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Abstract

The supply chain resilience and data analytics capability has generated increased interest in academia and among practitioners. However, existing studies often treat these two streams of literature independently. Our study model reconciles two different streams of literature: data analytics capability as a means to improve information-processing capacity and supply chain resilience as a means to reduce a ripple effect in supply chain or quickly recover after disruptions in the supply chain. We have grounded our theoretical model in the organizational information processing theory (OIPT). The four research hypotheses are further tested using responses from 213 Indian manufacturing organizations collected via a survey-based pre-tested instrument. We further test our model using variance based structural equation modelling, popularly known as PLS-SEM. All of hypotheses were supported. The findings of our study offer a unique contribution to information systems (IS) and operations management (OM) literature. The findings further provide numerous directions to the supply chain managers. Finally, we note our study limitations and provide further research directions.

Key words: *Data analytics, ripple effect, disruption, supply chain resilience, competitive advantage, structural equation modelling, organizational information processing theory*

1. Introduction

Due to globalization, the organizations are increasingly becoming competitive (Mishra et al. 2016; Chowdhury and Quaddus, 2017; Kwak et al. 2018). The participation of the organizations in the globalization process, which enable them to gain competitive advantage with the help of advanced technologies, capital investment and rich managerial experience (Shangquan, 2000; Chen et al. 2015; Kamalahmadi and Mellat Parast, 2016). Nevertheless, the globalization provides more development opportunities for the organizations; the globalization process also poses major risk to these organizations (Chopra and Sodhi, 2004; Bode et al. 2011; Sodhi et al. 2012;Li et al. 2015; Barroso et al. 2015; Ambulkar et al. 2015; Ho et al. 2015; Brusset and Teller, 2017; Brusset and Bertrand, 2018). Hence, the supply chains are becoming very vital component of the competitiveness of many organizations (Vlajic, 2015). Ponomarov and Holcomb (2009), argue that every activities of supply chain has inherent risk (Dolgui et al. 2018), that may cause unexpected disruption (Namdar et al. 2018). The disruptions may be due to act of natural hazards like major earthquakes, floods, tsunamis, hurricanes or other geologic processes and man-made disasters like terrorisms have potential to affect both revenue and cost (Ivanov et al. 2014). Hence, due to disruption arising from natural disasters or man-made disasters, the supply chain risk management remains a key topic for discussions among academics and practitioners (Tang, 2006, 2006a; Altay and Ramirez, 2010; Vlajic et al. 2013; Brandon-Jones et al. 2014; Mishra et al. 2016; Chowdhury and Quaddus, 2016; Lee et al. 2016; Ali et al. 2017; Sreedevi and Saranga, 2017; Dubey et al. 2018a). The disruptions in supply chains are on rise. In part, this may be ascribed to rises in events, such as natural disasters, but is also due to changes in supply chains (Brandon-Jones et al. 2014). For instance, there are several examples of disturbances and disruptions in supply chains [e.g. *terrorism piracy* (Somali, 2008); *earthquake* (Thailand, 1999; Haiti, 2010); Hurricane (Katrina, 2006), *floods* (Chennai, 2015), *explosion* (Bhopal gas tragedy, 1984; BASF plant in Ludwigshafen, 2016); *fire in plant* (e-commerce retail company ASOS, 2005; Phillips semiconductor plant in Albuquerque, New Mexico, 2000); *political crises* (post-disaster activities in Nepal, 2015); *strikes* (strikes at Maruti-Suzuki's Manesar unit, 2005, 2012; strikes at Hyundai plants, 2016) and many others] (Ivanov and Sokolov, 2010; Ivanov, 2018) has created scholarly interest in supply chain resilience and its impact on competitive advantage (Brandon-Jones et al. 2014; Chowdhury and Quaddus, 2017).

Bode et al. (2011) argue that practices like tighter coupling, increased complexities, lower inventory and geography dispersion may have reduced supply chains cost. However, the reduction in supply chain costs often creates greater vulnerabilities, which may erode the profit earned by these organizations in forms of disruptions, which may affect revenue and cost (Ellram et al. 2013; Brandon-Jones et al. 2014; Behzadi et al. 2017). As a result, many organizations, including Levi's, Nike, Enel, LafargeHolcim and INDI (United Nations Global Compact, 2016) are working with their partners in supply chains to create resilience. The concept of supply chain resilience has attracted significant attentions from operations management community is multidimensional and multidisciplinary (Ponomarov and Holcomb, 2009). The study of resilience has it's origins in social psychology. The concept of resilience carries numerous definitions across different across different disciplines (Bhamra et al. 2011; Burnard and Bhamra, 2011; Gunasekaran et al. 2015). We define supply chain resilience as *the property of supply chain, which enables the disrupted supply chain to recover its normal operating performance, within an acceptable period, after the disrupting forces are withdrawn or disappear* (cf. Brandon-Jones et al. 2014).

Previous studies have focused on supply chain disruptions (Wagner and Bode, 2006; Ivanov et al. 2017), causes of the supply chain disruptions (Craighead et al. 2007), effects on supply chain disruptions on organizational performance (Hendricks and Singhal, 2005) and management of supply chain risks (Tang, 2006a; Ivanov and Dolgui, 2018). Brandon-Jones et al. (2014) have found that information sharing and supply chain visibility, has significant effects on supply chain resilience. However, little attention has been paid to understand how organizations employ data analytics or supply chain analytics in the wake of supply chain disruptions (Fan et al. 2016). We utilize organizational information processing theory (OIPT) to help our understanding *how* and *when* organizations can create *supply chain resilience (SCRES)*. The OIPT argue that how organizations may organize and use information effectively, especially when they respond to high level of uncertainty (Galbraith, 1974). Based on OIPT, we examine how information's processing capabilities lead to improved resilience (Fan et al. 2016). Brandon-Jones et al. (2014) argue that supply chain visibility has positive and significant effect on supply chain resilience and robustness. Srinivasan and Swing (2018) argue that information systems literature broadly conceptualizes analytics capability as a technological enabled ability to process big data (i.e. volume, varieties, velocity, veracity and value) to derive valuable insights (Wamba et al. 2015; Kache and Seuring, 2017), thereby enabling the organizations to gain competitive advantage (Akter et al. 2016; Papadopoulos et al. 2017). Based on OIPT we can argue that earlier organizations have relied on mechanistic models of decision-making guided by rules, hierarchy, targets and goals (Galbraith, 1974). However, in the globalized era when organizations are vulnerable, the information processing capability plays a significant role to mitigate risks or develop mechanisms to address supply chain disruptions (Fan et al. 2016). To reduce information lead times and to improve the reliability of the information, the organizations need supporting infrastructure and processes that enable them to quickly acquire, process and analyse big data (Hazen et al. 2014; Gunasekaran et al. 2017). Srinivasan and Swink (2018) argue that insights gained through increased information processing capacity can reduce uncertainty, especially when markets are volatile and operational tasks are complex (i.e. highly interdependent).

In this study, we examine the associations between data analytics capability, supply chain resilience and competitive advantage under moderating effect of organizational flexibility. Largely, organizations acquire data from their supply chain partners to gain insights into potential risks and their disrupting effects on supply chains (Fan et al. 2016). Dubey et al. (2018) argue that supply chain collaboration is an important way to enhance information-processing capacity. Galbraith (1974) noted that the development of such external lateral relations increases the information process capacity of the organizations. Hence, availability of relevant, accurate and timely data from supply chain partners enables organizations to increase information-processing capacity and derive useful insights (Brandon-Jones et al. 2014). Organizations may utilize the available insights to improve the supply chain resilience and increase the competitive advantage. However, scholars (see, Sethi and Sethi, 1990; Upton, 1994; Srinivasan and Swink, 2018), argue that organizational flexibility, is the ability of the organizations that may deploy resources quickly, efficiently and effectively in response to sudden changes in the market conditions. Srinivasan and Swink (2018), argue that data analytics capability provides insights based on big data processing, on *what* to change to match environmental uncertainty, the organizational flexibility enables the firm *how* to change to match environmental uncertainty. Hence, based on Srinivasan and Swink (2018) arguments, we posit that the combination of data analytics capability and organizational flexibility is more positively associated with supply chain resilience and competitive advantage.

The main contribution of our study is to provide empirical evidence of associations between data analytic capability, organizational flexibility, supply chain resilience and competitive advantage, using 213 responses from supply chain managers. Next, we extend OIPT beyond general organizational design factors to address the exploitation of data analytics capability. The study further offers direction to the overwhelmed managers who often fails to understand that how complementary assets and capabilities are necessary to exploit the data analytics capability to enhance supply chain resilience and gain competitive advantage.

The organization of the manuscript as follows. Firstly, we introduce theoretical perspective and review the literature on OIPT. We then present our literature on data analytics capability, organizational flexibility, supply chain resilience and competitive advantage before presenting our theoretical model and hypotheses. Next, we explain our research design before presenting our data analyses. Next, we discuss our findings in context to theoretical implications, managerial implications and limitations & further research directions. Finally, we conclude our study.

