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The influence of big data analytics management capabilities on supply chain preparedness, alertness and agility

An empirical investigation

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Abstract

Purpose – The importance of big data analytics (BDA) on the development of supply chain (SC) resilience is not clearly understood. To address this, the purpose of this paper is to explore the impact of BDA management capabilities, namely, BDA planning, BDA investment decision making, BDA coordination and BDA control on SC resilience dimensions, namely, SC preparedness, SC alertness and SC agility.

Design/methodology/approach – The study relied on perceptual measures to test the proposed associations. Using extant measures, the scales for all the constructs were contextualized based on expert feedback. Using online survey, 249 complete responses were collected and were analyzed using partial least squares in SmartPLS 2.0.M3. The study targeted professionals with sufficient experience in analytics in different industry sectors for survey participation.

Findings – Results indicate BDA planning, BDA coordination and BDA control are critical enablers of SC preparedness, SC alertness and SC agility. BDA investment decision making did not have any prominent influence on any of the SC resilience dimensions.

Originality/value – The study is important as it addresses the contribution of BDA capabilities on the development of SC resilience, an important gap in the extant literature.

Keywords Business process management, Supply chain management, Resource-based view, Business value of IT

Paper type Research paper

Introduction

The recent business environment is heavily tormented by ever-increasing uncertainties and associated vulnerabilities (Ambulkar *et al.*, 2015). Such unstable environments have increased the importance of supply chain (SC) risk mitigation strategies and associated SC capabilities, i.e. SC resilience. Resilience in SCs have received well recognition as an important dynamic capability (Ponomarov and Holcomb, 2009; Pettitt *et al.*, 2010; Jüttner and Maklan, 2011; Ponomarov, 2012; Hohenstein *et al.*, 2015; Ambulkar *et al.*, 2015; Bellow, 2016; Mandal *et al.*, 2016; Lam and Bai, 2016; Li *et al.*, 2017). The essence of SC resilience is to restore operations to an optimal state or an improved state post-disruption (Jüttner and Maklan, 2011; Wieland and Wallenburg, 2013; Hohenstein *et al.*, 2015; Bellow, 2016).

While studies have explored several dimensions of SC resilience (Li *et al.*, 2017; Gu and Huo, 2017; Liu *et al.*, 2018; Chowdhury and Quaddus, 2017; Cheng and Lu, 2017), the importance of big data analytics (BDA) in the development of principal dimensions of SC resilience is still lacking. BDA combines two major concepts: big data that refers to the capacity to process data with following characteristics: volume, variety and velocity (Wang, Gunasekaran, Ngai and Papadopoulos, 2016). The ability to draw meaningful conclusions from data through application of statistics, mathematics, econometrics, simulations, optimizations or other techniques to aid firms for better decision making (Accenture Global Operations Megatrends Study, 2014). BDA has been extensively

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attracting research attention for verification of existing theories and also for effective decision making for organizations (Muhtaroglu *et al.*, 2013), especially in SC management (Wamba *et al.*, 2015; Wang, Gunasekaran and Ngai, 2016; Wang, Gunasekaran, Ngai and Papadopoulos, 2016). BDA therefore deploys advanced analytics tools to derive valuable knowledge from enormous data, aiding in effective decision making (Tan *et al.*, 2015). Most of the existing studies regarding the application of BDA within SC management have concentrated mainly on offering definitions through comprehensive literature reviews (Wamba *et al.*, 2015; Wang, Gunasekaran and Ngai, 2016; Wang, Gunasekaran, Ngai and Papadopoulos, 2016; Waller and Fawcett, 2013). Consequently, the existing literature on BDA is still under development and therefore calls for empirical testing and theory development (Arunachalam *et al.*, 2018; Wamba *et al.*, 2017). Extant studies has stressed that BDA can aid in different areas of effective SC management, for example, in supply network design through proper analysis of service-level and penalty cost data (Wang, Gunasekaran and Ngai, 2016; Wang, Gunasekaran, Ngai and Papadopoulos, 2016), in product design and development through analysis of customer purchase record and online behavior (Afshari and Peng, 2015), in demand planning (Chase, 2013; Hassani and Silva, 2015) and procurement (Wang, Gunasekaran and Ngai, 2016; Wang, Gunasekaran, Ngai and Papadopoulos, 2016; Fan *et al.*, 2015).

However, extant literature conceptualized BDA capabilities (Wamba *et al.*, 2017) as a third-order formative construct of BDA management capability, BDA personnel expertise capability and BDA infrastructure flexibility capability. Each of these was further conceptualized as a second-order formative constructs of several first-order latent variables. In this regard, we argue that BDA management capability is of prime importance for successful SC management as they are directed toward developing coordination and control through appropriate planning and investments (Wamba *et al.*, 2017). BDA management capabilities comprise of essential first-order capabilities of planning, investment decision making, coordination and control. BDA planning ensures that firms can effectively use data and information appropriate for planning future operation strategies. BDA investment decision-making capability aids firms to analyze and prioritize areas requiring investment for development. BDA coordination helps SC firms to effectively synchronize their operations through appropriate analysis and sharing of information. BDA control aids SC firms to maintain control over execution of key SC processes through appropriate analysis and information sharing. Hence, in line with extant literature (Wamba *et al.*, 2017), BDA management capabilities of planning, investment decision making, coordination and control are prominent for effective planning and deployment of strategies in SC management (Wamba *et al.*, 2017; Hazen *et al.*, 2014; Waller and Fawcett, 2013).

Extant literature has suggested two prominent dimensions of SC resilience: proactive and reactive (Ponomarov and Holcomb, 2009; Välikangas, 2010; Wieland and Wallenburg 2013; Durach *et al.*, 2015; Cheng and Lu, 2017). While the proactive strategy ensures the stability of the system to maintain its normal executions despite internal disturbances (Stonebraker *et al.*, 2009; Cheng and Lu, 2017); the reactive strategy focuses on rapidly responding to market changes in an uncertain business environment (Wieland and Wallenburg 2013; Durach *et al.*, 2015; Cheng and Lu, 2017). While studies emphasized either a proactive or reactive strategy sufficient for building SC resilience (Wieland and Wallenburg, 2013; Durach *et al.*, 2015), the combined effect of these strategies would lead more effective resilience (Li *et al.*, 2017). In this regard, Li *et al.* (2017) further added SC preparedness as the key to proactive dimension, while SC alertness and SC agility are key elements of the reactive dimension of SC resilience. Through SC preparedness, SCs can withstand disruptions, while maintaining connectedness and stability across processes, instead of adapting to changes through disruptions (Wallace and Choi, 2011). Furthermore, SC alertness aids in recognizing changes in a timely manner (Li *et al.*, 2008), while SC agility refers to the capability to respond in a fast manner to changes through required process re-configurations (Swafford *et al.*, 2006). Hence, SC preparedness, alertness and agility together constitute the mechanism through which SC resilience operates. As a result, the development of these key elements of SC resilience requires empirical attention. As BDA management capabilities ensures in effective SC management through appropriate planning, investments, coordination and control, their role in the development of key elements of SC resilience requires investigation. Accordingly, the current investigation addresses the following research questions:

RQ1. Do BDA management capabilities of planning, investment decision making, coordination and control influence SC preparedness?

RQ2. Do BDA management capabilities of planning, investment decision making, coordination and control influence SC alertness?

RQ3. Do BDA management capabilities of planning, investment decision making, coordination and control influence SC agility?

Theoretical background

BDA management capabilities

IT capabilities have been classified in several ways. While IT capabilities may be manifested through value, heterogeneity and imperfect mobility directed for competitive advantage (Bhatt and Gorver, 2005); IT infrastructure quality, IT business expertise and learning intensity of firms also influence the degree of competitive advantage (Bhatt and Gorver, 2005). An important classification of IT capabilities undersigns three important IT capabilities through socio-materialistic lens, namely, IT management capability, IT personnel capability and IT infrastructure capability.

