Computers & Industrial Engineering 172 (2022) 108629

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

Examining the influence of big data analytics and additive manufacturing on supply chain risk control and resilience: An empirical study

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ARTICLE INFO

Keywords:
Big Data Analytics
Additive Manufacturing
Risk Control
Supply Chain Resilience
Supply Chain Ripple Effect

ABSTRACT

Drawing upon the contingent resource-based perspective of supply chain resilience, this study tests whether fourth industrial revolution (4IR) technologies such as big data analytics (BDA) and additive manufacturing (AM) control risks and develop supply chain (SC) resilience under flexible orientation and control orientation. Primary data was collected from 190 samples in India and the PLS-SEM technique was then used to perform data analysis. The findings indicate that big data analytics and additive manufacturing can aid in risk control and in turn improve the SC resilience of a firm and further minimize the propagation of the supply chain ripple effect in case of disruption. This study sheds light on firms' 4IR resources (BDA and AM) that can be useful in developing risk control capabilities to deal with disruptions in supply chains. BDA, in particular, impacts risk intelligence, whereas AM impacts both preparedness and intelligence risk control. Distinguishing between BDA and AM is therefore important when firms are considering which technology to adopt. Therefore, for the sample analyzed, BDA has a prominent role in building risk control and resilience capabilities. These findings are an important contribution to SC risk management theory and this study also creates new research opportunities. Firms need to adopt collaborative planning, forecasting, smart manufacturing, and replenishments initiatives for vulnerable supply chain activities to reduce the SC ripple effect. Lastly, flexible, real-time production helps reduce the SC ripple effect.

1. Introduction

Today's supply chains are long and complex, which makes them quite vulnerable to disruptions that can ripple through these long chains in unpredictable ways (Scheibe and Blackhurst, 2019). Disruptions can happen due to natural catastrophes or they can be man-made (Rose, 2007). Their effects on supply chains can last for a long period and have serious consequences. The effect of disruption can be transmitted to other regions and actors in a supply chain (SC), which is known as the "ripple effect" (Ivanov et al., 2014).

Ripple effects can alter the SC structure and parameters (Ivanov et al., 2014). Hence, disruption risks present a new test for SC managers when dealing with resilient SCs (Ivanov and Dolgui, 2019). Ripple effects propagate quickly in the SC and have a major impact on SC output (Ivanov and Dolgui, 2019). It is essential to control the SC structural dynamics to enhance SC performance (Ivanov and Dolgui, 2019).

The dangers and uncertainties of global supply networks have been extensively acknowledged in the literature. Risk is the result of an uncertain event (Manuj and Mentzer, 2008). Supply, demand, operational and security are the main risks affecting global SCs' (Christopher and Peck, 2004).

Manuj and Mentzer (2008) indicated that global SC risk management strategies (postponement, speculation, hedging, control/share/transfer, security, avoidance) are dependent on the antecedents (temporal focus, SC flexibility, SC environment) and further impact the risk management

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https://doi.org/10.1016/j.cie.2022.108629

Available online 6 September 2022
0360-8352/

consequences.

In current times, SCs hedge against disruptions using common strategies such as overstocking raw materials, reserving capacities, and overstocking finished goods. However, these strategies are not cost-effective and can instead have adverse effects on the organization (Ivanov and Dolgui, 2019). Adopting the right risk management approaches is necessary to beat competitors, and gain a competitive edge (Ritchie and Brindley, 2007).

Blackhurst et al. (2005) has indicated two important concepts under disruption management - first, the discovery of the event and second, recovery from the event. It is vital to understand that the disruption is happening. Only then, the recovery can be initiated. Firms must have the speed to discover the disruption and as well as speed to recover after the event.

However, SC managers can control and manage risks (reduce severity) effectively if SC visibility is improved and real-time information is available (Bag et al., 2020a). This will reduce the SC ripple effects and reduce the financial cost and service impact (Ivanov and Dolgui, 2019). Previously, Brandon-Jones et al. (2014) argued that information connectivity and information sharing improve SC visibility. This is possible in the fourth industrial revolution (4IR) era (vertical, horizontal, and total business integration) (Telukdarie et al., 2018). Firms can leverage technologies like big data analytics (BDA) that can aid in tracing the underlying cause of disruption and monitoring the transmission of a disruption (Bueno et al., 2020; Ivanov and Dolgui, 2019; Kamble and Gunasekaran, 2020; Nakayama et al., 2020; Maheshwari et al., 2021). Companies like Amazon and Walmart monitor inventory and customer transactions using big data technologies. UPS uses big data to assess the performance of the logistics network (Rozados and Tjahjono, 2014). BDA utilizes descriptive analytics and predictive and prescriptive analytical techniques (Sivarajah et al., 2017) to scan the business environment, interpreting key information to respond to changes in the environment (Queiroz and Telles, 2018; Bag et al., 2021). Ranjan and Foropon (2021) argued that BDA is useful for building competitive intelligence in firms; however, firms prefer to use a centralized, informal process.

Likewise, additive manufacturing (AM) helps firms reconfigure SCs in this digital age (Tziantopoulos et al., 2019). AM benefits include on-demand manufacturing, product customization, minimized waste, manufacturing of complex parts, and lighter components (Tziantopoulos et al., 2019). AM can minimize risk-mitigating stock and capacity reservations. AM can also lower the need for maintaining backup contingent vendors (Yılmaz, 2020). AM can help reduce the ripple effect significantly as the number of SC layers are less and less complex, which can improve resilience. Therefore, 4IR technologies like BDA and AM have the potential to avert risks related to disruptions (Majeed et al., 2021). Interestingly, the recent systematic literature review performed by Spieske and Birkel (2021) revealed that BDA is appropriate for enhancing SC resilience, but there is a lack of evidence related to the effectiveness of AM. Earlier, Manavalan and Jayakrishna (2019) also pointed out that studies intended to examine and understand the effect of 4IR technologies and SC risk management are limited. Therefore, the inter-relationships between various 4IR technologies and SC resilience need further investigation (Ivanov and Dolgui, 2019; Bueno et al., 2020). This effect of 4IR on the SC ripple effect and on controlling disruption risks is a promising research opportunity (El Baz and Ruel, 2021; Yang et al., 2021). Hence, the first research question:

RQ1. How 4IR technologies, such as BDA and AM, control risks and develop SC resilience to decrease the propagation of ripple effects in the SC?

Literature has indicated that control orientation and flexible orientation act as moderating variables in many situations (Bag et al., 2019). Control orientation involves formal rules and policies. The main focus is on accomplishing the goals set by management (Liu et al., 2010). Control orientation can reduce supply chain ripple effects after a disruption (Ivanov et al., 2019b). Similarly, flexibility can improve the ability to minimize risks in the event of a SC interruption (Skipper and Hanna, 2009).