2. Underpinning Theories

2.1 Organizational Information Processing Theory (OIPT)

Srinivasan and Swink (2018) argue that organizations must organize and exploit the information effectively and efficiently while executing complex tasks. Galbraith (1973) argue that organizations have two options: firstly, they should either reduce their needs for information through "mechanistic" organizational means, or increase their information processing capacities. Overall, we can argue that OIPT deals with organizational design, their structures and capabilities to handle their information processing needs. Fairbank et al. (2006) argue that OIPT considers the linkage between information (key resource) and its management (i.e. the effective use of information) to gain competitive advantage. OIPT argue that an organization need to process information under increasing uncertainty to sustain certain level of performance. The uncertainty drives the need for information processing, whereby uncertainty is defined as "*the difference between the amount of information required to execute a task and the level of information already available with the organization*" (Galbraith, 1973, p.5). Galbraith (1973) has further suggested seven strategies to cope with various degree of uncertainty. When uncertainty is low, the organization may adopt any three strategies to cope with uncertainty are: (1) coordination by rule or programs; (2) employment of hierarchies; and (3) coordination by targets or goals. However, in case of high uncertainty, the organization may reduce information processing need via creating (4) slack resources; and (5) self-constrained tasks. Next, organization may increase information processing capacity via (6) investment in vertical information systems; and (7) by creating lateral relations. Additionally, Galbraith (1974) further suggested eight strategy to reduce uncertainty via the control of organization's environment through e.g., the long-term associations or coalitions. Further, proper alignment of the information processing needs and information processing needs capabilities enhances organizational performance (Premkumar et al. 2005; Srinivasan and Swink, 2015, 2018; Fan et al. 2016, 2017).

2.2 Data analytics capability

The analytics is at the forefront of the C-suite's agenda these days. Operating in extreme complex and highly regulated business environment, the organizations decision makers cannot rely on their gut. Hence, organizations have increasingly relied over business analytics capabilities to improve their decision-making abilities. Despite increasing popularity, the academic literature on data analytics capability is still underdeveloped (Hazen et al. 2016; Fang et al. 2016; Srinivasan and Swink, 2018; Acharya et al. 2018). The literature on data analytics carries inconsistent meaning. It is observed that researchers or practitioners often use data analytics, big data analytics, supply chain analytics and big data & predictive analytics interchangeably (see, Davenport, 2006; Waller and Fawcett, 2013; Agarwal and Dhar, 2014; Akter et al. 2016; Raffoni et al. 2017;Srinivasan and Swink, 2018), to describe the organizational capabilities that enable the organizations to collect, store and process data to derive useful insights which can provide competitive advantage to the organizations. The analytics capability is understood as the combination of tools, techniques and processes that enable the organization to process, organize, visualize, and analyze data to derive useful insights, which enables managers to take efficient and effective decision related to business and its related operations. Srinivasan and Swink (2018) argue that data analytics increases the information processing capacity, whereby organization gather data from various sources. Hence, we consider Srinivasan and Swink (2018), definition of data analytics in our study as the existing information systems literature emphasizes on analytics capabilities in terms of IT tools. However, Srinivasan and Swink (2018) includes both tools and processes.

2.3 Organizational flexibility

Organizational flexibility is the organizational ability, which enables the organizations to operate in more turbulent environment (Braunscheidel and Suresh, 2009; Sharma et al. 2010; Srinivasan and Swink, 2018). Volberda (1996, p. 361) defines organizational flexibility, as "*the flexibility is the degree to which an organization has variety of managerial capabilities and the speed at which they can be activated, to increase the control capacity of the management and improve the controllability of the organization*". Hence, we can argue that organizational flexibility can be perceived as organizational design task and managerial task. The organizational design task refer to the ability of the organizations to respond in right time to respond to the sudden external changes. This focuses on the controllability or changeability of the organizations, which often relies on creation of appropriate conditions that foster organizational flexibility. For instance, manufacturing flexibility often requires a technology with multipurpose machinery, universal equipment and extensive operational production repertoire. Similarly, innovation flexibility requires multifunctional teams, less hierarchical levels and minimum process regulations. Next, the managerial task refers to the managerial abilities that enables the organizations to respond to the turbulent environment. Srinivasan and Swink (2018) argue that organizational flexibility in terms of supply chain is defined as the ability of the supply chain managers to reconfigure their internal supply chains quickly and efficiently to adapt to the changing demand and supply market conditions.

2.4 Supply chain resilience

Adobor and McMullen (2018) argue that disruptions to supply chains can have significant economic impacts. Hence, managing risk and vulnerability associated with supply chains have attracted increasing attentions from practitioners and policy makers. Holling (1973) argue that resilience, the capacity of a system to adapt to change and deal with surprise while retaining the system's basic function and structure, has evolved as an important aspect for managing supply chain risk and vulnerability (Ponomarov and Holcomb, 2009; Pettit et al., 2010; Adobor and McMullen, 2018).The resilience is a multidisciplinary concept (Chowdhury and Quaddus, 2017). Ates and Bititci (2011) argue that resilience in organizational context as an organizational capability to survive in turbulent environment. In response to increasing disruptions resulting from unpredictable events, the resilience has become enormously important in supply chain perspectives (Ambulkar et al. 2015; Kim et al. 2015; Purvis et al. 2016; Jain et al. 2017; Dolgui et al. 2017; Chowdhury and Quaddus, 2017; Ivanov et al. 2018 a,b). Ponomarov and Holcomb (2009) argue that resilient firms are less vulnerable to the supply chain disruptions and are more capable of absorbing more shock resulting from supply chain disruptions. The supply chain resilience allows the organizations to deliver their products and services to the customer (Ambulkar et al. 2015). The existing literature recognize resilience as a multidisciplinary concept (Ponomarov and Holcomb, 2009; Chowdhury and Quaddus, 2017). Following, Holling (1973) work's, several scholars have termed supply chain resilience as the ability of supply chains to survive, adapt and grow in the face of turbulent change. In simple words, how quickly supply chains can return to its original state or move to a new, more desirable state after being disturbed (Christopher and Peck, 2004; Blackhurst et al. 2011; Bhamra et al. 2011; Pettit et al. 2013; Chopra and Sodhi, 2014; Brandon-Jones et al. 2015; Gunasekaran et al. 2015; Ali et al. 2017; Jain et al. 2017). Datta (2017) has noted based on systematic literature review of articles published in reputable peer reviewed journals that, literature on supply chain has grown exponentially following Christopher and Peck (2004) contribution; the research focusing on how organizations develop resilience is still limited. Based on review of existing literature we note that in an unexpected event like disaster, the collaboration among supply chain partners is critical for building resilience by reducing risk of disruption through communication, trust, sourcing decisions and information sharing. Secondly, under complexity information sharing on supply chain risk is essential for building resilience by reducing disruption risks, improving response time and building new business opportunities (see Ambulkar et al. 2015; Kamalahmadi and Mellat Parast, 2016; Chowdhury and Quaddus, 2017; Datta, 2017).

2.5 Competitive advantage

Porter (1985) describe competitive advantage as the way an organization can choose and implement generic strategies to achieve competitive advantage or sustain competitive advantage. Peteraf (1993) argue that competitive advantage is the ability of an organization to maintain or sustain above-normal returns. Porter (1985) suggested value chain model to assess the competitive advantage of the firm. However, Peteraf (1993) further argue that there are four cornerstones of the competitive advantage: heterogeneity, ex post limits to competition, imperfect mobility and ex ante limits to competition. Barney (1991) further argue that an organization can derive competitive advantage by creating bundles of strategic resources and / or capabilities. Reed and DeFillippi (1990) argue that competitive advantage can be derived from numerous sources. For instance, competitive advantage can be derived from various competencies. Competencies are within organization's control and can be exploited to generate competitive advantage for superior performance. Schilke (2014) argue that one of the common indicators of competitive advantage is superior performance. Following, Hill et al. (2014) we argue that: data quality (Hazen et al. 2014; Corte-Real et al. 2019) and technological innovation (Singh, 2011; Chen et al. 2015; Aydiner et al. 2019) are two important building blocks of competitive advantage.

3. Theoretical Framework and Hypotheses Development

The supply chain managers need to gather data from customers and suppliers to understand the degree of uncertainty. As supply chain disruptions may have negative impacts on economic performance (Hendricks and Singhal, 2005), the resilience may be created in supply chains to mitigate the risks resulting from supply chain disruptions (Christopher and Peck, 2004; Ponmarov and Holcomb, 2009; Wieland and Marcus Wallenburg, 2013; Brandon-Jones et al. 2014; Ambulkar et al. 2015; Brusset and Teller, 2017). The main objective of this paper is to theoretically and empirically establish the linkage between data analytics, supply chain resilience and competitive advantage. While prior studies, have supported linkage between resilience and competitive advantage (Sheffi, 2005; Webb and Schlemmer, 2006), data analytics and resilience (Papadopoulos et al. 2017; Mandal, 2017) and data analytics and competitive advantage (Chen et al. 2012; Akter et al. 2016; Srinivasan and Swink, 2018). What is less understood is that how data analytics capability impacts supply chain resilience and competitive advantage. Hence, based on OIPT perspective we can argue that supply chain resilience and competitive advantage as performance outcomes (see Figure 1).

