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Transforming Big Data Analytics into Supply Chain Resilience through Dynamic Capabilities and Management Practice

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Abstract

Supply chains are exposed to disruptions of growing frequency and severity, ranging from pandemics and geopolitical conflict to climate-related shocks, which has pushed Supply Chain Resilience (SCR) to the center of operations and management research. In parallel, organizations are investing heavily in Big Data Analytics (BDA) capability, the ability to acquire, integrate, and exploit large and varied data resources for decision-making. Although a growing body of empirical work links BDA capability to superior supply chain outcomes, the literature remains fragmented: Resilience research emphasizes network design and buffer capacity, analytics research emphasizes performance and efficiency gains, and few studies theorize the mechanism through which data-driven capabilities are converted into resilience. This conceptual paper addresses that gap by developing an integrative framework, termed Data-Driven Supply Chain Resilience (DDSCR), that combines the Resource-Based View (RBV), Dynamic Capabilities Theory (DCT), and the emerging literature on Artificial Intelligence (AI) and Industry 4.0 (I4.0) technologies in supply chain management. The framework positions BDA capability as a strategic resource that, through the dynamic-capability processes of sensing, seizing, and reconfiguring, is converted into three resilience capacities, anticipation, adaptation, and recovery, with digital-technology intensity and supply chain risk exposure acting as boundary conditions that shape the strength of this conversion. Nine theoretically grounded propositions are advanced to specify these relationships and their contingencies, and a three-stage analytics-resilience maturity roadmap is proposed to guide implementation. The paper contributes a parsimonious, testable model that reconciles previously disconnected research streams, offers managers a diagnostic vocabulary for assessing analytics-driven resilience maturity, and outlines a structural equation modeling agenda for future empirical validation. The paper closes with a discussion of the framework's theoretical and managerial implications, its boundary conditions, and its limitations, together with directions for future research.

Keywords: Supply chain resilience, Big data analytics, Dynamic capabilities, Resource-based view, Digital transformation, Supply chain risk management.

1 | Introduction

Supply chains have become longer, leaner, and more geographically dispersed over the past three decades, a configuration that has delivered substantial efficiency gains but has simultaneously made supply networks more vulnerable to disruption [1]. The COVID-19 pandemic exposed the fragility of globally distributed

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supply networks on an unprecedented scale, and a systematic review of the resulting body of work identified supply continuity, demand volatility, and recovery planning as the dominant concerns of researchers during and after the crisis [2]. Beyond the pandemic, firms now contend with an accumulating set of recurring shocks, geopolitical conflict, trade restrictions, extreme weather events, and cyber incidents that collectively have moved Supply Chain Resilience (SCR) from a peripheral risk-management concern to a first-order strategic priority [3]. SCR is commonly defined as the adaptive capability of a supply chain to prepare for, respond to, and recover from disruptions while maintaining continuity of operations at a desired level of connectedness and control [4], it is best understood not as a static property but as a capability that is built, exercised, and renewed over time [5].

Concurrently, a second and largely independent research trajectory has documented the rise of Big Data Analytics (BDA) as a source of competitive advantage. Organizations that develop the capability to capture, integrate, and analyze large volumes of internal and external data are found to make faster and better-informed decisions [6], and survey evidence from thousands of executives indicates that analytics leaders systematically outperform their peers on profitability and market responsiveness [7]. Within the operations literature specifically, a growing stream of empirical studies has connected BDA capability to supply chain agility, innovation, and performance outcomes [8-10]. More recent work has begun to draw an explicit line between BDA capability and resilience, showing that analytics maturity is associated with better disruption anticipation and faster recovery [11], [12].

Despite the intuitive appeal of connecting these two literatures, the theoretical bridge between them remains underdeveloped. The SCR literature has matured largely around structural and relational antecedents of resilience, redundancy, flexibility, collaboration, and network design [13-15], and, notwithstanding a small number of systematic reviews that acknowledge the potential contribution of analytics and Artificial Intelligence (AI) [16], [17], it has not yet articulated the internal cognitive and organizational mechanism by which data and analytics are converted into resilience capacity. Conversely, the BDA literature has been preoccupied with establishing a direct and largely linear relationship between analytics capability and firm or supply chain performance [18], [19] often without engaging the well-established resilience constructs of anticipation, adaptation, and recovery [20] that dominate the resilience literature, and without specifying the boundary conditions under which the analytics-resilience relationship should be expected to strengthen or weaken. The result is two parallel bodies of knowledge that reference similar phenomena, visibility, responsiveness, foresight, using different vocabularies and different theoretical lenses, and, critically, without a shared process model explaining how one becomes the other.

