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A csQCA study of value creation in logistics collaboration by big data: A perspective from companies in China

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ABSTRACT

This study aims to explore the logistics service value creation using big data in the collaboration between logistics service companies and stakeholders. Based on the dynamic capability theory (DCT), this paper constructs a theoretical framework of value creation in logistics collaboration with six big data-driven factors, namely connection, interaction, integration, synergy, reconfiguration, and innovation. The clear set qualitative comparative analysis (csQCA) method examines the value creation paths of logistics service companies in China through combinations of big data-driven elements in collaboration with stakeholders (e.g., suppliers, manufacturers, retailers, and customers). The results show that combinations of six factors driven by big data form three paths to create value for logistics service companies and these factors play unequal roles in improving the value of logistics services. This study provides considerable insight for logistics service managers, practitioners, and scholars that organizations should attach importance to the role of big data for value creation in logistics collaboration.

1. Introduction

In 2021, the value addition of digital economy in 47 countries worldwide was $38.1 trillion, accounting for 45% of their GDP [1]. According to Digital Economy Report 2021, it was noted that China and the United States are predominately digital driven economies with the ability to benefit from big data [2]. Although these countries are notably known for the employment of big data in their digital economy, some countries striving towards a digital driven economy have started gaining from the value created for their industries (e.g., agriculture, logistics service, tourism, healthcare, and others) [3–5]. Based on big data's relevance to economies, it is estimated that the global big data market spending will reach nearly $298.4 billion in 2024; thereby making big data an important value for firms, industries, and economies [6].

Big data is attracting significant attention in the logistics service field [7]. With the wide application of digital technologies in this field, such as artificial intelligence, IoT, cloud computing, and drones, companies collect, store, and process raw data from various sources by turning the potential data into value [8]. Such value is helping companies in their inventory management, warehousing solutions, order fulfillment, freight shipping, and other services by reducing waste, optimizing, and gaining revenue [9]. For example, UPS has developed the Orion system based on truck geolocation and traffic data to optimize 55,000 routes in its network, as well as provide customers with real-time delivery routes [10]. In China, JingDong (JD) uses big data to analyze the geographical relationship between delivery personnel, warehouses, and users to provide logistics personnel with optimal delivery routes, thus improving delivery speed and user experience [11]. Also, Saleem et al. (2020) examined big data in predicting technology innovation, logistics services, and SME performance in China, Pearl River Delta [12]. However, China's logistics service value creation by big data has not been fully explored [13]. Although the value of big data is captured by logistics service firms, understanding how value is created coupled with its associated factors that aid logistics service firms and their stakeholders achieve lean, optimized, and sustainable results are still limited [14–18].

An emerging phenomenon shows that data value enables logistics service companies to transform from a single transportation service role to a data integration center. Such transformation facilitates and gains a unique competitive advantage through sustainable collaboration between logistics service companies and stakeholders (e.g., suppliers, manufacturers, retailers, and customers). For example, Cainiao

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Network, a leading logistics service company in China, provides logistics solutions for merchants by integrating logistics data, saves transportation time and reduces transportation costs for logistics providers by integrating repeated order data, and provides diversified logistics service choices for consumers by predicting logistics information [19]. However, to date, the literature on big data in logistics services has focused on avenues for application (e.g., “agility”, “sustainability”, “visibility”), operations (e.g., “demand planning”, “production”, “inventory”), and firm benefits (e.g., “bullwhip effect”, “competitive edge”, “asset productivity”) [12,20,21]. In other words, these studies focus on the application of big data within logistics service companies, ignoring the fact that big data enhances collaboration between logistics companies and stakeholders to value creation [22–24].

To address these critical gaps, this study addresses the following two research questions:

RQ.1. What big data-driven factors facilitate value creation for logistics service companies in collaboration with stakeholders?

RQ.2. How do these factors combine to create value for logistics service companies?

Based on the dynamic capability theory (DCT), a theoretical framework on the six big data-driven factors (i.e., connection, interaction, integration, synergy, reconfiguration, and innovation) and logistics services value creation in collaboration is developed to gain a holistic view of addressing research gaps. The clear set qualitative comparative analysis (csQCA) is used to obtain multi-element paths by identifying a set of core elements [25]. Therefore, through the csQCA method, this study examines the framework, including the value creation paths formed by the combination of six elements and the importance of these elements driven by big data.

