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Article

Accepted Version

Behl, A., Gaur, J., Pereira, V., Yadav, R. and Laker, B. ORCID: https://orcid.org/0000-0003-0850-9744 (2022) Role of big data analytics capabilities to improve sustainable competitive advantage of MSME service firms during COVID-19- a multi-theoretical approach. Journal of Business Research, 148. pp. 378-389. ISSN 0148-2963 doi: https://doi.org/10.1016/j.jbusres.2022.05.009 Available at https://centaur.reading.ac.uk/104993/

To link to this article DOI: http://dx.doi.org/10.1016/j.jbusres.2022.05.009

Publisher: Elsevier

Role of Big Data Analytics Capabilities to improve Sustainable Competitive Advantage of MSME Service Firms during COVID-19- A Multi-Theoretical Approach

Abstract

The extant literature suggests that digital technologies (big data analytics, artificial intelligence, blockchain) help firms gain a competitive advantage. However, the studies do not focus on the micro, small and medium enterprises (MSME) sector. Moreover, MSMEs face various challenges, including significant supply chain disruption due to the COVID-19 pandemic. Hence, there was an urgent requirement to shift to digital technologies to survive during this difficult time. In the context of MSME, various positive changes are discussed in the recent literature. However, a dearth of studies discusses the role of big data analytics capabilities (BDAC) to gain sustainable competitive advantage (SCA). Our study aims to fill this gap and answer this question – How do BDAC help MSMEs gain SCA? To understand the phenomenon, we receive theoretical support from organizational information processing theory (OIPT) and institutional theory (IT). We develop a conceptual framework that links BDAC and SCA through supply chain coordination, swift trust, and supply chain risk. Additionally, the age and size of the firm are used as control variables. The data is collected from Indian service sector employees of MSMEs, resulting in 497 usable responses. We use PLS-SEM using Warp PLS 7.0 to test the hypotheses. A critical finding is that the BDAC indirectly impacts the SCA. Finally, the other findings, limitations, and scope for future research are discussed.

Keywords: Supply chain disruption; Supply chain coordination; Big data analytics; Sustainable competitive advantage; MSME; Service firms

1. Introduction

Big Data Analytics (BDA) has transformed business and has accelerated the pace of growth and expansion. Organizations have harnessed the power of BDA and artificial intelligence (AI) to gain a competitive advantage (CA) (Dahiya et al., 2021). The predictive analytics-powered BDA systems are also helping improve operational efficiency by minimizing risk and enhancing collaboration among various stakeholders in business operations. The most commonly used 5V's of big data: value, veracity, velocity, variety, and volume help businesses churn out the maximum from the given form of data (Dubey et al., 2018, 2019). The BDA ecosystem also helps firms answer "how" and "what" they need to do to maintain and gradually improve from their current position in the market (Wamba et al., 2018). With the rapid pace at which digitization of business and industry 4.0 practices have been adopted in every sector, it becomes essential for firms to use and adapt to BDA (Dubey et al., 2019; Potluri and Vajjhala 2021).

Sustainability in its contemporary form is measured in three aspects: environmental, social, and economic, which, when achieved, helps firms in sustainable development. However, in the economic, financial, and technological sustainability race, firms often fail to investigate reasons and solutions that help them stay invested in BDA-based solutions (Sheng et al. 2021). Thus, the once achieved CA by firms then remains no more sustainable. Studies also support that the real test of sustainability is during times of uncertainty (Modgil et al. 2021; Sheng et al. 2021; Yu et al. 2021). The ongoing COVID-19 pandemic is one such uncertain environment that disrupted many businesses. Studies have reported that while specific sectors were deeply negatively impacted, other sectors gained importance (Ivanov and Das 2020; Sheng and Saide 2021). Supply chain (SC) and logistics are such sectors that COVID-19 significantly impacted. While large firms managed to rely on reserves, the micro, small and medium enterprises (MSME) sector faced a severe backlash. It is reported that most of the firms in the MSME category that were low on the technology quotient faced a bottleneck to progress, and many of those also collapsed during COVID-19 (Bag et al., 2021; Modgil et al., 2021). Thus, sustainability is a significant concern for MSMEs that are highly vulnerable to risks and uncertainty.

Earlier studies have also used the lens of theories like resource-based view and dynamic capability view to explain relationships between firms' resources, their capabilities to use them, and CA drew from it (Baryannis et al., 2018; Bragazzi et al. 2020; Dubey et al. 2018, 2019). However, such theoretical arguments hold when a firm's internal resources are transformed into capabilities. Additionally, the role of social capital and firms' financial well-being is also essential to understand and practice the transition (Dahiya et al., 2021). However, due to their nature of business and lower technology investments (Potluri and Vajjhala 2021; Sandu et al. 2020), MSMEs do not find appropriate theoretical support to explain their CA, and more importantly, during uncertain situations times.

BDA and its contributions to explain CA is well reported (Bag et al., 2021; Dubey et al., 2019; Papadopoulos et al., 2017). However, two dimensions are missing that need to be factored in: first, the organization's size, which is symbolic of its resources, and second, the event of uncertainty. We aim to address these two issues in the current study. For an MSME to not only survive but also remain competitive in such uncertain times, it is crucial to study the institutional structure of the firm. The factors that explain the degree of resilience in these uncertain times can be explained using institutional theory (IT). Different components of IT explain how these social elements are created, diffused, adopted, and adapted over space and time; and how they fall into decline and disuse (Fauzi & Sheng, 2020; Scott, 1987). The theory maps and explains the internal strength and support of every firm. Institutions are transmitted by various carriers, including symbolic systems, relational systems, routines, and facts. With a disrupted SC, the revival of the MSME sector relies on the internal coping mechanism that IT can explain.

As we are studying the digital transformation of MSME with BDA, it is also essential to understand and use theoretical cues that further explain the exchange of information amongst various stakeholders within and outside the organization. We use organizational information processing theory (OIPT) (Galbraith, 1974) to explain how BDA has helped them achieve sustainable competitive advantage (SCA) during uncertain times. This theory identifies three critical concepts: information processing needs, information processing capability, and the fit between the two to obtain optimal performance. Typically, organizations have two strategies to cope with uncertainty and increased information needs: (1) develop buffers to reduce the effect of uncertainty, and (2) implement structural mechanisms and information processing capability to enhance the information flow and thereby reduce uncertainty (Gupta & George, 2016; Kamble et al., 2018). Thus, the OIPT works best with IT to explain the phenomenon of SCA.