Duclos et al. (2003) stated that flexibility in the SC includes the need for flexibility among all SC actors and information systems, because SCs' go beyond firms' boundaries, and flexibility strategies must also extend beyond the firm. Flexibility with regard to competitors can be achieved through volume and mix flexibility (Braunscheidel and Suresh, 2009; Zsidisin and Wagner, 2010). Literature indicates that contingency planning is a useful tool that can improve flexibility in the organization. Proper contingency planning sets out an action plan for timely and accurately fighting back against various risks (La Londe, 2005). Flexibility is found to be highly effective when preparedness for risk control is high (Skipper and Hanna, 2009). Hence, the second research question:

RQ2. How risk control influence SC resilience under flexible orientation and control orientation?

This study utilizes a contingent resource-based view to understand the relationship between specific resources (big data analytics and additive manufacturing), capabilities (preparedness and risk intelligence), and performance in terms of supply chain resilience and supply chain ripple effects. We have explained how and when firms can build supply chain resilience. The resource-based view (RBV) explains the bundling of resources to develop a competitive advantage (Barney, 1991), whereas contingent RBV explains that this is reliant on certain conditions (Brandon-Jones et al., 2014). Some contingencies influence the effectiveness of resource integration (Sirmon et al., 2011). Factors such as flexible orientation and control orientation can alter the influence of capabilities (preparedness and risk intelligence) on supply chain resilience.

This study takes the risk control and supply chain resilience-related theoretical debate to the next level by examining the contingent effects of flexible orientation and control orientation on the outcomes of risk control and further opens new research opportunities.

The next section presents the discussion on the theoretical foundation of the work followed by a discussion of the hypotheses. Section 3 presents the research strategy for the empirical survey. Section 4 presents the data analysis followed by a final Section 5, which deals with the discussion of findings and the final section presents the conclusion.

2. Theory development

2.1. Big data analytics (BDA)

Big data comprise vast amount of observational data to assist numerous types of judgments (Goes, 2014). Big data is characterized by five Vs' i.e., volume, velocity, variety, veracity, and value (George et al., 2016). Whereas, BDA is a term that refers to a method of collecting and analyzing data in order to provide solid information for making decisions using complex statistical and computational tools (Akter et al., 2016).

Organizations view the analytics process, which includes the deployment and usage of BDA tools, as a tool to improve operational efficiency, even though it has potential to develop new income streams and achieve competitive advantages over competitors (Sivarajah et al., 2017).

Big data analytical methods are descriptive analytics, inquisitive analytics, predictive analytics, prescriptive analytics and pre-emptive analytics. BDA analytical techniques can help firms to answer questions such as "What occurred in business?"; "Why is something occurring in business"; "what is expected to occur in future?"; "What to do at present?" and "what are the requirements to do more?" (Sivarajah et al., 2017). Various big data tools for analysis used by firms include Xplenty, Adverity, Dataddo, Apache Hadoop, CDH to name a few.[1] Literature has highlighted that BDA capabilities can effectively control risks and build

[1] https://www.softwaretestinghelp.com/big-data-tools/.

SC resilience (Akter et al., 2016; Kache and Seuring, 2017).

2.2. Additive manufacturing (AM)

AM is one of the most rapidly evolving and promising manufacturing technologies, with substantial advantages over traditional procedures (Vayre et al. 2012; Gibson et al., 2021).

The primary premise behind this technology is that a model created with a three-dimensional computer-aided design system may be directly manufactured without the requirement for process planning. Therefore, detailed planning is not necessary and basic dimensions along with the understanding of AM material and equipment are enough to produce AM-based products. The generic AM process involves developing the CAD file and further converting to STL file format, then transfer to the AM machine, followed by setting up the machine, building the part and then removal of the part from the machine, lastly the postprocessing and use of the part. Although liquid polymer systems, discrete particle systems, molten material systems, solid sheet systems are some of the popular AM systems; however, with recent advancements involves direct metal procedures. Technological advancements (accuracy and speed of machines) have made it possible to developed AM products in a cost-effective manner (Gibson et al. 2021). AM technologies have strategic potential to provide flexibility in this 4IR era (Tziantopoulos et al., 2019).

2.3. Risk control

Disruption risk control has been well acknowledged in the literature (Skipper and Hanna, 2009). Natural and man-made disasters result produce various risks for the supply chain. As supply chain risks rise, firms must build logistical processes and skills that will enable them to be ready (capable) to respond quickly and effectively while continuing to do business as usual (Ponomarov and Holcomb, 2009). Nonetheless, SC ripple effect is a major problem caused due to disasters (Manuj and Mentzer, 2008). SC ripple effect depends on the duration and severity of the disasters. Managing SC ripple effect requires advance design and planning of resilient SCs'. Reaction to disruptive events can be done using one of the following strategies- parametric adaptation (inventory), process adaptation (capacity flexibility) and structural adaptation (backup facility) (Ivanov et al., 2017).

2.4. Supply chain resilience

After the publication of the seminal work by Christopher and Peck (2004), in the early 2000s, SC resilience attracted a lot of attention. Resilience is a multifaceted and diverse notion. On the one hand, resilience has been the topic of scientific study in fields like developmental psychology and ecosystems for many years. On the other hand, it's a hot topic in fields like risk management and supply chain management that are still developing (Ponomarov and Holcomb, 2009).

Ponomarov and Holcomb (2009) defined resilience in context to SC as "*The supply chain's ability to anticipate and respond to unforeseen occurrences, as well as recover from them, by maintaining operations at the required level of connectedness and control over structure and function.*".

Another definition of SC resilience given by Tukamuhabwa et al. (2015) as "*The ability of a supply chain to anticipate and/or respond to interruptions, recover quickly and efficiently, and thereby advance to a post-disruption state of operations — ideally, one that is better than before the disruption*".

Literature indicates that demand management, supply management and information management capabilities are required in developing SC capabilities to build SC resilience (event readiness, efficient response and recovery) of firms (Ponomarov and Holcomb, 2009).

There are a variety of ways for boosting resilience, but expanding flexibility, building redundancy, forming collaborative supply chain connections, and improving supply chain agility have received the most attention (Tukamuhabwa et al., 2015). Furthermore, Pettit et al. (2019) argued that supply chain resilience is a complement to risk management rather than a replacement.

2.5. Supply chain ripple effect

Dolgui et al. (2018) described "*The ripple effect explains the impact of a disruption's propagation on supply chain performance as well as the breadth of disruption-based modifications in supply network structural design and planning parameters*.".