In similar lines, Wamba *et al.* (2017) conceptualized BDA capabilities as a third-order formative factor of three second-order formative factors: BDA management capability, BDA infrastructure flexibility capability and BDA personnel expertise capability. BDA management capabilities comprise of first-order capabilities of planning, investment decision making, coordination and control. BDA planning aids SC professionals in the development of procurement schedules, production schedules and risk mitigation strategy development through appropriate information collection, analysis and interpretation (Wamba *et al.*, 2017). BDA investment decision making helps SC professionals to develop their IT infrastructure to aid real-time information sharing and decision making. BDA coordination emphasizes operation synchronization among SC entities through real-time information sharing. BDA control ensures appropriate authority and control over SC operations among different SC entities through appropriate software and hardware technologies (Wamba *et al.*, 2017). The role of BDA management capabilities must be explored in their influence on the development of key SC resilience components, to understand their contribution to overall SC resilience development.

While the above conceptualization and classification of BDA capabilities followed that of IT capabilities; there is a difference between IT capabilities and BDA capabilities. While IT capabilities focus on the efficient implementation and usage of information technology resources and infrastructure, BDA capabilities focus more on data analysis, drawing meaningful insights and data-driven decision making. Hence, IT capabilities are more about the technical IT infrastructure (Bhatt and Gorver, 2005), while BDA capabilities are more concerned about the application of the IT infrastructure to share and analyze information to aid strategy formulation for routine and strategic operations (Wamba *et al.*, 2017).

Studies have explored several facets of BDA and their interfaces in SC management. Hazen *et al.* (2014) suggested that appropriate analysis of big data can lead to meaningful decisions for effective SC management. However, data quality must be monitored to ensure success of such managerial decisions for effective SC management. In this regard, Schoenherr and Speier-Pero (2015) further added that predictive analytics in SC has tremendous potential to transform SC management completely and, hence, universities should incorporate predictive analytics courses and applications in SC management. Furthermore, SC analytics "helps organizations measure the performance of various areas in logistics and supply chain management and provide them with the ability to establish a benchmark to determine value-added operations" (Wang, Gunasekaran, Ngai and Papadopoulos, 2016, p. 107). Such SC analytics found application across firms through four capability levels: functional, process-based, collaborative and agile SCA (Wang, Gunasekaran and Ngai, 2016; Wang, Gunasekaran, Ngai and Papadopoulos, 2016). Hence, SC analytics can act as a strategic resource for SC firms to overhaul SC operations for achieving optimal performance. In similar lines, Gunasekaran *et al.* (2017) found connectivity and information sharing to be positively related with big data and predictive analytics (BDPA) acceptance under mediating effect of top management commitment. Furthermore, such BDPA acceptance enhances BDPA assimilation and positively impacts SC performance and organizational performance. Hence, BDA can improve SC management, if can be strategically utilized. Zhong *et al.* (2016), in their extensive review of the state of BDA in SC management found that companies like Fedex Corporation, UPS, Royal Mail Group Limited, DHL express and several others are devising on several strategies to improve logistics and SC management through effective deployment of BDA. For example, Royal Mail Group planned to develop a multi-function capacity to use big data methods to encourage innovation in operations (LMG, 2014); DHL express started to publish reports to show the implementation of BDA to develop solutions for logistics problems (Martin *et al.*, 2013); and Fedex has successfully developed a solution for its customers to track their products, based on big data (Capron, 2013).

Addo-Tenkorang and Helo (2016), in their comprehensive literature review of big data in SC management between 2010 and 2015, found that BDA can add "value" – a fifth dimension, based on their applications across diverse industry segments. Traditionally, four dimensions, namely, variety, velocity, volume and veracity of BDA were identified. Consequently, the study proposed "Big data II" (IoT – value-adding) framework to enable SC managers to utilize BDA to complement their routine decision making and strategy development process. In this way, BDA can aid SC firms to enhance "value-addition" to effective SC management. While there is a persistent growth of big data, a scarcity of adequate data analytics techniques often restricts firms to realize the full benefits in terms of innovation offered by big data. In this regard, Tan *et al.* (2015) proposed an analytic infrastructure using deduction graph technique. The proposed analytic infrastructure would allow firms to successfully take advantage of big data to enhance their SC innovation capabilities. More recently, Tiwari *et al.* (2018) highlighted that BDA can aid in supplier management decision through providing insight on firm spending pattern (Panchmatia, 2015); can aid in supply network design through proper analysis of service level and penalty cost data (Wang, Gunasekaran and Ngai, 2016; Wang, Gunasekaran, Ngai and Papadopoulos, 2016); can aid in product design and development through analysis of customer purchase record and online behavior (Afshari and Peng, 2015); and can further aid in demand planning (Chase, 2013; Hassani and Silva, 2015), procurement (Wang, Gunasekaran and Ngai, 2016; Wang, Gunasekaran, Ngai and Papadopoulos, 2016; Fan *et al.*, 2015), production (Stich *et al.*, 2015; Katchasuwanmanee *et al.*, 2016), inventory logistics and distribution (Mehmood and Graham, 2015; Brouer *et al.*, 2016), SC agility (Giannakis and Louis, 2016) and sustainability (Wu *et al.*, 2017; Zhao *et al.*, 2017). Furthermore, Hazen, Skipper, Ezell and Boone (2016) suggested eight theories, namely, actor-network theory, social capital theory, institutional theory, resource-dependence theory, transaction cost economics, agency theory, resource-based view (RBV) and ecological modernization theory, to explore BDPA's influence on SC sustainability. Roßmann *et al.* (2017) undertook a Delphi survey to understand the future of BDA in SC management. Their study found that BDA likely to aid in accurate demand forecasting, improve supplier performance and decrease safety stocks. Arunachalam *et al.* (2018), through a comprehensive review of 82 papers, suggested that SC firms must deploy strategically to reap the vast potential in transforming SC operations. Furthermore, the study suggested several problems like privacy and security concerns, insufficient resources, behavioral issues, lack of skills, etc., to restrict the adoption of BDA. However, the success of BDA is transforming organization and SC operations depends on SC firms to develop their BDA capabilities. Hence, the current study further adds to the growing literature on BDA in SC management through exploring the influence of BDA management capabilities in the development of SC preparedness, alertness and agility.

The next section discussed the RBV and associated dynamic capability conceptualization of SC resilience. The subsequent section discusses the hypotheses development and research methodology. The study concludes with a discussion of the findings and managerial implications.

A dynamic capability view on SC preparedness, SC alertness and SC agility

The RBV of the firm (Barney *et al.*, 2001) has been instrumental in explaining the differences in firm performances. Hence, studies have found RBV extremely useful in exploring the development of SC management capabilities (Yu, Chavez, Jacobs and Feng, 2017; Chavez *et al.*, 2017; Yu, Jacobs, Chavez and Feng, 2017; Cheng and Lu, 2017; Huo *et al.*, 2016; Prajogo *et al.*, 2016). For example, Cheng and Lu (2017) investigated the impact of operating frontier, trajectory and absorptive capacity on the proactive and reactive dimension of SC resilience using RBV; Prajogo *et al.* (2016) utilized relational lens of RBV to understand several value chain processes between supply logistics integration and operational performance of firms. However, we content that SC resilience is an important dynamic capability (Teece *et al.*, 1997) that can be developed due to appropriate deployment of firm-level resources and capabilities with suitable integration at the SC level (Ponomarov, 2012; Ponomarov and Holcomb, 2009; Jüttner and Maklan, 2011; Wieland and Wallenburg, 2013).

RBV explained the difference in firm performance to different resource ownership of firms (Barney *et al.*, 2001). Employee skill and talent are usually referred to as intangible resources while firm infrastructure may be undersigned as tangible ones (Amit and Schoemaker, 1993). This RBV was further extended by Teece *et al.* (1997) suggesting that firms need to adapt to the changes and uncertainties in their business environment through suitable modifications in their resources, capabilities and routines. Firms' capacity to adapt to such dynamic changes to business conditions are referred to as dynamic capabilities (Teece *et al.*, 1997; Teece, 2016; Makadok, 2001; Eisenhardt and Martin, 2000). SC resilience is rightly attributed as a dynamic capability of SCs as they enable SC firms to restore operations in the event of a disruption (Ponomarov, 2012; Ponomarov and Holcomb, 2009; Chowdhury and Quaddus, 2017).

