

Article

Digital Service Innovation and Recovery Resilience in Supply Chain Network Interruption: An Opportunity Perspective

Yanjie Gou ^{1,2,*} , Maozeng Xu ¹ and Lucille Aba Abruquah ^{3,4} 

¹ School of Economics and Management, Chongqing Jiaotong University, Chongqing 400074, China; xmzrxhy@cqjtu.edu.cn

² School of Innovation and Entrepreneurship, Sichuan University of Arts and Science, Dazhou 635000, China

³ Research Global, Accra P.O. Box AN 18923, Ghana; labruquah@walsfoundation.org

⁴ Heritage and Cultural Foundation of Africa Foundation, Accra P.O. Box LG 586, Ghana

* Correspondence: 611200120002@mails.cqjtu.edu.cn

Abstract

The intricate structure of the supply chain network, combined with the uncertainty of the external environment, has made supply chains more fragile and disrupted normal logistics operations. In the digital economy age, the integration of digital technologies and innovation in services has become a vital means of facilitating the sustainable development of enterprise. However, few studies have explored how digital service innovation affects the resilience of recovery during a supply chain interruption. This study draws on opportunity theory to construct a theoretical framework for explaining how digital service innovation affects firm resilience, with a focus on examining the mediating role of opportunity search and opportunity linking, as well as the moderating role of big data analytics capabilities. Based on a survey conducted on the technology-based manufacturing enterprises in China, the results have shown the following: (1) Resilience of recovery is positively influenced by digital service innovation. (2) Opportunity searching and opportunity linking act as mediators between digital service innovation and resilience of recovery. (3) Big data analytical ability exerts a positive moderating effect on the association between digital service innovation and opportunity searching, as well as opportunity linking, which means that the greater the big data analytical ability, the greater the positive effect of digital service innovation on opportunity searching as well as opportunity linking. The current study expands the theoretical lens of digital service innovation, opportunity theory, and big data analytical ability to the area of supply chain disruption. It also offers practical insights for technology-based manufacturing enterprises in China seeking to enhance resilience of recovery during supply chain interruptions.

Keywords: supply chain network; resilience of recovery; digital service innovation; opportunity perspective



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1. Introduction

In today's digital economy, the role and sustainability of the supply chain network are crucial to firm growth and survival. A supply chain network is a strategic, data-driven approach for improving the flow of products, services, data, and finances across the entire supply chain framework. Thus, it encompasses the entire process, including the procurement of raw and processed materials, production, and distribution and delivery of the finished product or services. Additionally, the concept is linked with the management and coordination process of information and capital flows [1].

With the global economic growth slowdown (e.g., from 3.3% in 2024 to 3.2% in 2025 and 2.9% in 2026), the level of uncertainty related to the supply chain management process continues to increase daily. This can create a volatile high-risk environment, as any delays or discrepancies in the process, from the procurement of raw materials to the delivery of the finished product, can disrupt the entire manufacturing process [2,3]. Especially in an uncertain and turbulent environment, resilience can emerge as a key element of supply chain networks, as even the best-designed systems are susceptible to unpredictable events [4]. Resilience refers to the ability to deal with crises effectively, circumvent perils, and develop under antagonistic conditions [5]. Recovery resilience (RR) is the capability of people, structures, or communities to not only bounce back from, but to acclimatize, flourish, and improve amid succeeding misfortune, shock, or commotion. It accentuates erudition, solidifying and sprouting throughout the reconstruction process. In supply chain management, RR plays a critical role in maintaining continuity. The concept has gained significant attention from the academic community. Scholars have acknowledged that striving to solve the problems caused by supply chain disruption requires enterprises to react promptly and build or strengthen RR after the interruption to sustain their competitiveness in the marketplace [6]. They assert that enterprises must continuously maintain RR, not only relying on traditional skills within their supply chain management.

Digital technologies (such as digital service innovation (DSI)) can offer a sequence of opportunities and benefits for supply chain management enterprises to shape RR. Thus, they can infuse vitality into supply chain network management for improving RR [7]. Digital service innovation describes the expansion of new services through the use of digital technologies [8]. This concept is built on the capability to utilize connected products to synthesize value by means of digitally improved provider–customer dealings [9]. It permits enterprises to anticipate disruptions, alleviate risks in real-time, and swiftly reinstate operations.

Previous research has mostly focused on the linkages between digital technology adoption and RR [10]; supply chain design optimization and RR [11]; collaboration with suppliers and RR [12]; and crisis management strategies and RR [13]. However, this context views digital service innovation (DSI) as a promising approach to enhance RR strategies. From the extant works, even if some applications of DSI are employed in the environment of supply chain disruptions, academic studies currently overlook their underlying mechanisms.

First, digital technology can play valuable roles in an enterprise's operations. For instance, the concept can condense information asymmetry between upstream and downstream companies. It aids the monitoring process for interruptions related to the supply chain [14]. Particularly, digital technology tools such as DSI can offer a better approximation for customers' demands [15]. DSI can enhance the responsiveness and recovery rate of enterprises when facing network disruptions. However, the existing literature stresses only the impact of broad digital technology adoption on RR [10], ignoring the impact of DSI on RR. This article intends to address this substantial research gap with a comprehensive analysis.

Second, existing research has begun to examine supply chain resilience from a network perspective, emphasizing the need for companies to break through traditional linear supply chain thinking and instead use a supply network perspective to understand and respond to disruptions [16]. However, in order to further enhance overall resilience, future research also needs to focus on the interaction between policy networks, trade networks, and technology networks, and include more stakeholders such as governments in the analysis framework [17]. At the same time, the assessment of resilience should take into account both network structure indicators (such as connectivity and centrality) and operational

performance indicators (such as on-time delivery rate and recovery time), in order to more comprehensively consider the resilience and sustained operational level of the entire supply chain network [18].

The existing research fails to reveal the internal mechanism between DSI and RR from the perspective of opportunity theory. DSI can raise the opportunity ability of enterprises. By capitalizing on diverse DSI, enterprises can broaden their sources of information and search or link both inner and outer resource paths [19,20]. It can allow them to position themselves in the supply chain arena. This ability has a significant impact on RR, which is aligned with the explanatory logic of opportunity theory. Therefore, this article suggests that opportunity search (OS) and opportunity linking (OL) mediate the linkage between DSI and RR. OS can serve as a vital driver to enhance corporate risk management capabilities and the supply chain network's RR. For instance, with the availability of information, enterprises easily mobilize substitute suppliers, explore new logistics paths, or adjust production plans in response to disruption triggers [21–23]. Conversely, OL supports all players in the network to obtain a better understanding of the situation, thereby enabling better judgment regarding the impact of disruptions and the formulation of effective solutions [24]. Especially when a network interruption occurs, OL networks can be quickly activated based on digital service usage. This allows organizations to reduce their dependency on existing resource paths. This study intends to validate the mediating roles of OS and OL, to reveal the black box mechanism of DSI's impact on RR.

Third, the impact of DSI on opportunity search and linking will also be affected by the big data analytical capabilities of enterprises (BDAC). BDAC is an enterprise's capability to procure, hoard, develop, and analyze colossal, high-velocity, and diverse data sets to derive actionable insights, boost decision-making, and achieve competitive preeminence. A sound BDAC of enterprises can strengthen the firm's strategic service and opportunity search and linking, which in turn fosters more successful RR. However, the extant studies lack the discussion of the linkage between them. This article will explore the boundary effect of BDAC on the integration of DSI and opportunity, to fill this research gap.

This raises the following critical and underexplored questions:

RQ1: What is the impact of DSI on RR?

RQ2: What is the mechanism by which DSI influences RR?

RQ3: What are the boundary conditions for DSI's impact on RR?