Thus, using BDA, the MSMEs improve the flow of information amongst stakeholders and help them gain swift trust (ST), which is a crucial antecedent to improving efficiency. Nguyen et al. (2018) and Mandal (2018) further discussed how BDA could help improve supply chain coordination (SCC) among stakeholders. Additionally, the role of BDA in improving ST is also explained in the context of the humanitarian SC (Dubey et al., 2018, 2019). Therefore, we borrow the arguments from these published works in the context of the MSME sector. Lastly, we also extend the recent works of Mandal (2018), Katsaliaki et al. (2021), and Behl and Dutta (2020), which explains how BDA can contribute to ST and SCC in explaining the process of SCA. Therefore, we attempt to seek answers to the following research questions (RQs).

RQ1. How do big data analytics capabilities (BDAC) help MSMEs improve SCC and ST?

RQ2. How does BDAC help MSMEs reduce SC disruptions and supply chain risk (SCR) to gain SCA?

By answering the two questions, the study contributes to the exisiting body of knowledge in two ways. First, we discuss how BDAC can help MSME firms mitigate supply chain risk and help them gain sustainable competitive advantage. Unlike large firms that are capital intensive, MSME's lack capital and are also high on risk when it comes to adoption of any new technology. Moreover, the choice of implementing in any technology should ideally give them a fairly high and sustianbale competitive advantage as they would then compete with large sector firms as well which are at par with using big data analytics. Thus, our study offers empirical evidence to test this. Second, our study also contributes to the literature of supply chain disruptions which is as a result of ongoing pandemic. It has been reported that a fairly large number of MSME's faced losses and some of which had to shut down their business during COVID 19. A lot of such disrutions was seen as a result of lack of planning, strategizing their resources and improper use of new age technology. The study offers directions to MSME firms to understand how and why would an investment in BDA would help them combat suppl chain disruptions.

The study uses the MSME service sector in Indian geography to answer these two RQs. India is a growing economy for the MSME sector with new avenues and public policies to support them. India has approximately 6.3 crore MSMEs. As per the MSME Ministry data, as of May 16, 2021. MSMEs are encouraged to market their products on the e-commerce site, primarily through Government e-Marketplace (GeM). Some of the current government policies like "Factoring Regulation (Amendment)," "MSME Prerna," "Startup India" show that the sector has a promising future, and the growing usage of new and advanced technological interventions make it a critical case to be studied. AI and big data are not limited to large enterprises now; they propose a fantastic growth opportunity for MSMEs. Allowing small businesses to delegate tasks effectively and practice a faster and more innovative approach can help employees focus on more opportunities for business expansion. Having said this, the need of the hour to capitalize on this growth remains in the strategizing and aligning of these technologies with business goals. By appropriately prioritizing these technologies, MSMEs can achieve long-term success as scalable as AI, and big data redefines the technology landscape (Sandu et al., 2020; Shetty et al., 2020).

The advanced technloiges such as BDA help MSMEs gain competitive advantage. For example, Sariyer et al. (2021) show that by implementing BDA in quality management, the MSMEs could detect the defects, types of defects, and predict the rework quantities. Another study by Sharma et al. (2022) argues that use of AI, and IoT can help MSMEs on various dimensions including preventive maintenance, robotics, quality control, product design, and supply chain optimization. Additionally, the Blockchain technology can help MSMEs create a realiable, secure, and transparent tracking system (Mittal et al., 2021). The risk of theft of data may be reduced through cloud technology. Jha & Sahoo (2021) note that BDAC could help MSMEs not only retain their customers but also attract new customers by offering customized products.

The study presented as follows. Section 2 details theoretical arguments and discusses the need and fit of the IT and OIPT. Section 3 discusses the hypotheses of the study and proposes the theoretical framework. Section 4 lays out the research design adopted in the study. Section 5 present the results of pretesting the research instrument and results of the hypotheses testing. Section 6 discusses the theoretical and managerial implications of the study, while section 7 offers the conclusion, limitation, and future scope of the study.

2. Theoretical Foundation

The organizational information processing theory (OIPT), proposed by Galbraith (1974), posits that if the task uncertainty is extraordinary, decision-makers need to process a significant amount of information to achieve a given level of performance. Furhermore, Ferraris et al. (2021) note that decision-maker's problem solving skills (using right kind of information) positively affect firm's ability to improve performance amid disruption. According to Galbraith (1974), firms should either increase their information processing capabilities or reduce their information needs. Srinivasan and Swink (2015) opine that a firm can increase its information processing capabilities by investing in a vertical information system. Alternatively, information processing needs can be reduced by creating self-contained tasks and (or) creating slack resources. The reduction in information processing needs is not recommended as it obstructs the firm's responsiveness. In the context of the current study, due to COVID-19, the firms were dealing with a considerable level of uncertainty. The disruption was even more severe for MSMEs as they did not have well-established information systems in their SCs. Therefore, for the current study, the OIPT is the best fit.

Next, The Institutional Theory (IT) proposed by DiMaggio and Powell (1983) has been widely used in SC studies focusing on the adoption of new technologies or frameworks (Dubey et al. 2020). IT is instrumental when an organization needs to adopt a new practice or technology. The IT defines a concept known as institutional isomorphism, a combination of coercive pressure, mimetic pressure, and normative pressure. Institutional isomorphism provides impetus to an organization's efforts to improve its social and technological sustainability (Shibin et al., 2017). The studies in the information systems field have focused on developing and implementing various services (health, financial) in SMEs (Currie and Swanson 2009). In the current study, MSMEs need to adopt BDA to gain a sustainable competitive advantage (SCA). Therefore, IT provides solid theoretical support to our study.

3. Hypotheses development and theoretical model

Our study draws theoretical support from the OIPT and IT. Both theories emphasize an organization's efforts to adopt new technology or framework. Firstly, we provide the operational definition alongwith the scope of each construct relevant to the current study in Table 1. Next, we build our arguments from extant literature and establish linkages between relevant constructs to our study. Finally, we propose a conceptual framework based on the linkages established.