The main contributions of this paper are summarized as follows: (1) This study explores big data-driven logistics service value creation in China, benefiting the development of the digital economy and expanding the research scope. (2) It extends the understanding of previous research that has focused on a limited perspective of big data applications within companies. A theoretical framework of logistics service companies using big data to create value in collaboration with stakeholders is proposed. (3) This study introduces the csQCA approach to extend the research of organizational investment and deployment of big data resources and capabilities. In contrast to previous assumptions that all factors driven by big data are equally valued, the current study explores the value creation paths through the combination of six factors and the importance of these factors. These research results have guiding significance for the development of big data in logistics service practice.

The remainder of the research proceeds as follows: in Section 2, literature on big data and value creation, big data-driven logistics services is reviewed, and then conceptual framework development is introduced. In Section 3, the methodology is described. The results are provided in Section 4. The discussion is included in Section 5. Section 6 and Section 7 provide implications and conclusion, respectively.

2. Research background and conceptual framework development

2.1. Big data and value creation

With the development of digital technology, big data has a significant impact on the operation, cooperation, and strategy of different fields in digital economy [26]. Big data refers to real-time, large amounts of structured, semi-structured, and unstructured data, which are converted into value by specific technologies and analytical methods [27,28]. Considerable effort has been devoted to the study of the value that big data creates for organizations, such as providing value delivery, improving performance, developing competitive advantages, innovating products and services, and enhancing consumer experience [29–31]. In this research stream, big data creates value by promoting firm management actions because it offers the foundation for smart operational and strategic decisions [22,32,33]. Some literature has shown that organizations investing in big data technologies generate significant value in specific areas such as manufacturing, public transportation, logistics services, and e-commerce [21,34]. Although some efforts have been made to create value from big data, a deeper analysis of organizational challenges is still needed. For example, Vidgen et al. (2017) noted that organizations face challenges in coordinating and leveraging big data analytics when trying to generate value from big data [15]. Similarly, Mikalef (2019) indicated in their empirical evidence that there is limited knowledge of the environment affecting big data and the key factors shaping performance improvements when obtaining business value from big data investments [17]. Benefits and challenges firms derived from big data clearly indicate that more studies and investments in this research stream are needed in specific fields [6].

In the following, a review of the relevant literature on big data-driven value creation in logistics services is further presented.

2.2. Big data-driven logistics service

Big data is widely used in logistics services and helps companies create value [21,23,35,36]. Logistics service activities are the process by which logistics service companies provide basic and customized logistics services to be effective and efficient based on mutual benefit with stakeholders [37,38]. This indicates that value creation in logistics services is the integration of heterogeneous resources and capabilities of logistics service companies based on the interaction with stakeholders to co-create services/products [39,40]. With the help of big data, logistics service firms have closely connected stakeholders and formed a data-based network system that uses the effective information sharing resources of big data to create value [41]. Based on real-time insights, big data helps logistics service companies sense emerging opportunities and threats, generate insights into complex business relationships, such as collaboration and competition, and adapt them into operations and strategy [16,42,43]. Previous studies have found that big data helps companies to reduce logistics service costs, enable cross-regional tracking, support resource sharing, and improve trust and collaborative performance among stakeholders [44,45]. Although some scholars claim that the value of big data can be reflected in facilitating collaboration between logistics service firms and stakeholders, there is still a limited understanding of them [46,47]. For instance, Sodero et al. (2019) used a qualitative analysis approach to reveal that big data and predictive analytics (BDPA) is not easily transferable between collaborating RSC organizations and requires specific institutional and social contextual factors [48]. However, recent studies have focused on the consumer – logistics service firms with limited studies on logistic service firms and their stakeholders (e.g., suppliers, manufacturers, retailers, and consumers) [4,11,20].

Another interesting observation is factors that facilitate the spread of big data by successful logistics service firms. Some studies to date do attribute big data as the sole independent variable for firm performance [49], agility [50], decision making [51], co-innovation [52], or business value [53]. Only several logistics service studies have described the main factors that contribute to the improvement of organizational value. For example, Schlegel et al. (2020) classified big data analytic capabilities (BDAC) in a specific order into tangible BDAC, human BDAC, and intangible BDAC in sales and operations planning [54]. Mandal (2018) quantitatively analyzed the impact of expertise capabilities of big data analytics (BDA) personnel on the development of supply chain agility and divided BDA into BDA technical knowledge, BDA technical management knowledge, BDA business knowledge, and BDA relationship knowledge [55]. More so, Dubey (2020) investigated the use of connection factor by Indian manufacturing organizations to facilitate information sharing and visualization of logistics services [56]. However, the underlying assumption of most of these studies is that companies must pay equal attention to these elements [57,58]. Recently, scholars have put forward a new view that certain elements are more or less important in terms of value creation depending on the context of the environment [17,59,60].