To address the above questions, this article considers technology-based manufacturing enterprises in China as research samples. It constructs a theoretical framework, "DSI-BDAC-OS and OL-RR," from the perspective of opportunity theory. Firstly, the relationship between DSI and RR is confirmed. Secondly, it analyzes the mediating effects of opportunity search (OS) and opportunity linking (OL), respectively, on the association between DSI and RR. Finally, the moderating role of BDAC is confirmed. Overall, this study offers a theoretical contribution and practical significance through an integrated examination of DSI, RR, OS, OL, and BDAC.

2. Theory and Research Hypothesis

2.1. Theoretical Background and Conceptualization

2.1.1. DSI

Bilderbeek, Den Hertog [25] proposed an integrated concept of service innovation known as the "Four Dimensional Model," which involves novel service concepts, novel customer interfaces, novel delivery systems, and emerging technologies. These scholars believe that service innovation cannot be viewed only through product or service modification, but also through improvement in the delivery process and the technology utilized to facilitate such delivery processes. In recent years, certain academics have also have

recognized the evolution of digital technology, leading to a digital transformation process that has materialized, incorporating elements of digital technology and customer value into service innovation [26]. As a result, the literature is gradually presenting more tech-driven and digital characteristics [27]. Against this backdrop, a service innovation model driven by digital technology has emerged, commonly referred to as DSI.

Münch, Marx [28] asserted that DSI capability is a key competency for enterprises to realize DSI, encompassing modifications to organizational structure and processes, improvements in work practices, development of infrastructures, changes in corporate culture, and reconstructions of entire value chains or ecosystems. Similarly, Opazo-Basáez, Vendrell-Herrero [29] described DSI as the creation of new services using digital technology, building on product connectivity, and adding value through enhanced supplier and customer relationships enabled by digital technology. Based on these perspectives, this article defines DSI as innovation activities performed by enterprises that utilize digital technology, including blockchain, big data analysis, and AI for services and business processes, aiming to realize value co-creation with customer and supplier companies.

Previous studies have shown that digital capabilities can enhance supply chain performance by promoting supply chain integration and strengthening information sharing and collaborative configuration capabilities among enterprises [30]. At the same time, the innovative effects generated by digital transformation can spread along the supply chain network, drive innovation activities of upstream and downstream enterprises, and promote the formation of a supply chain innovation ecosystem [31]. In addition, the service-oriented transformation driven by digital technology further promotes the evolution of enterprises from product orientation to service orientation, providing new value creation paths for the digital upgrading of the supply chain [32]. For technology-based manufacturing enterprises in China, DSI has become a critical means for supply chain digitization, as transparency, efficiency, flexibility, and responsiveness can improve the thorough transformation and optimization of the supply chain structure [33].

2.1.2. OS and OL

Risk might be defined as the adverse result of uncertainty, while its counterpart is opportunity. Under uncertain conditions, risks and opportunities often move together. The issue that matters to companies is how to determine and efficiently transform potential opportunities [34] to create a competitive advantage. Hence, it becomes crystal clear that enterprises need to reinforce opportunity management, especially when the empowerment of DSI may act as a critical way to respond to interruption risks and improve recovery capability actively. This article divides the opportunity management process into two stages: searching and identifying opportunities. The existing literature lacks the separation of these two processes. Entrepreneurs and managers engage in a typical process of searching for information about potential entrepreneurial opportunities [35], also known as OS. It is in this process that decision-makers utilize the accumulated knowledge, as well as the information garnered from the current search process, to examine the potential opportunities. Shepherd and Levesque [36] asserted that OS is a decision rule guided by the optimal stopping model that assists in accepting, rejecting, or pursuing business opportunities. OS strategies generally fall into two categories: creative behavior and knowledge acquisition. Creative behavior includes seeking out problems and opportunities in the external context [37]. Based on the preceding statements, this paper defines the operating system as the information search behavior that enterprises use to discover and identify business opportunities in the external environment through various channels and methods. It is worth noting that OS and opportunity identification are not exactly the same. Opportunity identification emphasizes the judgment, evaluation, and confirmation

of potential business opportunities, while OS focuses more on the information search process before the opportunity is formed, that is, the behavior of enterprises discovering potential opportunity clues through environmental scanning, knowledge acquisition, and information collection. Therefore, OS can be seen as an important prerequisite stage for opportunity recognition, but it is not equivalent to opportunity recognition itself.

After identifying entrepreneurial opportunities, entrepreneurs evaluate their available resources and decide whether to integrate existing ones or acquire new resources through social networks to realize the opportunity [38]. Accordingly, this article contends that in the field of entrepreneurship, OL refers to the process of matching specific market demands with appropriate resources. Compared with concepts such as resource integration and inter organizational cooperation, OL emphasizes more the matching process between opportunities and resources. Resource integration focuses on the acquisition, allocation, and utilization of existing resources, while inter organizational cooperation focuses on establishing and maintaining collaborative relationships between enterprises; and OL focuses on how to effectively connect identified market opportunities with available resources through internal and external network relationships within the organization, thereby promoting the realization of opportunities. Therefore, resource integration and inter organizational cooperation can be seen as important ways to achieve OL, but they do not constitute OL itself. The concept involves identifying opportunities and aligning them with resources within social networks. From the viewpoint of social structures, ties within the network are not equal in strength. The strong ties, developed on the foundation of trust and emotional relations, facilitate the efficient transfer of information, and the process of converting the acquired knowledge into an opportunity becomes easier with the support of strong ties in the network. The weak ties, being less strong and, in reality, lacking trust and emotional aspects, are in larger quantity, and the reach of diverse information resources, in certainty, improves the chances of identifying the opportunities and aligning them with each other.

2.1.3. BDAC

With the rapid advancement of social informatization and digitization, the volume and speed of data generation have undergone a qualitative leap. Additionally, data types and sources are becoming more diversified. In real-time, traditional information technologies can no longer meet explosive and complex data processing and analysis [39]. Given the backdrop of digital transformation, big data analytical capability (BDAC) is emerging as a decisive strategic asset for enterprises. Gupta and George [40] identified that BDAC plays an important role in collecting and processing resources, which they categorized into three dimensions: tangible resources, intangible resources, and human resources. Likewise, Srinivasan and Swink [41] stressed the importance of data analysis and interpretation through visualization and other forms of analysis, ultimately applying this knowledge to business decisions in BDAC. Thus, this article defines BDAC as the “capacity of the enterprise to utilize technology to gather, analyze, and interpret a substantial amount of complex data, and then apply the knowledge gained from analysis to business decisions.” Existing research generally believes that BDAC is not only a data processing tool, but also a dynamic capability that helps businesses acquire, integrate, and utilize data resources. By real-time analysis and mining of massive data, enterprises can improve supply chain visibility, enhance information sharing quality, and optimize decision-making processes, thereby enhancing overall supply chain operational performance [42]. Furthermore, the creation of supply chain value does not come from BDAC itself, but from its synergistic effect with supply chain integration capabilities. Jiang et al. (2024) [43] found based on a sample of Chinese technology-based manufacturing enterprises that there is a significant complementary relationship between BDAC and internal integration, supplier integration,

and customer integration, and multiple capability configurations jointly determine the formation of supply chain resilience. This indicates that BDAC can enhance the ability of enterprises to cope with external uncertainties by promoting cross-organizational information collaboration and resource coordination. In this case, and for Chinese technology firms, to gain a competitive advantage under such a dynamic environment, firms must utilize advanced forms of analysis technology, software, and professionals to unlock value from extensive amounts of data. By integrating digital information sources and rapidly interpreting internal and external data [44], firms can discover and capitalize on opportunities to enhance their supply chain abilities.

