression results	Coefficients	STDEV	Coefficients	STDEV
Agility			0.531***	0.094
Tangible Resources	0.266*	0.115	0.368***	0.071
Human Skills	0.313**	0.122	-0.038	0.097
Intangible Resources	0.339*	0.155	-0.003	0.087
Listing Duration	0.006	0.054	-0.063	0.103
Services and Consumption[a]	0.163	0.176	-0.126	0.165
Manufacturing and Real Estate[a]	0.225	0.152	-0.307	0.170
Finance and Healthcare[a]	0.092	0.185	-0.275	0.189
R^2	0.637		0.653	
Direct effect				
		Direct effect	STDEV	95% CI
Tangible Resources -> SCRE		0.368***	0.071	[0.222, 0.502]
Human Skills -> SCRE		-0.038	0.097	[-0.216, 0.170]
Intangible Resources -> SCRE		-0.003	0.087	[-0.157, 0.191]

Note(s): *p<0.05, **p<0.01, ***p<0.001. [a]Dummy variable. STDEV = standard error; CI = confidence interval

Test for Mediation

To investigate whether agility mediates the influence of tangible resources, human skills, and intangible resources on supply chain resilience, this study employed Bootstrapping with 5000 resamples to examine the significance of both direct and indirect effects. As depicted in the table below, the direct effects of tangible resources (direct effect=0.368, STDEV=0.071, 95% CI: 0.222-0.502) on supply chain resilience are significant. The results reveal significant indirect effects of tangible resources (indirect effect=0.141, STDEV=0.070, 95% CI: 0.015-0.284) on supply chain resilience through agility. Therefore, agility partially mediates the impact of tangible resources on SCRE. However, even though the direct effect of human skills (direct effect=-0.038, STDEV=0.097, 95% CI: -0.216-0.170) and intangible resources (direct effect=-0.003, STDEV=0.087, 95% CI: -0.157-0.191) on supply chain resilience are insignificant, the indirect effect of human skills (indirect effect=0.166, STDEV=0.071, 95% CI: 0.018-0.300) and intangible skills (indirect effect=0.180, STDEV=0.081, 95% CI: -0.065-0.387) are significant. As a result, agility completely mediates human and intangible skills' impact on SCRE. In summary, H1a, H1b, and H1c are supported.

Table 5: Bootstrapping Analysis for Indirect Effects

Direct effect			
	Direct effect	STDEV	95% CI
Tangible Resources -> SCRE	0.368^{***}	0.071	[0.222, 0.502]
Human Skills -> SCRE	-0.038	0.097	[-0.216, 0.170]
Intangible Resources -> SCRE	-0.003	0.087	[-0.157, 0.191]
Indirect effect (bootstrapping analysis)			
	Indirect effect	Boot STDEV	95% Boot CI
Tangible Resources -> Agility ->SCRE (H1a)	0.141^{*}	0.070	[0.015, 0.284]
Human Skills -> Agility ->SCRE (H1b)	0.166^{*}	0.071	[0.018, 0.300]
Intangible Resources -> Agility ->SCRE (H1c)	0.180^{*}	0.081	[0.065, 0.387]

Note(s): $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$. STDEV = standard error; CI = confidence interval

Test for Moderation

H2a, H2b, and H2c respectively posit that TMP positively moderates the indirect effects of tangible resources, human skills, and intangible resources on SCRE. These three hypotheses pertain to the moderated-mediation effect of TMP. Considering the integrity of the data, moderation calculations were conducted using Stata and employed Bootstrapping with 5000 resamples. To mitigate potential multicollinearity issues, the variables in this study have been mean-centered. The computational outcomes are presented in Table 5.