This fragmentation is not merely an academic inconvenience. Practically, it leaves supply chain and information-technology executives without a coherent logic for prioritizing analytics investment as a resilience-building strategy, since existing frameworks tend to either treat analytics as a generic performance lever or treat resilience as an outcome of network design decisions taken in isolation from the firm's data and digital infrastructure. Theoretically, the absence of an integrative model constrains the field's ability to accumulate and compare findings, because studies that examine the analytics-resilience relationship do so using inconsistent constructs and, more importantly, without a shared explanation of the underlying mechanism connecting analytics capability, organizational capability renewal, and resilience capacity. Motivated by this gap, the present paper asks: Through what capability-based mechanism does BDA capability translate into SCR, and under what conditions is this translation strengthened or weakened?

To answer this question, the paper makes three contributions. First, it advances a novel integrative framework, Data-Driven Supply Chain Resilience (DDSCR), that is, to the authors' knowledge, the first to explicitly route the relationship between BDA capability and SCR through the three canonical dynamic-capability processes of sensing, seizing, and reconfiguring [21], [22] thereby supplying the missing process-level mechanism that prior work has implied but not modeled. Second, the paper theorizes digital-technology intensity (the organizational penetration of AI, the Internet of Things (IoT), and related Industry 4.0 (I4.0) technologies) and supply chain risk exposure as joint boundary conditions of the analytics-resilience relationship, integrating insights from the digital-twin and Industry 4.0 literature that have so far been discussed largely in isolation

from mainstream resilience theory [23], [24]. Third, the paper translates the conceptual model into nine falsifiable propositions and a three-stage maturity roadmap, providing both a concrete agenda for empirical validation using established survey and structural equation modeling methods, and a diagnostic tool that managers can use to benchmark their organization's analytics-driven resilience posture.

The remainder of the paper is organized as follows. Section 2 reviews the literature on SCR, BDA capability, the theoretical foundations of the Resource-Based View (RBV) and Dynamic Capabilities Theory (DCT), and emerging digital technologies, before synthesizing this material into an explicit statement of the research gap. Section 3 develops the DDSCR framework and defines its constituent constructs. Section 4 articulates the propositions that specify the relationships among these constructs and their boundary conditions. Section 5 discusses the theoretical and managerial implications of the framework and proposes a roadmap for its empirical validation. Section 6 concludes the paper with a summary of its contributions, its limitations, and directions for future research.

2 | Literature Review

2.1 | Theoretical Foundations: The Resource-Based View and Dynamic Capabilities

The theoretical foundation of this paper rests on two closely related streams of strategic management theory. The RBV holds that a firm's sustained competitive advantage derives from resources that are valuable, rare, imperfectly imitable, and non-substitutable [25]. Data and analytics infrastructure, on their own, rarely satisfy these criteria, since hardware and software can generally be purchased on comparable terms by competitors. It is the organizational capability to deploy such resources effectively, what the literature terms BDA capability, that is more difficult to imitate and therefore more likely to be a genuine source of advantage. This distinction motivates the second theoretical pillar of the paper, DCT. Dynamic capabilities are defined as the firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments [21], and are commonly disaggregated into three processes: sensing opportunities and threats, seizing opportunities through resource redeployment, and reconfiguring the resource base to sustain competitiveness [21]. Eisenhardt and Martin [22] further clarify that dynamic capabilities are best conceived not as a single mysterious asset, but as identifiable, learnable organizational and strategic routines through which firms achieve resource reconfiguration. This process view is particularly well suited to explaining resilience, which is inherently about how an organization changes its resource configuration in response to disturbance, and it is this process view that the DDSCR framework adopts as its organizing logic in Section 3.