The uncertainties in SC ripple effect could be hazard and deep uncertainty, involving disruption and creating exceptional risks that disturbs structures and performance. Disruptions affects SC outcomes and then spreads in the SC network which result in lower sales revenues, and business losses. However, proactive redundancy and flexibility can prevent such variations in the SC. Firms need to develop resistance and recovery policies and action plans to mitigate SC ripple effect (Dolgui et al., 2018).

2.6. Contingent resource-based perspective

The fundamental concept of the resource-based view (RBV) revolves around strategic resources that help firms gain a competitive advantage (Barney, 1991). Resources were initially considered under physical capital, human capital, and organizational capital (Barney, 1991). Later, financial capital, technological capital, and reputational capital were added (Grant, 1991). Resources are the tangible or intangible elements that a firm can acquire or has access to (Barney, 2001). Multiple resources are integrated to build capability (Sirmon et al., 2008). These competences can be exceptional to a particular firm and can prove to be superior to those of competitors.

SCs are associated with various risks and uncertainties. A focus on SC resilience is necessary to ensure that the SC structure returns to its original state as quickly as possible following the disruption incident. 4IR smart systems can enhance SC resilience due to capability enhancements and the progress of newer sets of skills (Kamble et al., 2018). We studied the effect of two specific organizational resources – BDA and AM – on SC risk control and the further impact on SC resilience. BDA and AM are considered primary resources for the application of 4IR technologies in risk management and control. Risk control, including preparedness and risk intelligence, is considered to be a capability that is deeply embedded in the SC and extremely valuable for the firm. This capability will impact the performance of the firm.

We considered improved SC resilience and lower propagation of the SC ripple effect under firm performance. We also examined the contingent effect of flexible orientation and control orientation on the relationship between SC risk control, SC resilience, and SC ripple effect (see Fig. 1). Improved SC risk control can increase SC resilience, but after an SC interruption, the contingent parameters in terms of the extra cost of enhancing risk control are crucial but vague in the literature. It is essential to explore options for developing control and building flexibility, as it is important to identify the parameters that will enhance risk control and generate a good return on investment.

2.7. Hypothesis development

2.7.1. Big data analytics and additive manufacturing

4IR has witnessed an overflow of big data due to enhanced computational power and the advancement of information and communication technologies (Bag et al., 2020b). Big data is characterized by high volume, high velocity, high variety, variability, and value proposition (Riggins and Wamba, 2015; Kamble and Gunasekaran, 2020). Big data is generated mostly in real-time settings. This is mainly possible due to the use of smartphones, social media such as Twitter, Instagram, Facebook, and the Internet of things, enabled by radio frequency identification and other wireless sensor networks (Riggins and Wamba, 2015).

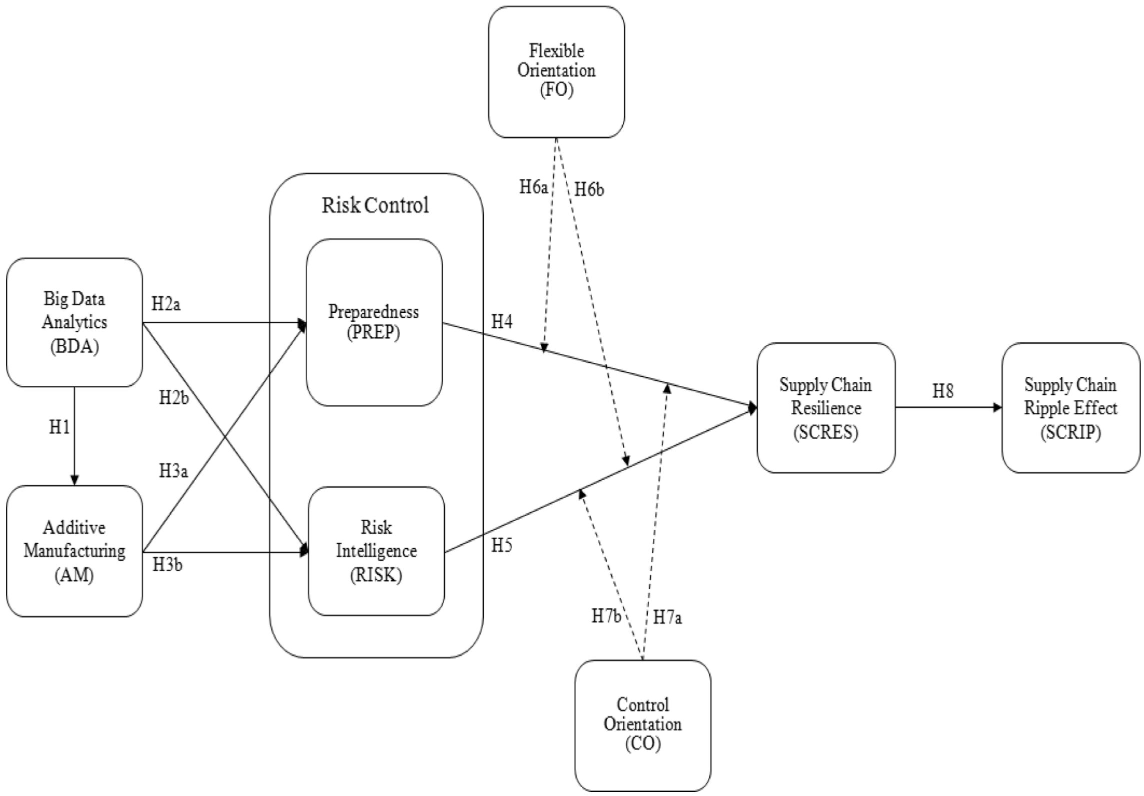

Fig. 1. Theoretical model.

Another interesting technology that has gained popularity in the 4IR is additive manufacturing (AM) (Haleem and Javaid, 2019). AM can be used to build three-dimensional products using the model designed through computer-aided design software (Yılmaz, 2020). The design can be drawn using advanced engineering software or the sample product can be directly scanned using 3D scanners to capture all the dimensions and then be transferred to the computer system. AM is therefore dependent on data sets, and it is now possible to access data quickly and further process it for new product development. AM adds material layer-by-layer to build the physical object (Haleem and Javaid, 2019).

Literature has indicated that big data has powered AM. The big data are linked through cloud computing and collaborative manufacturing, supported by complex design and instant analysis, and finally with AM (Gunasekaran et al., 2016; Dilberoglu et al., 2017). This technology uses advanced materials (polymers, ceramics, metals, etc.) to produce customized products (Maresch and Gartner, 2020; Gibson et al., 2021). The part of big data is significant in the entire process, and without big data, AM cannot achieve success (Majeed et al., 2019; 2021). Hence,

H1: Big data analytics has a positive impact on the firm's ability to undertake additive manufacturing.