The index of moderated mediation for intangible resources is 0.123 with a 95% confidence interval ranging from 0.011 to 0.246 (SE=0.060, 95% CI: 0.011-0.246), excluding 0, indicating a significant moderated mediation effect of TMP. Furthermore, the results suggest that the TMP level influences the indirect impact of intangible resources on SCRE through agility. Specifically, under low TMP conditions, the indirect effect of intangible resources on SCRE is insignificant (β=0.121, SE=0.135, 95% CI: -0.162-0.373), whereas it becomes significant at high TMP level (β=0.368, SE=0.073, 95% CI: 0.219-0.505). Moreover, the difference between low and high levels of TMP is obvious (β=0.247, SE=-0.062, 95% CI: 0.381-0.132). In summary, it can be confirmed that the indirect effect of intangible resources on SCRE through agility is positively moderated by TMP, which supports H2c.

However, based on testing results, it is evident that the 95% confidence intervals for both tangible resources (β=0.041, SE=0.044, 95% CI: -0.488-0.125) and human skills (β=0.144, SE=0.052, 95% CI: -0.090-0.114) in the moderated mediation index encompass 0. This indicates that the moderated mediation effect lacks significance. Consequently, there is insufficient support for hypotheses H2a and H2b.

Table 6: Regression on Agility, Moderation Effect of TMP, and Bootstrapping Analysis for Conditional Indirect Effects

	Model 3	
	Agility	
Regression results	Coefficients	STDEV
Tangible Resources	0.173	0.110
Human Skills	0.168	0.100
Intangible Resources	0.384^{**}	0.128

Top Management Participation (TMP)	0.204*	0.092
Tangible Resources×TMP	0.049	0.114
Human Skills×TMP	-0.303**	0.114
Intangible Resources×TMP	0.242*	0.104
Listing Duration	-0.001	0.056
Services and Consumption	0.062	0.168
Manufacturing and Real Estate	0.145	0.153
Finance and Healthcare	-0.160	0.176
R^2	0.701	

Conditional indirect effect (bootstrapping analysis)

	Moderator (TMP)	Indirect effect	Boot STDEV	95% Boot CI
Tangible Resources -> Agility -> SCRE	Low (-1 SD)	0.195	0.110	[0.009, 0.432]
	High (+1 SD)	0.276	0.058	[0.164, 0.388]
	Difference	0.081	0.052	[0.155, -0.044]
Human Skills -> Agility -> SCRE	Low (-1 SD)	0.286	0.120	[0.057, 0.513]
	High (+1 SD)	0.315	0.073	[0.172, 0.463]
	Difference	0.029	-0.047	[0.115, -0.050]
Intangible Resources -> Agility -> SCRE	Low (-1 SD)	0.121	0.135	[-0.162, 0.373]
	High (+1 SD)	0.368	0.073	[0.219, 0.505]
	Difference	0.247	-0.062	[0.381, 0.132]

Index of moderated mediation bootstrapping analysis

	Index	Boot STDEV	95% Boot CI
H2a	0.041	0.044	[-0.488, 0.125]
H2b	0.144	0.052	[-0.090, 0.114]
H2a	0.123	0.060	[0.011, 0.246]

Note(s): *p<0.05, **p<0.01, ***p<0.001. [a]Dummy variable. STDEV = standard error; CI = confidence interval

DISCUSSION AND IMPLICATIONS

With the advent of the big data era, although current research emphasizes the impact of BDAC on SCRE, there is a scarcity of in-depth exploration of the underlying mechanisms. This article, grounded in DCT and RBV, proposes a moderated mediation model. The model posits that agility mediates the relationship between BDAC and SCRE, while TMP moderates this mediation effect. Utilizing survey data from 114 senior managers of listed companies, the study findings support the theoretically constructed research model and unveil several key insights.

Firstly, this study employs RBV to disaggregate BDAC into tangible resources, human skills, and intangible resources and validate agility's mediating role in each of these dimensions. The results demonstrate that agility mediates between tangible resources, human skills, intangible resources, and SCRE. Regarding direct effects, only tangible resources impact SCRE, whereas human skills and intangible resources exhibit no influence, aligning with Mandal's (Mandal, 2019) conclusion that not all dimensions of BDAC affect SCRE.