However, studies have undersigned several dimensions of SC resilience (Liu *et al.*, 2018; Chowdhury and Quaddus, 2017; Cheng and Lu, 2017). Hence, to understand the development of SC resilience as a dynamic capability, it is required to understand the development of its component capabilities (Liu *et al.*, 2018). The study contends that the component capabilities of SC preparedness, SC alertness and SC agility are also higher order dynamic capabilities that can be developed to respond to environmental changes in a positive manner (Li *et al.*, 2017). SC firms need to prepare for uncertainties through appropriate contingency planning and development. SC alertness helps to aware SC firms of any upcoming emergency through real-time communication and information sharing (Li *et al.*, 2017). SC agility aids in responding to environmental changes at a fast pace. Hence, the study contends SC preparedness, SC alertness and SC agility as dynamic capabilities as they aid SC firms to adapt to environmental changes in a positive manner (Mandal *et al.*, 2016; Denrell and Powell, 2016).

In this regard, we argue in line with RBV and its dynamic capability extension (Teece, 2017) that such dynamic capabilities are higher order SC-level capabilities developed due to the suitable culmination of firm-level BDA-based management capabilities (Wilden *et al.*, 2016). BDA management capabilities of planning, investment decision making, coordination and control, when deployed appropriately, positively influence the development of SC preparedness, SC alertness and SC agility. These SC capabilities enable SCs to accumulate, convert and reorganize resources to respond and adapt to changing business scenarios.

Hypotheses development

BDA management capabilities and SC preparedness. BDA management capabilities are analytics-based capabilities that aid SC firms to collect, exchange and analyze information on a real-time basis and make meaningful decisions required for supporting routine and strategic operations of the SC (Wamba *et al.*, 2017). BDA planning ensures SC firms can develop their resource and production planning schedules through the appropriate decision making regarding procurement schedules and contingency planning. Further, BDA investment decision making aids SC firms to analyze resource investments and prioritize them based on available funds, and thereby aids in IT infrastructure development and implementation of emerging software technologies to support SC operations. BDA coordination aims to develop appropriate synchronization of operations of SC firms through real-time information sharing. BDA control aids SC firms to gain control over SC operations and synchronization through the collection, analysis and routine decision making through analytics.

SC preparedness is the capacity of an SC to tolerate the impact of probable changes (Tang, 2006). SC firms develop business contingency plans that make an SC ready to sustain well for different business scenarios (Christopher and Peck, 2004). Every SC firm has a certain set of routines and protocols that must be synchronized with one another based on mutual collaboration for responding to changes (Lee, 2004). Several established procedures are practiced for operation synchronization within SCs. In the first place, SC partner selection practice influences the stability of an SC network in uncertain business conditions (Krause *et al.*, 2007) because of partner's reliability (MacCarter and Northcraft, 2007) and motivation for collaboration (Cao and Zhang, 2011; Miles and Snow, 2007). Second, there should be real-time information sharing for transparency of forecasts, sales data and plans with SC partners (Hult *et al.*, 2004; Ketchen and Hult, 2007). Third, incentive schemes should be made transparent with clear policies and guidelines (Morgan *et al.*, 2007).

In this context, BDA planning and BDA investment decision making aid in appropriate SC partner selection through suitable performance monitoring and feedback in real time. BDA investment decision making suggests firms continue their existing partner relationship or to make new ones based on performance feedback and investment decisions. BDA coordination and control aids in enhanced SC preparedness through increased operation synchronization through sharing forecasts, sales data and plans. Hence, BDA management capabilities positively influence SC preparedness for unforeseen events. Accordingly, we hypothesize that:

H1a. BDA planning positively influences SC preparedness.

H1b. BDA investment decision making positively influences SC preparedness.

H1c. BDA coordination positively influences SC preparedness.

H1d. BDA control positively influences SC preparedness.

BDA management capabilities and SC alertness. SC alertness refers to a capability for identifying threats or changes in the business environment in a timely manner (Li *et al.*, 2009). Such challenges may arise from supplier network or operating business environment due to competitor's movement and strategies (Christopher and Holweg, 2011). It is required for SC focal firms to recognize problems and changes due to dynamicity in internal SC network for enhanced visibility in SCs (Christopher and Peck, 2004). Further, such higher visibility results in acknowledging complex interactions of firm's capabilities with changes in SC processes (Sambamurthy *et al.*, 2003).

BDA planning aids SC firms to develop business continuity plans for effectively addressing changes in their internal supplier network or the external business environment. BDA investment decision making aids SC focal firms to develop their resources and capabilities required for supporting their contingency plans. BDA coordination and control aid SC firms to develop a synergistic effort to respond in a positive manner to environmental changes. Hence, BDA management capabilities help SC firms to identify changes and respond to the same in a positive manner. Hence, we hypothesize that:

H2a. BDA planning positively influences SC alertness.

H2b. BDA investment decision making positively influences SC alertness.

H2c. BDA coordination positively influences SC alertness.

H2d. BDA control positively influences SC alertness.

BDA management capabilities and SC agility. SC agility implies an SC capability to respond to changes in a fast manner through suitable adaptation to environmental situations (Lee, 2004). SC agility also refers to an adaptation orientation in practicing different SC processes and SC facilities in the accomplishment of SC goals (Swafford *et al.*, 2006; Dubey *et al.*, 2017). Manuj and Mentzer (2008) suggested speed as the intrinsic quality of SC agility. Studies have highlighted SC agility goals in different ways. For example, SC agility aims to alter critical SC processes quickly to address dynamicity in supply/demand (Gligor and Holcomb, 2012), reduction of lead time and product development cycle times, etc. (Blome *et al.*, 2013). Hence, SC agility aims to respond in a positive manner to business environment changes.

BDA planning aids SC focal firms to alter their resource planning in a fast manner to meet changes in the marketplace on time. BDA investment decision making helps SC firms to carefully select resources for upgradation and development to obtain complimentary benefits for addressing market changes in a rapid manner. BDA coordination and control aids SC firms to re-align their individual resources and capabilities in a synergistic manner in a fast manner. Consequently, SC firms can respond quickly to environmental changes. Hence, we hypothesize that:

H3a. BDA planning positively influences SC agility.

H3b. BDA investment decision making influences SC agility.

H3c. BDA coordination positively influences SC agility.

H3d. BDA control positively influences SC agility.

Figure 1 shows the proposed hypotheses in a theoretical model.

Research methodology

Sample and data collection

The study employed several constructs with established scales of measurement. The constructs of BDA planning, investment decision making, coordination and control have developed scales based on recent literature (Wamba *et al.*, 2017). For SC preparedness, alertness and agility, extant scales of measurement were referred as benchmarks for further improvement (Li *et al.*, 2017). The study utilized Churchill's (1979) guidelines to develop

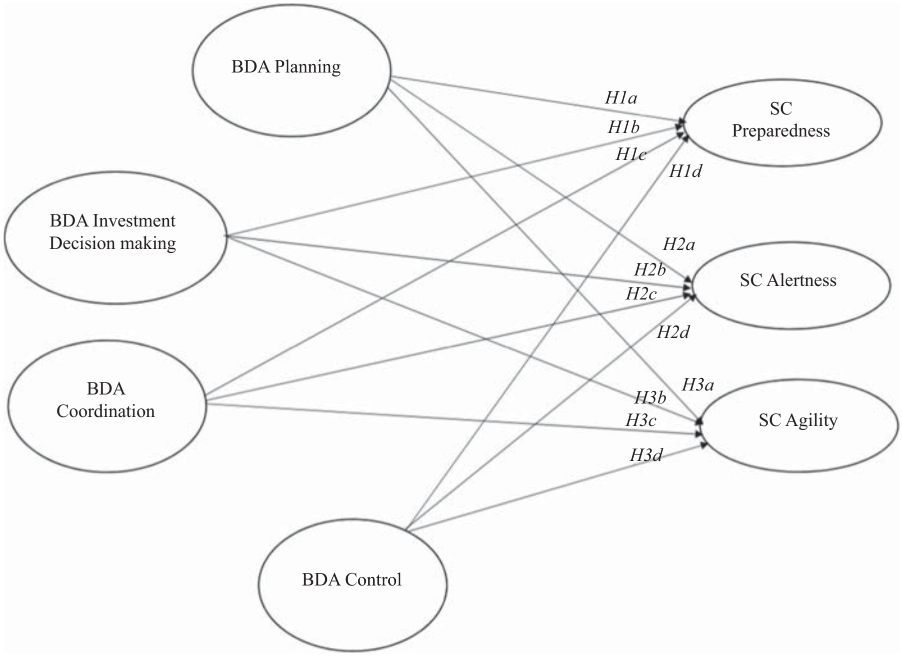

Figure 1.
Theoretical model

the measures. An expert team consisting of IT professionals engaged in analytics (with a minimum experience of five years) were chosen to review and revise the items (as necessary). Further, the measures were pre-tested with 32 IT professionals engaged in different industry sector involving SC management, increasing the face and content validity of the survey items. The final survey questionnaire was developed in Google Docs, and the survey link was mailed to 726 IT professionals with a minimum experience of two years in the field of analytics related to SC management. A list of such professionals was procured from a marketing research firm. The respondents were mailed a gentle reminder after a gap of two weeks. Repeated polite reminders were also made through phone (wherever possible). The survey participation also carried a token of appreciation of $3. These resulted in 249 final responses yielding a response rate of 34.29 percent. Table I shows the profile of final respondents.