2.7.2. Big data analytics and the firm's ability to remain prepared in case of SC disruption

Big data analytics has been extensively used in sourcing, production, marketing, logistics optimization, and operations management (Ivanov et al., 2019b). The benefits of BDA include better promotion action quality, effective demand forecasting resulting in improved SC visibility, and enhanced customer satisfaction (Hazen et al., 2016; Zhong et al., 2016; Ivanov et al., 2019b). Literature has indicated that BDA could aid in enhancing SC risk management and disaster resilience (Niesen et al., 2016; Papadopoulos et al., 2017). BDA can improve society through sustainable development of resilient disaster infrastructure and assist policymakers, scientists, and managers in developing appropriate policies and strategies to mitigate risks as well as prepare in case of SC disruption (Papadopoulos et al., 2017). Hence,

H2a: Big data analytics has a positive impact on the firm's ability to remain prepared in case of SC disruption.

2.7.3. Big data analytics and the firm's ability to manage risk in case of SC disruption

SC disruptions can happen due to many reasons ranging from changes in climate conditions to changes in the political environment or changes in technology. Disruptions can continue for shorter or longer periods depending on the nature of the disruption. Companies can use BDA applications to manage risks in case of SC disruption and contribute to sustainability (Hazen et al., 2016; Papadopoulos et al., 2017; Manavalan and Jayakrishna, 2019). BDA can help enhance visibility and provide information about the intensity of disruptions. Such data can be used to switch to local sourcing and adjust production lines to meet urgent customer delivery requirements (Bag et al., 2020b).

H2b: Big data analytics has a positive impact on the firm's ability to manage risk in case of SC disruption.

2.7.4. AM and the firm's ability to remain prepared in case of SC disruption

The benefits of AM include the development of complex components and customized products (Haleem and Javaid, 2019; Franco et al., 2020). It results in less waste of raw materials. Sample development is quick and custom batch development is possible without a lot of expenditure on tooling and production set-ups. Amazingly, prints can be done based on demand, making the SC very simple to operate with a low risk of inventory problems, as it does not require storage of final goods. 3D printing can be done in the delivery van on its way to distribute the product to the client or it can be done at the point of consumption (Rylands et al., 2016). These advantages help firms exploit AM in situations of SC disruption and easily resume normal operations afterward. Hence,

H3a: AM has a positive impact on the firm's ability to remain prepared in case of SC disruption.

2.7.5. AM and the firm's ability to manage risk in case of SC disruption

The business environment has become very dynamic over the last two decades (Ivanov et al., 2019b). With the rise of digital technologies, researchers have already examined and found certain inter-relationships existing between them (Ivanov et al., 2019b). Some positive links have been found between digital technologies and SC risk management. It was found that AM has the potential to manage risks in SCs. AM can be used to manufacture components and products (Franco et al., 2020) at any location in the SC, which adds a great deal of flexibility. This can reduce the number of layers of suppliers in the upstream part of the SC and reduce logistics needs (Ivanov et al., 2019b). Hence,

H3b: AM has a positive impact on the firm's ability to manage risk in case of SC disruption.

2.7.6. Preparedness of a firm and the firm's ability to have SC resilience in case of disruption

Literature indicates that the preparedness of a firm can lead to the development of SC resilience. Preparedness can involve critical infrastructure development and a focus on risk reduction aspects (Koot et al., 2020). Other initiatives include translating strategic agreements into operational plans to ensure preparedness. Many companies have established a matrix for the continuous review of preparedness. Lastly, it is important to practice mock drills and simulations to ensure the level of preparedness (Scholten et al., 2014). Hence,

H4: The preparedness of a firm positively impacts the firm's ability to have SC resilience in case of disruption.

2.7.7. Risk intelligence of a firm and the firm's ability to build SC resilience

Risk intelligence of a firm is essential in the volatile business environment. It entails developing an innovative system that can identify risks. Firms should be able to foresee future events and optimize. Firms can also hedge the risk portfolio through redundant resources for dual or multiple sourcing activities. Firms generally implement collaborative planning, forecasting, and replenishment initiatives for vulnerable SC activities (Jüttner and Maklan, 2011; Rajesh, 2019) to avert disruptions. This will allow the SC to quickly deal with disruptions and resume its original position (Brandon-Jones et al., 2014; Ivanov et al., 2019b; Nakayama et al., 2020).

H5: The risk intelligence of a firm positively impacts the firm's ability to build SC resilience.

2.7.8. Moderating role of flexible orientation

Flexibility is considered to be an important dimension of sustainable operations and has proven effective in volatile business environments. Uncertainties lead to SC risks, and supply and manufacturing flexibility can reduce production process risks significantly (Afshari et al., 2019). Flexibility can improve the ability to minimize risk exposure in the event of an SC disruption (Skipper and Hanna, 2009). Flexibility is found to be highly effective when preparedness for risk control is high. We argue that flexible orientation can strengthen/weaken the relationship between preparedness and SC resilience. Hence,

H6a: Flexible orientation positively moderates the relationship between preparedness and SC resilience.

We argue that flexible orientation can strengthen/weaken the relationship between risk intelligence and SC resilience. Hence,

H6b: Flexible orientation positively moderates the relationship between risk intelligence and SC resilience.

2.7.9. Moderating role of control orientation

Control orientation involves formal rules and policies. It is essential to follow rules in the firm and act accordingly. Manufacturing firms generally shield themselves against disruptions by sticking to the rules laid out by the management. Employees are more focused on productivity and modifying plans according to changes in internal and external situations. However, the standard operating process is followed in all circumstances. The main focus is on accomplishing the goals set by the management (Liu et al., 2010). Control orientation can reduce SC ripple effects after any disruption (Ivanov et al., 2019b). We argue that control orientation can strengthen/weaken the relationship between preparedness and SC resilience. Hence,

H7a: Control orientation positively moderates the relationship between preparedness and SC resilience.

We argue that control orientation can strengthen/weaken the relationship between risk intelligence and SC resilience. Hence,

H7b: Control orientation positively moderates the relationship between risk intelligence and SC resilience.

2.7.10. SC resilience of a firm and the firm's ability to control the SC ripple effect in case of disruption

SCs are very long and complex these days, which may lead to frequent disruptions. This has diverted the attention of SC managers towards SC resilience and building strategies to mitigate adverse SC ripple effects (Ivanov et al., 2019a). Firms need to have a disruption strategy in place to minimize the ripple effect that occurs after a disruption. Big data predictive analytics play a critical role in bouncing back after SC disruptions (Zhong et al., 2016). Modularization and standardization also help reduce the ripple effect. Other strategies include sourcing from numerous sources, flexible production systems, and smart manufacturing to minimize the ripple effect in the SC (Ivanov et al., 2014). Hence,

H8: The SC resilience of a firm positively impacts the firm's ability to control the SC ripple effect in case of disruption.