2.1.4. RR

Based on analysis of market dynamics, Chopra and Sodhi [45] describe supply chain resilience as the ability to resist, absorb, adapt, and continue from supply chain disruptions. Chowdhury and Quaddus [46] further break down supply chain resilience into three primary perspectives of readiness, response, and recovery. Recovery resilience in particular encompasses the ability of a supply chain to restore its operations after disruptions or damage. It could be evaluated in terms of recovery time, cost, interruption absorption, and loss reduction. Some scholars focus on recovery resilience (RR) based on the relationship within the supply chain network. According to these researchers, information sharing, communication, and collaboration could help increase process knowledge within the supply chain, making decision-making a collaborative process, and consequently enabling better prediction, readiness, and response to disruptions [47]. Therefore, this paper defines RR as the enterprise's ability to rapidly recover its regular operational status with the support of collaborative relationship network nodes when the enterprise's internal absorption and adaptation fail to maintain system performance after a supply chain network disruption. Supply chain management recovery resilience (RR) refers to an enterprise's ability to respond quickly to unexpected events, for the stability and continuity of supply chain operations. A resilient supply chain network can rapidly respond to shocks, mitigate cascading effects of disruptions, and minimize potential risks [48].

In the latest research, supply chain resilience is considered a dynamic capability system, whose essence is not simply to restore to the pre-disturbance state, but to maintain critical functions and achieve sustained adaptation after an impact occurs [49]. Furthermore, the formation of supply chain resilience relies on the collaborative configuration of multiple capabilities, rather than the independent action of a single capability. The complementary relationship between different capabilities is crucial for enhancing the supply chain's ability to cope with interruptions [50]. On this basis, relevant research further divides supply chain resilience into three dimensions: absorptive capacity, adaptive capacity, and recovery capacity. Among them, recovery capacity reflects the speed and degree of the supply chain's recovery to the target state after being disturbed, and it is one of the key dimensions for measuring supply chain resilience [51].

2.2. DSI and RR

The wave of globalization in the digital economy has accelerated the evolution of digitized technologies, propelling conventional supply chains into the digital age. Traditional supply chains may be associated with risks, such as information silos, caused by a low level of digital integration. This is a key impediment to the process that raises the level of resilience [52]. By contrast, integrating the supply chain with digital measures can help mitigate risks related to supply, manufacturing, demand, and distribution. It also aids the monitoring process for interruptions related to the supply chain [14].

At the enterprise level, DSI, as a crucial form of digital supply chain management, can enhance the responsiveness and recovery rate of enterprises when facing network disruptions. This is because DSI, when processing, with the aid of intense digital technological advancements, can accelerate the spreading of information between upstream and downstream companies within the supply chain network. Thus, it can enable members to appreciate and understand internal business processes [47]. Furthermore, digital technology can also assist the enterprises in better estimating customer demand [15]. As such, advanced digital technology can play a key role in condensing information asymmetry between upstream and downstream companies. Thus, providing better visibility for the enterprise's supply chain network helps prepare for countering risks associated with the supply chain network stoppage. This ultimately improves the RR.

Secondly, DSI provides digital platforms that enhance the collaborative capabilities of supply chain networks, promote operational efficiency, and offer enterprises a place to better cope with disruption events.

From a digital standpoint, supply chain service platforms enhance collaboration between entities [53] and improve the operability of diverse processes [54]. By embedding intelligence into traditional logistics models, DSI makes logistics leaner and more efficient [55]. It also leads to better integration of industrial chains with competitive advantages, and decreases enterprise redundancy, cost stickiness, and inefficient capital turnover. Additionally, it increases resource exchange between supply chain participants [53]. Moreover, when facing disruption events, supply chain service platforms provide assistance related to collaborative decision-making, resource sharing, and response actions for supply chain operations [47].

Based on this, this article proposes:

H1. *DSI has a positive effect on RR.*

2.3. The Mediating Role of OS

As the scale of uncertainty in today's supply chain network continues to rise, enterprise uncertainty and potential risks can be further magnified due to market dynamics complexities, which pose unforeseen challenges to the enterprise after interruption in terms of production downtime, logistics delays, inventory outages, decreased revenues of partners, and innovation in technology [56]. To address these challenges, there is always a need for improvement in the enterprise's sensitivity to interruption events. Within the current digital era, the DSI has disrupted the concept of managing supply chains and pathways for digital technologies, such as AI, BDA, and CC, enabling greater sensitivity to changes in complex environments [57]. Specifically in the context of interruption events, these digital technologies can be used effectively for rapid recovery.

In this situation, DSI considerably raises the OS capability of organizations. More importantly, digital infrastructures offer platforms for creating and exchanging information resources in service ecosystems [58]. By leveraging diverse digital technologies and tools, enterprises can broaden their sources of information and efficiently search for both inner and outer information [59]. It also provides unprecedented market insights for businesses, making it easier for them to quickly scan to identify risks, sense changes, and discover potential substitutes or resources should they be faced with supply chain disruption as triggers [60]. For instance, with the availability of information, enterprises easily mobilize substitute suppliers, explore new logistics paths, or adjust production plans in response to disruption triggers [21–23]. Such agility reduces dependence on single pathways and accelerates recovery. Therefore, OS serves as a vital driver in improving corporate risk management capabilities and the supply chain network's recovery resilience (RR).

Based on this, this article proposes that:

H2a. *DSI has a positive impact on OS.*

H2b. *OS has a positive effect on RR.*

H2c. *OS plays a mediating role between DSI and RR.*

2.4. The Mediating Role of OL

In the supply chain network disruption environment, effective alignment between market opportunities and certain resources becomes critical for achieving resilience recovery. DSI provides this process with more efficient means of matching resources and collaborating. With the aid of the service ecosystem and other online platforms, businesses can develop OL networks, superseding the conventional boundaries of the organization [61]. These platforms enable enterprises to leverage a broader collaboration network and quickly establish contacts with raw material suppliers, logistics service providers, and third-party manufacturers [20]. This enhanced connectivity enables enterprises to rapidly mobilize resources, achieve efficient opportunity resource balancing, and accelerate recovery after disruption.

Moreover, OL offers flexible response paths for enterprises to respond to unexpected supply chain disruptions, which allows for the integration and sharing of information associated with the supply chain between enterprises and their partners.

OL assists all players in the network in obtaining a better understanding of the situation, thereby enabling better judgment regarding the impact of disruptions and the formulation of effective solutions [24].

When a network interruption occurs, OL networks can be quickly activated based on digital service usage, enabling organizations to condense their dependency on existing resource paths. Based on OL, external resources can be quickly leveraged and orchestrated to produce new resource configurations based on varied dimensions, enabling organizations to connect with potential alternative suppliers, logistics, or other crucial partners [19,20]. The capacity to easily identify and lock in other products upstream and downstream of suppliers, or distributors, enables businesses to adapt quickly and effectively mitigate the negative impact of disruptions [62]. Furthermore, OL enables effective collaboration with others for joint decision-making and response actions, including co-investing in the advancement and sharing of novel technologies, hence accelerating the reconstruction and recovery of the supply chain network [63].