As shown in Table I, 48.59 percent of the respondents have experience between 5 and 10 years, and 22.89 percent have to experience between 10 and 15 years. Further, 22.89 percent were engaged in manufacturing analytics, 15.26 percent involved in construction analytics, 29.32 percent engaged in retail analytics and 10.44 percent were engaged in textile analytics. Overall, the diversified sample ensured greater generalizability and validity of the findings.

Measures

Our study involved four first-order factors from BDA management capabilities and three first-order factors, namely, SC preparedness, SC alertness and SC agility. The extant scales of these seven factors were used as an initial platform for further refinement by the guidelines of Churchill (1979). The study executed an extensive literature review for the seven constructs for identification of initial survey items. Further, an expert group consisting of six practitioners and four researchers (with extensive experience in analytics and SC management) were requested to criticize the scale items for their expression and clarity and suggest suitable modifications.

	No.	Percentage
Sector		
Manufacturing	57	22.89
Construction	38	15.26
Retail	73	29.32
Textile	26	10.44
Others	55	22.09
Age (years)		
less than 30	118	47.39
30–35	67	26.91
35–40	38	15.26
40 and above	26	10.44
Experience (years)		
less than 5	71	28.51
5–10	121	48.59
10–15	57	22.89

Table I.
Respondents profile

The final measures went pre-testing with 59 contacts chosen randomly from the contacts developed earlier. Of these 59 respondents, 17 were in manufacturing analytics with average experience > 6.5 years, 24 were in retail analytics with average experience > 7.25 years, 8 were in construction analytics and remaining 10 were in textile analytics with average experience > 8.25 years. Such a diversified and experienced sample suggested relevant face and content validity for the measures.

After suitable modifications and subsequent adaptations, every latent first-order factor had around four measurement items that were measured using a seven-point Likert scale (1 = strongly disagree, 7 = strongly agree).

Non-response bias

The study evaluated the presence/absence of non-response bias through early and late response comparison (Armstrong and Overton, 1977). The study did not find any significant differences between the means. Furthermore, the study employed Mann–Whitney *U*-tests for the two categories of responses that did not reveal any meaningful differences ($p > 0.05$) across firm size and industry. The findings suggested the absence of any significant non-response bias.

Common method bias

An assessment of common method bias was deemed necessary since a single participant per firm was approached. Analysis of Harman's single-factor test of common method bias (Podsakoff, 2003) showed seven factors with eigenvalues > 1, explaining 81.6 percent variance. The first factor explained 31.5 percent variance. Next, a confirmatory factor analysis to Harman's single-factor model was applied (Flynn *et al.*, 2010). The model's fit indices of $\chi^2/\mathrm{df} = 15.3$, NFI = 0.55, CFI = 0.61 and RMSEA = 0.15 suggested rejection of a single-factor model. Hence, common method bias is not of significant concern in this study.

Path modeling and hypotheses testing

The study executed an exploratory factor analysis to check if the items are loading appropriately. Barlett's test of sphericity evaluated to 10,484.75, and was significant. Further, KMO was 0.828 (threshold is 0.5), implying satisfactory results for exploratory factor analysis.

The factor analysis showed few items that did not load appropriately and therefore was eliminated (IDMC2, CON4, PREP1, ALERT3, AG2). Partial least squares was widely used for hypotheses testing (Peng and Lai, 2012). Apart from several major reasons like presence of formative construct, minimal sample size, non-normal data, etc., we argue that the current study employed PLS for hypotheses testing since path modeling is of the primary concerns here. Since the whole objective of this study is to check the validity of the proposed paths, we utilized PLS instead of structural equation modeling (SEM). SEM is more stringent in that several assumptions like multivariate normality, etc., must be satisfied. PLS is more relaxed in such sense and focuses on the validity of the path coefficients. In adherence to prescribed guidelines of Peng and Lai (2012), the study utilized PLS for checking the validity of the proposed paths. Further, a component-based approach is more practical so far as hypotheses testing are concerned. Also, PLS is deemed suitable for predictive purposes (Peng and Lai, 2012).

The sample size while using PLS should be > 10 times the number of items of the largest latent variable. Since significance tests are absent in PLS, a bootstrapping analysis was executed with 1,000 sub-samples (Chin, 1998; Peng and Lai, 2012) for calculating the path coefficient, statistical significance and allied parameters. The study assessed first reliability, followed by an assessment of convergent and divergent validity.

Table II shows the latent variables with item loadings and corresponding *t*-stats. Further, Table III shows the average variance extracted (AVE), Cronbach's α and composite reliability for each latent variable.

The study first assessed reliability using the criterion, Cronbach's $\alpha > 0.7$ (Chin, 1998). Since all the latent variables reported to have Cronbach's $\alpha > 0.7$, the measures are deemed reliable. Convergent validity was next assessed using multiple criteria: item loading > 0.70 and statistical significance; composite construct reliability > 0.80; and AVE > 0.50 (Fornell and Larcker, 1981). Further, discriminant validity was assessed using the criterion: the square root of AVE for each latent variable $>$ its correlations with other latent variables (Fornell and Larcker, 1981).

As indicated in Tables II and III, standardized item loadings range from 0.867 to 0.973, composite reliabilities range from 0.779 to 0.972 and AVE values range from 0.776 to 0.911. In Table IV, the square root of AVE for each construct is larger than its correlations with all other constructs. Hence, these results show a highly acceptable level of reliability, convergent and discriminant validity. In addition, we have included Table V showing cross-loadings as other quality criteria.

Structural model assessment

The study utilized partial least squares in SmartPLS 2.0.M3 to estimate the value of path coefficients. However, in line with Peng and Lai (2012), the study assessed the validity of the structural model. The study assessed the predictive relevance of the proposed model through suitably deploying the blindfolding procedure of SmartPLS 2.0.M3. Construct cross-validated redundancy of SmartPLS gives Stone–Geisser's Q^2. This is obtained by executing the blindfolding procedure.

Stone–Geisser's Q^2 of dependent variables in our model, i.e. SC preparedness, SC alertness and SC agility, are, respectively, 0.469, 0.148 and 0.245. Thereby, the model in the study possess adequate, predictable relevance ($Q^2 > 0$ indicates acceptable predictable relevance).