2.8. Control variables

As this study was conducted among various industrial sectors ranging from manufacturing to the service sector, the potentially negative influence of the industrial sector on SC ripple effects was treated as a control variable. Some industrial sectors involve high-level technology, some are capital intensive, while others are labor-intensive, and a few sectors are resource-intensive (Santoro and Chakrabarti, 2002). As per the work of Torugsa et al. (2012), on a scale of 1 to 5 (1 = "no impact at all" to 5 = "very high impact"), the target respondents were requested to respond and indicate their perception of the influence of the various sectors (banking, construction, consulting, education, food and beverages, human resources, industrial research, IT, logistics and SCM, and manufacturing) on the SC ripple effect during the previous six months.

3. Research design

The details of the research strategy implemented to collect data for this empirical study is discussed below.

3.1. Instrument development

The constructs and items were selected from past studies. BDA from the study of Gupta and George (2016); AM from the study of Le Bourhis et al. (2013) and Durach et al. (2017); preparedness from the study of Scholten et al. (2014); risk intelligence items from the study of Jüttner and Maklan (2011) and Rajesh (2019); SC resilience items from the study of Brandon-Jones et al. (2014) and Ivanov et al. (2019b); and the SC ripple effect items from the study of Ivanov et al. (2014). The moderating variables, i.e., flexible orientation, and control orientation were adapted from the study of Liu et al. (2010). The details on construct operationalization are shown in Appendix A.

A Likert scale (5-point basis) was used in the questionnaire. As per the work of Dubey et al. (2019), we had the structured questionnaire validated by four professors from top business schools in India and also by five SC experts from the industry. We received suggestions to alter the wording of four items regarding preparedness and risk intelligence and we changed the questionnaire before the survey accordingly.

3.2. Data collection

We employed a market research firm to collect the data. The market research firm collected the data for us, we used 190 responses. The data were collected from banking, construction, consulting, education, food and beverages, human resource firms, industrial research and development firms, information technology, logistics and transportation firms, manufacturing firms, and retail chains. The background of the respondents is shown in Table 1 and Table 2. We observed that 97 % of respondents have a postgraduate education level. 47 % of responses were received from manufacturing firms.

3.3. Common method bias (CMB)

Survey research often suffers from CMB, and therefore proper care was taken to avoid CMB (MacKenzie and Podsakoff, 2012). First, the questionnaire was checked by academic experts before administering the pilot survey. Second, clear instructions were given at the starting of the questionnaire to avoid any confusion among respondents. The survey was meant to last a maximum of fifteen minutes to avoid any kind of bias creeping into the responses. Lastly, we ran the traditional Harman's single factor test and found that thirteen factors emerged, out of which the first factor accounted for 21.03 % of the variance. This indicates that the data is not influenced by CMB.

3.4. Non-response bias

Non response bias was checked as per suggestion of Armstrong and Overton (1977). The request for data collection was sent in September 2019 and e-mails were directed to 840 possible respondents by the market research company. Thereafter, 75 responses were received. However, the market research company followed up in October 2019 and received another set of 115 responses. We then instructed the market research company to stop the survey and thanked them for its efforts.

Therefore, in total, we received 190 responses. The response rate was 22.61 %, which is acceptable in social science research. Since the data was gathered in two stages, we compared both waves, early (75 responses) and late (115 responses), using Levene's test.

The results show that all the values are non-significant which establishes homogeneity in the samples.

4. Data analysis

Partial least squares-based structural equation modeling (PLS-SEM) and covariance-based SEM (CB-SEM) are the two approaches commonly used in empirical research. Hair Jr. et al. (2017) suggested guidelines for choosing PLS-SEM or CB-SEM. We followed the guidelines and further used WarpPLS Version 7.0, a leading PLS-based software tool. One of the major reasons for using PLS-SEM is the explanation and prediction objective. A second reason is the consideration of a mix of formative and reflective measurement model specification. Lastly, we considered smaller samples for this study, which makes PLS-SEM a suitable tool for analysis (Hair et al., 2011; Hair Jr. et al., 2017). We followed the five steps in WarpPLS to perform the analysis. The significance level considered in this study is 0.05, so the confidence level was set at 0.95.

Table 1
Age group and educational qualification of the employees.

Educational Qualification	Age Group 20–30	31–40	41–50	51–60	60+	Total
Graduate	1	3	1	–	–	5
Post-Graduate	–	87	87	10	1	185
Total	1	90	88	10	1	190

4.1. Measurement model

We assessed the model fit with the data and found all of them to be within acceptable limits. The average path coefficient was found to be 0.346, $p < .001$, the average R-squared was 0.396, $p < 0.001$, and the average block VIF was found to be 2.279.

We also checked the causality indices and found them to be within acceptable limits. Simpson's paradox ratio was 0.750 (acceptable if $\geq$ 0.7, ideally = 1), the R-squared contribution ratio was 0.940 (acceptable if $\geq$ 0.9, ideally = 1), and the statistical suppression ratio was 0.917 (acceptable if $\geq$ 0.7).

We checked content validity, discriminant validity, and nomological validity and found them satisfactory. To ensure content validity, the questionnaire was validated by four academic experts. To check discriminant validity, we assessed the correlations among latent variables with the square roots of AVEs and found that the criteria were met (see Table 3). To ensure nomological validity, we identified theoretically-supported relationships from past studies and further used the scale to gather data to study the relationships in this study. The Cronbach's alpha coefficients indicate that all values are above 0.70 and acceptable.

4.2. Endogeneity test

We performed endogeneity tests related to the exogenous variables in the model. BDA and AM are considered as antecedents to preparedness for risk management and risk intelligence, and not the other way round (Mani et al. 2017). Therefore, we do not think that endogeneity is a problem in this study. However, we checked the endogeneity test by conducting the Durbin-Wu-Hausman test. The results indicated that the parameter estimate for the residual was non-significant. It was therefore proven that endogeneity has not biased our theoretical model.

4.3. Hypothesis tests

We used WarpPLS software to perform the hypothesis testing. We used the p values to decide to accept or not accept the research hypotheses. The model after testing is shown in Fig. 2.