3.1 Data analytics and supply chain resilience

Srinivasan and Morgan (2018) argue that organization's that are capable of building demand and supply chain visibility are better positioned to develop and deploy systems and processes that support data analytics capability. Barratt and Oke (2007) have conceptualized supply chain visibility as an organizational capability. Juttner and Maklan (2011) further argue that supply chain visibility is a desired capability, which may reduce the negative impacts of a supply chain disruption. Hence, we argue that those organizations that invest in developing analytics capability are likely to also invest in visibility, because visibility provides the raw data upon which analytics systems process and operate. Based on Srinivasan and Morgan (2018) arguments that visibility and analytics capabilities as being complementary, in the sense that each supports the other. The extant literature provides enough empirical evidence that improved supply chain visibility capability may reduce both the probability and impact of supply chain disruption (Christopher and Lee, 2004) and further it leads to enhanced supply chain resilience (Juttner and Maklan, 2011; Brandon-Jones et al. 2014; Ivanov et al. 2016). Kleindorfer and Saad (2005) argue that it is a requirement of supply chain risk process to have visibilities of vulnerabilities in entire supply chain. Hence, the use of data technology which may help managers to identify possible threats or sources of disruption so they can develop business continuity plans that may help to speed up recovery in the event of disruption. Thus,

H1: *Data analytics has positive impact on supply chain resilience.*

3.2 Data analytics and competitive advantage

Competitive advantage refers to the extent to which an organization can generate a defensible position over their competitors (Porter, 1985). Kwak et al. (2018, p.7) further argue that there are visible "*thrusts to improve competitive advantage such as cost, growth, reliability, quality, time-to market, new product introduction, product line breadth, order fill rate, order/ shipment information, increased customer service, efficient capital deployment, delivery dependability and flexibility"*. LaValle et al. (2011) have noted that top performing organizations use analytics five times more than low performers. Akter et al. (2016) argue that big data analytics capability has positive impact on organizational performance. Sheng et al. (2017) further argue that organizations are increasingly exploiting big data to improve organizational competitiveness. Gunasekaran et al. (2017) have further noted that the big data & predictive analytics capability has positive impact on supply chain and organizational performance. Corte-Real et al. (2019) argue that BDA can lead to competitive advantage, if supported by good quality of data. Thus,

H2: *Data analytics has positive impact on competitive advantage*

3.3 Supply chain resilience and competitive advantage

Kwak et al. (2018) argue that high level of environmental, technological, demand and supply uncertainties have significant influence on the competiveness of the organizations. Hence, different levels of supply chain risk management capacity related to those uncertainties may confer different level of competitive advantage (Colicchia and Strozzi, 2012). Elahi (2013) argue that risk management capability may not yield quick returns on investment in short time. However, in long run the investment in risk management capability is an important source of competitive advantage. Resilience is regarded as proactive as well as reactive capability of the organization. Hence, resilience can prevent the negative impact of supply chain disruptions as well as can help to recover to an acceptable level of performance in an acceptable time after being affected by an event (Wieland and Marcus Wallenburg, 2013). Wieland and Marcus Wallenburg (2013) further noted that organization could achieve competitive advantage via resilience capability. Thus,

H3: *Supply chain resilience has positive impact on competitive advantage*

3.4 Organizational flexibility, data analytics, supply chain resilience and competitive advantage

Srinivasan and Swink (2018) argue that data analytics capability of the organization provides insights leading to decisions based on current data gathered from multiple sources. However, the organizations needs flexibility to implement decisions quickly and efficiently, especially decisions that span various functions (Galbraith, 1973, 1974). Supply chain flexibility has been noted as one of the key levers to reduce supply chain risk in many studies (Ivanov et al. 2014; Sreedevi and Saranga, 2017; Dubey et al. 2018c). Hence, we posit that organizations can more effectively take advantage of new insights gained from data analytics capability when they possess high levels of organizational flexibility. Organizations with better organizational flexibility are better capable to cope with environmental uncertainties (Sreedevi and Saranga, 2017) and gain competitive advantage (Elahi, 2013; Kwak et al. 2018). Consequently, organizations have better capabilities to improve supply chain resilience than those organizations who often relies on decisions based on limited data sets or mechanistic model of processing data to extract insights from raw data. Thus,

H4a/b: *Organizational flexibility positively moderates the relationship between data analytics capability and: (a) supply chain resilience and (b) competitive advantage.*

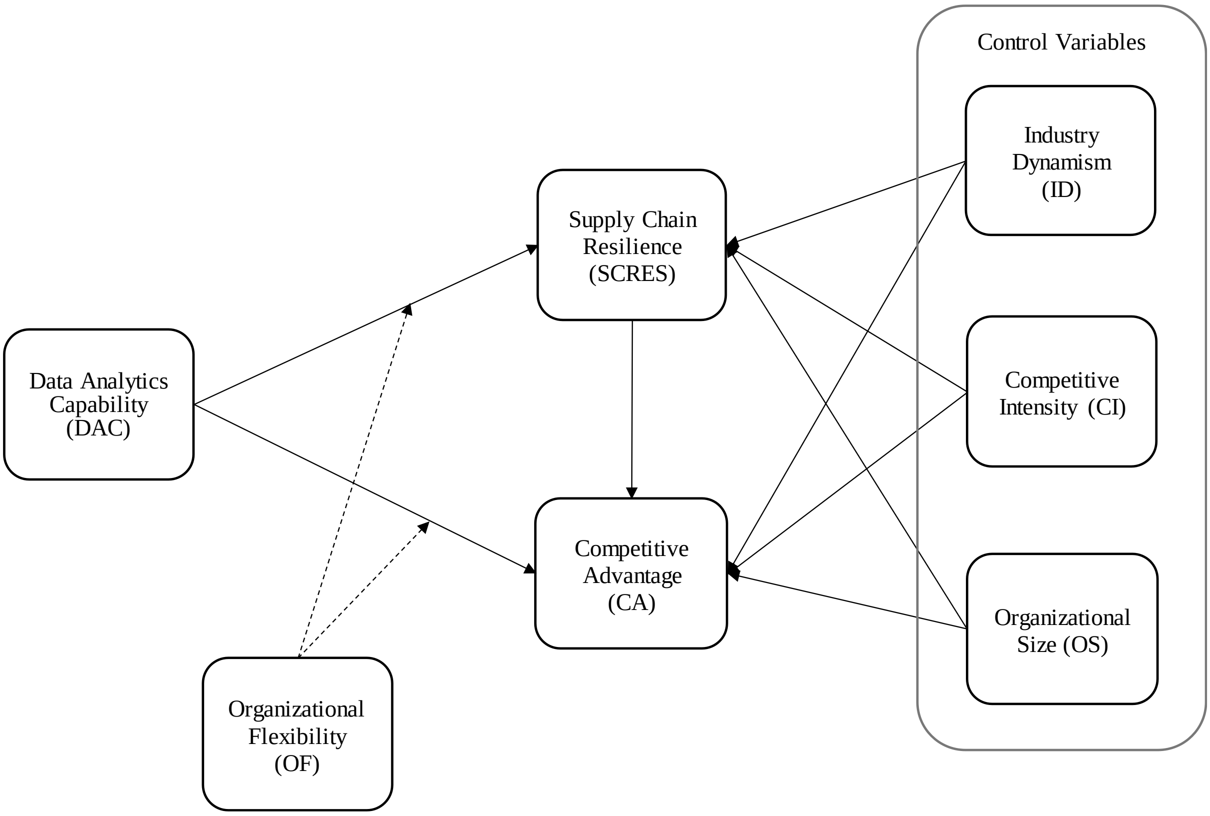

Figure 1: Theoretical framework

4. Research Design

4.1 Sample and Data Collection

The unit of analysis employed in this study was the level of a manufacturing plant. Hence, we designed our instrument for single respondent. The data was gathered in 2016, through a survey, to test our theoretical framework. CII NAOROJI Godrej Centre for Manufacturing Excellence administered this cross-sectional survey in collaboration with Boston Consulting Group, India. Our sampling frame consisted of senior level supply chain managers included in CII NAOROJI Godrej Centre for Manufacturing Excellence database. Our research team sent e-mail invitations to 912 supply chain managers in production, logistics, procurement and information systems functions drawn from CII NAOROJI Godrej Centre for Manufacturing Excellence database. These senior level supply chain managers are most likely to have relevant knowledge concerning information flows between supply chain partners, internal data analytics initiatives and supply chain risk management measures. Two waves of invitations were sent over a period of four weeks.

The survey responses were thoroughly examined and we have dropped some of the responses based on the following criteria. We followed key informant approach and screened those from respondents whose titles were not related to supply chain or its related functions. The resulting sample held senior managerial positions such as Vice President, General Manager, CXO (C-Suite Managers), Director, Head, Senior Manager and Manager. We also included responses from Analyst and Planner. Next, we eliminated some of the responses, which contained missing information. The resulting dataset has 213 responses, representing an effective response rate of 23.35%. We provide profile of the respondents in Table 1.

Table 1: Profile of the responding organizations

Title	Number	Percentage
Annual sales revenue		
Under $ 10 Million	35	16.43
$11-25 Million	50	23.47
$26-50 Million	50	23.47
$51-75 Million	25	11.74
$76-100 Million	8	3.76
$101-250 Million	15	7.04
$251-500 Million	20	9.39
Over $ 501 Million	10	4.69
Total	213	
Number of Employees		
0-50	8	3.76
51-100	13	6.10
101-200	35	16.43
201-500	74	34.74
501-1000	51	23.94
1001+	32	15.02
Total	213	
Industry sector		
Automotive & transport	78	36.62
Machinery and industry equipment	25	11.74
Mining and metals	16	7.51
Electrical equipment	23	10.80
Pulp and paper	7	3.29
Ruber and plastic products	38	17.84
Chemical products	26	12.21
Total	213	

Since we have used survey based approach, the potential biases exists in our study. We tested non-response bias following Armstrong and Overton (1977) suggestions. We compared the early respondents, late respondents and non-respondents (a sub sample of 45 respondents was selected at random from the initial contact list. We observed no significant difference between early and late respondents on any of the variables used in our study. Similarly, there was no significant difference between respondents and non-respondents in terms of organization size. Taken together, these statistical results suggest that non-response bias may not possess serious threat to our findings.

4.2 Measures

We have adopted established scales from literature following Malhotra and Grover (1998) suggestions. This was feasible for measures of data analytics, organizational flexibility, supply chain resilience and competitive advantage. We made minor modifications in wording of the items based on the feedback from pretests in order to improve scale performance. All scales were designed in five-point Likert format anchored as, 1= strongly disagree and 5= strongly agree (Malhotra and Grover, 1998; Eckstein et al. 2015).

In addition, we have used three control variables, which may influence the exogenous and endogenous variables and may cause unwanted sources of variance. Firstly, we account for organization size as Wagner and Neshat (2012), noted in their study that larger organizations are more vulnerable to disruption and use number of employees in the organization as a measure of size . Secondly, we included industry dynamism in order to level out the effects of the disruption across industry segments. We measured industry dynamism on five-point Likert format anchored as, 1= strongly disagree and 5= strongly agree. Thirdly, we control the competitive intensity which is the degree of to which a firm perceives the intensity of its competition in the market (Wagner et al. 2012) and may have impact on supply chain risk (Trkman and McCrmack, 2009). Appendix 1 shows the summary of the items used for measures.