2.2 | Supply Chain Resilience: Concept, Evolution, and Antecedents

The concept of SCR was popularized by Christopher and Peck [5], who characterized a resilient supply chain as one able to return to its original state, or move to a new, more desirable state, after being disturbed. Sheffi and Rice [26] extended this view by linking resilience to a firm's redundancy and flexibility investments, arguing that flexibility, cross-trained staff, interchangeable production lines, and multiple suppliers tend to be more cost-effective than redundancy alone. Ponomarov and Holcomb [4] synthesized the early literature into a widely cited definition of SCR as the adaptive capability to prepare for and respond to disruptions, make timely and cost-effective decisions, and return to normal operational performance. Pettit et al. [20] operationalized resilience through a balance between vulnerability factors, which increase susceptibility to disruption, and capability factors, which enhance the ability to anticipate, cope with, and recover from disruption; their SCR assessment framework remains one of the most frequently cited diagnostic tools in the field.

Subsequent empirical work has identified a range of antecedents of SCR. Craighead et al. [1] showed that the severity of a supply chain disruption is jointly determined by the design characteristics of the supply chain (density, complexity, node criticality) and the mitigation capabilities available to the firm, an early indication

that resilience is co-produced by structure and capability rather than by structure alone. Jüttner and Maklan [27], studying firms during the 2008-2009 global financial crisis, found that supply chain risk management practices strengthened flexibility, visibility, velocity, and collaboration, and that these four capabilities in turn improved perceived resilience. Ambulkar, Blackhurst, and Grawe [28] developed and validated a scale for firm-level resilience to supply chain disruptions and demonstrated that resource reconfiguration, an explicitly dynamic-capability construct, was a significant driver of resilience, while formal risk management planning alone was not sufficient.

Brandon-Jones et al. [14] distinguished between SCR and supply chain robustness and showed, using a contingent resource-based lens, that visibility and connectivity are resources whose effect on performance depends on the level of environmental complexity the firm faces. Wieland and Wallenburg [15] similarly distinguished an agile, change-oriented dimension of resilience from a robust, stability-oriented dimension, and showed that relational competencies such as communication and cooperation strengthen both. Scholten and Schilder [13] demonstrated that inter-organizational collaboration, encompassing information sharing, collaborative communication, and joint decision-making, is a key mechanism by which visibility and velocity are converted into resilience.

Tukamuhabwa et al. [29], in a comprehensive review of the field, concluded that despite two decades of research, SCR still lacked an integrative theoretical foundation and called explicitly for future work to draw on organizational theories such as dynamic capabilities to explain how resilience is built rather than merely what resilience consists of, a call that motivates the framework developed in Section 3 of this paper. More recently, Ivanov and Dolgui [30] proposed the related notion of supply chain viability, arguing that in the wake of long-duration, simultaneous disruptions such as pandemics, resilience concepts developed for localized disruptions must be extended to consider the survivability of the entire supply-demand network over time, a perspective that reinforces the need for continuous, data-enabled monitoring rather than one-off contingency planning.

2.3 | Business and Big Data Analytics Capability

The concept of BDA capability originates in the information-systems literature on the strategic use of data. Davenport [6] argued that firms that "compete on analytics" build organization-wide capabilities in data quality, statistical and quantitative expertise, and executive commitment to fact-based decision-making, rather than relying on isolated analytical projects. LaValle et al. [7], drawing on a large multi-industry survey, found that top-performing organizations were twice as likely as their lower-performing peers to use analytics to guide future strategy rather than merely to explain past performance.

Gupta and George [18] formalized BDA capability as a higher-order construct comprising tangible resources (data, technology, and basic infrastructure), human resources (technical and managerial skills), and intangible resources (data-driven culture and organizational learning), and showed that this capability, rather than data or technology resources in isolation, is what generates competitive performance. Akter et al. [8] similarly decomposed BDA capability into management, technology, and talent capabilities and demonstrated that alignment between these capabilities and business strategy is a significant predictor of firm performance. Mikalef et al. [31], in a systematic review of the BDA capability literature, confirmed the convergence of the field on this multi-dimensional resource-based conceptualization and identified organizational, not merely technological, capability as the primary locus of competitive value.