Next, the study evaluated the effect of the latent predictor variables, i.e. BDA planning, BDA investment decision making, BDA coordination and BDA control on SC preparedness, alertness and agility using Cohen f^2. Table VI shows the relative effect sizes using Cohen f^2. According to Cohen (1988), f^2 values of 0.35, 0.15 and 0.02 are considered large, medium and small, respectively. Hence, we conclude that BDA planning, investment decision making,

	Loadings	*t*-stats
BDA planning capability (PLAN) (adapted from Wamba et al., 2017)		
As a key SC member, your firm continuously examines innovative opportunities for the strategic use of business analytics	0.933	47.62
As a key SC member, your firm implement adequate plans for the utilization of business analytics	0.972	151.82
As a key SC member, your firm perform business analytics planning processes in prescribed ways	0.949	44.72
As a key SC member, your firm frequently modify business analytics plans to better adapt to changing conditions	0.964	99.18
BDA investment decision-making capability (IDMC) (adapted from Wamba et al., 2017)		
Regarding investments in business analytics, your firm evaluates the effect they will have on the productivity of the employees' work	0.933	43.34
Regarding investments in business analytics, your firm projects how much these options will help end users make quicker decisions	0.969	120.95
Regarding investments for business analytics, your firm estimates the cost of training that end users will need	0.949	40.37
Regarding investments for business analytics, your firm estimates the time managers will need to spend overseeing the change	0.956	92.82
BDA coordination capability (COORD) (adapted from Wamba et al., 2017)		
In your firm, business analysts and line people meet regularly to discuss important issues	0.779	12.77
In your firm, business analysts and line people from various departments regularly attend cross-functional meetings	0.925	42.50
In your firm, business analysts and line people coordinate their efforts harmoniously	0.916	37.76
In your firm, information is widely shared among business analysts and line people so that those who make decisions or perform jobs have access to all available know-how	0.898	37.67
BDA control capability (adapted from Wamba et al., 2017)		
In your organization, the responsibility for analytics development is equally distributed	0.904	33.51
Your firm is confident that analytics project proposals are properly appraised	0.955	66.03
Your firm constantly monitors the performance of the analytics function	0.951	71.02
Your firm is better than competitors in connecting (e.g. communication and information sharing) parties within a business process	0.935	86.24
SC preparedness (adapted from Li et al., 2017)		
Your business unit select firms that are easy to work with as SC partners	0.957	95.84
Your business unit select trustworthy firms for developing SC partnerships	0.951	74.88
Your business unit frequently shares forecasts, sales data and plans with your SC partners	0.932	44.97
Your business unit develops contingency plan jointly with SC partners for increasing SC stability	0.947	81.15
SC alertness (adapted from Li et al., 2017)		
Your business can detect sudden changes in demand	0.894	34.72
Your business unit can detect threats to SC network	0.951	79.12
Your business unit can identify new technologies for increasing SC visibility	0.928	37.65
Your business unit can detect unexpected changes in physical flow throughout the SC	0.926	56.55
SC agility (adapted from Li et al., 2017)		
Your business unit can rearrange SC resources to address sudden demand fluctuations	0.893	36.68
Your business unit can adjust SC processes to reduce lead time	0.966	28.28
Your business unit can accommodate changes in SC processes to increase on-time delivery	0.940	44.77
Your business unit can synchronize SC processes to reduce non-value-added activities	0.960	79.13

Notes: SC, supply chain; BDA, big data analytics. All constructs were measured on a seven-point Likert scale with 1 = strongly disagree and 7 = strongly agree

Table II. Final measurement items

coordination and control are influential in their effect on SC preparedness, alertness and agility (Table VII).

Peng and Lai (2012) recommended the evaluation of a global goodness-of-fit index (Tenenhaus *et al.*, 2005) for assessing the holistic quality of the proposed model; however, later studies questioned its validity (Henseler and Sarstedt, 2013). Still, as a best practice, we calculated $\text{GOF}: \sqrt{\text{average communality}} \times \sqrt{\text{average } R^2} = \sqrt{0.871} \times \sqrt{0.332} = 0.537$.

This GOF evaluates the measurement model quality through average communality and the quality of the complete structural model in terms of average R^2 (Peng and Lai, 2012). Further, the sample size of 249 is well above the minimum sample size requirement of 140 as determined by the "5 times" rule of thumb (Hair *et al.*, 2006).

Using PLS, the study evaluated the path values and associated significance (*t*-statistics). Table VIII summarizes the results of hypotheses testing. Most of the hypotheses were supported except *H1b*, *H2b* and *H3b*. The proposed model explained 53 percent variance in SC preparedness, 18.1 percent in SC alertness and 28.6 percent in SC agility. Following Chin (1998), R^2 values of 0.67, 0.33 and 0.19 suggest substantial, moderate and weak predictive power, respectively, of the model under consideration. Hence, the proposed model exhibited sufficiently strong predictive ability.

Figure 2 summarizes the hypotheses testing results in a structural model.

Discussion

The study hypothesized positive effects of BDA planning, BDA investment decision making, BDA coordination and BDA control on SC resilience dimensions, namely, SC preparedness, SC alertness and SC agility. Results suggested that the model explained 53 percent variance in SC preparedness, 18.1 percent in SC alertness and 28.6 percent variance in SC agility. Further, the study found support for nine of the proposed hypotheses.

H1a–H1d posited positive effects of BDA planning, investment decision making, coordination and control of SC preparedness. The path coefficients are positive and significant for *H1a*, *H1c* and *H1d* (0.348, 0.623 and 0.345, respectively). Hence, *H1a*,

Table III. AVE, composite reliability and Cronbach's α of constructs

Construct	Items	Item loadings	Composite reliability	AVE	Cronbach's α
BDA planning	4	0.933–0.972	0.976	0.911	0.967
BDA investment DM	4	0.933–0.969	0.974	0.906	0.965
BDA coordination	4	0.779–0.925	0.932	0.776	0.903
BDA control	4	0.904–0.955	0.965	0.876	0.952
SC preparedness	4	0.932–0.957	0.971	0.896	0.961
SC alertness	4	0.894–0.951	0.959	0.855	0.943
SC agility	4	0.893–0.966	0.966	0.879	0.953

Table IV. Discriminant validity

	$X1$	$X2$	$X3$	$X4$	$X5$	$X6$	$X7$
BDA control ($X1$)	*0.935*						
BDA coordination ($X2$)	0.163	*0.881*					
BDA investment decision making ($X3$)	0.337	0.483	*0.951*				
BDA planning ($X4$)	0.251	0.501	0.549	*0.954*			
SC agility ($X5$)	0.070	0.445	0.290	0.415	*0.937*		
SC alertness ($X6$)	0.107	0.321	0.115	0.313	0.826	*0.924*	
SC preparedness ($X7$)	0.418	0.588	0.400	0.146	0.165	0.122	*0.946*

Note: Diagonal: Sqrt of AVE

	BDA control	BDA coordination	BDA investment decision making	BDA planning	SC agility	SC alertness	SC preparedness
AG1	0.004	0.430	0.299	0.409	*0.893*	0.437	0.144
AG3	0.059	0.418	0.286	0.391	*0.966*	0.268	0.171
AG4	0.109	0.406	0.264	0.381	*0.940*	0.394	0.143
AG5	0.089	0.414	0.239	0.375	*0.950*	0.196	0.161
ALERT1	0.027	0.291	0.098	0.293	0.203	*0.894*	0.114
ALERT2	0.090	0.294	0.101	0.261	0.354	*0.951*	0.123
ALERT4	0.139	0.301	0.136	0.313	0.597	*0.928*	0.107
ALERT5	0.129	0.302	0.089	0.289	0.492	*0.926*	0.108
CON1	*0.904*	0.129	0.267	0.171	0.068	0.077	0.410
CON2	*0.955*	0.189	0.329	0.252	0.043	0.060	0.415
CON3	*0.951*	0.142	0.334	0.244	0.084	0.149	0.377
CON5	*0.935*	0.149	0.336	0.277	0.066	0.118	0.359
COORD1	0.122	*0.779*	0.452	0.472	0.353	0.279	0.340
COORD2	0.151	*0.925*	0.405	0.471	0.422	0.332	0.524
COORD3	0.184	*0.916*	0.433	0.417	0.391	0.254	0.586
COORD4	0.113	*0.898*	0.428	0.425	0.399	0.274	0.589
IDMC1	0.312	0.448	*0.933*	0.513	0.298	0.137	0.364
IDMC3	0.330	0.468	*0.969*	0.521	0.274	0.088	0.384
IDMC4	0.299	0.442	*0.949*	0.508	0.248	0.079	0.362
IDMC5	0.341	0.478	*0.956*	0.545	0.282	0.130	0.411
PLAN1	0.231	0.478	0.519	*0.933*	0.359	0.273	0.133
PLAN2	0.262	0.496	0.545	*0.972*	0.412	0.301	0.166
PLAN3	0.224	0.465	0.527	*0.949*	0.390	0.298	0.131
PLAN4	0.239	0.476	0.504	*0.964*	0.421	0.321	0.128
PREP2	0.445	0.561	0.380	0.131	0.138	0.102	*0.957*
PREP3	0.462	0.544	0.386	0.108	0.137	0.085	*0.951*
PREP4	0.303	0.598	0.423	0.181	0.194	0.144	*0.932*
PREP5	0.362	0.525	0.324	0.137	0.160	0.136	*0.947*

Table V. Cross-loadings of the items

Construct	Dependent variable	f^2
BDA planning	SC preparedness	0.38
BDA investment decision making	SC preparedness	0.04
BDA coordination	SC preparedness	0.56
BDA control	SC preparedness	0.104
BDA planning	SC alertness	0.163
BDA investment decision making	SC alertness	0.07
BDA coordination	SC alertness	0.255
BDA control	SC alertness	0.136
BDA planning	SC agility	0.168
BDA investment decision making	SC agility	0.12
BDA coordination	SC agility	0.192
BDA control	SC agility	0.253

Table VI. Cohen f^2 values

H1c and *H1d* are supported. Again, *H2a–H2d* posited positive effects of BDA management capabilities on SC alertness. The path coefficients are positive and significant for *H2a*, *H2c* and *H2d* (0.288, 0.258 and 0.186, respectively). Hence, *H2a*, *H2c* and *H2d* are supported.