5. Data Analyses and Results

Henseler et al. (2014) argue that SEM is not a single technique, but a synthesis of procedures developed in econometrics and psychometrics. Ullman (2006, p.35) define SEM as, "…*a collection of statistical techniques that allow a set of relations between one or more independent variables (IVs), either continuous or discrete, and one or more dependent variables (DVs), either continuous or discrete, to be examined*..". In our study, we have used WarpPLS 5.0, which is a structural equation modelling (SEM) software. The software employ the partial least squares (PLS) method or in short form we can refer it as PLS SEM. Kock

(2014, 2015) argue that WarpPLS 5.0 is based on classical PLS algorithms combined with factor-based PLS algorithms for SEM. Factor based PLS algorithms generates estimates of both true composites and factors, fully accounting for measurement error (Hair et al. 2016). Peng and Lai (2012) further argue that PLS is a prediction oriented tool which further allows researchers to assess the predictive validity of the exogenous variables. In general PLS is better suited for explaining complex relationships as it avoids two serious problems: inadmissible solutions and factor indeterminacy (Peng and Lai, 2012; Henseler et al. 2014; Dijkstra and Henseler, 2015; Hazen et al. 2015; Kaynak et al. 2015; Moshtari, 2016; Akter et al. 2017). Our study aims to examine the prediction or explanatory power of data analytics capability. The relationships between two variables -data analytics capability and supply chain resilience are not examined in literature; therefore, there is no theoretical foundation, which explain the relationships between these two variables, which make PLS the most suitable technique for data analysis (Peng and Lai, 2012). We have carried our model estimation based on Peng and Lai (2012) suggestions in two stages: examining the reliability and validity of the measurement model and analysing structural model.

5.1 Measurement model

Summary statistics of the variables are presented in Table 2. We note that scale composite reliability (SCR) of each constructs used in Figure 1 are above 0.70 and their average variance extracted (AVE) are above 0.5 (see Appendix 1), indicating that the measurements used in our study are reliable and the latent construct account for at least 50% of the variance in the items. This clearly suggests that our study clearly possess convergent validity. As shown in Appendix 2, the loadings are in an acceptable range and they are significant at the 0.01 level. Fornell and Larcker (1981) argue that if the square root of the AVE is greater than all of the inter-construct correlation, it is a strong evidence of sufficient discriminant validity. The results in Table 3 suggest that our model possess discriminant validity.

Table 2: Summary statistics of variables

	N	Mean	Std. Dev.	Min.	Max.
BDAC	213	3.93	0.82	1	5
OF	213	3.82	0.53	1	5
SCRES	213	3.84	0.57	1	5
CA	213	3.92	0.63	1	5
ID	213	4.44	0.64	1	5
CI	213	4.06	0.7	1	5

Notes: DAC, data analytics capability; OF, organizational flexibility; SCRES, supply chain resilience; CA, competitive advantage; ID, industry dynamism; CI, competitive intensity

Table 3: Correlations among major constructs

	DAC	OF	SCRES	CA	ID	CI
DAC	**0.73**					
OF	0.52	**0.95**				
SCRES	0.15	0.54	**0.92**			
CA	0.12	0.27	0.19	**0.92**		
ID	0.28	0.11	-0.05	0.09	**0.88**	
CI	-0.22	-0.12	0.09	-0.04	-0.09	**0.77**

√ (AVE) are in bold

Notes: DAC, data analytics capability; OF, organizational flexibility; SCRES, supply chain resilience; CA, competitive advantage; ID, industry dynamism; CI, competitive intensity

5.2 Common method bias

Since we have collected data from a single source, there is a potential for CMB (Podsakoff and Organ, 1986). Podsakoff et al. (2003), argue that in case of self-reported data, there is potential for common method biases resulting from multiple sources such as consistency motif and social desirability. Hence, we designed our survey to minimize the CMB effect using different scale formats and anchors for independent, moderating and dependent variables. In addition, we performed several statistical analyses to assess the severity of CMB. First, following Podsakoff et al. (2003) we performed conservative version of Harman's one-factor test. The results from this test showed that the single factor explains 40.17 percent (approx.), of total variance, demonstrating that CMB is not a significant concern. However, following Ketokivi and

Schroeder (2004) arguments, Harman's one-factor test is not a robust assessment of CMB. Hence, to ensure that CMB is not a major concern in our study, we further used a method introduced by Lindell and Whitney (2001), which is a partial correlation technique, which is often referred as the correlational marker technique, for controlling method variance using a marker variable that may be theoretically unrelated to the substantive variable in the study. Using this method, we first chose the six-item scale that measured competitive advantage, which provided the lowest positive correlation (r=0.12) between the MV marker and other variables, to adjust the construct correlations and statistical significance (Lindell and Whitney, 2001). We have not observed any significant correlational value, which turned into in-significant after further analyses. Although, CMB cannot be eliminated in case of single source self-reported data. However, we have ensured via correlational marker technique that CMB is not a serious issue in our study.

Guide and Ketokivi (2015) have noted that causality is an important issue, which should be examined prior to hypotheses test. Hence, to address the causality issue which is often considered as a pre-requisite step before conducting hypotheses test. In our study we have conceptualized, data analytics capability as an exogenous variable to the supply chain resilience and competitive advantage, but not the other way around. We performed Durbin-Wu-Hausman test (see, Davidson and MacKinnon, 1993). We observed that the parameter estimate for the residual was insignificant; suggesting that the data analytics capability is not the dependent variable but it is an independent variable in our current setting. Finally, following Kock (2015) suggestions we performed nonlinear bivariate causality direction ratio (NLBCDR). The desired acceptable value of NLBCDR should be greater than 0.7. In our model our NLBCDR=0.875, which is greater than the cut off value. Hence, based on these results we can argue that endogeneity is not a serious concern in our study. We have further tested the model fit and quality indices (see, Appendix 3).

5.3 Hypotheses testing

Figure 2 presents the estimates obtained via PLS SEM analysis. The model explain significant amount of variance for supply chain resilience (R^2=0.29) and competitive advantage (R^2=0.72). We have reported the PLS path coefficients and the corresponding p values for the model in Table 4 (H1-H3) and Table 5 (H4a/b). The links DAC→SCRES (β=0.41, $p<0.01$), DAC→CA (β=0.23, $p<0.01$) and SCRES→CA (β=0.36, $p<0.01$) are positively related. Thus, we can argue based on beta values and their corresponding p values that hypotheses H1, H2 and H3 were supported. The control variables, industry dynamism, competitive intensity and organizational size, do not have significant effect in this model (see Table 4).

Table 4: Structural Estimates (H1-H3)

Hypothesis	Effect of	Effect on	β	p	Result
H1	DAC	SCRES	0.41	***	Supported
H2	DAC	CA	0.23	***	Supported
H3	SCRES	CA	0.36	***	Supported
Control variables					
	ID	CA	0.08	*	Not significant
	CI	CA	0.03	*	Not significant
	OS	CA	-0.06	*	Not significant
	ID	SCRES	0.001	*	Not significant
	CI	SCRES	-0.125	*	Not significant
	OS	SCRES	-0.021	*	Not significant

*Notes: DAC, data analytics capability; SCRES, supply chain resilience; CA, competitive advantage; ID, industry dynamism; CI, competitive intensity; OS, organizational size. *** p<0.01; *p>0.1*

Next, our hypothesis H4 were tested for moderation effect of organizational flexibility on the path connecting data analytics capability and supply chain resilience (H4a) and data analytics capability and competitive advantage (H4b). Addressing H4a ($\beta=0.71$, $p<0.01$) and H4b ($\beta=0.17$, $p=0.01$), were found supported (see Table 5).

Table 5: Structural Estimates (H4a/b)

Hypothesis	Effect of	Effect on	β	p	Result
H4a	DAC*OF	SCRES	0.71	***	Supported
H4b	DAC*OF	CA	0.17	***	Supported

*Notes: DAC, data analytics capability; SCRES, supply chain resilience; CA, competitive advantage; OF, organizational flexibility. *** $p<0.01$*

Next, we have examined the explanatory power of our proposed theoretical model. For this, we have examined the explanatory power (R^2) of the endogenous construct. The R^2 for SCRES is 0.29 which is moderately strong and for CA is 0.72 which is strong (Chin, 1998) (Figure 2). We further examined the f^2 value of the DAC using Cohen f^2 formula. Consequently, the effect size of DAC on SCRES is 0.411 and on CA is 0.048 (see Table 6) which were greater than cut off value 0.0. Next, we have examined the model's capability to predict, Stone-Geiser's Q^2 for endogenous constructs were SCRES (0.202) and CA (0.631) (see Table 6) for DAC which is greater than zero, indicating acceptable predictive relevance (Peng and Lai, 2012).