Based on this, this article proposes that:

H3a. *DSI has a positive impact on OL.*

H3b. *OL has a positive effect on RR.*

H3c. *OL plays a mediating role between DSI and RR.*

2.5. The Moderating Role of BDAC

With the continually increasing amounts of data, the challenge of handling large amounts of data within acceptable time and resource constraints has emerged as one of the biggest issues for conventional architecture and infrastructure. To effectively extract value from these data, organizations increasingly need specialized tools and methods designed for big data processing. Consequently, big data analysis has become a crucial factor for enterprises to discover hidden information and obtain a competitive advantage in the market [64]. Within the digital economy, the importance of BDAC is particularly evident [65]. Since digital technology involves data capture, IoT sensors, and Web Crawlers,

it can significantly enable data-informed decisions within supply chain management activities, and risks and efficiencies can be efficiently managed [66]. BDAC exerts a significant moderating role in these dimensions. Firstly, based on the DSI procedure, BDAC broadens the digital search landscape, leading businesses to adapt to and understand market changes and make rapid decisions about opportunities to rebuild supply chain capabilities [67]. Secondly, although the service ecosystem and digital platform developed through DSI have improved enterprises' ability to access and process information resources, BDAC has further strengthened this capability (Borges et al., 2021 [68]). The utilization of advanced analysis capabilities enables them to collect valuable signals concerning customers, suppliers, and users, and examine possible opportunities within the value of the information. Thirdly, when DSI empowers supply chain networks, the explosive growth and complexity of real-time data often exceed the capacity of firms to process and analyze it effectively [39]. BDAC addresses this challenge by filtering and cleaning complex datasets, eliminating redundancy and noise [69]. This substantially improves data quality, allowing enterprises to extract high-value information, dynamically identify alternative resources, and rapidly connect with potential partners.

Based on this, this article proposes:

H4a. *BDAC positively regulates the link between DSI and OS, which means that the stronger BDAC, the greater the positive impact of DSI on OS.*

H4b. *BDAC positively regulates the link between DSI and OL, which means that the stronger BDAC, the greater the positive impact of DSI on OL.*

The theoretical framework adopted in this article is illustrated in Figure 1.

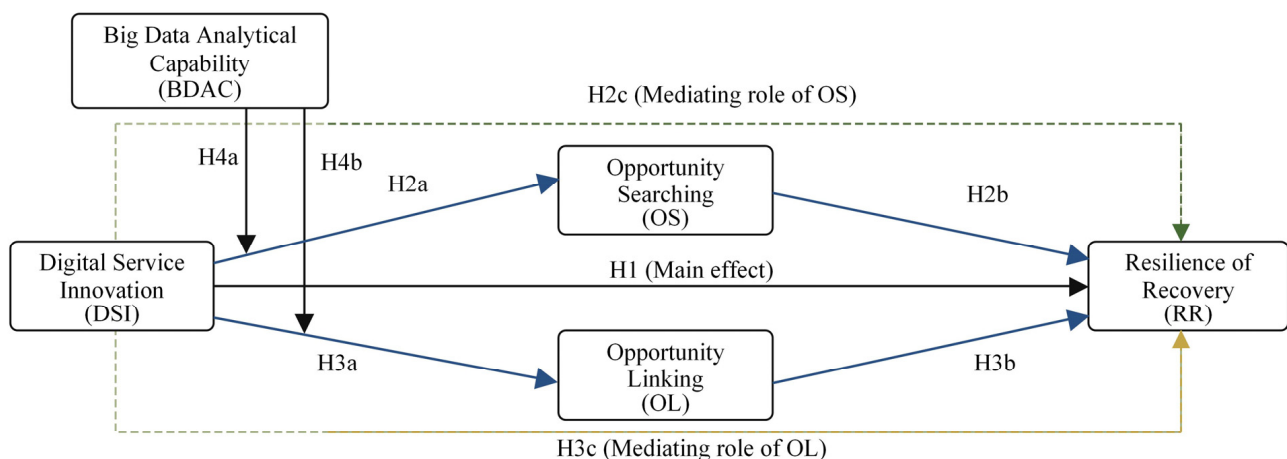


Figure 1. Theoretical framework. Note: The black arrow in the middle represents the main effect; the blue and green arrows above represent the mediating path of OS; the blue and yellow arrows below represent the mediating path of OL; the black solid lines on the left represent the two moderating paths of BDAC.

3. Data Collection, Measurement, and Analysis

3.1. Variables Measurement

Drawing on the research by Barrett, Davidson et al. (2015) [58], this paper measures digital service innovation in three areas, namely new processes, new services, and new products: (1) Our company uses digital technology to streamline service processes and improve response efficiency; (2) We apply digital technology to user interaction systems to identify user needs more quickly and enhance service quality; (3) We embed digital

technology into existing products, upgrading them in line with customer service needs to create products that better meet customers' personalized requirements.

Opportunity Linkage

Drawing on the research by Wang et al. (2012) [70] and J. Chen & Liu (2020) [71], this paper measures opportunity linkage across three dimensions: identification, connection, and reconfiguration. The specific items are as follows: (1) Our company proactively monitors changes in the market environment and promptly adjusts product production or sales processes to capitalize on potential opportunities; (2) Our company can quickly connect emerging opportunities with suitable internal employees or external partners; (3) Our company is able to assess the potential value of market opportunities and flexibly reallocate resources accordingly.

Opportunity Search

Drawing on the research by Heinonen et al. (2011) [37], we identify potential opportunity search processes through proactive exploration, competitive scanning, and creative behavior. The specific items are as follows: (1) Our company proactively and systematically seeks out opportunities or needs in the market that have not yet been identified; (2) Our company is able to identify potential opportunities by observing industry developments, competitors' moves, and market trends; (3) Our company is able to transform existing problems into business opportunities in innovative and unique ways.

Big Data Analytics Capabilities

Drawing on the research by Gupta, George et al. (2016) [40], big data analytics capabilities are measured across four dimensions: data acquisition, digital technology, human resources, and digital management. The specific items are: (1) Compared to similar companies, we have a certain advantage in acquiring internal and external data and promoting business analytics; (2) We are skilled at using digital tools such as cloud computing and visualization for data processing; (3) We have a sufficient pool of big data talent and a training system in place to carry out digital initiatives; (4) We continuously evaluate and improve our business rules based on insights derived from data, treating data as a tangible asset.

Resilience to Supply Network Disruptions

Drawing on the research by Wiedmer et al. (2021) [72], this paper measures resilience to supply chain disruptions from three perspectives: supply recovery, logistics recovery, and product diversity. Specifically, the items are as follows: (1) Compared with firms in the same industry, we have multiple flexible and interchangeable supply sources, giving us a certain advantage in supply recovery; (2) Compared with firms in the same industry, we have a certain advantage in the flexibility of our logistics system; (3) Compared with firms in the same industry, we have a certain advantage in product diversity.

Control Variables

To reduce the impact of potential confounding factors, this article includes several enterprise level control variables that may affect the dependent variable. Specifically, controlling the nature of ownership is because companies with different types of ownership may have differences in governance structure, resource allocation, and strategic decision-making; Controlling the scale of enterprises is because larger enterprises usually have richer organizational resources and operational capabilities; Controlling research and development intensity is because this reflects the level of innovation investment of the enterprise and may affect the strategic and operational results of the enterprise; Controlling subsidies is because external policy support may affect the availability of resources and

business performance of enterprises; Controlling net profit is because a company's financial condition affects its ability to respond to external environmental changes and carry out strategic activities. These variables are mainly included as control variables in the model, with the aim of excluding other possible explanations, rather than testing the core theoretical relationship of this article. The coefficient reflects whether these enterprise characteristics are still significantly correlated with the dependent variable after controlling for the core explanatory variable.

3.2. Data Collection

This paper takes technology-based manufacturing enterprises in China as the research object and acquires data by distributing questionnaires to senior executives of technology-based manufacturing enterprises through the alumni platform (DBA/MBA/EMBA). Before the questionnaire survey, this study obtained permission (NO) from the ethics committee of the authors' institutions and informed consent from the respondents. Specifically, it includes on-site interviews, pre-research, and formal research.