Within the supply chain domain specifically, Wang et al. [19] reviewed applications of BDA across procurement, production, and logistics and concluded that the greatest value from analytics accrues when it is embedded in cross-functional decision processes rather than deployed as a standalone analytical tool. Wamba et al. [9] provided empirical evidence that the effect of BDA on firm performance is mediated by dynamic capabilities, directly supporting the theoretical logic that analytics capability alone is insufficient and must be converted into organizational action to generate value, precisely the conversion mechanism that the DDSCR framework formalizes for the resilience context. Gunasekaran et al. [10] extended this logic to supply

chain and organizational performance specifically, showing that the assimilation of big data and predictive analytics improves performance primarily when supported by a resource-based organizational culture that values evidence over intuition.

Kache and Seuring [32] cautioned, however, that the integration of BDA into supply chain management is not automatic, identifying data quality, cross-organizational data sharing, and the redesign of decision-making processes as persistent challenges that determine whether analytics investment translates into operational benefit.

Waller and Fawcett [33], in an early call to the field, argued that supply chain scholars needed to develop new theory specifically to explain how data science and predictive analytics reshape supply chain design, rather than treating analytics purely as a technical add-on to existing supply chain models, a call this paper answers directly for the resilience context.

Dubey et al. [12], studying humanitarian supply chains, found that BDA capability combined with an organizational culture of collaboration and swift trust significantly improved supply chain performance under conditions of extreme urgency and uncertainty, offering an early empirical bridge between analytics capability and disruption-context outcomes that closely parallel commercial resilience settings.

2.4 | Emerging Digital Technologies and Supply Chain Risk Management

A parallel and increasingly influential literature examines how specific digital technologies, AI, the IoT, and I4.0 more broadly, affect supply chain risk and resilience. Baryannis et al. [16], in a systematic review of supply chain risk management and AI, found that machine learning and optimization techniques are increasingly used for risk identification and prediction but that their integration with established risk-management frameworks and with resilience strategy remains immature, and they explicitly called for research connecting AI-enabled prediction to resilience-building action.

Ivanov and Dolgui [23] proposed the digital supply chain twin, a dynamic, data-driven digital replica of the physical supply network, as a means of simulating disruption scenarios and evaluating recovery policies before a disruption occurs, effectively operationalizing the sensing and seizing processes of dynamic-capability theory in a supply chain risk context.

Ralston and Blackhurst [24], however, offered an important qualification, arguing that I4.0 technologies can simultaneously enhance and erode resilience: while they improve visibility and responsiveness, they can also introduce new interdependencies, cybersecurity exposure, and single points of failure that increase vulnerability, implying that the resilience benefit of digital technology is conditional rather than automatic.

Modgil et al. [17], studying the COVID-19 context, found that AI adoption strengthened SCR primarily through improved demand forecasting and dynamic rerouting of logistics, but that the effect was moderated by organizational readiness and top-management support.

Zamani et al. [11], synthesizing 23 empirical studies in a systematic literature review, mapped AI and BDA applications onto the four resilience phases of readiness, response, recovery, and adaptability, and concluded that while readiness and response applications are relatively mature, applications supporting long-term adaptability remain underexplored, an observation that directly informs the anticipation-adaptation-recovery structure of the resilience capacities proposed in Section 3.

Belhadi et al. [34], comparing the automobile and airline industries during the COVID-19 outbreak, found that firms which had previously invested in digital and analytical capabilities were able to reconfigure operations and supply relationships substantially faster than those relying primarily on physical redundancy, providing a cross-industry empirical illustration of the capability-based logic this paper formalizes.

2.5 | Synthesis and Research Gap

Read together, four observations emerge from this review. First, the SCR literature has converged on a shared conceptual vocabulary of anticipation, adaptation, and recovery but has not systematically connected this vocabulary to the internal, capability-based mechanism by which firms build these capacities [4], [20]. Second, the BDA capability literature has independently converged on a resource-based, capability-oriented conceptualization of analytics value and a subset of this literature has already shown that dynamic capabilities mediate the analytics-performance relationship in general but this mediating logic has rarely been applied specifically to resilience outcomes [8-10], [18], [31].

Third, the digital-technology and AI literature demonstrates that specific technologies can enable resilience-enhancing action such as scenario simulation and demand sensing [11], [17], [23] but also cautions that technology adoption is not unconditionally beneficial and depends on organizational and risk-context moderators [24].