Table 1. Operational definition and scope of each construct

Acronym	**Definition**	**Source**	**Scope in the current study**
BDAC	Big data analytics capabilities (BDAC) are broadly defined as the competence to provide business insights using data management, infrastructure (technology) and talent (personnel) capability to transform business into a competitive force	(Akter et al., 2016)	The current study restricts its interst to data management and technological infrastructure capabilities.
ST	Swift trust (ST) is an essential arrangment bringing temporary teams together with a clear purpose and common task for a finite period of time	(Dubey et al., 2018)	Our study focuses on trustworthyness of people, processes, knowledge, and third-party.

SCC	Supply chain coordination (SCC) is concerned with managing dependencies between various supply chain members and the joint efforts of all supply chain members to achieve mutually defined goals.	(Arshinder et al., 2007)	We restrcit our interest to information flow, contracts, joint efforts on cost minimization, evaluatiing risks and rewards, and standardization of rules
SCR	Supply chain risk (SCR) includes material flow risk, information flow risk and financial flow risk that cause supply chain disruptions.	(Mani et al., 2017)	Our study focuses on managing operational risks (for example, supplier, maintenance, safety, inspection)
SCA	Sustainable competitive advantage (SCA) is achieved if the firm possesses resources with valuable, rare, inimitable, and non-substitutable attributes	(Huang et al., 2015)	Our study focuses on the firm's profit, cost, product, service, and market share.

The linkage between Big Data Analytics Capabilities and Supply Chain Coordination

SCC is crucial in integrating information from internal departments and various actors involved in the SC process to enhance overall performance (Sawik 2009; Singh 2011). More specifically, coordination is of utmost importance to MSMEs as they must break the isolation of their actors involved in the SC process to face global competition. On the flip side, globalization also allows MSMEs to collaborate with large organizations and focus on their core expertise. To reap the benefits of globalization. MSMEs should ensure effective coordination among the actors involved in the SC (Kumar et al., 2014). BDA has emerged as the game-changer in the SC by enabling organizations to outshine in the rapidly changing environment (Gunasekaran et al. 2016; Nguyen et al. 2018) as it improves the efficiency & effectiveness of decisions at strategic as well as the operational levels (Maroufkhani et al., 2020; Shamim et al., 2020; Wamba et al., 2017). BDAC refers to the organizational capability to organize and process a massive chunk of data that can be used for value creation for the organization (Wamba et al., 2017). It is established that performance of the firms that have developed more BDAC is better than those who have lower BDAC (Ferraris et al., 2019). However, most organizations have not invested in big data to transform their SC as it requires a high initial investment of acquiring technology and software (Sanders, 2016). BDAC plays a crucial role in SCC and information sharing (Chen et al., 2016). However, companies should ensure that they use BDA in all SC functions rather than emphasizing one function (Sanders, 2016). Jiang (2019) proved with the help of simulation that big data information analytics is crucial in SCC as it reduces the bullwhip effect and enhances the overall effectiveness and efficiency of the SC. Even in the context of the humanitarian SC, which is considered more complex due to many uncertainties, language, cultural barriers. BDAC reported a significant positive impact on coordination among various actors involved in the process (Dubey et al., 2018). Liu et al. (2020) researched green agri-food SCC considering information services based on BDA and blockchain technology. The findings reported that revenue-sharing and cost-sharing contracts could better motivate the SC members to coordinate the process. More recently, Bresciani et al. (2021) argued that big data can enhance both direct and indirect collaborative innovation processes between SC members. Based on this discussion, we propose hypothesis H1.

H1: Big Data Analytics Capabilities of MSME significantly improve supply chain coordination

The linkage between Big Data Analytics Capabilities and Swift trust

Swift trust (ST) is vital among the actors of a temporary group, as it brings the team together with a clear objective and common purpose for a defined period (Shibin et al., 2017). ST is primarily researched in the context of disaster management and humanitarian SC, as an actor have less time to trust each other and coordinate in such a way to meet their objectives (Dubey et al., 2018; Papadopoulos et al., 2017). However, researchers have advocated that it can be used in other scenarios such as information and communication technology (ICT) to interact among various members of different teams at distant places as if there was already trust among them (Caby-Guillet et al., 2016). Birchall and Giambona (2007) also mentioned the importance of ST in virtual learning communities among SMEs managers. More specifically, when different geographically dispersed teams interact using ICT to achieve their common objective, swift trust becomes crucial.

Dubey et al. (2018) studied the mediating effect of ST between BDAC and SCC. However, no mediating effect was reported. Therefore, the direct relationship between BDAC and ST is comparatively less explored. For example, Dubey et al. (2019) explored this association and reported a positive impact of BDAC on ST among actors involved in the humanitarian SC. Furthermore, Roßmann et al. (2018) mentioned that BDA would improve the overall SC performance. However, this transition from the traditional SC method to a new one will increase the importance of trust. Therefore, it is crucial to explore the relationship direct relationship between BDAC and ST. Specifically, most organizations nowadays focus on their core strength and opt for contractual agreement/contractual governance to govern other inter-firm exchanges (Lee & Cavusgil, 2006). In such a situation, mutual trust and commitment become of utmost importance for the organizations (Shamim et al., 2020). Similarly, in the case of MSMEs that use BDAC and information sharing among various inter-organization teams to achieve a common objective, it will be interesting to understand how BDAC impacts the ST among these teams/members. Hence, we postulate H2:

H2: Big Data Analytics Capabilities of MSME firms have a significant positive impact on the Swift Trust

The linkage between Supply Chain Coordination, Swift Trust, and Supply Chain Risk

Supply chain risk (SCR) is one of the major concerns for organizations as the risk susceptibility is contingent on other components of their SC (Faisal et al., 2006). Unlike uncertainty, risk warrants uncertain results of known probabilities, which are also unknown (Christopher & Peck, 2004). Nowadays, organizations are more exposed to SCR as they have become lean and agile and depend on outside support, which adds to their overall vulnerability (Faisal et al., 2006; Tang 2006). This creates barriers for managers to maintain seamless SC flow (Babu et al., 2020). In the context of Indian MSMEs, most of the risk in SCC arises due to sharing sensitive information among various SC actors, demand seasonality, and changing raw material prices (Kumar and Singh 2017). However, this risk can be mitigated by proper collaboration/coordination among the partners involved in the SC process (Tang, 2006). Singh (2011) emphasized reducing the SCR through a coordinated effort among the SC partners. Adhikari et al. (2020) also signify the importance of coordination in the textile industry among SC members in reducing risk by focusing on a suitable risk allocation process. Based on this discussion, we propose:

H3: Supply chains with higher supply chain coordination experience significantly lower supply chain risks

Trust is one of the crucial points in most transactions as it can involve risk and social uncertainty (Lu et al., 2016). However, in a situation like COVID-19, the SC partners needed to trust each other quickly. Therefore, ST becomes extremely important when more uncertainties are involved (Papadopoulos et al., 2017). Although ST has extensively been used in humanitarian SC studies, the current pandemic situation applies to almost all kinds of SCs.