First, this article conducted on-site interviews with enterprises and invited five senior executives to offer suggestions for revision regarding the questions in the questionnaire. These suggestions include whether the questions are unambiguous, whether the question settings align with the actual situation of the enterprise, and whether the measurement of variables is reasonable, etc. Then, this article collected suggestions from senior executives and modified the questionnaire.

Secondly, from 25 June 2025 to 28 June 2025, this study collected 35 questionnaires to conduct pre-research. The results indicated that both the reliability and validity of the questionnaires were satisfactory. This demonstrates that the questionnaire is well-designed and can be distributed on a large scale.

Finally, this study conducted a data collection exercise. From 29 June 2025 to 15 July 2025, it distributed 370 questionnaires to manufacturing executives. The study retrieved 298 questionnaires from the exercise. After eliminating invalid samples, 294 valid samples were obtained, with an effective rate of 79.46%.

The samples of this study are all from enterprises with certain technological attributes in the Chinese manufacturing industry. Therefore, the research conclusions of this article are mainly applicable to technology-based manufacturing enterprises in the Chinese context.

The statistical characteristics of the sample are set out in Table 1.

Table 1. Sample characteristics.

Characteristics	Category	Quantity	Percentage	Characteristics	Category	Quantity	Percentage
Respondent Age	18–30	87	29.6	Subsidies (RMB)	<0.2 million	90	30.6
	31–45	94	32.0		0.2–0.5 (exclude) million	61	20.7
	46–55	74	25.2		0.5–2 (exclude) million	47	16
	>=56	39	13.3		2–10 (exclude) million	49	16.7
					10 million or above	47	16

Table 1. Cont.

Characteristics	Category	Quantity	Percentage	Characteristics	Category	Quantity	Percentage
Respondent Gender	Male	103	35.0	R&D (input by sales)	<2%	64	21.8
	Female	191	65.0		2–4% (exclude)	58	19.7
Respondent Education	Undergraduate below	25	8.5		4–8% (exclude)	68	23.1
	Undergraduate	162	55.1		8–20% (exclude)	64	21.8
	Postgraduate and above	107	36.4		20% or above	40	13.6
Firm Age (years)	3–5	68	23.1	Net profit (compared to other companies in the field)	Very low	70	23.8
	6–9 (exclude)	79	26.9		Lower	63	21.4
	10–14 (exclude)	67	22.8		General	65	22.1
	15–19 (exclude)	52	17.7		Higher	57	19.4
	20 years or above	28	9.5		Very high	39	13.3
	<50	53	18	Ownership	Private enterprises	130	44.2
Firm Size (number of employees)	50–199	80	27.2		State-owned enterprise	164	55.8
	200–499	66	22.4				
	500–1999	55	18.7				
	2000 or above	40	13.6				

4. Empirical Study

4.1. Common Method Deviation Test

Firstly, to check whether there are common method deviations in the sample, the study carried out PCA. The results showed that five factors were extracted, and the first factor accounted for only 27.971% of the total variance, far below the commonly accepted threshold of 40%. This implies that the data used in this study were not significantly affected by common method bias.

Secondly, exploratory factor analysis was conducted on the questionnaire data to validate the scale structure, using the maximum variance rotation method to maximize the explanatory power of the factors. The results showed that the factor loading distribution of each measurement on the factors was highly congruent with the predicted construct in the theoretical framework proposed (see details in Table 2 below). This demonstrated that the measurement scale deployed in the scholarship has good dimensional discriminant validity.

Table 2. Factor analysis.

Items.	1	2	3	4	5
Q1	0.043	0.198	0.862	0.094	0.233
Q2	0.070	0.169	0.862	0.149	0.205
Q3	0.032	0.148	0.864	0.180	0.187
Q4	0.018	0.877	0.176	0.166	0.115
Q5	0.009	0.863	0.175	0.044	0.236
Q6	−0.006	0.902	0.137	0.088	0.129
Q7	0.055	0.066	0.108	0.880	0.147
Q8	0.026	0.127	0.163	0.867	0.180
Q9	−0.001	0.104	0.130	0.851	0.252

Table 2. *Cont.*

Items.	1	2	3	4	5
Q10	0.901	−0.006	0.046	−0.009	0.023
Q11	0.905	0.041	0.068	0.036	−0.002
Q12	0.904	−0.002	0.015	−0.010	0.082
Q13	0.897	−0.004	0.016	0.075	0.093
Q14	0.061	0.143	0.256	0.210	0.795
Q15	0.055	0.142	0.190	0.268	0.791
Q16	0.090	0.237	0.209	0.164	0.806

4.2. Reliability and Validity Testing

In this research, SPSS 26.0 and AMOS 23.0 were used to test the questionnaire data in detail.

From a reliability test perspective, Cronbach's alpha coefficient was applied to assess the internal consistency of each variable first. The findings revealed that the Cronbach's alpha values among the four major variables were 0.919, 0.915, 0.904, and 0.919, respectively. All exceeded the recommended level of 0.7 in relation to acceptable constructs, thereby having high internal consistency in measurement.

Additionally, the CR values for the four latent constructs were calculated to provide a fair assessment of their reliability; the outcomes were 0.949, 0.946, 0.933, and 0.949, respectively. All these measures exceeded the recommended 0.7 standard in their reliability. Therefore, this measurement instrument poses high internal consistency, overall reliability, and measurement stability.

In terms of validity tests, the KMO measurement and the BS test should be used to test the appropriateness of factor analysis data. From the test, the KMO values for the five variables were 0.755, 0.754, 0.746, 0.860, and 0.730, all of which exceeded the required level of 0.7. Hence, the data were appropriate for further factor analysis. Next, to test the discriminant validity, the AVE values for each construct were calculated one after the other for further evaluation of the discriminant validity of the research variables. The values of AVE were all above the standard level of 0.5, being 0.840, 0.839, 0.930, 0.818, and 0.907, respectively, for the constructs, signifying the appropriateness of the discriminant validity for the variables. Overall, the research variables have shown good measurement quality in terms of comprehensive reliability and discriminant validity. The relevant data are presented in Table 3.

Table 3. Reliability and validity test.

Variable	Items	Factor Loadings	KMO	Cronbach's α	CR	AVE
DSI	DSI 1	0.921	0.755	0.905	0.940	0.840
	DSI 2	0.917				
	DSI 3	0.912				
OL	OL 1	0.913	0.754	0.904	0.940	0.839
	OL 2	0.911				
	OL 3	0.923				
OS	OS 1	0.894	0.746	0.888	0.817	0.930
	OS 2	0.911				
	OS 3	0.906				
BDAC	BDAC 1	0.902	0.860	0.926	0.947	0.818
	BDAC 2	0.906				
	BDAC 3	0.907				
	BDAC 4	0.903				

Table 3. Cont.

Variable	Items	Factor Loadings	KMO	Cronbach's α	CR	AVE
RR	RR 1	0.877	0.730	0.846	0.766	0.907
	RR 2	0.867				
	RR 3	0.881				

In terms of model fit and structural validity, AMOS software was used to conduct confirmatory factor analysis to evaluate the rationality of the model structure. The results indicated that the benchmark model outperformed other candidate models, with fit indices of $\chi^2/df = 1.166$, IFI = 0.995, NFI = 0.966. All values fall within the recommended ideal ranges, indicating a strong match between the model and the data. Overall, the construct validity of the measurement model was satisfactory.

4.3. Descriptive Sample Analysis

The mean, standard deviation, and correlation of each variable are listed in Table 4. The results reveal a significant positive correlation between DSI and RR, with a correlation coefficient of 0.521 ($p < 0.01$). Similarly, OL and RR reveal a significant positive correlation ($r = 0.422$, $p < 0.01$), and OS and RR are also positively correlated ($r = 0.489$, $p < 0.01$). These outcomes align with the theoretical expectations of this study. Moreover, none of the correlation coefficients exceeded the commonly used threshold of 0.7, indicating that multicollinearity was not a serious concern. This conclusion is further supported by the value of VIF across all regression models, which were below the critical threshold of 10, indicating that the models were free from collinearity issues and exhibited good statistical robustness.