Based on the above research and analysis, the existing literature does not consider how to create value for logistics services companies through big data from the perspective of collaboration. Moreover, these studies show the role of factors driven by big data in capturing logistics services value, nonetheless, there are few studies focus on big data-driven elements and its combination in logistics collaboration for value creation in logistics services. Therefore, the next section constructs a conceptual framework to explain the six data drivers that facilitate logistics service companies to create value in collaboration with stakeholders.

2.3. Conceptual framework development

The use of big data in logistics services has changed the collaborative relationship between logistics service companies and stakeholders such as manufacturers, suppliers, consumers, retailers, and others. Traditional logistics service model gradually does not match the requirements of flexibility and sustainability of logistics services in the context of big data [61]. This paper extends the dynamic capability theory (DCT), especially Teece et al. (1997) proposed that companies achieve competitive advantage mainly through reconfiguration, learning and integration [62]. And by referring to the relevant literature on big data and logistics services, six factors of value creation driven by big data are formed, as shown in Table 1.

Table 1
Big data-driven factors in logistics service collaboration.

Factor	Definition	Feature	Sources
Connection	Through the Internet technology platform, logistics service providers and stakeholders are connected to form networks.	Seamless, mesh structure	[63]; [64]; Daugherty, Bolumole, and Grawe 2019
Interaction	Through communication, learning, and mutual influence, the various actors involved in the logistics chain establish an interdependent relationship for the efficient movement of goods.	Real-time, bi-directional	Chen, Preston, and Swink 2015; [64]; Daugherty, Bolumole, and Grawe 2019
Integration	The fragmented and separated logistics resources, elements, and organizations are adjusted to create a unified whole.	Platform-based structural integration	Chen, Preston, and Swink 2015; [65]; Dubey et al., 2018; [36]
Synergy	Acting together for the good of the whole by coordinating operations between different organizations and gaining additional performance relative to their operations.	Based on the collective Make decisions	[64]; [66]; [67]
Reconfiguration	Reallocation of the value chain in terms of concepts, elements, and organizational structures to adapt to changes in the environment by treating data as an independent element.	Data-based conversion of online and offline	[63]; [23]; [68]
Innovation	Information, technology, and knowledge can flow and collide more efficiently, innovation ideas can be quickly mined by big data, and the innovation capacity of enterprises can be effectively enhanced to achieve knowledge stock renewal.	Open innovation paradigm	Chen, Preston, and Swink 2015; [67,69,70]

Note: compiled by authors.

DCT describes how organizations integrate, build, and reconfigure internal and external resources and capabilities to rapidly respond to an unpredictable changing environment [71]. To survive and prosper in changing conditions, organizations must develop dynamic capabilities to create, expand and modify their way of being, thereby influencing organizational value creation [72]. Thus, dynamic capabilities are also unique organizational processes that integrate, reconfigure, acquire and release resources [73]. The DCT considers big data as a resource/capability to facilitate value creation and analyzes its potential for multiple purposes [52]. Moreover, since big data tools are used to different degrees in different companies and the process of value creation from big data varies, the use of dynamic capabilities helps to understand the complexity of the relationship between logistics service companies and stakeholders and the misalignment of resources [74].

Connection and value creation. Connection is a prerequisite for the development and integration of logistics service firms driven by big data. This connection is more important than the data itself because the value of isolated data cannot be mined and analyzed to generate economic value. Digital technology and the Internet make it possible for logistics service companies to collect a large amount of scattered logistics information from scattered logistics service activities, and further expand the object, method, and boundary of logistics services through big data analysis [64]. Big data-driven connection enhances the trust relationship between logistics service companies and stakeholders, as well as reduces the uncertainty and unpredictability of transactions between them [63]. Therefore, the big data-driven connection is a strong link that connects logistics service companies and stakeholders into a seamless network structure, reduces customer costs and strengthens the connection relationship, and realizes the value return of logistics services by using economies of scope and network effects [75].

Interaction and value creation. Interaction in logistics services is reflected in the effectiveness and efficiency of communication between multiple types of stakeholders. In order to compensate for the traditional limitations of delayed information, short-term, singular, and indirect interactions, big data enabled interactions in logistics services to have the advantages of being parallel, real-time, and long-term [20]. It's clear that online communication not only reduces the cost of "search and selection", but also increases the trust relationship between participants and facilitates the transfer of knowledge between them. Moreover, big data analytics changes the interaction of logistics service members from one-way to multilateral interaction. In other words, logistics service companies classify stakeholders into different levels through big data analysis, such as gathering consumers with the same value proposition to promote their autonomous learning [76]. In addition, big data improves the frequency of interaction, such as human-machine interaction, intra-node, and inter-node interaction, thus realizing a win-win value exchange between logistics service companies and stakeholders [77].