Table 6: R^2, Prediction and Effect Size

Construct	R^2	Q^2	f^2 in relation to	
			SCRES	CA
DCA	-	-	0.202	0.631
OF	-	-		
SCRES	0.29	0.411		
CA	0.72	0.048		

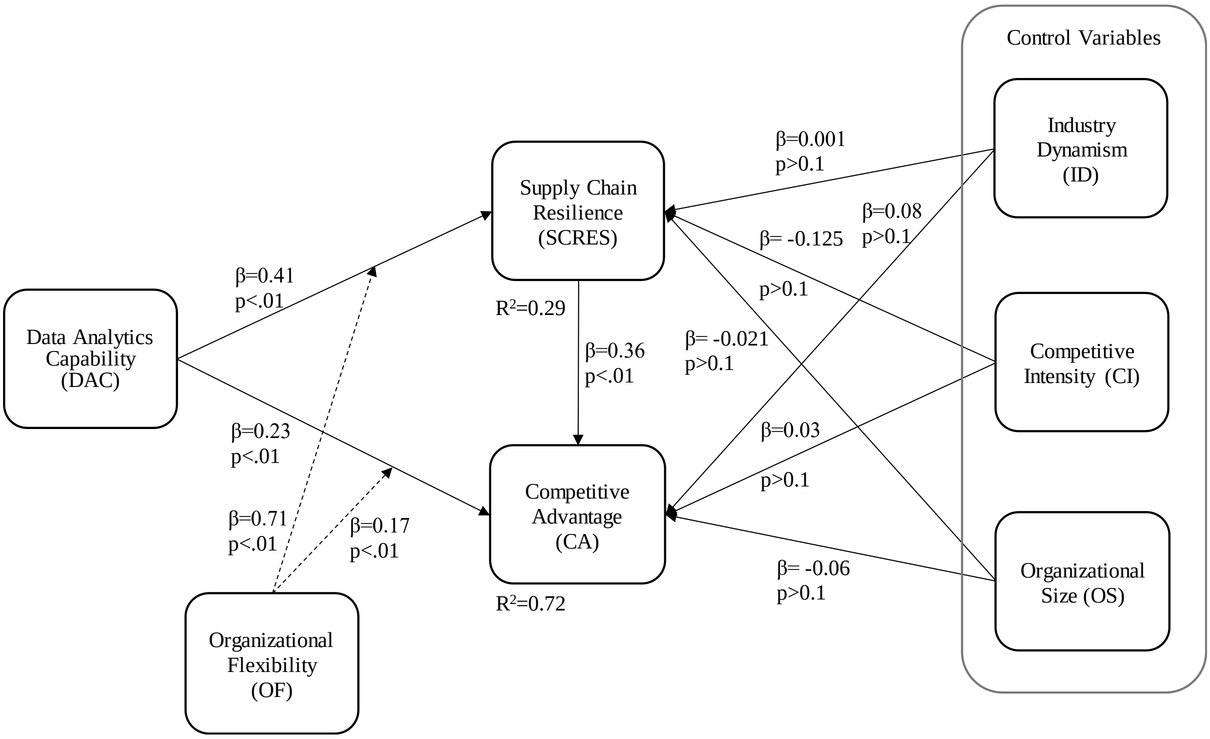

Figure 2: Research model

6. Discussion

The results obtained via statistical analyses paint an interesting picture of the linkages and the complementarities among data analytics capability, organizational flexibility, supply chain resilience and competitive advantage during supply chain disruptions. Table 4 and 5 provides a detailed summary of the evidence our data provides in support or non-support of the hypotheses generated in our study based on extensive review of literature. Overall, these findings have substantial implications for research and managers.

6.1 Implications for research

Our interest in investigating the role of data analytics capability on supply chain resilience and competitive advantage under moderating effects of organizational flexibility was triggered by two facets of supply chain resilience. Wieland and Marcus Wallenburg (2013) argue that the existing literature on supply chain resilience have conceptualized as both as the proactive capability (i.e. take desired action before it is a final necessity) or the reactive capability (i.e. ability to recover in desirable time after experiencing a crisis). Building on Branden-Jones et al. (2014) findings that supply chain visibility act as an antecedent of supply chain resilience. Christopher and Lee (2004) argue that supply chain visibility may further help to mitigate supply chain via improved confidence, reduced interventions and improved decision making. Srinivasan and Swink (2018) argue on the basis of empirical investigation that both demand and supply visibility are significantly associated with developing analytics capability. Although, Brandon-Jones et al. (2014) have established based on empirical study that supply chain visibility has positive impact on supply chain resilience. However, the relationship between data analytics capability and supply chain resilience has not been empirically explored. Hence, our study make a useful contribution by empirically testing the linkage between data analytics capability and supply chain resilience. In this way, we further extend the Brandon-Jones et al. (2014) arguments that how data technology capability can be exploited to build supply chain resilience. Based on Wamba et al. (2015) arguments, we further argue that, the availability of big data characterized by 5V's (i.e. volume, velocity, variety, veracity and value) is a prerequisite for building big data capability. The existing operations management (OM) literature provides rich evidence that supply chain visibility contributes to better organizational performance (Barrat and Oke, 2007) and supply chain resilience (Brandon-Jones et al. 2014), our results further provides underlying explanation. The visibility may be due to access to complete and recent information derived via processing of raw data. Indeed, our results further suggest that data analytic capability is a means by which visibility improves supply chain resilience and further leads to competitive advantage. Our results suggest that access to big data and better data processing capability coupled with human skills to extract valuable insights via effective coordination skills, domain knowledge and data science. Thus, the findings of our study make a useful contribution to the OM and IS literature.

Secondly, Barratt and Oke (2007) argue that competitive advantage stem from the ways in which technologies are exploited, rather than from the technologies themselves. Akter et al. (2016) and Gunasekaran et al. (2017) provides empirical results, which provides a clear evidence that how organizations can exploit big data and analytics capability to gain competitive advantage. However, it is still not understood how the data analytics capability can provide competitive during disruptions in supply chains. To further address this important unanswered question in OM and IS literature, we have empirically tested the impact of data analytics capability on supply chain resilience and competitive advantage under moderating effect of organizational flexibility. These results make useful contributions to scholarly debates at the intersection of OM and IS literature (see, Kache and Seuring, 2017; Papadopoulos et al. 2017).

Thirdly, our results suggest the importance of data analytics capability as a complementary capability of the organization, which often operates under high uncertainties. Hence, our study extend the OIPT (Galbraith, 1973, 1974), beyond specific organizational factors to address the utility of emerging technologies. The data analytics tools and techniques are gaining increasing acceptance among practitioners. Hence, researchers need to broaden their understanding related to pros and cons of data analytics capabilities under high uncertainties.

6.2 Implications to managers

Our study offers a number of useful implications for supply chain managers when they face high level of uncertainty. Galbraith (1973, 1974) argue that managers should use the available information effectively, especially when they execute their tasks that involve high degree of uncertainty. Galbraith (1973, 1974) further argue that in case of high degree of uncertainty, the organization may create:

Slack resources or self-contained tasks

In case of disruptions, organizations may face demand or supply uncertainties or may be both at the same time. In such case to address supply uncertainty, managers may build safety stock closer to the markets and build better distribution capability (Lee, 2002).

Increasing information processing capacity

In order to increase information-processing capacity, the managers may focus on building lateral relations and vertical information systems. Wieland and Marcus Wallenburg (2013) and Dubey et al. (2018a) have contributed in this direction by utilizing relationship theory that how trust among partners in supply chain network can leads to better coordination. However, our results further suggest managers that by investing in vertical information systems organizations can increase the information processing capacity with minimal resource costs. Hence, by investing in data analytics capability an organization can improve supply chain resilience and competitive advantage.

Further, our study provides empirical results to the managers that those organizations, which can quickly and efficiently adapt to rapid changing demand, supply and technology market conditions may perform better during supply chain disruptions and possess better capability to recover after experiencing a crisis. Lee (2004) argue that supply chain adaptability is a desired characteristics of supply chains which was empirically established (see, Eckstein et al. 2015;

Dubey et al. 2018). Hence, managers must appreciate that the use of data analytics capability hinges upon the ability of the organization to adapt to changing environments.

7. Conclusion, Limitations and Further Research Directions

Drawing broadly on OIPT, the data analytics capability may be used by the organization to increase the information processing capacity under uncertain scenarios. Based on this assumption posited by Srinivasan and Swink (2015, 2018), we have developed a theoretical model (see Figure 1). Our theoretical model reconciles the independent contributions of two well-established streams in the literature: studies that explain the use of data analytics capability to increase the data processing capacity (IS) and those that focuses on supply chain resilience and competitive advantage (OM). We attempt to explicate how data analytics capability under moderating effect of organizational flexibility improves the supply chain resilience and competitive advantage. We further tested our four research hypotheses based on 213 Indian manufacturing organizations. Our findings support our hypothesized relationships. This study contributes to the data analytics capability literature from organizational information processing perspective, supply chain resilience and competitive advantage.

Although, our study offers useful contributions to research, we further note limitations of our study. We suggest researchers and practitioners to evaluate our study results and contributions in the light of its limitations. First, we have grounded our theoretical model in OIPT. Hence, our research hypotheses are based on our constructs (Figure 1). Like any theory driven research, our theoretical issues are compounded by measures that do not truly capture data analytics capability and supply chain resilience. Hence, to address some of these limitations of the theory driven research, the use of multi-methods may provide better understanding of complex phenomena in supply chains. Secondly, we have used cross-sectional data. However, future study may utilize longitudinal data to further broaden our current understanding of data analytics capability and its impact on supply chain resilience. Thirdly, we collected data from single source. As we have noted in our data analyses section that single source, data may pose potential biases. Hence, in future based on Ketokivi and Schroeder (2004) suggestions, the data should be gathered from multiple sources to minimize the common method bias.

Appendix 1: Measures

Construct	Reference	Item	Description
Data analytics capability (DAC)	Akter et al. (2016); Srinivasan and Swink (2018)	DAC1	We use advanced tools and analytical techniques (e.g., simulation, optimization, regression) to take decision.
		DAC2	We use information extracted from various sources of data to take decision.
		DAC3	We use data visualization technique (e.g., dashboards) to assist users or decision-maker in understanding complex information.
		DAC4	Our dashboards display information, which is useful for carrying out necessary diagnosis.
		DAC5	We have connected dashboard applications or information with the manager's communication devices.
Organizational flexibility (OF)	Sethi and Sethi (1990); Upton (1994)	OF1	We can quickly change organizational structure to respond to supply chain disruptions.
		OF2	Our organization can cost effectively respond to supply chain disruptions.
		OF3	Our organization is more flexible than our competitors in changing our organizational structure.
Supply chain resilience (SCRES)	Brandon-Jones et al. (2014)	SCRES1	Our organization can easily restore material flow.
		SCRES2	Our organization would not take long to recover normal operating performance.
		SCRES3	The supply chain would quickly recover to its original state.
		SCRES4	Our organization can quickly deal with disruptions.
Competitive advantage (CA)	Tracey et al. (1999); Vorhies and Morgan (2005)	CA1	Our customer are satisfied with our product quality.
		CA2	We deliver value to our customer.
		CA3	We deliver in right time what our customers want.
		CA4	Our market share growth is significant in comparison to our customers.