Table 4. Mean, SD, and correlation.

Variables	1	2	3	4	5	6	7	8	9	10	11
1. Age	1										
2. Size	0.017	1									
3. Ownership	0.041	−0.071	1								
4. FS	−0.065	−0.081	0.304 **	1							
5. RD	0.061	0.130 *	−0.191 **	−0.132 *	1						
6. NP	−0.082	0.047	0.055	0.104	−0.041	1					
7. DSI	0.041	0.021	−0.289 **	−0.317 **	0.347 **	−0.017	1				
8. OL	0.095	0.076	−0.330 **	−0.233 **	0.301 **	−0.089	0.404 **	1			
9. OS	0.108	0.040	−0.230 **	−0.192 **	0.379 **	−0.059	0.358 **	0.272 **	1		
10. BDAC	−0.027	0.036	−0.050	−0.097	0.061	−0.107	0.109	0.035	0.072	1	
11. RR	0.063	0.085	−0.304 **	−0.411 **	0.441 **	−0.124 *	0.521 **	0.422 **	0.489 **	0.146 *	1
12. Mean	2.636	2.827	0.558	2.667	2.857	2.769	4.085	3.954	3.967	4.076	3.827
13. SD	1.275	1.304	0.497	1.461	1.347	1.358	1.773	1.801	1.795	1.784	1.579

$n = 294$, ** $p < 0.01$, * $p < 0.05$.

5. Empirical Results

This study employed SPSS 26.0, AMOS 23.0, and PROCESS (a plugin in SPSS 26.0) software to conduct regression analysis to test the research hypotheses.

5.1. Main Effects and Mediating Effects

Table 5 presents the results of regression analysis for the primary and mediation effect models conducted using SPSS 26.0.

To test the relationship between different variables, multiple regression equations (M1 to M8) have been formulated. Control variables, independent variables, and mediating variables were introduced step by step, allowing for systematic evaluation of the support for each hypothesis.

In Model M1, only the control variables were included with RR as the dependent variable. The results showed that ownership was significantly negatively correlated with

RR. FS also showed a negative effect, while RD had a significant positive impact on RR. These findings align with the operational logic of enterprises in practice.

Table 5. Regression analysis of main effect and mediation effect models.

Variables	DV: RR M1–M3				DV: OL M5–M6		DV: OS M7–M8	
	M1	M2	M3	M4	M5	M6	M7	M8
1. Age	0.020(0.06)	0.014(0.056)	0.003(0.056)	−0.006(0.054)	0.079(0.076)	0.074(0.073)	0.086(0.076)	0.082(0.074)
2. Size	0.005(0.059)	0.021(0.055)	0.016(0.054)	0.024(0.053)	0.020(0.074)	0.033(0.072)	−0.022(0.074)	−0.011(0.073)
3. Ownership	−0.135(0.162) **	−0.08(0.154)	−0.048(0.156)	−0.054(0.149)	−0.251(0.205) ***	−0.205(0.201) ***	−0.140(0.205) *	−0.104(0.204)
4. FS	−0.313(0.055) ***	−0.237(0.053) ***	−0.229(0.052) ***	−0.225(0.051) ***	−0.115(0.069) *	−0.051(0.069)	−0.099(0.069)	−0.050(0.070)
5. RD	0.369(0.058) ***	0.275(0.057) ***	0.251(0.057) ***	0.205(0.057) ***	0.228(0.073) ***	0.149(0.074) **	0.335(0.073) ***	0.273(0.075) ***
6. NP	−0.068(0.056)	−0.078(0.053)	−0.069(0.052)	−0.071(0.051)	−0.048(0.071)	−0.057(0.069)	−0.019(0.071)	−0.026(0.070)
7. DSI		0.325(0.045) ***	0.283(0.046) ***	0.27(0.044) ***		0.272(0.059) ***		0.214(0.060) ***
8. OL			0.155(0.045) **					
9. OS				0.255(0.043) ***				
9. R2	0.329	0.410	0.427	0.460	0.175	0.231	0.171	0.204
10. F	24.898 ***	30.128 ***	28.269 ***	32.218 ***	11.327 ***	13.540 ***	11.062 ***	11.750 ***

$n = 294$, *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

In Model M2, DSI was introduced in addition to the control variables. M2 showed that DSI was significantly positively correlated with RR ($\beta = 0.325$, $p < 0.001$), providing support for hypothesis 1.

In Model M3, the mediator variable OL was added into the regression model. The analysis showed that OL also had a significant positive impact on RR ($\beta = 0.155$, $p < 0.01$), thus confirming its mediating role in the link between DSI and RR. Hence, H3b is supported.

In Model M4, the other mediating variable, OS, was added. The results indicated that OS positively influences RR with a β value of 0.255 and a p -value less than 0.001, thus reinforcing H2b. Hence, OS mediates the relationship between DSI and RR.

For a better understanding of the mechanism by which the mediation pathway is formed, this study further analyzed the effect of DSI on OL and OS.

In Model M5, only the control variables included OL as the dependent variable. It was found that ownership and RD had a significant positive correlation with OL, while the effect of FS had a significant negative correlation with OL.

In Model M6, the independent variable was DSI, which was entered alongside the control variable. The outcome revealed that the beta value for the regression of DSI and OL was $\beta = 0.272$, $p < 0.001$, demonstrating that DSI had a positive impact on OL. This verifies H3a.

The Model M7 also investigated the effect of the control variable on OS. The model demonstrated that RD had a positive influence on OS, while the ownership variable had a negative impact on OS.

Finally, in Model M8, after introducing the independent variable DSI, the outcomes showed that the regression coefficient of DSI on OS was $\beta = 0.214$, $p < 0.001$, indicating that DSI was significantly positively correlated with OS. This proves H2a.

5.2. Testing the Mediating Roles of OS and OL

Hence, based on the outcomes derived from Models M2, M3, and M6, the current study hypothesizes that OL positively mediates the association between DSI and RR. Additionally, based on the results derived from Models M2, M4, and M8, the current study hypothesizes that OS positively mediates the linkage between DSI and RR.

To establish the robustness of the above-mentioned mediating hypotheses, the current study employed the bootstrap technique. Select Model 4 in PROCESS (v3.5) software (specifically the model number in the software), set the confidence interval to 95%, and select 5000 bootstrap iterations. Then run the software to obtain Tables 6 and 7.

Table 6. Bootstrap analysis of the mediating variable OL.

Types		Effect	S. E	LLCI	ULCI	%
OL	T. E	0.2894	0.0453	0.2002	0.3786	100%
	D. E	0.2519	0.0463	0.1607	0.3431	87.04%
	I. E	0.0375	0.0146	0.0117	0.0694	12.96%

Table 7. Bootstrap analysis of the mediator variable OS.

Types		Effect	S. E	LLCI	ULCI	%
OS	T. E	0.2894	0.0453	0.2002	0.3786	100%
	D. E	0.2409	0.0443	0.1536	0.3281	83.24%
	I. E	0.0485	0.0172	0.0190	0.0851	16.76%

Table 6 shows that the direct effect of OL is 0.2519, while the indirect effect is 0.0375. The corresponding confidence intervals are [0.1607, 0.3431] and [0.0117, 0.0694], respectively, neither of which includes 0. The study demonstrates that the mediating effect of OL on the relationship between DSI and RR is statistically significant, thereby supporting H3c.