Integration and value creation. Logistics service participants achieve an efficient flow of resources, information, and services in an integrated network, to reduce supply chain costs and improve responsiveness [78]. According to the characteristics of big data and logistics service industry, logistics service companies have the advantages of integration capabilities and resources [36]. On the one hand, big data, as a heterogeneous strategic resource, can be used by companies to create business value and gain competitive advantages through its integration [23]. For example, with the development of e-commerce, logistics services are gradually forming platform-centric operational models and networked logistics systems [19]. On the other hand, the integration of logistics services driven by big data has shifted from being based on logistics processes to being based on platforms. This enables logistics services companies not only to obtain horizontal integration, vertical integration, and network logistics system, but also to obtain the integration of digital, capital, and human resources, thus achieving the overall improvement of social, economic, and environmental benefits.

Synergy and value creation. Logistics synergy involves more formal relationships, goals, and actions where logistics service companies and stakeholders are mutual and compatible [66]. As Xue et al. (2005) argued that synergy manifests itself in the common actions of various parts within and outside the firm through coordinated operations and cooperation with the overall benefit as the goal [67]. Driven by big data, logistics service companies optimize operations reasonably through the analysis and prediction of different data types. At the same time, logistics service companies also use big data analysis to develop planning from crude to intensive development, pay more attention to the overall collaborative benefits, and reduce the game behavior between the participants [67]. For example, digital collaborative initiatives such as shared warehouse and transport capacity have the potential to improve the efficiency and reliability of the logistics industry through information exchange and data integration between organizations, as well as architectures that support virtual logistics clusters [64]. As a result, big data-driven logistics services are conducive to digital collective decision-making behavior to realize value.

Reconfiguration and value creation. Data, as a new production factor, reconfigures the logistics service collaboration process to adapt to environmental changes and increases the possibility of selection among various factors [23]. The combination of these factors transforms the collaborative relationship between logistics service companies and stakeholders into a complex and indivisible network based on data. This network forms new service experiences and new business models around consumers. For example, logistics service companies use big data analysis to enhance dynamic information processing and quickly convey consumer demand to manufacturers and retailers to achieve accurate demand forecasting [68]. In addition, reconfiguration is mainly reflected in the concept, elements, organizational structure, and value chain. For example, in terms of the value chain, logistics service companies are customer-oriented and based on big data analysis and data mining to achieve the integration of online and offline, improve operational efficiency, enhance customer service experience, and form a new business model. Therefore, the big data-driven reconfiguration of logistics services takes data as an independent element, forms a new business model, realizes the customer-oriented value chain, and promotes the growth of the overall benefit of logistics services.

Innovation and value creation. Big data-driven innovation in logistics services is an open innovation category based on data, information resources, and technology. It breaks the organizational boundary of traditional closed innovation paradigm, promotes the flow of knowledge (especially tacit knowledge), purposefully integrates internal and external resources, and improves the innovation performance of the company. Big data-driven innovation combines incremental and radical innovation to motivate logistics service firms and stakeholders to achieve co-innovation and maintain long-term collaborative relationships. Logistics service companies use this innovative way to integrate internal and stakeholder resources and knowledge to improve the innovation performance of companies. As shown by Liu (2014) and Dubey et al. (2018), big data analytics constitutes the major difference between high and low-performing companies as it allows firms to identify new business opportunities more proactively and quickly [23,79]. Accordingly, big data-driven innovation is conducive to predicting consumers' purchase needs, accelerating the evolution of logistics service companies, eliminating malicious imitation and attack from competitors, and improving performance.

Based on the above analysis, this study constructs the theoretical framework for big data-driven logistics service companies to create value in logistics collaboration, as shown in Fig. 1. The configuration solution in Fig. 1 reflects the element configurations, which are higher level combinations. According to Woodside (2013), the configuration of these elements may generate several different combinations to create value for logistics service firms in the collaboration with stakeholders [25].