Fourth, and consistent with Tukamuhabwa et al.'s [29] explicit call, no existing framework integrates these three streams, resilience theory, BDA capability theory, and dynamic-capabilities process theory, into a single, testable model that specifies both the mechanism and the boundary conditions of the analytics-resilience relationship. This is the gap that the DDSCR framework, developed in the following section, is designed to close.

3 | The Data-Driven Supply Chain Resilience Framework

3.1 | Framework Overview and Constructs

Building on the theoretical foundations reviewed in Section 2, this paper proposes the DDSCR framework, illustrated in *Fig. 1*. The framework comprises five constructs, organized into three layers. The first layer is the resource layer, represented by BDA capability, defined consistent with Gupta and George [18] and Akter et al. [8] as the organizational ability to combine data, technology, and human and managerial skill to generate decision-relevant insight.

The second layer is the process layer, represented by the three dynamic-capability processes of sensing, seizing, and reconfiguring which together describe how BDA capability is converted into organizational action [21], [22]. The third layer is the outcome layer, represented by three resilience capacities, anticipation, adaptation, and recovery, adapted from the vulnerability-capability structure proposed by Pettit et al. [20] and the preparedness-response-recovery structure proposed by Ponomarov and Holcomb [4]. Two contingency constructs, digital-technology intensity and supply chain risk exposure, are positioned as boundary conditions that moderate the strength of the relationships between the process layer and the outcome layer. *Table 1* summarizes the definition and representative theoretical sources of each construct.

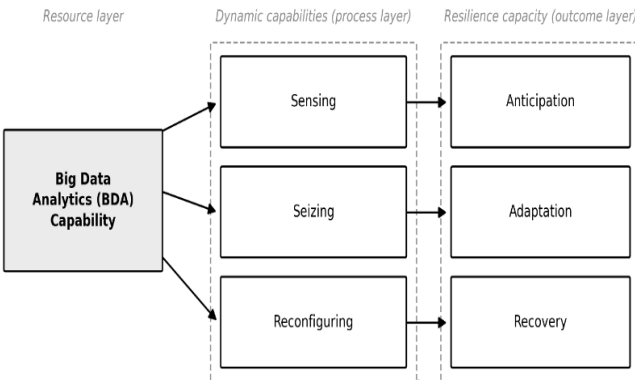


Fig. 1. The DDSCR conceptual framework.

Table 1. Definitions and representative theoretical sources of the DDSCR framework's core constructs.

Construct	Definition	Representative Source(s)
BDA capability	Organizational ability to combine data, technology, and human and managerial skill to generate decision-relevant insight.	Gupta and George [18], Akter et al. [8]
Sensing	Continuous scanning of internal operations and the external environment for weak signals of change.	Teece et al. [21]
Seizing	Mobilizing resources to capture an identified opportunity or counter an identified threat.	Teece et al. [21]
Reconfiguring	Ongoing renewal of the resource base, structures, and routines to sustain fit with a changed environment.	Eisenhardt and Martin [22]
Anticipation	Capacity to foresee potential disruptions before they materialize.	Pettit et al. [20]
Adaptation	Capacity to adjust operations, sourcing, and logistics in real time as a disruption unfolds.	Ponomarov and Holcomb [4]
Recovery	Capacity to restore, and in some cases improve upon, prior performance after a disruption.	Sheffi and Rice [26]
Digital-technology intensity	Organizational penetration of AI, IoT, and other Industry 4.0 (I4.0) technologies.	Ralston and Blackhurst [24], Ivanov and Dolgui [23]
Supply chain risk exposure	Degree to which a firm's supply network is exposed to potential sources of disruption.	Craighead et al. [1], Jüttner and Maklan [27]

Fig. 1 depicts the overall architecture of the framework: BDA capability is shown feeding into the three dynamic-capability processes, which in turn feed into the three resilience capacities, with the two contingency constructs drawn as moderating arrows acting on the process-to-outcome relationships. This architecture makes explicit what prior resilience frameworks have generally left implicit: That resilience capacities are not a direct output of data or technology, but the output of an organizational conversion process that uses data as its raw material.