		CA5	We are able to acquire new customers.
		CA6	We have reached our financial goals.
Industry dynamism (ID)	Brandon-Jones et al. (2014)	ID1	Our product and services become outdated.
		ID2	Our organization continuously introduces new products and services.
		ID3	Our organization introduces new operating processes.
		ID4	The customers taste and preferences in our industry changes fast.
Competitive intensity (CI)	Ramaswamy (2001)	CI1	The market concentration in our industry is high.
		CI2	The competitive rivalry within our industry is high.
		CI3	The new entrants in our industry is high.
Organization size	Kim (2009)	OS	Number of employees

Appendix 2: Loadings of the indicator variables, SCR and AVE

Construct	Item	Factor loadings (λi)	Variance (λi²)	Error (ei)	SCR	AVE
Data technology capability	DAC1	0.73	0.53	0.47	0.82	0.53
	DAC2	0.62	0.38	0.62		
	DAC3	0.87	0.75	0.25		
	DAC5	0.67	0.44	0.56		
Organizational flexibility	OF1	0.95	0.91	0.09	0.97	0.91
	OF2	0.95	0.90	0.10		
	OF3	0.96	0.91	0.09		
Supply chain resilience	SCRES1	0.82	0.67	0.33	0.96	0.85
	SCRES2	0.96	0.93	0.07		
	SCRES3	0.97	0.95	0.05		
	SCRES4	0.92	0.84	0.16		
Competitive advantage	CA1	0.81	0.65	0.35	0.97	0.84
	CA2	0.96	0.91	0.09		
	CA3	0.95	0.91	0.09		
	CA4	0.94	0.88	0.12		
	CA5	0.91	0.83	0.17		
	CA6	0.93	0.87	0.13		
Industrial dynamism	ID1	0.79	0.63	0.37	0.93	0.77
	ID2	0.96	0.91	0.09		
	ID3	0.96	0.92	0.08		

	ID4	0.79	0.63	0.37		
Competitive intensity	CI1	0.93	0.87	0.13	0.79	0.60
	CI2	0.93	0.87	0.13		

Appendix 3: Model fit and quality indices

Model fit and quality indices	Value from analysis	Acceptable if	Reference
APC	0.201, p=0.011	p<0.05	Rosenthal and Rosnow (1991)
ARS	0.456, p<0.001	p<0.05	
AVIF	1.667, p<0.001	p<0.05	Kock (2015)
Tenenhaus GoF	0.529	Large if ≥ 0.36	Tenenhaus et al. (2005)

References

Acharya, A., Singh, S. K., Pereira, V., & Singh, P. (2018). Big data, knowledge co-creation and decision making in fashion industry. *International Journal of Information Management*, *42*, 90-101.

Adobor, H., & McMullen, R. S. (2018). Supply chain resilience: a dynamic and multidimensional approach. *The International Journal of Logistics Management*, *29*(4), 1451-1471.

Agarwal, R., & Dhar, V. (2014). Big data, data science, and analytics: The opportunity and challenge for IS research. *Information Systems Research*, 25(3), 443-448.

Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., & Childe, S. J. (2016). How to improve firm performance using big data analytics capability and business strategy alignment?. *International Journal of Production Economics*, *182*, 113-131.

Akter, S., Fosso Wamba, S., & Dewan, S. (2017). Why PLS-SEM is suitable for complex modelling? An empirical illustration in big data analytics quality. *Production Planning & Control*, *28*(11-12), 1011-1021.

Ali, I., Nagalingam, S., & Gurd, B. (2017). Building resilience in SMEs of perishable product supply chains: enablers, barriers and risks. *Production Planning & Control*, *28*(15), 1236-1250.

Altay, N., & Ramirez, A. (2010). Impact of disasters on firms in different sectors: implications for supply chains. *Journal of Supply Chain Management*, *46*(4), 59-80.

Ambulkar, S., Blackhurst, J., & Grawe, S. (2015). Firm's resilience to supply chain disruptions: Scale development and empirical examination. *Journal of Operations Management*, *33*, 111-122.

Armstrong, J. S., & Overton, T. S. (1977). Estimating nonresponse bias in mail surveys. *Journal of Marketing Research*, 14(3), 396-402.

Ates, A., & Bititci, U. (2011). Change process: a key enabler for building resilient SMEs. *International Journal of Production Research*, *49*(18), 5601-5618.

Aydiner, A. S., Tatoglu, E., Bayraktar, E., Zaim, S., & Delen, D. (2019). Business analytics and firm performance: The mediating role of business process performance. *Journal of Business Research*, *96*, 228-237.

Barroso, A. P., Machado, V. H., Carvalho, H., & Machado, V. C. (2015). Quantifying the Supply Chain Resilience. In *Applications of Contemporary Management Approaches in Supply Chains*. InTech, pp. 13-38.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, *17*(1), 99-120.

Barratt, M., & Oke, A. (2007). Antecedents of supply chain visibility in retail supply chains: a resource-based theory perspective. *Journal of Operations Management*, *25*(6), 1217-1233.

Behzadi, G., O'Sullivan, M. J., Olsen, T. L., Scrimgeour, F., & Zhang, A. (2017). Robust and resilient strategies for managing supply disruptions in an agribusiness supply chain. *International Journal of Production Economics*,191, 207-220.

Bhamra, R., Dani, S., & Burnard, K. (2011). Resilience: the concept, a literature review and future directions. *International Journal of Production Research*, *49*(18), 5375-5393.

Blackhurst, J., Dunn, K. S., & Craighead, C. W. (2011). An empirically derived framework of global supply resiliency. *Journal of Business Logistics*, *32*(4), 374-391.

Bode, C., Wagner, S. M., Petersen, K. J., & Ellram, L. M. (2011). Understanding responses to supply chain disruptions: Insights from information processing and resource dependence perspectives. *Academy of Management Journal*, *54*(4), 833-856.

Brandon-Jones, E., Squire, B., Autry, C. W., & Petersen, K. J. (2014). A contingent resource-based perspective of supply chain resilience and robustness. *Journal of Supply Chain Management*, *50*(3), 55-73.

Braunscheidel, M. J., & Suresh, N. C. (2009). The organizational antecedents of a firm's supply chain agility for risk mitigation and response. *Journal of Operations Management*, *27*(2), 119-140.

Brusset, X., & Teller, C. (2017). Supply chain capabilities, risks, and resilience. *International Journal of Production Economics*, *184*, 59-68.

Brusset, X., & Bertrand, J. L. (2018). Hedging weather risk and coordinating supply chains. *Journal of Operations Management*, 64, 41-52.

Burnard, K., & Bhamra, R. (2011). Organisational resilience: development of a conceptual framework for organisational responses. *International Journal of Production Research*, *49*(18), 5581-5599.

Chen, H., Chiang, R. H., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. *MIS quarterly*, *36*(4),1165-1188.

Chen, D. Q., Preston, D. S., & Swink, M. (2015). How the use of big data analytics affects value creation in supply chain management. *Journal of Management Information Systems*, *32*(4), 4-39.

Chin, W. W. (1998). Commentary: Issues and opinion on structural equation modeling. *MIS Quarterly*, 22(1), pp. Vii-Xvi.

Chopra, S., & Sodhi, M. S. (2004). Managing risk to avoid supply-chain breakdown. *MIT Sloan Management Review*, *46*(1), 53-61.

Chopra, S., & Sodhi, M. S. (2014). Reducing the risk of supply chain disruptions. *MIT Sloan Management Review*, *55*(3), 73-80.

Chowdhury, M. M. H. & Quaddus, M. (2016). Supply chain readiness, response and recovery for resilience. *Supply Chain Management: An International Journal*, *21*(6), 709-731.

Chowdhury, M. M. H., & Quaddus, M. (2017). Supply chain resilience: Conceptualization and scale development using dynamic capability theory. *International Journal of Production Economics*, *188*, 185-204.

Christopher, M., & Peck, H. (2004). Building the resilient supply chain. *The International Journal of Logistics Management*, *15*(2), 1-14.

Christopher, M., & Lee, H. (2004). Mitigating supply chain risk through improved confidence. *International Journal of Physical Distribution & Logistics Management*, *34*(5), 388-396.

Colicchia, C., & Strozzi, F. (2012). Supply chain risk management: a new methodology for a systematic literature review. *Supply Chain Management: An International Journal*, *17*(4), 403-418.

Côrte-Real, N., Ruivo, P., & Oliveira, T. (2019). Leveraging Internet of Things and Big Data Analytics Initiatives in European and American Firms: Is data quality a way to extract business value?. *Information & Management*. https://doi.org/10.1016/j.im.2019.01.003.

Craighead, C. W., Blackhurst, J., Rungtusanatham, M. J., & Handfield, R. B. (2007). The severity of supply chain disruptions: design characteristics and mitigation capabilities. *Decision Sciences*, *38*(1), 131-156.

Datta, P. (2017). Supply network resilience: a systematic literature review and future research. *The International Journal of Logistics Management*, *28*(4), 1387-1424.

Davenport, T. H. (2006). Competing on analytics. *Harvard Business Review*, *84*(1), 98, 1-9.

Davidson, R., & MacKinnon, J. G. (1993). *Estimation and inference in econometrics*. Oxford University Press, New York.