In terms of indirect effects, this study underscores the significance of agility as a pivotal mediating variable. Agility aids companies in swiftly adjusting production modes in response to changes, thereby mitigating market disruptions, reshaping organizational forms, and promptly addressing customer demands (Hohenstein et al., 2015). Given agility's mediating effect across all three dimensions of BDAC, companies can further strengthen agility to foster supply chain resilience. Moreover, the findings correspond to the hierarchical structure theory of DCT, indicating that BDAC, as a lower-order capability, facilitates the development of higher-order agility, thereby assisting companies in gaining competitive advantages (Ambrosini & Bowman, 2009; Winter, 2003).

Moreover, our investigation into moderated mediation revealed that TMP effectively enhances agility as a mediator in the impact of intangible resources on SCRE. The reason intangible resources are influenced by TMP, unlike the other two dimensions, may arise from their higher context dependency (Teece, 2014). Meanwhile, TMP can aid companies in fostering an appropriate atmosphere and corporate culture and boosting employees' willingness to learn (Liang et al., 2007). This symbiotic relationship leads to mutual reinforcement. This finding is also consistent with DCT, which suggests that the degree to which lower-order capabilities affect higher-order capabilities varies depending on the environment (Ambrosini & Bowman, 2009). Overall, this paper provides valuable insights for a deeper understanding of the impact of BDAC on SCRE.

Theoretical Implications

This study significantly enriches the existing literature on SCRE by empirically demonstrating the critical role of BDAC in enhancing SCRE. It goes beyond previous research, which largely viewed BDAC as a monolithic concept, by breaking it down into tangible resources, human skills, and intangible resources and exploring their interactions with agility and SCRE (Dubey et al., 2021; Singh & Singh, 2019). This dissection allows for a deeper understanding of how BDAC components individually contribute to supply chain resilience.

The research clarifies the mechanisms by which BDAC influences SCRE, particularly highlighting agility's mediating role. Leveraging the DCT, it illustrates that BDAC, as a lower-level dynamic capability, fosters SCRE by enhancing agility, a higher-level capability crucial for adapting to market shifts and optimizing internal and supply chain-wide information analysis.

Additionally, the study underscores the moderating role of TMP in enhancing the impact of intangible resources on SCRE, a perspective rarely considered in existing literature. By empirically showing how environmental factors influence the transition between lower-order and higher-order capabilities, this research extends DCT and offers a nuanced view of the dynamic interactions at play, providing comprehensive insights into the ways BDAC can be leveraged to bolster SCRE.

Managerial Implications

This study provides actionable insights for managers on utilizing BDAC to enhance SCRE. Firstly, the research underscores that BDAC extends beyond tangible resources like data and analytics tools to include crucial human and intangible resources. In the digital age, companies should invest not only in advanced data analytics technologies but also in developing the skills of their workforce (Gupta & George, 2016). Enhancing technical literacy among management and staff, and fostering a supportive organizational culture are essential steps for improving decision-making and responsiveness to market changes.

Secondly, the importance of agility within organizations cannot be overstated. Agility allows for more flexible responses to external changes and swift corrective actions during disruptions (Aslam et al., 2018). It is vital across the entire supply chain to enhance data visibility and operational efficiency, which in turn bolsters overall SCRE. Managers are encouraged to foster agility at both the organizational and supply chain levels to navigate the dynamic market and supply chain environments effectively.

Lastly, the involvement of top management in the implementation of BDAC projects is crucial (Hu et al., 2012). Our findings indicate that active participation by top managers not only increases focus on big data capabilities among employees but also ensures better resource allocation, thereby enhancing the efficiency of BDAC implementation. Proactive leadership by top management is essential for fully leveraging BDAC to achieve superior SCRE.

Limitations and Future Research

While this article contributes significantly to research on SCRE, it also highlights several areas for further investigation. The study primarily examines the mediating role of agility and the moderating effect of TMP in the relationship between BDAC and SCRE. Future research could expand this focus to include other potential mediators and moderators, such as modular innovation and strategic decision-making, to provide a more comprehensive understanding of how BDAC impacts SCRE.