3.2 | From Sensing to Anticipation: The Analytics-Resilience Mechanism

The explanatory core of the DDSCR framework is the claim that each dynamic-capability process maps onto a corresponding resilience capacity, illustrated in *Fig. 2*.

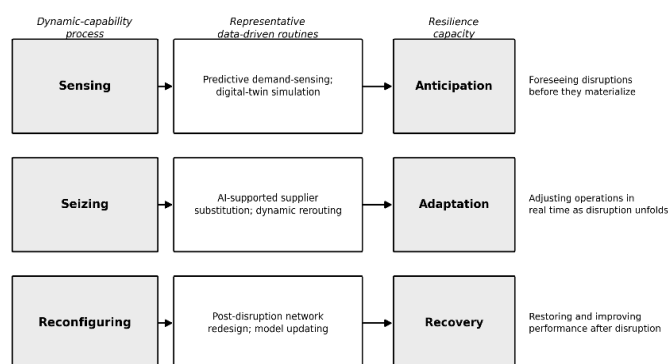


Fig. 2. The sensing-seizing-reconfiguring mechanism linking BDA capability to anticipation, adaptation, and recovery.

Sensing, the continuous scanning of internal operations and the external environment for weak signals of change [21], is the process through which BDA capability is converted into anticipation, the resilience capacity

to foresee potential disruptions before they materialize [20]. Predictive analytics, demand-sensing algorithms, and digital-twin simulation [23] are concrete organizational routines through which sensing is operationalized in a data-driven supply chain. Seizing, the process of mobilizing resources to capture an identified opportunity or to counter an identified threat [21], is the process through which BDA capability is converted into adaptation, the resilience capacity to adjust operations, sourcing, and logistics in real time as a disruption unfolds [4]. Dynamic rerouting, AI-supported supplier substitution, and real-time inventory reallocation [17] exemplify seizing in this context. Reconfiguring, the ongoing renewal of the resource base, organizational structures, and routines to sustain fit with a changed environment [22], is the process through which BDA capability is converted into recovery, the resilience capacity to restore, and in some cases improve upon, prior performance levels once the acute phase of a disruption has passed [26]. Post-disruption network redesign informed by disruption analytics, and the institutionalization of lessons learned through updated forecasting models, exemplify reconfiguring. This process-to-capacity mapping gives the framework its central theoretical claim: BDA capability does not generate resilience directly, but does so only to the extent that it is metabolized through the sensing-seizing-reconfiguring cycle, a claim formalized as propositions in Section 4.

4 | Propositions Linking Analytics Capability, Dynamic Capabilities, and Resilience

4.1 | Direct and Mediated Relationships

Building on the mechanism described in Section 3.2, the first set of propositions specifies the mediated relationship between BDA capability and resilience.

P1. BDA capability is positively associated with the strength of a firm's dynamic capabilities (sensing, seizing, and reconfiguring).

P2. Dynamic capabilities are positively associated with SCR capacity (anticipation, adaptation, and recovery).

P3. Dynamic capabilities mediate the relationship between BDA capability and SCR capacity, such that the direct effect of BDA capability on resilience is weaker than its indirect effect through dynamic capabilities.

P3 follows directly from the mediated-mechanism logic established for firm performance generally by Wamba et al. [9] and Gunasekaran et al. [10], applied here specifically to the resilience outcome that prior analytics research has largely left untheorized [29]. Because sensing, seizing, and reconfiguring are sequential and cumulative processes [21], the framework further predicts an ordered pattern of association between each process and its corresponding resilience capacity:

P4. Sensing capability is more strongly associated with anticipation than with adaptation or recovery.

P5. Seizing capability is more strongly associated with adaptation than with anticipation or recovery.

P6. Reconfiguring capability is more strongly associated with recovery than with anticipation or adaptation.

4.2 | Moderating Role of Digital Technology Intensity and Risk Exposure

The second set of propositions addresses the boundary conditions under which the mediated relationship specified in *P1–P6* is strengthened or weakened.

P7. Digital-technology intensity (organizational penetration of AI, IoT, and I4.0 technologies) positively moderates the relationship between BDA capability and dynamic capabilities, such that this relationship is stronger for firms with higher digital-technology intensity.