Furthermore, *H3a–H3d* posited positive effects of BDA management capabilities on SC agility. The path coefficients are positive and significant for *H3a*, *H3c* and *H3d* (0.281, 0.310 and 0.210, respectively). Hence, *H3a*, *H3c* and *H3d* are supported. The study, therefore, did

Table VII.
Average R^2 and AVEs

Construct	R^2	Communality (AVE)
BDA planning	–	0.911
BDA investment decision making	–	0.906
BDA coordination	–	0.776
BDA control	–	0.876
SC preparedness	0.53	0.896
SC alertness	0.181	0.855
SC agility	0.286	0.878
Average	0.332	0.871

Table VIII.
Results of hypotheses testing

Summary of hypotheses testing				
No.	Relationship	Path coefficient	t-values	Supported?
H1a	BDA planning (+) → SC preparedness	0.348	3.030	Yes
H1b	BDA investment decision making (+) → SC preparedness	0.174	1.325	No
H1c	BDA coordination (+) → SC preparedness	0.623	6.116	Yes
H1d	BDA control (+) → SC preparedness	0.345	3.549	Yes
H2a	BDA planning (+) → SC alertness	0.288	2.784	Yes
H2b	BDA investment decision making (+) → SC alertness	0.105	1.164	No
H2c	BDA coordination (+) → SC alertness	0.258	2.279	Yes
H2d	BDA control (+) → SC alertness	0.186	2.197	Yes
H3a	BDA planning (+) → SC agility	0.281	2.879	Yes
H3b	BDA investment decision making (+) → SC agility	0.057	0.079	No
H3c	BDA coordination (+) → SC agility	0.310	3.116	Yes
H3d	BDA control (+) → SC agility	0.210	2.457	Yes

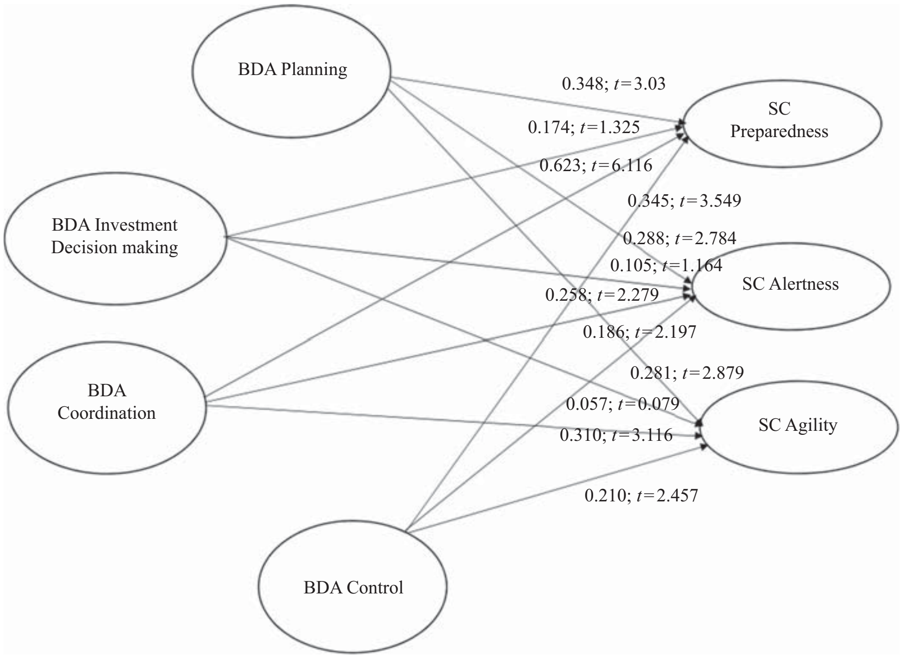

Figure 2.
Structural model results

not find support for *H1c*, *H2c* and *H3c*, thereby indicating that BDA investment decision making may not be an important enabler for SC preparedness, SC alertness and SC agility.

The findings, therefore, established BDA planning, BDA coordination and BDA control as significant enablers of SC preparedness, SC alertness and SC agility. The study identified that the extant literature is yet to explore the importance of BDA in the development of SC capabilities, especially SC risk management capabilities. SC resilience is an effective risk mitigation capability as it enables SCs to restore operations when disrupted. In this arena, the study identified three dimensions of SC resilience based on extant literature (Li *et al.*, 2017).

Hence, the study contributed prominently to the identified gaps in the literature of BDA and SC management interfaces, by recognizing the importance of big data management capabilities in the development of SC resilience dimensions. The study posited each of the SC resilience dimensions as an important dynamic capability that could be developed due to the proper deployment of BDA management capabilities. Hence, the study also contributed in utilizing the dynamic capability extension (Teece, 2016) of RBV in comprehending the importance of BDA capabilities on SC resilience.

Implications

With the use of advanced analytical tools, BDA can derive meaningful insights from vast amounts of data to aid timely decision making (Tan *et al.*, 2015). While sensors, barcodes and RFID were widely being used to enhance integration and coordination in SCs, BDA had the potential of changing the game in traditional SC management (Fawcett and Waller, 2014; Dubey *et al.*, 2016) through decreased operational costs and enhanced customer satisfaction (Sheffi, 2015; Ramanathan *et al.*, 2017). However, extant studies were mostly limited to conceptual investigations (Arunachalam *et al.*, 2018; Addo-Tenkorang and Helo, 2016) and, therefore, empirical examinations regarding BDA in SC management was encouraged (Wamba *et al.*, 2017; Arunachalam *et al.*, 2018). While the potential for enhancing SC performance was suggested (Nguyen *et al.*, 2017), only 17 percent of firms have implemented BDA in one or more SC function (Wang, Gunasekaran and Ngai, 2016; Wang, Gunasekaran, Ngai and Papadopoulos, 2016). This can be attributed to the lesser recognition of benefits associated with BDA for many organizations, due to which they are hesitant to invest for BDA (Arunachalam *et al.*, 2018). Hence, our study contributed through an empirical study to identify the potential benefits of BDA capabilities in the development of SC preparedness, SC alertness and SC agility.

Our study has several implications for theory development and SC managers. First, the study utilized the dynamic capability view (Teece *et al.*, 1997; Teece, 2016) to explore the importance of BDA management capabilities (BDA planning, BDA investment decision making, BDA coordination and BDA control) on SC resilience dimensions. The study therefore advanced dynamic capability theory to explore the development of SC preparedness, SC alertness and SC agility through BDA management capabilities.

First, the study underscored that BDA planning, BDA coordination and BDA control are prominent enablers of SC preparedness. SC preparedness aims to select partners that are reliable and willing to collaborate for enhancing sustainability of SC operations (Li *et al.*, 2017). BDA planning, therefore, can aid focal firms to analyze past performance data of potential suppliers and make appropriate decisions. Furthermore, this analysis of past performance also aids in effective supplier performance management (Talluri and Narasimhan, 2004). Furthermore, BDA planning also helps in supplier management decision through appropriate analysis of spending pattern (Panchmatia, 2015). BDA coordination allows focal SC firms to share their production forecasts and sales data in real-time mode with their suppliers, thereby leading to enhanced transparency. Such a real-time information sharing aids in building sustained SC partnerships, required for building effective resilience.