The findings shows that there is an optimistic relationship between BDA → RISK ($\beta = 0.19$), BDA → AM ($\beta = 0.62$), AM → PREP ($\beta = 0.58$), AM → RISK ($\beta = 0.52$), PREP → SCRES ($\beta = 0.20$), RISK → SCRES ($\beta = 0.47$), and SCRES → SCRIP ($\beta = 0.57$) (refer to Table 4). The control variable did not show any significant effect on the model.

5. Discussion

This work scrutinized the effect of AM and BDA on SC risk control and SC resilience because research in this area is limited. We developed the theoretical model using the contingent resource-based perspective. The theoretical implications and practical implications are provided below.

5.1. Theoretical implications

The study intends to address two gaps in the literature. First, to establish the fact that BDA and AM can help with risk control and further develop SC resilience. Second, to establish that building SC resilience can decrease the propagation of SC ripple effects.

To address the first research gap, we examined H1, H2a, H2b, H3a, H3b, H4, H5, and H8. Next, to address the second gap, we examined H6a, H6b, H7a, and H7b.

The findings indicate that BDA has a positive relationship with AM. Some of the relevant works in this direction include those of Aggour et al. (2019), Chan et al. (2018), Majeed and Peng (2019), and Liu et al. (2020). Advanced analytics enhance the reliability and repeatability of AM, which ultimately requires data. Big data sets are generated and

Table 2
The domain of work vs role of the employee in the organization.

Domain of Work	Role in the Organization											
	AVP/ VP/ EVP	Board Member	Business Analyst/ Analyst	Consultant	Finance Executive	Director/ CEO/ Founder	Engineer	Logistics Manager	Manager/ Sr. Manager	Project Coordinator	Sales/ Marketing Executive	Total
Banking/ Insurance/ Financial Services	8	2	–	2	–	2	–	–	1	–	–	15
Construction/ Real Estate/ Infrastructure	–	–	–	1	–	2	1	–	–	–	–	4
Consulting	1	–	–	14	–	–	–	3	–	–	–	18
Education/ Research	1	4	–	1	–	–	–	–	–	–	–	6
Food & Beverage	–	3	–	–	–	6	–	3	–	–	–	12
Human Resource (HR)	1	–	–	1	–	–	–	–	–	–	–	2
Industrial Research & Development (R&D)	2	–	–	1	–	1	–	1	–	1	–	6
IT Hardware	1	3	–	–	–	–	–	–	1	–	–	5
IT Services/ Software	7	3	–	2	–	–	–	–	–	–	–	12
Logistics and Supply Chain	–	–	–	–	–	1	–	15	1	–	–	17
Manufacturing	9	12	6	16	3	22	–	17	4	–	2	91
Retail	–	1	–	–	–	1	–	–	–	–	–	2
Total	30	28	6	38	3	35	1	39	7	1	2	190

Table 3
Discriminant validity checking.

	BDA	AM	PREP	RISK	FO	CO	SCRES	SCRIP
BDA	**0.794**							
AM	0.613	**0.743**						
PREP	0.356	0.601	**0.737**					
RISK	0.488	0.636	0.659	**0.646**				
FO	0.419	0.537	0.410	0.531	**0.600**			
CO	0.412	0.640	0.610	0.640	0.583	**0.611**		
SCRES	0.528	0.704	0.448	0.583	0.521	0.571	**0.648**	
SCRIP	0.448	0.620	0.619	0.644	0.457	0.516	0.559	**0.581**

utilized during the AM lifecycle (Aggour et al., 2019). Big data and predictive analytics can also be used for estimating AM costs (Chan et al., 2018). A BDA-based framework can be used to optimize the production performance of the AM process (Majeed et al., 2019). The above studies, therefore, support our first hypothesis.

Following the literature review, we conceptualized that BDA has a positive influence on the preparedness of a firm in terms of risk control. However, H2a was not supported. This is an interesting finding of our work. The underlying reason could be the focus of Indian firms on risk intelligence by leveraging BDA rather than focusing on preparedness. The second finding indicates that big data analytics have a positive impact on the firm's ability to manage risk in cases of SC disruption about risk intelligence (Koot et al., 2020). Hence H2b is supported. BDA, for the sample, analyzed, therefore assists firms with identification and decision making in terms of operational risk rather than preparing firms for potential disruptions. Our argument is strengthened based on the suggestions of Ivanov et al. (2019b). Our findings corroborate those of the previous study of Mani et al. (2017) and Ivanov et al. (2019b). The third finding indicates that AM has a positive impact on the firm's ability to remain prepared in case of SC disruption, and AM also has a positive impact on the firm's risk intelligence in terms of SC disruption. Hence H3a and H3b were supported. Our findings corroborate those of the previous study of Ivanov et al. (2019a). The hypothesis concerning preparedness for risk control and SC resilience, i.e., H4, is also supported. The findings indicate that the risk intelligence of a firm positively influences the firm's ability to demonstrate SC resilience in case of disruption. Hence, H5 was supported. This finding corroborates that of the previous study of Christopher et al. (2003).

Our study also highlights that the SC resilience of a firm positively impacts the firm's ability to control the SC ripple effect in case of disruption. Hence, H8 was supported. This finding corroborates the finding of Dolgui et al. (2018). The following findings answer the second research question. They indicate that H6a and H6b, i.e., the moderating effect of flexible orientation on the relationship "preparedness and SC resilience" and "risk intelligence and SC resilience", were supported. Finally, the findings indicate that H7a (moderating effect of control orientation on path preparedness and SC resilience) was supported while H7b (moderating effect of control orientation on path risk intelligence and SC resilience) was not supported. Our theoretical contribution lies in the theoretically-guided findings that highlight the importance of resources that a firm needs to build risk control and in turn resilience capabilities. By using 4IR technologies such as BDA and AM, which act as firm resources, it could be possible to help firms to develop capabilities for risk control in SCs. This article highlights the roles of BDA and AM as part of the RBV, which adds to the literature in the SCM realm.