P7 is grounded in the digital-twin and I4.0 literature, which shows that technologies such as digital twins provide the infrastructural means by which sensing and seizing are executed at scale and in real time [23]. However, consistent with Ralston and Blackhurst's [24] finding that I4.0 technologies can introduce new vulnerabilities alongside new capabilities, the framework further predicts a qualification:

P8. Supply chain risk exposure positively moderates the relationship between dynamic capabilities and resilience capacity up to a threshold, beyond which the moderating effect weakens as the complexity and interdependency introduced by high digital-technology intensity begin to offset the benefits of dynamic capability.

Finally, drawing on Belhadi et al.'s [34] cross-industry evidence that pre-existing digital investment, rather than disruption-time investment, explained differences in reconfiguration speed:

P9. The positive effect of BDA capability on resilience capacity is stronger for firms that developed their dynamic capabilities prior to a disruption than for firms that attempt to build such capabilities during or after a disruption.

Collectively, *P1–P9* render the DDSCR framework empirically tractable: Each construct in *Fig. 1* and *Fig. 2* corresponds to an established measurement tradition in the literature (for example, the BDA capability scales of Akter et al. [8] and Gupta and George [18], and the resilience scale of Ambulkar et al. [28]), such that the full model could, in principle, be estimated using a single cross-sectional or longitudinal survey instrument, a possibility elaborated in Section 5.3.

5 | Implications for Theory, Practice, and Future Empirical Validation

5.1 | Theoretical Implications

The DDSCR framework makes three principal theoretical contributions. First, it responds directly to Tukamuhabwa et al.'s [29] call for an integrative theoretical foundation for SCR by embedding resilience within dynamic-capabilities theory rather than treating it as a free-standing construct explained solely by structural antecedents such as redundancy and network design. Second, it extends the BDA capability literature, which has already established that dynamic capabilities mediate the analytics-performance relationship in general [9], by specifying this mediation mechanism in fine-grained, process-specific terms (*P4–P6*) rather than as an undifferentiated aggregate effect. Third, it reconciles the optimistic view of digital technology found in the AI-resilience literature [11], [17] with the more cautious view found in the I4.0-vulnerability literature [24] by modeling digital-technology intensity as a moderator with a bounded, rather than a monotonically positive, effect (*P8*).

5.2 | Managerial Implications

For practitioners, the framework offers a diagnostic vocabulary that moves the conversation about resilience investment beyond a binary choice between "more redundancy" and "more analytics." Because the framework specifies that resilience capacity depends on the conversion of BDA capability through sensing, seizing, and reconfiguring routines, managers evaluating an analytics investment can ask a more precise question than whether the investment improves data quality or dashboard visibility: they can ask which of the three dynamic-capability processes the investment is intended to strengthen, and which of the three resilience capacities, anticipation, adaptation, or recovery, that process is expected to improve. This process-capacity mapping (*Fig. 2*) can be used as a simple audit tool: A firm strong in predictive demand sensing but weak in cross-functional reconfiguration routines, for example, should expect strong anticipation but weak recovery, and should prioritize investment accordingly. *P9* further implies a timing lesson consistent with Belhadi et al.'s [34] findings: because dynamic capabilities are cultivated through practice, organizations that wait until a disruption occurs to build analytics-enabled reconfiguration routines are structurally disadvantaged relative to those that have institutionalized these routines beforehand.

5.3 | A Roadmap for Empirical Validation

To move from conceptual framework to empirical theory, the propositions in Section 4 require systematic testing. *Fig. 3* proposes a three-stage maturity roadmap, descriptive, predictive, and prescriptive analytics

maturity, that can serve as both a practical implementation sequence for firms and a natural basis for operationalizing digital-technology intensity as a graded, rather than binary, moderator in future empirical work.

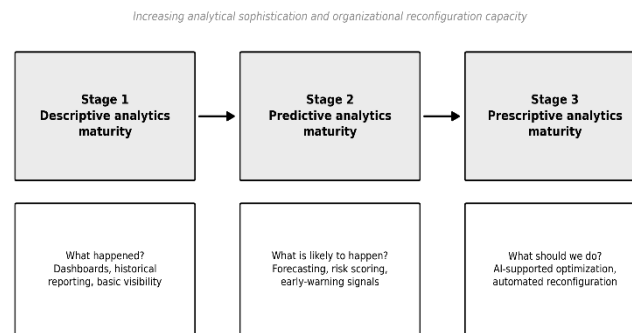


Fig. 3. A three-stage maturity roadmap for implementing DDSCR.