Dijkstra, T. K., & Henseler, J. (2015). Consistent and asymptotically normal PLS estimators for linear structural equations. *Computational Statistics & Data Analysis*, *81*, 10-23.

Dubey, R., Gunasekaran, A., Childe, S. J., Papadopoulos, T., Blome, C., & Luo, Z. (2018a). Antecedents of resilient supply chains: an empirical study. *IEEE Transactions on Engineering Management*, 65(1),X-X.

Dubey, R., Altay, N., Gunasekaran, A., Blome, C., Papadopoulos, T., & Childe, S. J. (2018b). Supply chain agility, adaptability and alignment: empirical evidence from the Indian auto components industry. *International Journal of Operations & Production Management*, 38(1), 129-148.

Dubey, R., Gunasekaran, A., & Childe, S. J. (2018c). Big data analytics capability in supply chain agility: The moderating effect of organizational flexibility. *Management Decision*. https://doi.org/10.1108/MD-01-2018-0119.

Dolgui, A., Ivanov, D., & Sokolov, B. (2018). Ripple effect in the supply chain: an analysis and recent literature. *International Journal of Production Research*, 56(1-2), 414-430.

Eckstein, D., Goellner, M., Blome, C., & Henke, M. (2015). The performance impact of supply chain agility and supply chain adaptability: the moderating effect of product complexity. *International Journal of Production Research*, *53*(10), 3028-3046.

Elahi, E. (2013). Risk management: the next source of competitive advantage. *Foresight*, *15*(2), 117-131.

Ellram, L. M., Tate, W. L., & Petersen, K. J. (2013). Offshoring and reshoring: an update on the manufacturing location decision. *Journal of Supply Chain Management*, *49*(2), 14-22.

Fairbank, J. F., Labianca, G. J., Steensma, H. K., & Metters, R. (2006). Information processing design choices, strategy, and risk management performance. *Journal of Management Information Systems*, *23*(1), 293-319.

Fan, H., Cheng, T. C. E., Li, G., & Lee, P. K. (2016). The effectiveness of supply chain risk information processing capability: an information processing perspective. *IEEE Transactions on Engineering Management*, *63*(4), 414-425.

Fan, H., Li, G., Sun, H., & Cheng, T. C. E. (2017). An information processing perspective on supply chain risk management: Antecedents, mechanism, and consequences. *International Journal of Production Economics*, *185*, 63-75.

Fang, K., Jiang, Y., & Song, M. (2016). Customer profitability forecasting using big data analytics: A case study of the insurance industry. *Computers & Industrial Engineering*, *101*, 554-564.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39-50.

Galbraith, J. R. (1973). *Designing complex organizations*. Addison-Wesley Longman Publishing Co., Inc..

Galbraith, J. R. (1974). Organization design: An information processing view. *Interfaces*, *4*(3), 28-36.

Gupta, M., & George, J. F. (2016). Toward the development of a big data analytics capability. *Information & Management*, *53*(8), 1049-1064.

Gunasekaran, A., Subramanian, N., & Rahman, S. (2015). Supply chain resilience: role of complexities and strategies. *International Journal of Production Research*, 53, 6809-6819.

Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S. F., Childe, S. J., Hazen, B., & Akter, S. (2017). Big data and predictive analytics for supply chain and organizational performance. *Journal of Business Research*, *70*, 308-317.

Guide, V. D. R., & Ketokivi, M. (2015). Notes from the editors: Redefining some methodological criteria for the journal. *Journal of Operations Management*, (37), v-viii.

Hair Jr, J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2016). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage Publications.

Hazen, B. T., Boone, C. A., Ezell, J. D., & Jones-Farmer, L. A. (2014). Data quality for data science, predictive analytics, and big data in supply chain management: An introduction to the problem and suggestions for research and applications. *International Journal of Production Economics*, *154*, 72-80.

Hazen, B. T., Overstreet, R. E., & Boone, C. A. (2015). Suggested reporting guidelines for structural equation modeling in supply chain management research. *The International Journal of Logistics Management*, *26*(3), 627-641.

Hazen, B. T., Skipper, J. B., Boone, C. A., & Hill, R. R. (2016). Back in business: Operations research in support of big data analytics for operations and supply chain management. *Annals of Operations Research*, 1-11.

Hendricks, K. B., & Singhal, V. R. (2005). An empirical analysis of the effect of supply chain disruptions on long-run stock price performance and equity risk of the firm. *Production and Operations Management*, *14*(1), 35-52.

Henseler, J., Dijkstra, T. K., Sarstedt, M., Ringle, C. M., Diamantopoulos, A., Straub, D. W., ... & Calantone, R. J. (2014). Common beliefs and reality about PLS: Comments on Rönkkö and Evermann (2013). *Organizational Research Methods*, *17*(2), 182-209.

Hill, C. W., Jones, G. R., & Schilling, M. A. (2014). *Strategic management: theory: an integrated approach (11th Edition)*. Cengage Learning: Canada.

Ho, W., Zheng, T., Yildiz, H., & Talluri, S. (2015). Supply chain risk management: a literature review. *International Journal of Production Research*, *53*(16), 5031-5069.

Holling, C. S. (1973). Resilience and stability of ecological systems. *Annual Review of Ecology and Systematics*, *4*(1), 1-23.

Ivanov, D., & Sokolov, B. (2010). *Adaptive supply chain management*. Eds. (Ivanov, D and Sokolov, B),Springer Science & Business Media: London.

Ivanov, D., & Sokolov, B. (2013). Control and system-theoretic identification of the supply chain dynamics domain for planning, analysis and adaptation of performance under uncertainty. *European Journal of Operational Research*, *224*(2), 313-323.

Ivanov, D., Sokolov, B., & Dolgui, A. (2014). The Ripple effect in supply chains: trade-off 'efficiency-flexibility-resilience' in disruption management. *International Journal of Production Research*, *52*(7), 2154-2172.

Ivanov, D., Dolgui, A., Sokolov, B., & Ivanova, M. (2017). Literature review on disruption recovery in the supply chain. *International Journal of Production Research*, *55*(20), 6158-6174.

Ivanov, D., & Dolgui, A. (2018). Low-Certainty-Need (LCN) supply chains: a new perspective in managing disruption risks and resilience. *International Journal of Production Research,* 1-18.

Ivanov, D., Dolgui, A., & Sokolov, B. (2018a). The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics. *International Journal of Production Research*, 1-18.

Ivanov, D., Dolgui, A., & Sokolov, B. (2018b). Scheduling of recovery actions in the supply chain with resilience analysis considerations. *International Journal of Production Research*, *56*(19), 6473-6490.

Ivanov, D. (2018). Uncertainty and Risks (Chapter 2). *Structural Dynamics and Resilience in Supply Chain Risk Management (Eds. Ivanov, D),* pp. 19-44. Springer International Publishing: London.

Jain, V., Kumar, S., Soni, U., & Chandra, C. (2017). Supply chain resilience: model development and empirical analysis. *International Journal of Production Research*, *55*(22), 6779-6800.

Jüttner, U., & Maklan, S. (2011). Supply chain resilience in the global financial crisis: an empirical study. *Supply Chain Management: An International Journal*, *16*(4), 246-259.

Kache, F. & Seuring, S. (2017). Challenges and opportunities of digital information at the intersection of Big Data Analytics and supply chain management. *International Journal of Operations & Production Management*, *37*(1), 10-36.

Kamalahmadi, M., & Parast, M. M. (2016). A review of the literature on the principles of enterprise and supply chain resilience: Major findings and directions for future research. *International Journal of Production Economics*, *171*, 116-133.

Kaynak, R., Sert, T., Sert, G., & Akyuz, B. (2015). Supply chain unethical behaviors and continuity of relationship: Using the PLS approach for testing moderation effects of inter-organizational justice. *International Journal of Production Economics*, *162*, 83-91.

Kim, S. W. (2009). An investigation on the direct and indirect effect of supply chain integration on firm performance. *International Journal of Production Economics*, *119*(2), 328-346.

Kim, Y., Chen, Y. S., & Linderman, K. (2015). Supply network disruption and resilience: A network structural perspective. *Journal of Operations Management*, *33*, 43-59.

Kleindorfer, P. R., & Saad, G. H. (2005). Managing disruption risks in supply chains. *Production and Operations Management, 14*(1), 53-68.

Kock, N. (2014). Advanced mediating effects tests, multi-group analyses, and measurement model assessments in PLS-based SEM. *International Journal of e-Collaboration (IJeC)*, *10*(1), 1-13.

Kock, N. (2015). WarpPLS 5.0 user manual. *Laredo, TX: ScriptWarp Systems*, Laredo, Texas, USA.

Kwak, D. W., Seo, Y. J., & Mason, R. (2018). Investigating the relationship between supply chain innovation, risk management capabilities and competitive advantage in global supply chains. *International Journal of Operations & Production Management*, 38(1), 2-21.

LaValle, S., Lesser, E., Shockley, R., Hopkins, M. S., & Kruschwitz, N. (2011). Big data, analytics and the path from insights to value. *MIT Sloan Management Review*, *52*(2), 21-32.

Lee, B. K., Zhou, R., de Souza, R., & Park, J. (2016). Data-driven risk measurement of firm-to-firm relationships in a supply chain. *International Journal of Production Economics*, *180*, 148-157.

Lee, H. L. (2002). Aligning supply chain strategies with product uncertainties. *California Management Review*, *44*(3), 105-119.

Lee, H. L. (2004). The triple-A supply chain. *Harvard Business Review*, *82*(10), 102-113.

Li, G., Fan, H., Lee, P. K., & Cheng, T. C. E. (2015). Joint supply chain risk management: an agency and collaboration perspective. *International Journal of Production Economics*, *164*, 83-94.

Lindell, M. K., & Whitney, D. J. (2001). Accounting for common method variance in cross-sectional research designs. *Journal of Applied Psychology*, *86*(1), 114-121.