Additionally, the data for this study were exclusively collected from publicly traded companies, which typically have longer operating histories, larger scales, and more developed infrastructures and decision-making processes than small and medium-sized enterprises (SMEs). While the choice of publicly traded companies aligns with the research objectives, it may limit the generalizability of the findings to SMEs. However, it is noteworthy that the outcomes of this study align well with findings from case studies within SME contexts, suggesting potential applicability across different business scales. Future studies could address these limitations by incorporating data from a broader range of company types, enhancing the generalizability of the research.

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APPENDIX

APPENDIX A: Questionnaire

Measure	Item	Mean	S.D.	Reference
Tangible Resources				
Data	DATACA1: We have access to very large, unstructured, or fast-moving data for analysis.	3.42	0.98	
	DATACA2: We integrate data from multiple internal sources into a data warehouse or mart for easy access.	3.63	0.98	
	DATACA3: We integrate external data with internal to facilitate high-value analysis of our business environment.	3.69	1.02	
Technology	DATACA4: We have explored or adopted parallel computing approaches (e.g., Hadoop) to big data processing.	3.23	1.11	
	DATACA5: We have explored or adopted different data visualization tools.	3.67	0.98	
	DATACA6: We have explored or adopted new forms of databases such as Not Only SQL(NoSQL) for storing data.	3.50	1.03	
Basic Resources	DATACA7: Our 'big data analytics' projects are adequately funded.	3.46	1.05	
	DATACA8: Our 'big data analytics' projects are given enough time to achieve their objectives.	3.48	0.98	
Human Skills				
Managerial Skills	DAHUCA1: Our 'big data analytics' managers are able to understand the business need of (and collaborate with) other functional managers, suppliers, and customers to determine opportunities that big data might bring to our business.	3.51	0.95	(Mikalef et al., 2020)
	DAHUCA2: Our 'big data analytics' managers are able to coordinate big data-related activities in ways that support other functional managers, suppliers, and customers.	3.53	0.96	
	DAHUCA3: Our 'big data analytics' managers are able to understand and evaluate the output extracted from big data.	3.52	0.97	
Technical Skills	DAHUCA4: Our 'big data analytics' staff has the right skills to accomplish their jobs successfully.	3.54	0.94	
	DAHUCA5: Our 'big data analytics' staff is well trained.	3.52	0.98	
Intangible Resources				
Data-driven Culture	DSDM1: We base our decisions on data rather than on instinct.	3.89	0.80	
	DSDM2: We are willing to override our own intuition when data contradict our viewpoints.	3.82	0.81	
Organizational Learning	DAINTA1: We are able to acquire new and relevant knowledge.	3.88	0.86	
	DAINTA2: We have made concerted efforts for the exploitation of existing competencies and exploration of new knowledge	4.05	0.71	
Agility	Agility1: We continuously pay close attention to actions of our competitors.	4.05	0.80	
	Agility2: We always try to forecast consumer preference changes.	3.89	0.89	(Liang et al., 2017)
	Agility3: We are alert to economic shift.	4.08	0.76	

	Agility4: We implement rapidly new competitive strategies with regard to actions of our competitors.	3.85	0.79	
	Agility5: We quickly react to fundamental changes with regard to our customers.	3.93	0.82	
	Agility6: We respond quickly to changes in economic transformation.	3.77	0.90	
Top Management Participation	TMP1: The senior management of our firm actively articulates a vision for the organizational use of Digital transformation.	3.88	0.83	
	TMP2: The senior management of our firm actively formulates a strategy for the organizational use of Digital transformation.	3.85	0.84	(Gopalakrishna-Remani et al., 2019)
	TMP3: The senior management of our firm actively establishes goals and standards to monitor the Digital transformation implementation.	3.79	0.82	
Supply Chain Resilience	SCRE1: We are able to cope with changes brought by the supply chain disruption.	3.67	0.81	
	SCRE2: We are able to adapt to the supply chain disruption easily.	3.39	0.86	
	SCRE3: We are able to provide a quick response to the supply chain disruption.	3.69	0.81	(Ambulkar et al., 2015)
	SCRE4: We are able to maintain high situational awareness at all times.	3.68	0.74	