Ganesan (2018) mentioned that a higher level of ST among partners might mitigate the risk perception and strengthen the relationship. Also, ST plays a crucial role in risk mitigation among the exchange partners as it minimizes the uncertainty of their actions (Ireland & Webb, 2007; Mishra et al., 2016).

Furthermore, various studies signify the role of ST in reducing SCR (Dubey et al. 2019; Dubey et al. 2020; Papadopoulos et al. 2017; Tatham and Kovács 2010). Furthermore, (McLaren & Loosemore, 2019)also highlighted that ST could mitigate, especially when a high degree of independence and uncertainty is involved. Therefore, based on the above discussion, we propose:

H4: Supply chains with higher swift trust in MSME experience significantly lower supply chain risks.

The linkage between Supply Chain Risk and Sustainable Competitive Advantage

The SCR is defined in several ways by researchers. The researchers have used SC vulnerability, SC disruption, and SCR interchangeably. Christopher and Peck (2004) note that SCs arvulnerable to risks from within or outside the SC. Mani et al. (2017) argue that various risks (foe example, information flow risk, financial flow risk, and material flow risk) could disrupt the SC. While adopting and implementating BDA, the MSMEs face several challenges such as shortage of technological resources, lack of skille human resource, shortage of financial resources, data security, among others (Potluri & Vajjhala, 2021). Because of the size and other resource limitations, the risk evaluation is not done analytically (Panigrahi, 2012). Therefore, the MSMEs are prone to higher risks than large organizations.

A SC that can manage the risks efficiently performs better on environmental, social, and financial dimensions (Giannakis & Papadopoulos, 2016). SCs should innovate consistently to lower the SC disruption risk to provide the firms SCA (Tseng et al., 2019). According to Singh

& Kumar (2020) Indian SMEs and MSMEs need to collaborate with the suppliers and use the latest technologies to reduce their risks associated with the supply chain process. Mainly, MSMEs feel the risks of fluctuating demand, varying price, and information exchange while working on supply chain coordination (Singh et al., 2012), limiting them to take competitive advantage with other firms (Singh & Kumar, 2020). Liao et al. (2017) argue that SC collaboration lowers the SC risks, which provides CA to the firms. Mani et al. (2017) provide evidence of using BDA to mitigate the SC risks, which would provide SCA to the firms. Kwak et al. (2018) note that SCs with lower risks gain CA. Based on the above discussion, we propose the following hypothesis:

H5: Supply chains with a lower level of risks experience a significantly higher sustainable competitive advantage.

Having established the linkages between the constructs relevant to our study, we present the conceptual framework of our study in Figure 1.

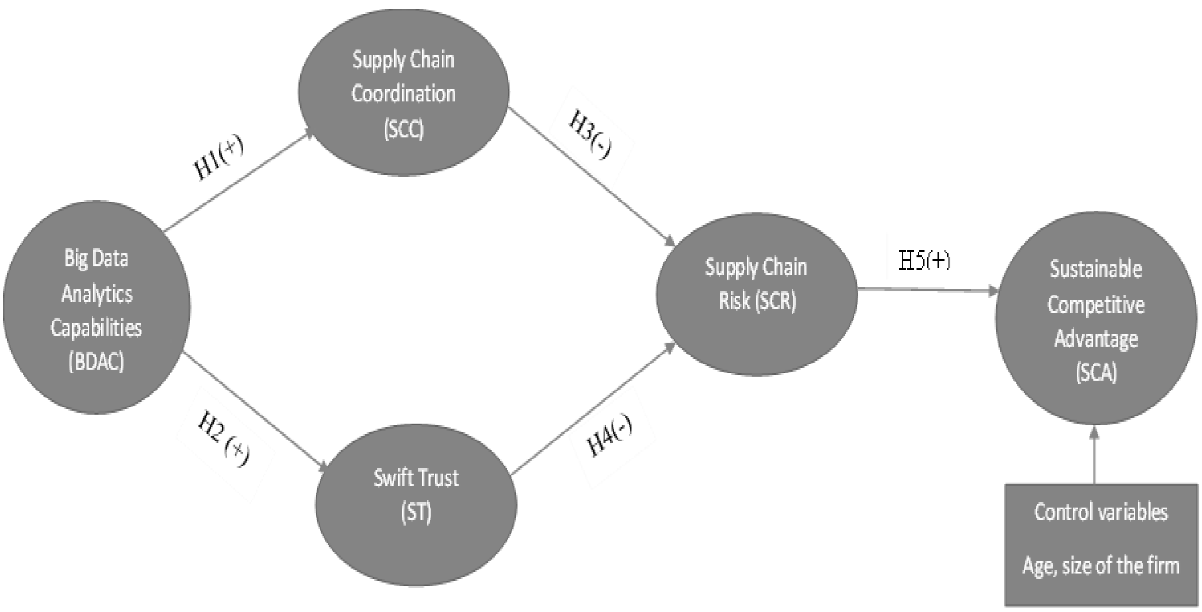

Figure 1. Theoretical Framework

Apart from the relevant construct, we use the age and size of the firms as control variables. While age is defined in the number of years since establishment, the firm's size is defined by the government's MSME definition (based on investment).

4. Research Design

The proposed hypotheses are tested using primary data collected from the MSME sector in India. The current study collects data across different services provided to test the hypotheses on diverse data. To maintain consistency, we only collected data from the service sector firms. While earlier studies have studied the role of BDA in the manufacturing sector to a large extent, primarily based on the expansion of industry 4.0 practices, we propose to see if BDAC would help service sector MSME firms gain SCA. As most service firms work on the business-to-customer model, the deployment of BDA tools would help them understand customers better through their business operations.