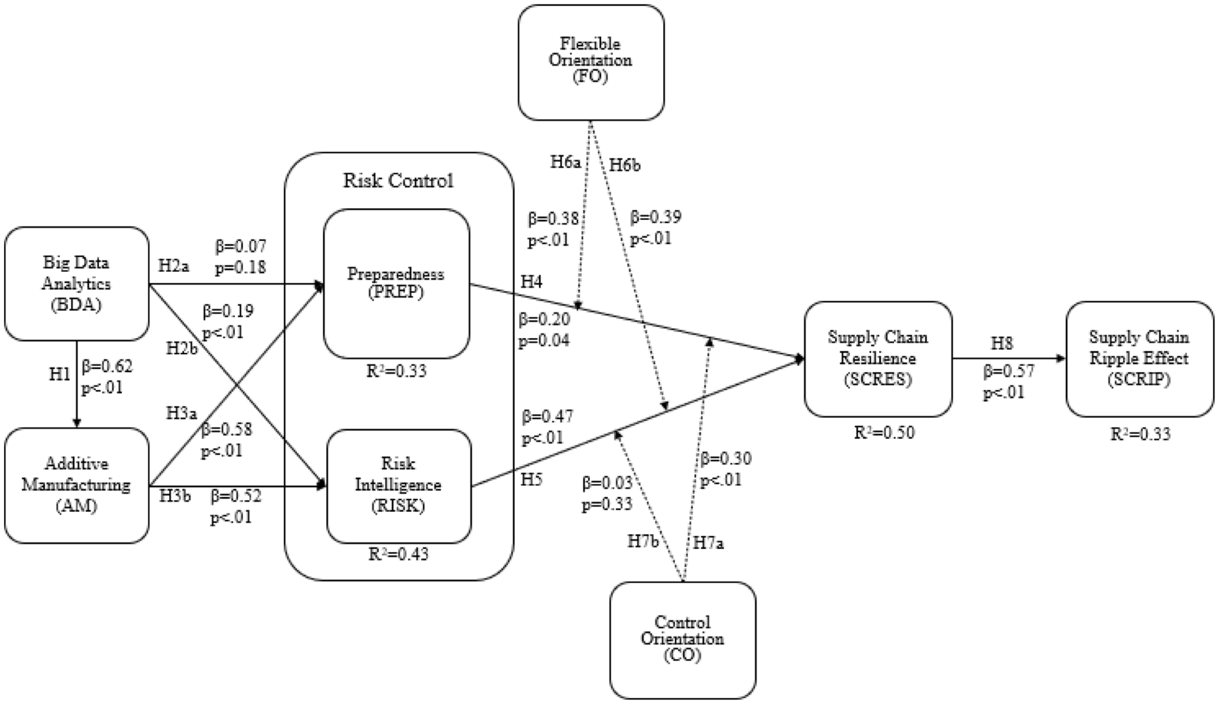

Fig. 2. Model after testing.

Table 4
Hypothesis testing results.

Hypothesis	β and p-value	Supported (Yes/No)
H1: BDA has a positive impact on the firm's ability to undertake additive manufacturing	β = 0.62, p <.01	Yes
H2a: BDA has a positive impact on the firm's ability to remain prepared in case of SC disruption	β = 0.07, p = 0.18	No
H2b: BDA has a positive impact on the firm's ability to manage risk in case of SC disruption	β = 0.19, p <.01	Yes
H3a: AM has a positive impact on the firm's ability to remain prepared in case of SC disruption	β = 0.58, p <.01	Yes
H3b: AM has a positive impact on the firm's ability to manage risk in case of SC disruption	β = 0.52, p <.01	Yes
H4: Preparedness of a firm positively impacts the firm's ability to have SC resilience in case of disruption	β = 0.20, p = 0.04	Yes
H5: Risk intelligence of a firm positively impacts the firm's ability to have SC resilience in case of disruption	β = 0.47, p <.01	Yes
H6a: Flexible orientation positively moderates the relationship between preparedness and SC resilience	β = 0.38, p <.01	Yes
H6b: Flexible orientation positively moderates the relationship between risk intelligence and SC resilience	β = 0.39, p <.01	Yes
H7a: Control orientation positively moderates the relationship between preparedness and SC resilience	β = 0.30, p <.01	Yes
H7b: Control orientation positively moderates the relationship between risk intelligence and SC resilience	β = 0.03, p = 0.33	No
H8: SC resilience of a firm positively impacts the firm's ability to control the SC ripple effect in case of disruption	β = 0.57, p <.01	Yes

5.2. Practical implications

This study draws attention on the resources of firms that assist them in developing capabilities to deal with disruptions in SCs. BDA and AM play important roles in building risk control capabilities. BDA, in particular, impacts risk intelligence, whereas AM impacts both preparedness and intelligence risk control. Therefore, distinguishing between BDA and AM is important when firms are considering which technology to adopt. In addition, for the sample analyzed, BDA has a prominent role in building risk control and resilience capabilities.

Prof. Hau Lee in 2002, in his article, "aligning SC strategies with product uncertainties" talked about functional products and innovative products and further matched the SC strategies with respect to supply uncertainty and demand uncertainty. Considering innovative products, where the demand uncertainty is high and supply uncertainty is low, firms must use responsive SC strategy; whereas, high demand and high supply uncertainty require firms to use agile SC strategy. BDA can be an extremely useful technology for improving operational excellence in responsive and agile SCs. BDA is useful in sensing threats and seizing new opportunities to further develop reconfiguration ability. BDA can work in both situations (high and low supply uncertainty). However, AM can be more useful in responsive SC since a stable supply process is required to work with partners and suppliers in developing AM-based products.

Our study highlights that BDA is effective in risk intelligence only, but AM is effective in the risk intelligence and preparedness process of firms. This will increase the resilience of firms to SC disruptions and minimize the impact of ripple effects.

Risk intelligence is important from a risk control perspective: companies need to improve their risk intelligence abilities. They need to develop unique systems that can identify the risk of conflict between the firm and community activities. Companies need to be able to foresee and optimize according to a legal framework and existing regulations for future events. They need to adopt collaborative planning, forecasting, and replenishment initiatives for vulnerable SC activities.

In terms of developing SC resilience to lower SC ripple effects, any disaster can create disruptions in the SC. Disruptions, depending on their intensity, can cause adverse effects that can last for a long period or even several months. It has been seen that companies that can easily restore material flow quickly do not take long to resume their normal operating performance.

SC managers need to have a disruption management strategy in place to reduce the ripple effect. It has been proven that modularization and standardization help reduce the ripple effect. In addition, multiple sourcing capacities can minimize the ripple effect. Lastly, flexible and real-time production help reduce the ripple effect.

SC ripple effect impact the financial costs and customer service levels. Using BDA based risk intelligence building approaches can be immensely useful in demand and supply management, scheduling and logistics management. Whereas, AM technology can be useful to add flexibility in production and improve resilience. This will help the firm to balance customer services and operational performance in the recovery stage. Hence, managers need to pay careful attention to leveraging BDA and AM technologies for building a resilient SC.