3. Methodology

3.1. Analytical method

This study applied the clear set qualitative comparative analysis (csQCA) method, which combines "qualitative" (case-oriented) and "quantitative" (variable-oriented) research [80]. There are four main reasons for adopting the csQCA method in this study. First, based on cross-case comparative analysis, the csQCA approach seeks causal relationships between condition combinations and outcomes and distinguishes the condition combination that outcomes occur or do not occur [81]. Accordingly, this method is suitable for exploring the path of value creation (outcome) achieved by multiple big data-driven factors (conditions). Second, csQCA is not limited to the sample size in processing data. It is a kind of "case oriented" analysis technique because its sample size belongs to the situation of small and medium samples. Thus, it is suitable for the research of big data-driven logistics services in the early stage of development. Third, the assumption of "concurrent causality" in csQCA is appropriate for the multi-factor causality study explored in this study. Fourth, the csQCA method is based on the assumptions of asymmetry and equivalence, which allows for scientific analysis of cases in asymmetric situations, in line with the choice of combining successful and unsuccessful cases in this study.

3.2. Sample and procedures

The sample selection is mainly based on the following three criteria: first, there are both successful and unsuccessful cases as support, in line with the need for theoretical saturation of traditional case studies. Second, considering the availability of information and the diversity of sources, the selected cases cover various types of logistics services as widely as possible, thus enhancing the universality of the findings. Third, the cases are selected from authoritative logistics case libraries or cases that have been publicly reported in the media. The sources of data collection include authoritative logistics websites, relevant books, and journals, which have the characteristics of a stable "data triangle". According to the criteria of case selection, six elements require at least 16–25 samples [82]. Therefore, this study selects 20 typical logistics service firms using big data in various fields (No. 1–15 are successful cases, and No. 16–20 are failed cases).

3.3. Variable setting and data processing

This study takes connection, interaction, integration, synergy, reconfiguration, and innovation as conditional variables and value creation as explanatory variables, which were assigned a value of "0" or "1" respectively, where "0" means false and "1" means true.

Conditional variables. First, connection. If logistics service providers and stakeholders are effectively connected under the use of big data, the code is "1", otherwise, the code is "0". Second, interaction. If the logistics service company is driven by big data to realize parallel and real-time interactions among all participants, in collaboration with stakeholders, the code is "1", otherwise, the code is "0". Third, integration. If the logistics service company adjusts the scattered and isolated logistics resources to establish a unified whole and achieve the cooperation effect driven by big data, the code is "1", otherwise, the code is "0". Fourth, synergy. If the operation level of logistics service is driven by big data to realize the common action of all parts within and across companies, the code is "1", otherwise, the code is "0". Fifth, reconfiguration. If big data

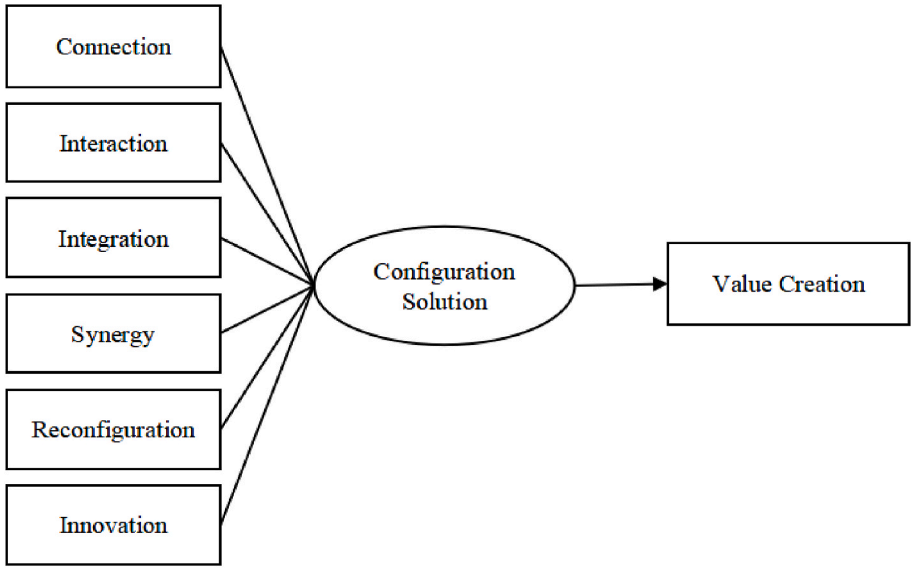

Fig. 1. Big data-driven logistics services value creation theoretical model.

is used to reconstruct the value creation of logistics service companies in terms of concept, elements, organizational structure and value chain, the code is "1", otherwise, the code is "0". Sixth, innovation. If the innovation of logistics service under the use of big data is generally through demand-pull innovation or technology-push innovation, the binary of these two kinds of innovation exists at the same time, coded as "1", otherwise, coded as "0".