Table 7 indicates that the direct effect of OS is 0.2409, while the indirect effect is 0.0485. The corresponding confidence intervals are [0.1536, 0.3281] and [0.0190, 0.0851], respectively, and neither includes 0. The study demonstrates that the mediating effect of OS is significant, thereby supporting H2c.

5.3. Moderating Effects

In this paper, DSI and BDAC are dispersed, and regression analysis is carried out. The results are shown in Table 8.

Table 8. Moderating Effects of BDAC.

Variables	DV: OL M9	DV: OS M10
	M9	M10
Age	0.074(0.072)	0.084(0.073)
Size	0.034(0.071)	−0.012(0.072)
Ownership	−0.175(0.200) **	−0.076(0.204)
FS	−0.062(0.068)	−0.057(0.069)
RD	0.140(0.073) *	0.263(0.074) ***
NP	−0.054(0.068)	−0.019(0.069)
DSI	0.255(0.059) ***	0.194(0.059) **
BDAC	−0.019(0.052)	0.029(0.053)
DSI × BDAC	0.175(0.029) **	0.166(0.03) **
R2	0.256	0.226
F	12.181 ***	10.519 ***

$n = 294$, *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. (S.E).

Table 8 shows that the moderating effect of BDAC on the correlation between DSI and OL is 0.175 ($p < 0.01$). The study demonstrates that BDAC positively moderates the relationship between DSI and OL. Thus, higher levels of BDAC strengthen the positive impact of DSI on OL. The study demonstrates that BDAC positively moderates the relationship between DSI and OL. Thus, higher levels of BDAC strengthen the positive impact of DSI on OL. This verifies hypothesis4b. Similarly, the result of M10 shows that the moderating effect of BDAC on the relationship between DSI and OS is 0.166, $p < 0.01$. This indicates that BDAC also has a positive regulatory effect on the relationship between DSI and OS, that is, the larger the BDAC, the greater the positive impact of DSI on OS. Therefore, assuming hypothesis4a is proved.

Furthermore, this study generated an effect graph for moderation. As shown in Figure 2, the slope of the relationship between DSI and OL becomes steeper as BDAC increases. This suggested that at the same level of DSI, OL rises with higher levels of BDAC, further supporting hypothesis4b.

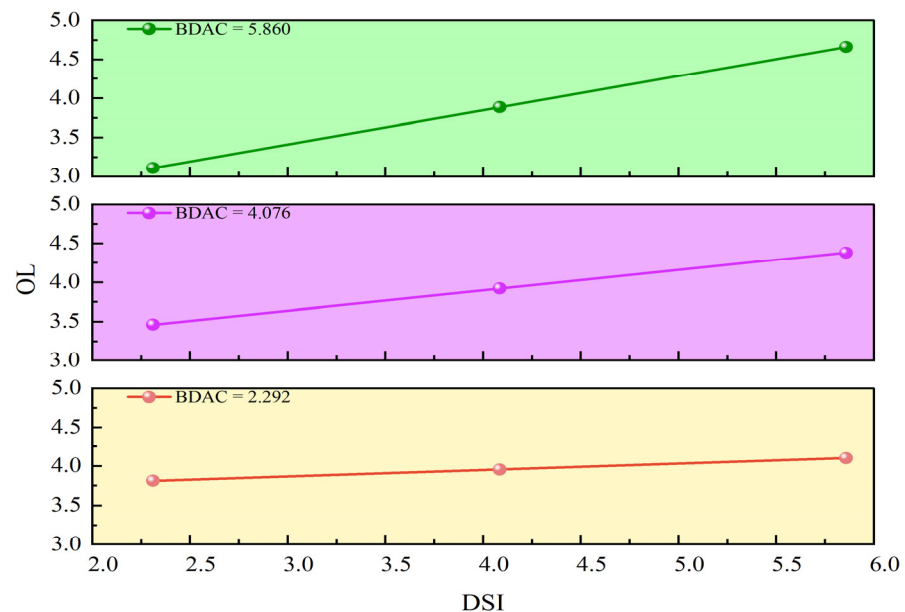


Figure 2. The moderating effect of BDAC on DSI-OL.

Figure 3 shows that as BDAC increases, the slope of the relationship between DSI and OS also becomes steeper. This indicates that, at the same DSI level, OS increases with higher levels of BDAC. These findings further confirm the moderating role of BDAC within the framework of this article, providing additional support for hypothesis4a.

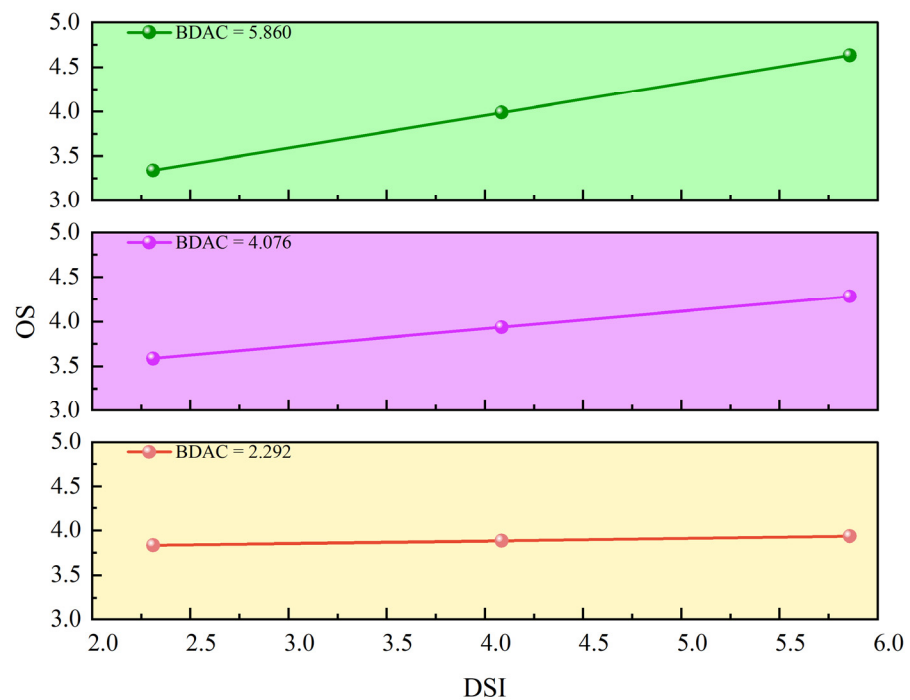


Figure 3. The moderating effect of BDAC on DSI-OS.

6. Discussion and Implications

6.1. Theoretical Contributions

This article's theoretical contributions are primarily manifested in three dimensions as follows.

Firstly, our analysis advances a more nuanced understanding of the association between DSI and RR in the technology-based manufacturing enterprises in China. Existing research mainly focuses on the adoption of digital technologies, digital transformation, and the impact of digital capabilities on supply chain resilience/elasticity [30–32], and has conducted isolated studies on service innovation and supply chain risk management. However, research on how digital service innovation (DSI) promotes resilience recovery is relatively limited. Compared with existing research, this article focuses on DSI's ability to integrate digital technology and service innovation, emphasizing its ability to enhance enterprises' ability to cope with supply chain disruptions through service restructuring and value co-creation. Our findings prove that DSI has a significant positive impact on enterprise RR. DSI can enhance the responsiveness and recovery rate of enterprises when facing network disruptions. DSI, supported by digital technology, leverages advanced tools such as big data, AI, and blockchain [73] to transform and optimize the supply chain network. Such transformation significantly enhances the transparency, efficiency, flexibility, and responsiveness of the supply chain network [27], thereby enhancing the market competitiveness and innovation capability of technology-based enterprises [74]. This research makes a significant contribution to the field of DSI and RR. The fine-grained result addresses the gap in the literature and also empirically indicates that DSI exerts a positive influence on RR. Therefore, this article not only expands the research on the antecedents of supply chain resilience under the digital background, but also further enriches the theoretical understanding of the impact of digital service innovation capability on supply chain resilience.