6. Conclusion

Drawing upon the contingent resource-based perspective of SC resilience and robustness, this study tests the relationship between (a) BDA and AM, (b) BDA, AM, and risk control, (c) risk control and SC resilience under flexible orientation and control orientation, and (d) SC resilience and the SC ripple effect. The data were gathered from 190 respondents and the hypotheses were tested using the variance-based partial least squares (PLS-SEM) method. All the important criteria such as validity (including content validity, discriminant validity, and nomological validity), reliability, model fit indices, and causality assessment indices were checked (and found satisfactory) before testing the model. The tested model indicates that the path "BDA and the firm's ability to undertake AM" is significant. Second, "BDA has a positive impact on the firm's ability to manage risk in case of SC disruption". Third, "AM has a positive impact on the firm's ability to remain prepared in case of SC disruption". Fourth "AM has a positive impact on the firm's ability to manage risk in case of SC disruption". Fifth, "the preparedness and risk intelligence of a firm positively influences the firm's ability to demonstrate SC resilience in case of disruption". Sixth, "flexible orientation positively moderates the relationship between preparedness and SC resilience". Seventh, "flexible orientation positively moderates the relationship between risk intelligence and SC resilience". Eighth "control orientation positively moderates the relationship between preparedness and SC resilience" and finally, "the SC resilience of a firm positively impacts the firm's ability to control the SC ripple effect in case of disruption". Our contribution lies in the theoretically-guided findings, which can assist firms in setting up appropriate strategies to control risks and further develop SC resilience to minimize SC ripple effects that generally occur after any disaster. Like any other study, this study suffers from a small number of limitations. First, this study was conducted in a developing economy (India) using a cross-sectional survey. Therefore, the results cannot be generalized to all developed nations. Secondly, the study only considered selected 4IR technologies. Future studies can include a modification of the theoretical model by including other 4IR technologies (resources) and conduct data collection from developed nations to further compare the results. The model can also be extended by examining contingency-based supply base complexity. Future researchers can also examine the effect of institutional pressures on the resources (big data analytics and additive manufacturing), which further influences risk control and performance outcome (SC resilience).

CRediT authorship contribution statement

Shivam Gupta: Conceptualization, Project administration, Writing – original draft. **Surajit Bag:** Writing – original draft, Supervision, Resources, Writing – review & editing. **Sachin Modgil:** Data curation, Investigation, Visualization. **Ana Beatriz Lopes de Sousa Jabbour:** Methodology, Formal analysis. **Ajay Kumar:** Data curation, Validation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. . Operationalisation of constructs

Latent Variable	Items	Constructs
Big Data Analytics (BDA) (Gupta and George, 2016)	**Data (D)**	
	D1	Our organization have access to big data
	D2	We integrate data from multiple internal sources into a data warehouse or mart for easy access
	D3	We integrate external data with internal to facilitate high-value analysis of our business environment
	Technical Skills (TS)	
	TS1	We provide BDA training to our employees
	TS2	We hire new employees that already have the BDA skills
	TS3	Our BDA staff has the right skills to accomplish their jobs successfully
	TS4	Our BDA staff has suitable education to fulfill their jobs
	TS5	Our BDA staff holds suitable work experience to accomplish their jobs successfully
	TS6	Our BDA staff is well trained
	Managerial Skills (MS)	
	MS1	Our BDA managers understand and appreciate the business needs of other functional managers, suppliers, and customers
	MS2	Our BDA managers can work with functional managers, suppliers, and customers to determine opportunities that big data might bring to our business
	MS3	Our BDA managers can coordinate big data-related activities in ways that support other functional managers, suppliers, and customers
	MS4	Our BDA managers can anticipate the future business needs of functional managers, suppliers, and customers
	MS5	Our BDA managers have a good sense of where to apply big data
	MS6	Our BDA managers can understand and evaluate the output extracted from big data
Additive Manufacturing (AM) (Le Bourhis et al., 2013; Durach et al., 2017)	AM1	In our firm, AM and 3D printing contribute to less energy consumption in the manufacturing
	AM2	In the manufacturing processes of our firm material consumption is less with the additive manufacturing technology
	AM3	AM improves the process flexibility and fulfills the demand in the SC faster
	AM4	AM helps in redesigning the SC networks into the decentralized and distributed production network
	AM5	In our firm, we have very little inventory due to the 3D manufacturing facility

(*continued on next page*)

(*continued*)

Latent Variable	Items	Constructs
	AM6	Due to additive manufacturing, we can reduce the transportation costs
	AM7	AM improves the product development time and contributes towards agile SC
Preparedness (PREP) (Scholten et al., 2014)	PREP1	We translate our strategic agreements to operational plans to ensure our preparedness
	PREP2	We evaluate the preparedness of our SC through scientific measurements
	PREP3	We have established a matrix for continuous review of our preparedness
	PREP4	We practice mock-drills and simulations to ensure our preparedness
Risk Intelligence (RISK) (Jüttner and Maklan, 2011; Rajesh, 2019)	RISK1	Our firm has developed a unique system that identifies the risk of conflict between the firm and community activities
	RISK2	Our firm can foresee and optimize according to the legal framework and existing regulations for future events
	RISK3	We hedge the risk portfolio through redundant resources for dual or multiple sourcing activities
	RISK4	We have adopted collaborative planning, forecasting, and replenishment (CPFR) initiatives for vulnerable SC activities
SC Resilience (SCRES) (Brandon-Jones et al., 2014; Ivanov et al., 2018)	SCRES1	Our firm can easily restore material flow
	SCRES2	Our firm would not take long to recover normal operating performance
	SCRES3	The SC would quickly recover to its original state
	SCRES4	Our firm can quickly deal with disruptions
Flexible Orientation (FO) (Liu et al., 2010)	FO1	The glue that holds our firm together is loyalty and tradition.
	FO2	Our firm is a very dynamic and entrepreneurial place.
	FO3	The glue that holds our firm together is the commitment to innovation and development.
	FO4	Our firm emphasizes growth through developing new ideas.
Control Orientation (CO) (Liu et al., 2010)	CO1	The glue that holds our firm together is formal rules and policies.
	CO2	Our firm emphasizes permanence and stability.
	CO3	Our firm is a very production-oriented place and people are concerned with getting the job done
	CO4	Our firm emphasizes outcomes and achievement.
SC Ripple Effect (SCRIP) (Ivanov et al., 2014)	SCRIP1	Our firm has a disruption strategy in place to reduce the ripple effect in the SC
	SCRIP2	In our firm, we can measure the impact of any SC disruption and execute stability control
	SCRIP3	The policies of the firm can recover from any SC disruption
	SCRIP4	Big data predictive analytics play a major role to bounce back in case of SC disruption scenarios in our firm
	SCRIP5	Modularization and standardization help in reducing the ripple effect in our SC
	SCRIP6	Multiple sourcing capacity of our firm leads to reduction of ripple effect in our SC
	SCRIP7	Flexible and real-time production helps in reducing the ripple effect in our SC

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