The outcome variable is value creation. Three dimensions of operational efficiency, customer experience and new business model are considered as the criteria to measure whether value creation is realized. If all three dimensions are achieved, a code of "1" is assigned, and if not, a code of "0" is assigned.

4. Results and findings

4.1. Constructing the truth table

In this study, fsQCA3.1b software is applied to analyze the data, which follows three steps. First, a truth table is constructed using the fuzzified data (see Table 2). This process matches the combination of causal conditions to the number of cases and affiliation, respectively.

4.2. Clear set qualitative comparative analysis

Second, the necessity of each condition variable is tested before conducting a clear set qualitative comparative analysis. Among them, consistency indicators reflect the extent to which the sample cases support the existence of the set theory. When the consistency is greater than 0.9, the cause condition variable is a necessary condition for the outcome variable [82]. The coverage is used to reflect the degree to which the conditional variables explain the occurrence of the outcome. Thus, a larger value of coverage indicates that the causal condition variables have stronger explanatory power for the outcome variable. As shown in Table 3, the consistency of the three variables of connection, interaction and integration among the condition variables is greater than 0.9, and the coverage is greater than 0.75, indicating that these three variables are necessary conditions for the value creation of big data-driven logistics services. However, the necessity of the remaining three condition variables (synergy, reconfiguration, innovation) is less than 0.9, which suggests that these condition variables need to be included in the third step to further explore the configuration of high

Table 3
Necessity tests of value creation.

Variable name		Outcome variable : value creation	
		Consistency	Coverage
Connection (CO)	CO	1.000	0.750
	~CO	0.000	-nan(ind)
Interaction (IA)	IA	1.000	0.882
	~IA	0.000	0.000
Integration (IG)	IG	0.933	0.933
	~IG	0.067	0.200
Synergy (SY)	SY	0.733	0.917
	~SY	0.267	0.500
Reconfiguration (RE)	RE	0.667	0.909
	~RE	0.333	0.556
Innovation (IN)	IN	0.067	0.250
	~IN	0.933	0.875

Table 2
Truth table.

Connections (CO)	Interaction (IA)	Integration (IG)	Synergy (SY)	Reconfiguration (RE)	Innovation (IN)	Value creation (VC)	Frequency
1	1	1	1	0	0	1	5
1	1	1	1	1	0	1	5
1	1	1	0	1	0	1	3
1	1	0	1	1	0	1	1
1	1	1	0	1	1	1	1
1	0	0	1	0	0	0	1
1	1	0	0	0	1	0	1
1	1	0	0	1	1	0	1
1	0	1	0	0	1	0	1
1	0	0	0	0	0	0	1

value creation.

Third, conditional combination analysis is used to measure the impact of different combinations of causal condition variables on the results, thus the configuration of high value creation is obtained (see Table 4). Three kinds of solutions are formed: complex, parsimonious, and intermediate solutions (default criteria: consistency threshold of 0.8 and case frequency threshold of 1). The core and edge conditions are distinguished according to the intermediate and simple solutions. If a precondition has both simple and intermediate solutions, it is a core condition; if only intermediate solutions appear, it is judged as an auxiliary condition. The overall consistency (consistency = 1.000) is above the threshold value of 0.74 [83], indicating that each configuration of high value creation is sufficient, and the coverage index indicates that each configuration has substantial explanatory power.

4.3. Condition combination analysis

As shown in Table 4, the six condition variables form three different paths. The net coverage of C1 (unique coverage = 0.333) is higher than that of C2a (unique coverage = 0.067) and C2b (unique coverage = 0.267). Thus, C1 is considered the "primary path", and C2a and C2b are considered the "secondary path". Since the holistic case analysis helps to understand the impact of condition configuration on results, three configuration combinations of big data-driven logistics service value creation are regressed into sample cases.

The primary path C1 shows that logistics service companies use big data to achieve value creation in collaboration with stakeholders, which is manifested in strengthening connection and interaction, synergistically improving operational performance, and reducing operating costs through platform integration. C1 contains cases 2, 4, 5, 7, 8, 9, 10, 11, 12, and 14. Taking Case 2 as an example, a logistics company establishes a family-oriented logistics service platform and logistics management system to connect the upstream and downstream of the supply chain with comprehensive information to promote the flow of business, information, and capital. The company's logistics management system integrates logistics resources to achieve "zero-link logistics" and to form a common bond of interest with stakeholders. The use of big data breaks down organizational segregation and facilitates isolation and facilitates the shared participation of internal departments and external stakeholders in decision-making.