Secondly, most existing research focuses on the direct relationship between digital capabilities and supply chain resilience, with little exploration of the opportunity formation process and its underlying mechanisms. Compared with existing research, this article introduces the concepts of opportunity search (OS) and opportunity linking (OL) from the perspective of opportunity theory, revealing the specific transmission pathways through which DSI affects the recovery elasticity. In the existing studies, it has been recognized that failure in a single organization has the potential to spread across the entire supply chain. This might impair the performance of other organizations and, in severe cases, the entire chain might also break down. The use of digital technologies in service innovations has accelerated the dissemination of information across upstream and downstream partners. Empowered by big data and cloud computing, enterprises could more accurately predict changes in user demand [58], although this also raises the challenge of information overload [75]. For technology-based manufacturing enterprises in China, deep search enables the identification of opportunities in digital design and manufacturing [76], while effective information acquisition and processing remain prerequisites for business identification and innovation [77]. The present study develops and validates a theoretical model of "DSI-BDAC-OS and OL-RR," which conceptualizes how OS and OL mediate the relationship between DSI and RR. It stresses the utilization of information by enterprises to reshape opportunity processes through DSI for RR, aligning it with enterprise tactics and building on the previous work of scholars. Therefore, this article not only verifies the direct association of DSI on restoring resilience, but also further explains its underlying mechanism, thus responding to the insufficient attention paid to the "how digital capabilities work" in existing research. In doing so, this article builds upon and expands the theoretical application and boundaries of opportunity theory in the DSI.

Thirdly, this study extends the application of opportunity perspective theory to the context of DSI and supply chain network disruptions. Traditional opportunity perspective theory emphasizes that social networks facilitate the search, recognition, evaluation, and exploitation of entrepreneurial opportunities by strengthening entrepreneurial motivation and alertness, thereby providing rich information and resources, and reducing transaction costs, all of which are positively associated with opportunity identification and development. Building on this, this article argues that advanced digital technology enables enterprises to collect, analyze, and predict data more effectively, monitor key nodes and risks in real time following interruptions, and strengthen data-driven decision-making. Additionally, DSI can enhance communication and cooperation among internal and external stakeholders to improve collective responsiveness. In this way, the study enriches opportunity perspective theory by situating it within the contexts of digital transformation and supply chain resilience.

Fourthly, this article proposes and empirically verifies the moderating role of BDAC, thereby identifying effective boundary conditions for the impact of DSI on OS and OL. While DSI empowers enterprises by injecting digital technologies, it also generates a significant increase in available data and information [68], which poses substantial challenges for information processing and predictive capabilities. This study argues that BDAC, as an important manifestation of technological capability and infrastructure, is capable of extending the boundaries of the search for the suppliers, customers, and users, and of extracting and processing valuable insights from vast but often fragmented data sources [78]. Compared with existing research, although the literature has shown that BDAC can enhance supply chain integration capabilities, operational performance, and organizational resilience (Gopal, Jiang), its important contextual conditions for playing a role in digital service innovation (DSI) have not received sufficient attention. This article further reveals that BDAC does not directly act on restoring resilience, but rather enhances the ability of DSI to transform into OS and OL, thereby constituting the key boundary of DSI's impact on supply chain resilience. Based on opportunity theory, our scholarship emphasizes the positive moderating effect of BDAC on the association between DSI and the opportunity perspective measures (OS and OL). It enriches the research on the linkage between DSI and opportunity dimensions (OS and OL) from the perspective of opportunity theory. The current study offers a novel insight into extending the existing use of BDAC in the fields of DSI and supply chain disruption, while developing a unique theoretical association for BDAC to RR.

6.2. Managerial Implications

The practical implications of the research may be captured in the following three aspects:

Firstly, using data obtained from technology-based manufacturing enterprises in China, this study proves that DSI has a positive impact on RR. The results suggest that technology-based enterprises could utilize DSI to optimize their supply chain recovery efforts after a disruption. Thus, technology-based manufacturing enterprises should proactively introduce or promote digital tools such as automation, big data, Internet of Things, and cloud computing into operational processes to simplify integrating or creating innovative resources, which, in turn, can enhance transparency, efficiency, flexibility, and speed, leading to improved recovery timeliness and resilience of technology-based manufacturing enterprises. Additionally, executives must allocate a budget for DSI activities to boost the enterprise's innovation prowess. Investing in DSI tools can enable enterprises to strengthen RR.

Secondly, our study discovered that OS and OL mediate the association between DSI and RR. This suggests the significance of opportunity theory in enterprise management. When organizations improve RR through DSI, they start to view the problem from the perspective of opportunity theory. They utilize OS and OL as they use different channels to acquire information. After gaining a broad understanding of the situation, enterprises build a foundation for subsequent development, mobilize internal resources, and connect with external stakeholders, thereby expanding the opportunity realization process. Therefore, the study suggests that technology-based manufacturing enterprises should strengthen the quality and comprehensiveness of information that they acquire through OS and OL, which, in turn, improves the speed and efficiency of RR. Additionally, enterprises must recruit talent from different industries and markets to enrich opportunity search and link.

Thirdly, as businesses identify and connect with various opportunities, it is crucial to recognize the essential role of BDAC in the effective search, processing, and analysis of information. Therefore, technology-based manufacturing enterprises should use data mining and analysis to process valuable market information.

6.3. Limitations and Future Study

Although this study expands on related research involving DSI, RR, OS, OL, and BDAC, it still has two main limitations:

Firstly, the limitations of data samples. This study focuses on technology-based manufacturing enterprises in China, and the relevant conclusions mainly reflect supply chain recovery management in the Chinese context. However, due to differences in institutional environments, levels of digital infrastructure development, and supply chain organizational models among different countries, the applicability of research conclusions in other countries or regions may be limited. In addition, there are significant differences in technology intensity and supply chain complexity among different industries, so caution should be exercised when promoting to traditional manufacturing or service industries. Future research can further expand cross-industry and cross-national samples to validate the external validity and robustness of conclusions.

Secondly, the limitations of variable design. The opportunity perspective and BDAC measurement indicators used in this study have certain novelty, and the related variables are mainly constructed based on the existing literature and combined with enterprise practice, and tested for reliability and validity. However, due to the strong situational dependence of BDAC and opportunity-related abilities, their measurement may still be influenced by subjective perception bias and differences in corporate information disclosure. In addition, some variables may be difficult to fully characterize the complex dynamic characteristics of numerical ability and opportunity recognition processes, which to some extent limits the comprehensiveness of the measurements. Future research can combine objective data or multi-source data methods to further optimize and validate relevant variables.

Finally, the limitations of the method. This study relies on self-reported data from a single respondent and cross-sectional survey design, which may to some extent lead to common methodological biases and limit the strict identification of causal relationships. Although this article randomized the order of measurement items during the questionnaire design phase and used methods such as Harman's single factor test for preliminary control in empirical analysis, cross-sectional data is still difficult to fully characterize in terms of the dynamic causal relationships between variables. Therefore, future research can consider using data from multiple time points or sources to further improve the robustness and causal explanatory power of research conclusions.

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Data Availability Statement: The datasets used in this study are available from the corresponding authors on reasonable request.

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Abbreviations

Summary of abbreviations and full terms

Abbreviation	Full Term
DSI	digital service innovation
RR	recovery resilience
OS	opportunity search
OL	opportunity linking
BDAC	big data analytical capabilities

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