Earlier studies that have explored the power of BDA have used it as a resource that has helped firms to gain CA (Mikalef et al. 2020; Singh and Del Giudice 2019). However, with growing resources and their capacity to be used in businesses, it will no more contribute to CA according to Barney's resource-based view theory. Moreover, studying SCA with customer-centric firms is critical, which can be improved by mitigating risks. Our study collects data on constructs used in the model – "big data analytics capability," "supply chain coordination," "swift trust," "supply chain risk," and "sustainable competitive advantage." We also record data for "size of the firm" and "age of the firm" used as moderators of the study.

We followed the guidelines of Ketokivi and Schroeder (2004) to collect empirical data from multiple sources of the same organization and report their average as one data entry to get a true picture of the sector and get diversity in responses from every eligible organization. The target respondents are key stakeholders in the firm working on SC management and digitization interface. Some of the prominent profiles of the same include supply chain managers, digital supply chain analysts, procurement executives, and supply chain analysts. The primary role of these specialists is to work in applied areas of SC management and improve its efficiency through digital solutions. The list of the target firms was extracted from the National Portal of India and the Ministry of Micro, Small, and Medium Enterprise. As of March 31, 2021, the listed firms were used as a population for our study. We validated the information from the databases mentioned above to double confirm the authenticity of the data. It is in line with the previous studies (Bhat et al. 2020; Maheshwari et al. 2020).

4.1 Survey Instrument- Design and usage

The survey design approach uses a two-stage process, starting from defining the constructs operationally as the first step and then exploring the essential measurement items to measure the scope (Dubey et al. 2020; Eckstein et al. 2014). The list of constructs and their measurement items can be referred to from Appendix 1. We explored each construct's dimensions by performing a systematic review and studying previous literature in operations management that has used similar constructs. We developed a working definition of the constructs, then validated by experts using a Delphi approach. Delphi techniques helped us further validate our theoretical understanding of the constructs through a practical viewpoint. In translating the working definition to the operational definition, we also ensured that the contextual understanding and applicability were not compromised (Behl et al., 2021; Dubey et al., 2019). The responses to items are collected on a five-point Likert scale with responses ranging from 5 (strongly agree) to 1 (strongly disagree). Most empirical cross-sectional studies have used similar scales that ensure variability amongst responses (Salem et al., 2019; Srinivasan and Swink 2018; Rialti et al., 2019).

The scale is pretested using experts. Then, the pilot tested it using 45 samples collected from the MSME sector in India to understand if the respondents faced any difficulty understanding and responding to the survey questions. For pretesting, we borrowed experts from the Delphi study to share their opinion on the final questionnaire regarding its content, flow, and wording (Rialti et al., 2019). It helped us ensure that the survey instrument is free from ambiguity and offers a clear and comprehensive overview of items (DeVellis, 1991). We further validated the instrument in the context of the study using Dillman (2011) approach. We deleted some items that were either unnecessary or out of context for the study. As the last step to validate the survey instrument, we shared the final survey with 13 senior researchers and managers who have worked in the MSME sector and have earned a doctorate to validate the overall questionnaire. It helped us in finalizing our survey instrument for our study.

4.2 Data Collection

Data collection is done using an online form designed on Google forms. Responses were received between August 10, 2021, to September 15, 2021. The respondents were contacted over an email using stratified random sampling and wherever required within the same firm using snowball sampling. A total of 2450 potential respondents were contacted over email, of which we received a total of 572 responses using multiple follow-ups and reminders. Each applicable and valid respondent was also rewarded with an Amazon voucher of INR 150 (approximately $2). To maintain anonymity, we used a disclaimer clearly stating that the data will be collected and used for academic purposes. Data is collected from MSME sector employees, and thus to verify the information, we verified their official email addresses. In addition, a careful examination is conducted to scan the data points based on the requirements for the study.

The final tally of data used for the analysis is 497, corresponding to an acceptable participation rate. If multiple data points from the same organization are more than one, we took an average of the data and reported it as one data unit. The nature of the data is cross-sectional and may have some errors in the process of collecting data. Thus, it is critical to assess any non-response bias, which is checked using Armstrong and Overton's (2018) guidelines. In addition, we performed Analysis of Variance (ANOVA) to test the difference between the response received from phases 1 and 2. The test results confirm that (P = 0.294) there is no difference between the two groups, and there is a minimal scope of non-response bias.

5. Data Analysis and Results

We use partial least square structured equation modeling (PLS-SEM) to test the hypotheses. The traditional approach of using PLS-SEM in most of the software uses a factor-based approach. However, its effectiveness and efficiency are often challenged. We use Warp PLS 7.0 to address the criticisms in the literature regarding the choice of the modeling approach. We followed the guidelines of Kock (2019) that establish the rationale for using a composite-based method PLS-SEM. The recent literature initiates a debate between factor-based SEM v/s composite-based SEM and their applications in management (Kock, 2019). The existing school of thought relies on the traditional SEM approach, wherein latent variables are estimated as a weighted average of indicators. This approach also excludes the measurement error while performing calculations (Henseler et al., 2014; Kock 2019). However, excluding measurement error in PLS-SEM modeling often leads to limited or non-capturing of certain forms of biases, which further dampens the effect reported in path coefficients in the structural model. Thus, to overcome these issues, we used the guidelines of Kock (2019) and performed hypotheses testing using Warp PLS 7.0 in the study.

5.1 Multi-Rater Agreement Measures

The study uses data from key stakeholders from the MSME sector, and it is often seen that multiple stakeholders from the same organization filled the questionnaire. In such a situation, we need to assess the validity of the responses received from three or more respondents from the same organization. While some studies claim to remove the additional data points from the same organization, others claim that such an action would result in a steep and significant drop in the reliability of the data. Therefore, we used the guidelines of Ketokivi and Schroeder (2004) and performed an inter-rater agreement using four different methods. All methods help in establishing the validity and help in supporting the authenticity of the data for its further testing. We performed a battery of tests like paired sample t-test, interclass correlation coefficient, ratio method, and percentage method (Boyer & Verma, 2000; Ketokivi & Schroeder, 2004) (Refer to Table 2 for the results). Based on the four tests, we confirm that the data is acceptable and appropriate for the analysis.