Such partnerships help in enhanced preparedness for addressing disruptions. BDA control aids focal firms to gain better control through real-time analysis of data and adequate monitoring. Hence, the firms in an SC can plan well their contingency plans efficiently for addressing uncertainties (Wu *et al.*, 2017). Hence, the study suggests that managers should train their employees for effectively using in their routine and strategic operations.

Second, the study proved that BDA planning, BDA coordination and BDA control are critical for developing SC alertness. SC alertness aims to identify changes in internal network and external business environment that can be potential threats for SC survival (Li *et al.*, 2017). BDA planning aids focal firms to detect such changes through appropriately analyzing and monitoring business changes. Furthermore, focal SC firms can detect changes in internal and external environment more readily due to higher coordination lead by big data (Gunasekaran *et al.*, 2017). SC firms can have therefore had better control over their operations and, hence, can plan for addressing disruptions for maintaining sustainability (Zhao *et al.*, 2017). Hence, managers should emphasize their peers and employees to use BDA to plan and coordinate SC operations. BDA control would aid SC firms to alert their partners of any potential changes in the business conditions, while maintaining stability over operations (Wamba *et al.*, 2017).

Third, the study also highlighted BDA planning, BDA coordination and BDA control as prominent enablers of SC agility. SC agility aims to respond to market changes in a fast manner (Li *et al.*, 2017). BDA planning therefore aids SC firms to detect and respond to market changes in a fast manner through timely information sharing, monitoring, decision making and strategy implementation (Giannakis and Louis, 2016). BDA coordination helps SC firms to develop synchronization of operations with one another. Such synchronized effort aids SC firms to respond in a unified and speedy manner. BDA control help SC firms to maintain stability over SC operations for enhanced sustainability (Wu *et al.*, 2017), while allowing them to address changes in a fast pace (Giannakis and Louis, 2016). Hence, managers should develop plans for upgrading their IT infrastructure required for effective functioning of BDA.

Fourth, our study showed that BDA investment decision making does not have any prominent influence on SC preparedness, SC alertness and SC agility. This may be attributed to the fact that SC capabilities require effective development of contingency plans and synchronized effort for enhanced risk mitigation and disaster preparedness. The decisions for developing BDA infrastructure and associated technologies are not directly related to the development of SC preparedness, SC alertness and SC agility.

Limitations and future research

Our study explored the importance of BDA management capabilities on the development of important SC resilience dimensions. Using dynamic capability view, the study posited BDA management capabilities of planning, investment decision making, coordination and control are important enablers of SC preparedness, SC alertness and SC agility. However, like other survey-based studies, the current investigation also has its limitations. Based on extant literature (Wamba *et al.*, 2017), the study concentrated on established dimensions of BDA management capabilities. However, the study did not explore the influence of BDA infrastructure flexibility and BDA personnel expertise capability on SC resilience dimensions. Second, the study relied on single informant approach per organization. Although sufficient care has been taken to ensure reliability and validity of our findings, future studies should resort to multiple informant approach for increased generalizability and validation. Future studies should explore the role of other BDA-based capabilities in the development of SC resilience dimensions. Furthermore, many studies have connoted several other dimensions of SC resilience (Gu and Huo, 2017; Liu *et al.*, 2018; Chowdhury and Quaddus, 2017; Cheng and Lu, 2017). Future studies can explore the importance of BDA-based capabilities in the development of other SC resilience dimensions.

References

Accenture Global Operations Megatrends Study (2014), "Big data analytics in supply chain: hype or here to stay?", available at: www.accenture.com/us-en/Pages/insight-global-operations-megatrends-big-data-analytics.aspx (accessed December 7, 2014).

Addo-Tenkorang, R. and Helo, P.T. (2016), "Big data applications in operations/supply-chain management: a literature review", *Computers & Industrial Engineering*, Vol. 101 No. 11, pp. 528-543.

Afshari, H. and Peng, Q. (2015), "Using big data to minimize uncertainty effects in adaptable product design", *ASME 2015 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, Boston, MA, August 3-5*.

Ambulkar, S., Blackhurst, J. and Grawe, S. (2015), "Firm's resilience to supply chain disruptions: scale development and empirical examination", *Journal of Operations Management*, Vol. 33 No. 1, pp. 111-122.

Amit, R. and Schoemaker, P.J. (1993), "Strategic assets and organizational rent", *Strategic Management Journal*, Vol. 14 No. 1, pp. 33-46.

Armstrong, J.S. and Overton, T.S. (1977), "Estimating nonresponse bias in mail surveys", *Journal of Marketing Research*, Vol 14 No. 3, pp. 396-402.

Arunachalam, D., Kumar, N. and Kawalek, J.P. (2018), "Understanding big data analytics capabilities in supply chain management: unravelling the issues, challenges and implications for practice", *Transportation Research Part E: Logistics and Transportation Review*, Vol. 114 No. 6, pp. 416-436.

Barney, J., Wright, M. and Ketchen, D.J. Jr (2001), "The resource-based view of the firm: Ten years after 1991", *Journal of Management*, Vol. 27 No. 6, pp. 625-641.

Bellow, E. (2016), "Supply chain resilience", in Bals, L. and Tate, W. (Eds), *Implementing Triple Bottom Line Sustainability into Global Supply Chains*, 1st ed., Greenleaf, Austin, TX, pp. 34-57.

Bhatt, G.D. and Grover, V. (2005), "Types of information technology capabilities and their role in competitive advantage: an empirical study", *Journal of Management Information Systems*, Vol. 22 No. 2, pp. 253-277.

Blome, C., Schoenherr, T. and Rexhausen, D. (2013), "Antecedents and enablers of supply chain agility and its effects on firm performance: a dynamic capabilities perspective", *International Journal of Production Research*, Vol. 51 No. 4, pp. 1295-1318.

Brouer, B.D., Karsten, C.V. and Pisinger, D. (2016), "Big data optimization in maritime logistics", in Emrouznejad, A. (Ed.), *Big Data Optimization: Recent Developments and Challenges, Vol. 18*, Springer International Pub. of the Series Studies in Big Data, Heidelberg, pp. 319-344.

Cao, M. and Zhang, Q. (2011), "Supply chain collaboration: impact on collaborative advantage and firm performance", *Journal of Operations Management*, Vol. 29 No. 3, pp. 163-180.

Capron, E. (2013), "How big data has delivered for FedEx for 25 years: SAP business innovation", available at: http://blogs.sap.com/innovation/big-data/big-data-deliveredfedex-25-years-0887095

Chase, C.W. Jr (2013), "Using big data to enhance demand-driven forecasting and planning", *The Journal of Business Forecasting*, Vol. 32 No. 2, pp. 27-32.

Chavez, R., Yu, W., Jacobs, M. and Feng, M. (2017), "Data-driven supply chain management, manufacturing capability and customer satisfaction", *Academy of Management Proceedings*, Vol. 2017 No. 1.

Cheng, J.H. and Lu, K.L. (2017), "Enhancing effects of supply chain resilience: insights from trajectory and resource-based perspectives", *Supply Chain Management: An International Journal*, Vol. 22 No. 4, pp. 329-340.

Chin, W.W. (1998), "The partial least squares approach to structural equation modeling", *Modern Methods for Business Research*, Vol. 295 No. 2, pp. 295-336.

Chowdhury, M.M.H. and Quaddus, M. (2017), "Supply chain resilience: conceptualization and scale development using dynamic capability theory", *International Journal of Production Economics*, Vol. 188 No. 6, pp. 185-204.

Christopher, M. and Holweg, M. (2011), "Supply chain 2.0 = : managing supply chains in the era of turbulence", *International Journal of Physical Distribution & Logistics Management*, Vol. 41 No. 1, pp. 63-82.

Christopher, M. and Peck, H. (2004), "Building the resilient supply chain", *The International Journal of Logistics Management*, Vol. 15 No. 2, pp. 1-14.

Churchill, G.A. Jr (1979), "A paradigm for developing better measures of marketing constructs", *Journal of Marketing Research*, Vol 16 No. 1, pp. 64-73.

Cohen, J. (1988), *Statistical Power Analysis for the Behavioral Sciences*, 2nd ed., Erlbaum, Hillsdale, NJ.

Denrell, J. and Powell, T. (2016), "Dynamic capability as a theory of competitive advantage: contributions and scope conditions", *Handbook on Dynamic Capabilities*, University Press, Oxford.