Methodologically, the constructs specified in *Table 1* map onto existing, previously validated measurement scales: BDA capability can be operationalized using the multi-dimensional scales of Gupta and George [18] or Akter et al. [8]; resilience capacity can be operationalized using the vulnerability-capability instrument of Pettit et al. [20] or the disruption-resilience scale of Ambulkar et al. [28], and digital-technology intensity can be operationalized using I4.0 technology-adoption indices consistent with those used by Ralston and Blackhurst [24] and Modgil et al. [17]. A cross-sectional survey of supply chain and information-technology executives, analyzed using covariance- or variance-based structural equation modeling with the mediation and moderated-mediation tests appropriate to *P1–P9*, would allow the framework to be tested as an integrated system rather than piecemeal. A longitudinal or event-based design (for example, comparing firms before and after a common exogenous disruption) would additionally allow *P9*'s temporal claim to be tested directly, following the systematic-review methodology guidance of Tranfield et al. [35] for ensuring the resulting body of evidence remains cumulative and comparable across studies.

6 | Conclusion

This paper set out to address a specific and consequential gap in the supply chain management literature: the absence of an integrative, capability-based explanation of how BDA capability is converted into SCR. Building on the RBV [25], DCT [21], [22] and a comprehensive review of the resilience [4], [20], [29] and analytics [8], [9], [18] literatures, the paper developed the DDSCR framework, which routes BDA capability through the dynamic-capability processes of sensing, seizing, and reconfiguring to produce the resilience capacities of anticipation, adaptation, and recovery, subject to the boundary conditions of digital-technology intensity and supply chain risk exposure. Nine propositions (*P1–P9*) and a three-stage maturity roadmap operationalize this framework for future empirical testing.

The framework's principal value lies in reconciling two research streams that have developed largely in parallel. By demonstrating, at the level of theory, exactly where and how resilience research and analytics-capability research intersect, the paper answers Tukamuhabwa et al.'s [29] long-standing call for an integrative theoretical foundation for SCR, while extending the dynamic-capabilities mediation logic already established for general firm performance [9] into the specific and increasingly urgent context of disruption resilience. For managers, the framework replaces an undifferentiated notion of "investing in analytics for resilience" with a precise diagnostic logic linking specific analytical investments to specific dynamic-capability processes and specific resilience outcomes.

As a conceptual contribution, this paper is naturally subject to limitations that also define its most immediate directions for future research. The framework and its propositions have not yet been empirically tested; although each construct was deliberately mapped onto existing, validated measurement instruments to facilitate testing, the strength and even the direction of the proposed relationships, particularly the bounded

moderation effect proposed in P8, remain to be confirmed using the structural equation modeling agenda outlined in Section 5.3. The framework was also developed at a general, cross-sectoral level of abstraction; because supply chain risk exposure and digital-technology intensity are likely to vary systematically across industries such as healthcare, automotive, and humanitarian logistics, future research should examine whether the strength of the proposed relationships is industry-contingent, extending the cross-industry comparative logic already applied by Belhadi et al. [34] to a wider range of sectors. In addition, the framework's temporal claim (P9) implies a need for longitudinal or event-based empirical designs that are more demanding to execute than cross-sectional surveys but are necessary to establish whether dynamic capabilities must indeed be cultivated before, rather than during, a disruption. Finally, as generative AI and increasingly autonomous analytics systems become embedded in supply chain decision-making, future work should examine whether the sensing-seizing-reconfiguring mechanism itself changes in nature, and not merely in intensity, when the analytical actor is not only assisting but in some cases substituting for human managerial judgment, a boundary condition the present framework does not yet address and that is likely to become increasingly consequential for both the theory and the practice of SCR.

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Author Contribution

The author was solely responsible for all aspects of this work, including conceptualization, literature synthesis, framework development, and writing.

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Data Availability

This is a conceptual paper. No new empirical data were generated or analyzed. All arguments developed in this paper are supported by the published literature cited in the References section.

Conflicts of Interest

The author declares no conflict of interest.

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