Table 2: Measures of inter rate agreement

	Interclass correlation coefficient	Ratio Method	Percentage Method (%)	Paired t-test
BDAC	0.33	0.76	82	Not significant
SCC	0.37	0.77	81	Not significant
ST	0.29	0.79	84	Not significant
SCR	0.30	0.82	93	Not significant
SCA	0.31	0.81	89	Not significant
EXP	0.36	0.84	84	Not significant

BDAC – Big Data Analytics Capabilities; SCC – Supply Chain Coordination; ST – Swift Trust; SCR – Supply Chain Risk; SCA – Sustainabble Competitive Advantage; EXP – Size of the firm

5.2 Measurement Model – Reliability and Validity

We followed a two-stage approach for testing the reliability and validity of the data. First, the reliability is tested by checking if the Cronbach's alpha value is more than 0.7 (Hair Jr et al., 2017). We also calculated the composite value of Cronbach's alpha for the instrument and individually for each construct. We found that the range of alpha values was from 0.79-0.87, which confirmed reliability. We also performed a split-half method using a random data distribution into two buckets as confirmatory analysis. The results further validated the reliability of the instrument. Next, to test the model's validity, we also used a two-step approach suggested in the literature (Peng & Lai, 2012; Salem et al., 2019). First, we used reflective constructs to examine the validity by performing the confirmatory factor analysis (CFA) (Fornell & Larcker, 1981). Table 3 reports scale composite reliability (SCR) and average variance extracted (AVE) of the data. Results assets that factor loadings are found to be greater than 0.5, with the value of SCR more than 0.7 and the value of AVE greater than 0.5. Thus, following Fornell and Larcker's (1981) guidelines, we confirm that convergent validity is established at construct and indicator levels.

Table 3: Convergent Validity Measures

Items	Factor Loadings	Variance	Error	SCR	AVE
BDAC1	0.78	0.61	0.39	0.97	0.6
BDAC2	0.82	0.67	0.33		
BDAC3	0.73	0.53	0.47		
BDAC4	0.77	0.59	0.41		
SCC1	0.72	0.52	0.48	0.97	0.59
SCC2	0.69	0.48	0.52		
SCC3	0.79	0.62	0.38		
SCC4	0.79	0.62	0.38		
SCC5	0.84	0.71	0.29		
ST1	0.68	0.46	0.54	0.54	0.5
ST2	0.72	0.52	0.48		
ST3	0.77	0.59	0.41		
ST4	0.66	0.44	0.56		
SCR1	0.68	0.46	0.54	0.90	0.53
SCR2	0.79	0.62	0.38		
SCR3	0.72	0.52	0.48		
SCA1	0.77	0.59	0.41	0.92	0.52

SCA2	0.73	0.53	0.47		
SCA3	0.67	0.45	0.55		
SCA4	0.77	0.59	0.41		
SCA5	0.72	0.52	0.48		
EXP1	0.8	0.64	0.36	0.87	0.61
EXP2	0.76	0.58	0.42		
AGE1	0.67	0.45	0.55	0.89	0.49
AGE2	0.7	0.49	0.51		
AGE3	0.72	0.52	0.48		

BDAC – Big Data Analytics Capabilities; SCC – Supply Chain Coordination; ST – Swift Trust; SCR – Supply Chain Risk; SCA – Sustainabble Competitive Advantage; EXP – Size of the firm; AGE – Age of the firm

We then tested for divergent validity as the second step in our structural model using the hetrotrait-monotrait ratio of correlations (HTMT test) and Fornell and Larcker (1981) criterion. The HTMT test (refer to Table 4) tests the discriminant validity between the reflective constructs. We found the values to be more than 0.90, indicating sufficiency in discriminant validity for all the constructs (Henseler et al., 2014).

Table 4: HTMT values

	BDAC	SCC	ST	SCR	SCA	EXP
BDAC						
SCC	0.335					
ST	0.352	0.210				
SCR	0.425	0.427	0.307			
SCA	0.301	0.563	0.297	0.521		
EXP	0.228	0.245	0.311	0.325	0.338	

BDAC – Big Data Analytics Capabilities; SCC – Supply Chain Coordination; ST – Swift Trust; SCR – Supply Chain Risk; SCA – Sustainabble Competitive Advantage; EXP – Size of the firm

5.3 Common Method Bias and Causality Assessment

We collect primary empirical data for our study using a systematically designed questionnaire. Podsakoff and Organ (1986) discussed various primary data issues, and common method bias (CMB) is critical. Podsakoff et al. (2003) indicate that CMB is often a result of variations in responses caused by the instrument rather than the predispositions of the respondents. Various studies have claimed that it is difficult to eliminate the chances of having CMB in the data. However, its effect can be reduced by following the guidelines of Ketokivi and Schroeder (2004). We performed two tests to ensure that the data did not suffer from CMB. First, we performed the contemporary Harman's single factor test that indicates that a single factor explains 27.47% of the overall variance. While most studies report Harman's single factor test sufficient, we further validate the same using Lindell and Whitney's (2001) guidelines and perform a correlation marker technique. Second, we picked up an unrelated variable and tested its effect in the model. We found a significantly low difference between the unadjusted and adjusted correlations scores. Referring to the guidelines of Lindell and Whitney (2001) and the results found from the statistical tests, we conclude that the study does not suffer from the problem of CMB.

As a final step, most empirical studies quote that hypothesis testing often misses the test of causality. Therefore, we referred to the guidelines of Kock (2017) and calculated the nonlinear bivariate causality direction ratio (NLBCDR). The guidelines report that the acceptable value is greater than or equal to 0.7. We found the NLBCDR ratio to be 0.82, which is higher than the threshold value. It confirms that causality is not a critical issue in this study. The other statistical values that form the indices for quality and model fit are reported in Table 5.

Table 5: Causality Assessment Indices

Causality Assessment Indices	**Values (Threshold Values if any)**
Sympson's Paradox Ratio (SPR)	0.772 (Acceptable if ≥ 0.7)

R^2 contribution ratio	0.939 (Acceptable if ≥ 0.9)
Statistical Suppression Ratio (SSR)	0.803 (Acceptable if ≥ 0.7)
Non-linear bivariate causality direction ratio (NLBCDR)	0.818 (Acceptable if ≥ 0.7)

5.4 Model Fit and Indices

The model fit and quality indices (Average path coefficient (APC), Average R^2, and Average block VIF) are reported in Table 6. These indices predict the relationship between latent variables. The APC and Average R^2 values are significant at ($P < 0.001$), and the Average block VIF is accepted as it is less than the threshold value. Tenenhaus GoF is a single goodness of fit value based on the AVE estimates and R^2 (Shibin et al., 2017; Tenenhaus et al., 2005). Tenenhaus GoF is 0.682 in our model, which is large as it is ≥ 0.36.