The secondary path C2a indicates that logistics service companies use big data to create value through strengthening the connection and interaction with stakeholders, improving operational performance, and restructuring ideas, organizations, and value chains. This path includes cases 3, 4, 8, 10, 11, and 14. Taking case 3 as an example, the company develops the Vizi logistics management platform to solve the problems of difficult tracking of the dispatching system, insufficient management of the distribution process, and low operational efficiency. In addition, logistics service companies build a platform to connect all stakeholders, unify data types and collect information resources through standardized interfaces, and enable collaborative operation through big data analytics.

The secondary path C2b shows that the value creation achieved by logistics service companies using big data is manifested in strengthening the connectivity and interaction with stakeholders, reducing logistics costs through integration, and obtaining new business models by reconstructing concepts, value chains and cooperation forms. This path contains cases 1, 6, 13, and 15. For example, the logistics company in Case 1 develops several systems to connect and interact with stakeholders, such as a driver response system, an intelligent routing system, and a dispatch engine system. The company also integrates the existing data of freight vehicles in the city, pushes accurate business information to drivers through data analysis, and reconstructs the logistics service value chain.

Table 4
Configuration of big data-driven logistics service value creation.

Conditions	Configuration solutions		
	C1	C2a	C2b
Connection (CO)	•	•	•
Interaction (IA)	●	●	●
Integration (IG)	●		●
Synergy (SY)	●	●	⊗
Reconfiguration (RE)		●	●
Innovation (IN)	⊗	⊗	
Consistency	1.000	1.000	1.000
Raw coverage	0.667	0.400	0.267
Unique coverage	0.333	0.067	0.267
Overall consistency	1.000		
Overall coverage	1.000		

Note: ● means the condition exists, ⊗ means the condition does not exist, "blank" means the condition may or may not exist in the configuration; ⊗ indicates a core condition, • or ⊗ indicates a marginal condition.

5. Discussion

In order to explore how to create value through big data in logistics services, this study investigates the factors and paths of logistics service companies using big data to create value in collaboration with stakeholders. This study solves RQ.1 by constructing the theoretical framework of value creation by six big data-driven factors, namely, connection, interaction, integration, synergy, reconfiguration, and innovation. To address RQ.2, the current study uses csQCA method and survey data from logistics service companies in China to examine possible paths of value creation through a combination of big data-driven elements. The results show that the combination of six elements driven by big data forms three paths to realize value creation. These elements have different importance and functions in the three paths, which are as follows.

The findings confirm that connection and interaction elements are contained in three paths. It indicates that connection and interaction are fundamental factors for big data to create value for logistics service companies in collaboration with stakeholders. The results also support that the interaction factor driven by big data is conducive to increasing the trust relationship between logistics service companies and stakeholders, consolidating long-term cooperative relationships, and realizing organizational value [76,84]. In contrast, big data-driven connection plays a smaller role than interaction in the value creation of logistics services companies. The findings imply that logistics service companies rely on the development of existing technologies and various forms of resource allocation for a big data-driven connection. This will only expand the scope of big data applications, rather than deepen collaboration. This is in line with the literature that only a few companies have fully exploited the potential of their big data, and few have applied it to collaboration [4,17,50].

The results show that the integration or synergy elements appear separately or simultaneously in the three paths. When the integration and synergy work together, a primary path with the highest explanatory power is generated. This shows that most logistics service companies consider both big data-driven integration and synergy to achieve value creation in logistics service collaboration. In addition, the other two secondary paths both include the reconfiguration factor. This suggests that when a logistics service company cannot meet the integration and synergy at the same time, the company considers the reconfiguration to promote the value creation of the organization in collaboration. These findings extend the DCT's view that integration, synergy and reconfiguration are important capabilities for big data-driven logistics service companies to create value in collaboration with stakeholders [24,85].

The findings indicate that the innovation element is marginal or nonexistent conditions. It suggests that the impact of the big data-driven innovation has not been fully explored. The results may be related to the development environment, such as the shortage of logistics and data talents, and the imperfect legal system [43]. Existing literature points out that many companies are trying to improve innovation through big data, but many are still unsure whether the use of big data is positively correlated with its results, and others have failed to use big data to improve innovation [86].

In summary, the findings suggest that the six elements driven by big data form a primary path and two secondary paths, which are substituted for each other. These findings support the argument that organizations use big data to create value in the logistics service sector [51]. As stated by Gupta and George(2016), achieving organizational goals is not only about big data technologies, but more importantly about the insights generated by the diffusion of these technologies in the organization [59]. Moreover, the results show that the importance of big data-driven elements for companies to create value is different, which is consistent with Mikalef (2019) [17]. This breaks the assumption of most of the existing literature: all companies must pay equal weight to these elements [14,20,58].