APPENDIX B: Fornell-Larcker in Phase One

	(1)	(2)	(3)	(4)
(1)Managerial	0.950			
(2)Technical	0.832	0.963		
(3)Data-driven Culture	0.426	0.448	0.881	
(4)Organizational learning	0.498	0.493	0.457	0.945

APPENDIX C: HTMT in Phase One

	(1)	(2)	(3)	(4)
(1)Managerial				
(2)Technical	0.890			
(3)Data-driven Culture	0.521	0.558		
(4)Organizational learning	0.546	0.548	0.574	

APPENDIX D: Fornell-Larcker in Phase Two

	(1)	(2)	(3)
Agility	0.842		
SCRE	0.756	0.865	
TMP	0.674	0.563	0.931

APPENDIX E: HTMT in Phase Two

	(1)	(2)	(3)
Agility			
SCRE	0.827		
TMP	0.733	0.614	

APPENDIX F: Higher-order Construct Validation

Model Construct	Measures	Outer Loadings	Outer Weights	VIF	t-Value	Significance
Data	DATACA1	0.876	0.233	3.156	13.572	p<0.001
	DATACA2	0.919	0.366	3.617	21.787	p<0.001
	DATACA3	0.942	0.488	3.454	31.570	p<0.001

Technology	DATACA4	0.901	0.335	4.159	18.810	p<0.001
	DATACA5	0.899	0.410	2.755	17.035	p<0.001
	DATACA6	0.931	0.355	3.724	25.459	p<0.001
Basic Resources	DATACA7	0.972	0.557	4.153	65.644	p<0.001
	DATACA8	0.962	0.477	5.183	44.073	p<0.001
Managerial	DAHUCA1	0.946	0.349	5.059	75.114	p<0.001
	DAHUCA2	0.960	0.349	5.814	96.232	p<0.001
	DAHUCA3	0.943	0.355	6.312	71.833	p<0.001
Technical	DAHUCA4	0.964	0.528	3.701	112.250	p<0.001
	DAHUCA5	0.962	0.511	4.183	99.823	p<0.001
Data-Driven Culture	DSDM1	0.871	0.547	1.438	23.485	p<0.001
	DSDM2	0.890	0.588	1.640	34.676	p<0.001
Organizational Learning	DAINTA1	0.943	0.521	2.633	73.637	p<0.001
	DAINTA2	0.946	0.537	2.606	90.919	p<0.001
Tangible Resources	Data	0.878	0.243	3.024	18.493	p<0.001
	Technology	0.857	0.086	3.302	15.851	p<0.001
	Basic Resources	0.985	0.724	3.556	66.189	p<0.001
Human Skills	Managerial	0.905	0.269	3.247	17.241	p<0.001
	Technical	0.989	0.765	3.247	80.105	p<0.001
Intangible Resources	Data-Driven Culture	0.894	0.664	1.264	11.650	p<0.001
	Organizational Learning	0.807	0.503	1.264	7.799	p<0.001
Agility	Agility1	0.838	0.198	2.844	23.155	p<0.001
	Agility2	0.711	0.165	1.838	7.857	p<0.001
	Agility3	0.824	0.180	2.427	17.055	p<0.001
	Agility4	0.917	0.216	4.724	56.553	p<0.001
	Agility5	0.879	0.210	3.693	36.450	p<0.001
	Agility6	0.870	0.213	4.004	36.015	p<0.001
SC/Organization Resilience	SCRE1	0.883	0.298	2.606	37.206	p<0.001
	SCRE2	0.853	0.257	2.390	23.754	p<0.001
	SCRE3	0.872	0.287	2.432	22.405	p<0.001
	SCRE4	0.854	0.314	2.092	26.773	p<0.001
Top Management Participation	TMP1	0.928	0.381	3.270	37.981	p<0.001
	TMP2	0.939	0.326	4.176	51.706	p<0.001
	TMP3	0.925	0.368	3.283	41.888	p<0.001