Table 6: Model Fit and quality indices parameters

Model fit and quality indices	**Values (Threshold Values if any)**
Average Path Coefficient (APC)	0.289 (P <0.001)
Average R^2	0.798 (P <0.001)
Average block VIF	3.87 (Acceptable if value ≤ 5)
Tenenhaus GoF	0.682 (Large if value ≥ 0.36)

5.5 Hypotheses Testing

Hypotheses result of our study are provided in Table 7. H1 (BDAC → SCC) is supported (β = 0.762; P <0.01), which means a positive relationship between BDAC and SCC, it is consistent with previous findings (Chen et al., 2016; Dubey et al., 2018; Jiang, 2019). Next, H2 (BDAC → ST) is also supported (β = 0.678; P < 0.01), which is in line with findings of previous studies (Caby-Guillet et al., 2016; Dubey et al., 2019). H3 (SCC → SCR) is negatively supported (β = -0.652); P < 0.01), suggesting SCC lowers the risks in the SCs (Adhikari et al. 2020; Singh

2011; Tang 2006). H4 (ST → SCR), which tests the relationship between ST and SCR, is not supported. Finally, H5 (SCR → SCA) is supported (β = -0.578); $P < 0.01$), which suggests that SCs with lower risks tend to gain SCA (Giannakis & Papadopoulos, 2016; Kwak et al., 2018; Mani et al., 2017). Apart from our main hypotheses, we also checked the effects of age and size of the firm on SCA. Our results indicate that the effect of size is significant, whereas the effect of age is insignificant.

Table 7: Hypotheses Testing Results

Hypothesis	**Effect of**	**Effect On**	**B**	***P*-value**	**Results**
H1	BDAC	SCC	0.762	***	Supported
H2	BDAC	ST	0.678	***	Supported
H3	SCC	SCR	-0.652	***	Supported
H4	**ST**	**SCR**	**-0.038**	*****	**Not Supported**
H5	SCR	SCA	-0.578	***	Supported
	Age	**SCA**	**0.031**		**Not Supported**
	Exp	SCA	0.243	***	Supported

*** $P < 0.01$, ** $P < 0.05$, * $P < 0.10$

BDAC – Big Data Analytics Capabilities; SCC – Supply Chain Coordination; ST – Swift Trust; SCR – Supply Chain Risk; SCA – Sustainabble Competitive Advantage; EXP – Size of the firm; AGE – Age of the firm

Next, Table 8 present the R^2, Q^2, and F^2 values. The R^2 value, which describes the explanatory power of the constructs. In our findings, the R^2 for SCC, ST, SCR, and SCA are 0.78, 0.84, 0.45, and 0.57, respectively, which are acceptable. Further, the Q^2 values, which indicate the prediction capability of the model. The model is a strong predictor of SCC, ST, SCR, and SCA in our study. Finally, we also report each predictor's effect size. In our study, all F^2 values are either medium or large.

Table 8: R^2, prediction and effect size

Construct	R^2	Q^2	F^2 in relation to			
			SCC	**ST**	**SCR**	**SCA**
BDAC	--	--	0.35	0.21		
SCC	0.78	0.69			0.38	
ST	0.84	0.74			0.31	
SCR	0.45	0.68				0.29
SCA	0.57	0.63				

BDAC – Big Data Analytics Capabilities; SCC – Supply Chain Coordination; ST – Swift Trust; SCR – Supply Chain Risk; SCA – Sustainabble Competitive Advantage

6. Discussion

Today, BDA plays a crucial role in the organization's SC system (Liu & Yi, 2016). The present study investigates the role of BDAC to gain SCA for MSMEs that operate in the service sector. The findings presented exciting insights about the relationship among BDAC, SCC, ST, SCR, and SCA. The study is among the initial research in MSMEs to understand the impact of BDAC on SCC that further leads to SCA.

The result reported that the BDAC of MSMEs significantly influences their SCC (H1) and ST (H2) among various actors involved in the SC process. Chen et al. (2016) show that BDA positively influences supply chain coordination and information sharing among supply chain actors, affecting an organization's value creation. Its unique information processing capability provides a competitive advantage to the firms. Furthermore, Dubey et al. (2019) show that BDAC positively influences ST and collaborative performance of the SC. The findings are consistent with Chen et al. (2016 and Dubey et al. (2019), proving the importance of BDAC in improving supply chain coordination and developing swift trust among the supply chain members for MSMEs.

SCC among firms negatively influenced the SCR (H3). The finding is in line with previous research (Adhikari et al., 2020; Tang, 2006) that confirms the role of coordination among various SC actors to minimize the SCR. The result emphasizes that MSMEs should visualize the possible benefits of SCC to mitigate the risk associated with the SC as coordination strategies will help these organizations reduce their uncertainties by managing interdependencies properly among the actors (Kumar & Singh, 2017). On the other hand, ST did not report any significant impact on SCR (H4). The finding contradicts earlier studies that have emphasized the role of ST, mainly in the humanitarian SC (Dubey et al., 2019; Papadopoulos et al., 2017). We spoke to a few respondents to understand the reason behind this contradictory result. Almost all the respondents' opined that ST is a new term for them, which and they thought ST does not apply to MSMEs. Also, swift trust has been used primarily on disaster relief teams/ humanitarian logistics, temporary organizations, and virtual teams (Curnin et al., 2015; Zakaria & Mohd Yusof, 2020), and comparatively a new term for MSMEs. Further, swift trust is fragile (Brad Crisp & Jarvenpaa, 2013) and not emphasized much on the interpersonal relationship (Zakaria & Mohd Yusof, 2020), but focuses on knowledge sharing (Pinjani & Palvia, 2013), which could concern MSMEs to share the knowledge and information with a temporary team.

Finally, SCR was found negatively related to SCA (H5). This result is in line with previous studies (Kwak et al., 2018; Mani et al., 2017). However, most of the studies use various constructs to establish the relationship. For example, SC resilience, SC disruption risk, SC financial risks, SC risk mitigation strategies were used by the researchers (Gaur et al. 2020; Giannakis and Papadopoulos 2016; Mishra et al. 2016; Singh and Singh 2019). Nonetheless, all the studies indicate the firms gain SCA if they can lower the risks related to various functions of the SC.