5.1. Implications

5.1.1. Theoretical implications

The study provides the following theoretical implications. First, this study reveals the process of big data creating value in the field of logistics services in China. Despite a lot of research on the value of big data, there is still a lack of research on how big data creates value in specific fields and regions [12,34]. The results of this study extend previous research by using other fields and countries. This helps broaden the perspective and relationship between big data and value creation.

Second, this study proposes to understand the relationship between big data and logistics service value creation from the perspective of organizational collaboration. Previous studies have mainly focused on the application of big data in logistics services firms and a single stakeholder perspective [41,50,55]. This study develops a theoretical framework of big data-driven factors (i.e., connection, interaction, integration, synergy, reconfiguration, and innovation) to create value for logistics service companies in collaboration with stakeholders, which is an unexplored area to date. Furthermore, our research extends the DCT that big data as a unique competitive differentiator enables firms with multiple capabilities to create value [71,85].

Third, while most studies have shown the important role of organizations using big data in value creation, there is limited empirical evidence to substantiate these claims. This study uses the csQCA method to explain the value creation path through the combination of elements driven by big data. The results show that logistics service companies form three value creation paths through the six big data-driven elements in collaboration with stakeholders, and these paths have an alternative role. In addition, the findings of this paper distinguish the importance of big data-driven elements for the value creation of logistics services.

5.2. Practical implications

This study provides several useful implications for managers working in logistics services. First, the current study investigates how logistics service companies in China use big data to create value. This helps logistics service managers and practitioners learn from the experience of organizations using big data to achieve value creation as China benefits from big data [2]. Moreover, in the context of logistics services, due to the high degree of uncertainty and complex environment, the results will further motivate managers involved in logistics service activities to utilize big data to improve the value of logistics services in digital economy.

Second, previous research has noted that the collaboration between logistics service companies and stakeholders is closer and the value creation process is more complex due to the investment of big data [34,87]. As a complement to the above, this study points out that factors driven by big data create value for logistics service firms in collaboration with stakeholders. These big data-driven factors include connection, interaction, integration, synergy, reconfiguration, and innovation, which are considered by scholars to be important organizational capabilities. This provides managers with guidelines on how to develop their data, especially in logistics collaboration. Big data-driven factors also help managers develop data collaboration strategies.

Third, this study provides three implementable paths for big data-driven value creation in logistics service companies. Logistics service managers and practitioners should choose the right path for big data-driven value creation, according to their company's level of digitization. Current results indicate that organizational managers can create value through different combinations of elements driven by big data. Therefore, logistics service managers should focus on cultivating appropriate big data capabilities according to the company's situation to gain competitiveness.

6. Conclusion

Drawing extensively on the DCT, this study proposes a theoretical framework with six big data-driven factors (i.e., connection, interaction, integration, synergy, reconfiguration, and innovation) to facilitate organizational value creation in logistics collaboration. Through csQCA, this study examines the combination of these elements, namely the paths of logistics service value creation. This paper uses the survey data of logistics service firms from China to test the research. The findings show that through the combination of six elements driven by big data, three paths of value creation in logistics collaboration are formed, and these paths can be substituted with each other. Current research shows that the six data-driven elements have different importance to the value creation of logistics service companies in collaboration with stakeholders. Therefore, this study harmonizes the contributions of two well-established streams in the literature, that is, big data as an organizational capability to create value for logistics service companies. The current research provides a new perspective for logistics service managers, practitioners, and scholars to focus on the value creation of big data-driven factors in logistics collaboration.

Limitations and future research are as follows. First, although it is the first time to analyze the factors and paths of logistics service value creation by big data from the perspective of collaboration, current research did not distinguish the types of stakeholders and consider other background factors, such as the company size and dependence of stakeholders. It will be meaningful to compare the role of big data for logistics service value creation by a logistics service company and different stakeholders. Second, the csQCA method used in this study does not include the concept of large sample size and time. Future research should use alternative methods to complement the shortcomings of this model. Third, this study discusses the value creation of big data-driven logistics service companies in China. It will be interesting to consider cross-country comparative studies to better understand big data practices in logistics services.

Author statement

Qiaohong Pan - Writing – original draft, Software, Methodology, Writing – review & editing;; **Wenping Luo** - Conceptualization, Writing review & editing; **Yi Fu** - Writing – original draft, Conceptualization, Data curation.

Declaration of competing interest

No potential conflict of interest was reported by the author(s).

Data availability

The authors are unable or have chosen not to specify which data has been used.

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