Namdar, J., Li, X., Sawhney, R., & Pradhan, N. (2018). Supply chain resilience for single and multiple sourcing in the presence of disruption risks. *International Journal of Production Research*, *56*(6), 2339-2360.

Mishra, D., Sharma, R. R. K., Kumar, S., & Dubey, R. (2016). Bridging and buffering: Strategies for mitigating supply risk and improving supply chain performance. *International Journal of Production Economics*, *180*, 183-197.

Malhotra, M. K., & Grover, V. (1998). An assessment of survey research in POM: from constructs to theory. *Journal of Operations Management*, *16*(4), 407-425.

Mandal, S.(2017). The influence of organizational culture on healthcare supply chain resilience: moderating role of technology orientation. *Journal of Business & Industrial Marketing*, *32*(8), 1021-1037.

Moshtari, M. (2016). Inter-Organizational Fit, Relationship Management Capability, and Collaborative Performance within a Humanitarian Setting. *Production and Operations Management*, *25*(9), 1542-1557.

Papadopoulos, T., Gunasekaran, A., Dubey, R., & Fosso Wamba, S. (2017). Big data and analytics in operations and supply chain management: managerial aspects and practical challenges. *Production Planning & Control*, *28*(11-12), 873-876.

Papadopoulos, T., Gunasekaran, A., Dubey, R., Altay, N., Childe, S. J., & Fosso-Wamba, S. (2017). The role of Big Data in explaining disaster resilience in supply chains for sustainability. *Journal of Cleaner Production*, *142*, 1108-1118.

Peng, D. X., & Lai, F. (2012). Using partial least squares in operations management research: A practical guideline and summary of past research. *Journal of Operations Management*, *30*(6), 467-480.

Peteraf, M. A. (1993). The cornerstones of competitive advantage: A resource-based view. *Strategic Management Journal*, *14*(3), 179-191.

Pettit, T. J., Croxton, K. L., & Fiksel, J. (2013). Ensuring supply chain resilience: development and implementation of an assessment tool. *Journal of Business Logistics*, *34*(1), 46-76.

Podsakoff, P. M., & Organ, D. W. (1986). Self-reports in organizational research: Problems and prospects. *Journal of management*, *12*(4), 531-544.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879.

Ponomarov, S. Y., & Holcomb, M. C. (2009). Understanding the concept of supply chain resilience. *The International Journal of Logistics Management*, *20*(1), 124-143.

Porter, M.E. (1985). Competitive advantage: Creating and sustaining superior performance. New York: Free Press.

Premkumar, G., Ramamurthy, K., & Saunders, C. S. (2005). Information processing view of organizations: an exploratory examination of fit in the context of interorganizational relationships. *Journal of Management Information Systems*, *22*(1), 257-294.

Purvis, L., Spall, S., Naim, M., & Spiegler, V. (2016). Developing a resilient supply chain strategy during ‘boom’and ‘bust’. *Production Planning & Control*, *27*(7-8), 579-590.

Raffoni, A., Visani, F., Bartolini, M., & Silvi, R. (2017). Business Performance Analytics: exploring the potential for Performance Management Systems. *Production Planning & Control*, *29*(1), 51-67.

Ramaswamy, K. (2001). Organizational ownership, competitive intensity, and firm performance: An empirical study of the Indian manufacturing sector. *Strategic Management Journal*, *22*(10), 989-998.

Reed, R., & DeFillippi, R. J. (1990). Causal ambiguity, barriers to imitation, and sustainable competitive advantage. *Academy of Management Review*, *15*(1), 88-102.

Rosenthal, R., & Rosnow, R. L. (1991). *Essentials of behavioral research: Methods and data analysis*. McGraw-Hill Humanities Social.

Ketokivi, M. A., & Schroeder, R. G. (2004). Perceptual measures of performance: fact or fiction?. *Journal of Operations Management*, *22*(3), 247-264.

Schilke, O. (2014). On the contingent value of dynamic capabilities for competitive advantage: The nonlinear moderating effect of environmental dynamism. *Strategic Management Journal*, *35*(2), 179-203.

Sethi, A. K., & Sethi, S. P. (1990). Flexibility in manufacturing: a survey. *International Journal of Flexible Manufacturing Systems*, *2*(4), 289-328.

Shangquan, G. (2000). Economic globalization: trends, risks and risk prevention. *Economic & Social Affairs, CDP Background Paper*, *1*.

Sharma, M. K., Sushil., & Jain, P. K. (2010). Revisiting flexibility in organizations: exploring its impact on performance. *Global Journal of Flexible Systems Management*, *11*(3), 51-68.

Sheffi, Y. (2005). The resilient enterprise: overcoming vulnerability for competitive advantage. *MIT Press Books*, *1*.

Sheng, J., Amankwah-Amoah, J., & Wang, X. (2017). A multidisciplinary perspective of big data in management research. *International Journal of Production Economics*, 191, 97-112.

Singh, S. K. (2011). Organizational innovation as competitive advantage during global recession. *Indian Journal of Industrial Relations*, 46(4), 713-725.

Singhal, V., Flynn, B. B., Ward, P. T., Roth, A. V., & Gaur, V. (2008). Empirical elephants—Why multiple methods are essential to quality research in operations and supply chain management. *Journal of Operations Management*, *26*(3), 345-348.

Sodhi, M. S., Son, B. G., & Tang, C. S. (2012). Researchers' perspectives on supply chain risk management. *Production and Operations Management*, *21*(1), 1-13.

Sreedevi, R., & Saranga, H. (2017). Uncertainty and supply chain risk: The moderating role of supply chain flexibility in risk mitigation. *International Journal of Production Economics*, *193*, 332-342.

Srinivasan, R., & Swink, M. (2015). Leveraging supply chain integration through planning comprehensiveness: An organizational information processing theory perspective. *Decision Sciences*, *46*(5), 823-861.

Srinivasan, R., & Swink, M. (2018). An investigation of visibility and flexibility as complements to supply chain analytics: An organizational information processing theory perspective. *Production and Operations Management*, 27(10), 1849-1867.

Tang, C. S. (2006). Perspectives in supply chain risk management. *International Journal of Production Economics*, *103*(2), 451-488.

Tang, C. S. (2006a). Robust strategies for mitigating supply chain disruptions. *International Journal of Logistics: Research and Applications*, *9*(1), 33-45.

Tenenhaus, M., Vinzi, V. E., Chatelin, Y. M., & Lauro, C. (2005). PLS path modeling. *Computational Statistics & Data Analysis*, *48*(1), 159-205.

Tracey, M., Vonderembse, M. A., & Lim, J. S. (1999). Manufacturing technology and strategy formulation: keys to enhancing competitiveness and improving performance. *Journal of Operations Management*, *17*(4), 411-428.

Trkman, P., & McCormack, K. (2009). Supply chain risk in turbulent environments—A conceptual model for managing supply chain network risk. *International Journal of Production Economics*, *119*(2), 247-258.

Ullman, J. B. (2006). Structural equation modeling: Reviewing the basics and moving forward. *Journal of Personality Assessment*, *87*(1), 35-50.

Upton, D. M. (1994). The management of manufacturing flexibility. *California Management Review*, *36*(2), 72-89.

Vlajic, J. V., van Lokven, S. W., Haijema, R., & van der Vorst, J. G. (2013). Using vulnerability performance indicators to attain food supply chain robustness. *Production Planning & Control*, *24*(8-9), 785-799.

Volberda, H. W. (1996). Toward the flexible form: How to remain vital in hypercompetitive environments. *Organization Science*, *7*(4), 359-374.

Vorhies, D. W., & Morgan, N. A. (2005). Benchmarking marketing capabilities for sustainable competitive advantage. *Journal of Marketing*, *69*(1), 80-94.

Wagner, S. M., & Bode, C. (2006). An empirical investigation into supply chain vulnerability. *Journal of Purchasing and Supply Management*, *12*(6), 301-312.

Wagner, S. M., & Neshat, N. (2012). A comparison of supply chain vulnerability indices for different categories of firms. *International Journal of Production Research*, *50*(11), 2877-2891.

Wagner, S. M., Grosse-Ruyken, P. T., & Erhun, F. (2012). The link between supply chain fit and financial performance of the firm. *Journal of Operations Management*, *30*(4), 340-353.

Waller, M. A., & Fawcett, S. E. (2013). Data science, predictive analytics, and big data: a revolution that will transform supply chain design and management. *Journal of Business Logistics*, *34*(2), 77-84.

Wamba, S. F., Akter, S., Edwards, A., Chopin, G., & Gnanzou, D. (2015). How 'big data' can make big impact: Findings from a systematic review and a longitudinal case study. *International Journal of Production Economics*, *165*, 234-246.

Wang, G., Gunasekaran, A., Ngai, E. W., & Papadopoulos, T. (2016). Big data analytics in logistics and supply chain management: Certain investigations for research and applications. *International Journal of Production Economics*, *176*, 98-110.

Wang, X., Tiwari, P., & Chen, X. (2017). Communicating supply chain risks and mitigation strategies: a comprehensive framework. *Production Planning & Control*, 28 (13),1023-1036.

Webb, B., & Schlemmer, F. (2006). Resilience as a source of competitive advantage for small information technology companies. In *IFIP International Working Conference on the Transfer and Diffusion of Information Technology for Organizational Resilience* (pp. 181-197). Springer, Boston, MA.

Wetzels, M., Odekerken-Schröder, G., & Van Oppen, C. (2009). Using PLS path modeling for assessing hierarchical construct models: Guidelines and empirical illustration. *MIS Quarterly*, 33(1),177-195.

Wieland, A., & Marcus Wallenburg, C. (2013). The influence of relational competencies on supply chain resilience: a relational view. *International Journal of Physical Distribution & Logistics Management*, *43*(4), 300-320.