6.1. Theoretical and managerial implications The study makes the following theoretical contribution to the extant literature. First, the present research is among the initial studies that focus on BDAC of the service sector of Indian MSMEs, which the previous researchers have ignored. Second, the study shows the applicability of organizational information processing theory (OIPT) and Institutional theory (IT) in explaining and understanding the impact of BDAC on SCA through SCC, ST, SCR in the Indian MSMEs sector. The conceptual model establishes linkages between constructs that lead BDAC to SCA.The existing studies discuss sustainability while discussing digital technologies. However, our study establishes the link between BDAC and SCA through SCC, ST, and SCR. Third, this study attempted to understand swift trust in MSMEs context as previous studies focusing on swift trust have mainly considered its applicability in temporary settings (hastily formed supply chains) such as virtual teams, military operations, and humanitarian logistics ((Curnin et al., 2015; Zakaria & Mohd Yusof, 2020).

The findings will show the direction to the MSMEs that investing in big data analytic capability may help them take a sustainable competitive advantage in the long run as BDAC is the future of the supply chain (Dubey et al., 2018; Fawcett & Waller, 2014). Concerning managerial implications, the supply chain managers of MSMEs may use our results to improve their supply chain performance, mainly supply chain coordination. For example, MSMEs may want to share critical information and data with their partners to use their BDAC. Such initiatives will foster trust and improve coordination and visibility among various supply chain actors (Akter et al., 2016). More specifically, when the uncertainty is high, as it is during COVID-19, improved coordination and superior trust among supply chain actors will help reduce supply chain risk and make the supply chain more resilient. As we observed during COVID-19, the resilient SCs could survive during this uncertain time (Bag et al., 2021). All these efforts will provide the SCs with an SCA. The finding will help MSMEs understand the importance of information sharing and the usage of big data analytics as these companies have faced challenges at multiple levels on logistics and supply chain during the pandemic .

7. Conclusion, limitations, and scope for future research

The businesses continuously strive to gain a competitive advantage in the competitive market. Oliver (1997) and Huang et al. (2015) discuss shifting from a temporary competitive advantage to SCA. The focus of our study is on MSMEs that operate in the service sector. MSMEs face several challenges due to limited resources and fierce competition at global level. The disruptions in the SCs due to the COVID-19 pandemic have manifolded these challenges. However, advanced practices (for example, blockchain, machine learning, big data analytics) have proven to be helping MSMEs overcome such challenges (Bag et al. 2021; Modgil et al. 2021; Sheng et al. 2021; Yu et al. 2021). Drawing broadly on organizational information processing theory (OIPT) and institutional theory (IT), this research attempts to understand the influence of BDAC on MSMEs in providing SCA. In particular, the BDCA is an effective tool for MSMEs to reduce SC issues (Shibin et al., 2017). The current study focuses on BDCA and investigates its role in achieving SCA through supply chain coordination, swift trust, and supply chain risk. The findings suggest that the MSMEs should use BDAC for better coordination and build trust among supply chain partners as BDAC will ease the information-sharing process across the partners. It also confirms that SCC negatively influences the SCR making the supply chain more risk resilient, leading to overall SCA. The findings also suggest that MSMEs gain SCA if they work on their BDAC.

Like any other study, our study also has a few limitations, and future studies can address them. First, we collect data from the respondent at a single point in time, i.e., cross-sectional data. Although cross-sectional data is a valid method, it has its limitations (for example, CMB) (Ketokivi & Schroeder, 2004; Shibin et al., 2017). Future studies can address this issue and collect longitudinal data. Second, we collect data from Indian MSMEs to test our hypotheses. Future studies may collect data from other countries to test the cross-cultural differences and validate our results (Ferraris et al., 2019). Third, the generalizability of our study is not easy because of the sampling design. Future studies can use simple random sampling to address this concern. Finally, we acknowledge that we may not have all the constructs as we draw our theoretical support from the OIPT and IT. Future studies can use other theories to address this gap.

Appendix 1. ***Constructs and measurement scales***

Construct	Items measured	Adapted Source(s)	Measurement Scale
Big Data Analytics Capabilities (BDAC)	BDAC1: We use advanced tools (like optimization/regression/simulation) for data analysis.	Akter et al. (2016; Srinivasan and Swink (2018)	Five-point Likert scale
	BDAC2: We use data visualization techniques to assist decision-makers in understanding complex information extracted from large data		
	BDAC3: Our dashboards display information, which is useful for carrying out the necessary diagnosis.		
	BDAC4: We have connected dashboard applications or information with the manager's communication devices.		
Swift Trust (ST)	ST1: I find my colleagues trustworthy	Robert et al. (2014); Tatham and Kovács (2010)	Five-point Likert scale
	ST2: Most people tell the truth about their knowledge		
	ST 3: Clear rules for classification of processes and procedures		
	ST4: Trust based on third party reference		
Supply Chain Coordination (SCC)	SCC1: Standardization of Rules	Rice and Hoppe (2001); Shukla (2016)	Five-point Likert scale
	SCC2: Evaluating risks and rewards		
	SCC3: Joint cost minimization		
	SCC4: Use of electronic data interchange		
	SCC5: Management of supply chain contracts		

Supply Chain Risk (SCR)	SCR1: Preventing operations risks (e.g. select a more reliable supplier, use clear safety procedures, preventive maintenance)	Donadoni et al. (2018)	Five-point Likert scale
	SCR2: Detecting operations risks (e.g. internal or supplier monitoring, inspection, tracking)		
	SCR3: Recovering from operations risks (e.g. task forces, contingency plans, clear responsibility).		
Sustainable Competitive Advantage (SCA)	SCA1: Compared with our competitors, we have higher profit growth rate	Anwar (2018); Bhat and Darzi (2018); Sigalas and Papadakis (2018); A. Singh and Verma (2019)	Five-point Likert scale
	SCA2: Compared with our competitors, we have higher sales revenue growth rate		
	SCA3: Compared with our competitors, we have lower operating costs		
	SCA4: Compared with our competitors, we have better product and service quality		
	SCA5: Compared with our competitors, we have increasingly higher market share		

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