Dubey, R., Gunasekaran, A., Childe, S.J., Wamba, S.F. and Papadopoulos, T. (2016), "The impact of big data on world-class sustainable manufacturing", *The International Journal of Advanced Manufacturing Technology*, Vol. 84 No. 4, pp. 631-645.

Dubey, R., Altay, N., Gunasekaran, A., Blome, C., Papadopoulos, T. and Childe, S. (2017), "Supply chain agility, adaptability and alignment: empirical evidence from the Indian auto components industry", *International Journal of Operations and Production Management*.

Durach, C.F., Wieland, A. and Machuca, J.A.D. (2015), "Antecedents and dimensions of supply chain robustness: a systematic literature review", *International Journal of Physical Distribution & Logistics Management*, Vol. 45 Nos 1/2, pp. 118-137.

Eisenhardt, K. and Martin, J. (2000), "Dynamic capabilities: what are they?", *Strategic Management Journal*, Vol. 21 Nos 10/11, pp. 1105-1122.

Fan, Y., Heilig, L. and Voß, S. (2015), "Supply chain risk management in the era of big data", *International Conference of Design, User Experience, and Usability, Springer International Publishing*, pp. 283-294.

Fawcett, S.E. and Waller, M.A. (2014), "Supply chain game changers – mega, nano, and virtual trends – and forces that impede supply chain design (i.e., building a winning team)", *Journal of Business Logistics*, Vol. 35 No. 3, pp. 157-164.

Flynn, B.B., Huo, B. and Zhao, X. (2010), "The impact of supply chain integration on performance: a contingency and configuration approach", *Journal of Operations Management*, Vol. 28 No. 1, pp. 58-71.

Fornell, C. and Larcker, D.F. (1981), "Structural equation models with unobservable variables and measurement error: algebra and statistics", *Journal of Marketing Research*, Vol 18 No. 3, pp. 382-388.

Giannakis, M. and Louis, M. (2016), "A multi-agent based system with big data processing for enhanced supply chain agility", *Journal of Enterprise Information Management*, Vol. 29 No. 5, pp. 706-727.

Gligor, D.M. and Holcomb, M.C. (2012), "Antecedents and consequences of supply chain agility: establishing the link to firm performance", *Journal of Business Logistics*, Vol. 33 No. 4, pp. 295-308.

Gu, M. and Huo, B. (2017), "The impact of supply chain resilience on company performance: a dynamic capability perspective", *Academy of Management Proceedings*, Vol. 2017 No. 1.

Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S.F., Childe, S.J., Hazen, B. and Akter, S. (2017), "Big data and predictive analytics for supply chain and organizational performance", *Journal of Business Research*, Vol. 70 No. 1, pp. 308-317.

Hair, J.F.J., Black, W.C., Babin, B.J., Anderson, R.E. and Tatham, R.L. (2006), *Multivariate Data Analysis*, Pearson Education, Inc., Vol. 6, NJ.

Hassani, H. and Silva, E.S. (2015), "Forecasting with big data: a review", *Annals of Data Science*, Vol. 2 No. 1, pp. 5-19.

Hazen, B.T., Boone, C.A., Ezell, J.D. and 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*, Vol. 154 No. 8, pp. 72-80.

Hazen, B.T., Skipper, J.B., Ezell, J.D. and Boone, C.A. (2016), "Big Data and predictive analytics for supply chain sustainability: a theory-driven research agenda", *Computers & Industrial Engineering*, Vol. 101 No. 11, pp. 592-598.

Henseler, J. and Sarstedt, M. (2013), "Goodness-of-fit indices for partial least squares path modeling", *Computational Statistics*, Vol 28 No. 2, pp. 1-16.

Hohenstein, N.O., Feisel, E., Hartmann, E. and Giunipero, L. (2015), "Research on the phenomenon of supply chain resilience: a systematic review and paths for further investigation", *International Journal of Physical Distribution & Logistics Management*, Vol. 45 No. 1/2, pp. 90-117.

Hult, G.T.M., Ketchen, G. Jr and Slater, S.F. (2004), "Information processing, knowledge development, and strategic supply chain performance", *Academy of Management Journal*, Vol. 47 No. 2, pp. 241-253.

Huo, B., Han, Z. and Prajogo, D. (2016), "Antecedents and consequences of supply chain information integration: a resource-based view", *Supply Chain Management: An International Journal*, Vol. 21 No. 6, pp. 661-677.

Jüttner, U. and Maklan, S. (2011), "Supply chain resilience in the global financial crisis: an empirical study", *Supply Chain Management*, Vol. 16 No. 4, pp. 246-259.

Katchasuwanmanee, K., Bateman, R. and Cheng, K. (2016), "Development of the energysmart production management system (e-ProMan): a big data driven approach, analysis and optimization", *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, Vol. 230 No. 5, pp. 1-7.

Ketchen, G. Jr and Hult, T.M. (2007), "Bridging organization theory and supply chain management: the case of best value supply chains", *Journal of Operations Management*, Vol. 25 No. 2, pp. 573-580.

Krause, D.R., Handfield, R.B. and Tyler, B.B. (2007), "The relationships between supplier development, commitment, social capital accumulation and performance improvement", *Journal of Operations Management*, Vol. 25 No. 2, pp. 528-545.

Lam, J.S.L. and Bai, X. (2016), "A quality function deployment approach to improve maritime supply chain resilience", *Transportation Research Part E: Logistics and Transportation Review*, Vol. 92 No. 8, pp. 16-27.

Lee, H.L. (2004), "The triple-a supply chain", *Harvard Business Review*, Vol. 82 No. 10, pp. 102-112.

Li, X., Goldsby, T.J. and Holsapple, C.W. (2009), "Supply chain agility: scale development", *International Journal of Logistics Management*, Vol. 20 No. 2, pp. 408-424.

Li, X., Chung, C., Goldsby, T.J. and Holsapple, C.W. (2008), "A unified model of supply chain agility: the work-design perspective", *International Journal of Logistics Management*, Vol. 19 No. 3, pp. 408-435.

Li, X., Wu, Q., Holsapple, C.W. and Goldsby, T. (2017), "An empirical examination of firm financial performance along dimensions of supply chain resilience", *Management Research Review*, Vol. 40 No. 3, pp. 254-269.

Liu, C.L., Shang, K.C., Lirn, T.C., Lai, K.H. and Lun, Y.V. (2018), "Supply chain resilience, firm performance, and management policies in the liner shipping industry", *Transportation Research Part A: Policy and Practice*, Vol. 110, pp. 202-219.

LMG (2014), "Big potential in big data: business services", available at: www.royalmail.com/marketing-services-regular/marketreach

MacCarter, M.W. and Northcraft, G.B. (2007), "Happy together? Insights and implications of viewing managed supply chains as a social dilemma", *Journal of Operations Management*, Vol. 25 No. 2, pp. 498-511.

Makadok, R. (2001), "Toward a synthesis of the resource-based and dynamic-capability views of rent creation", *Strategic Management Journal*, Vol. 22 No. 5, pp. 387-401.

Mandal, S.R., Sarathy, R., Korasiga, V.R., Bhattacharya, S. and Dastidar, S.G. (2016), "Achieving supply chain resilience: the contribution of logistics and supply chain capabilities", *International Journal of Disaster Resilience in the Built Environment*, Vol. 7 No. 5, pp. 544-562.

Manuj, I. and Mentzer, J.T. (2008), "Global supply chain risk management strategies", *International Journal of Physical Distribution & Logistics Management*, Vol. 38 No. 3, pp. 192-223.

Martin, J., Moritz, G. and Frank, W. (2013), "Big data in logistics a DHL perspective on how to move beyond the hype", DHL Customer Solutions and Innovation, Troisdorf, pp. 1-30.

Mehmood, R. and Graham, G. (2015), "Big data logistics: a health-care transport capacity sharing model", *Procedia Computer Science*, Vol. 64 No. 9, pp. 1107-1114.

Miles, R.E. and Snow, C.C. (2007), "Organization theory and supply chain management: an evolving research perspective", *Journal of Operations Management*, Vol. 25 No. 2, pp. 459-463.

Morgan, N.A., Kaleka, A. and Gooner, R.A. (2007), "Focal supplier opportunism in supermarket retailer category management", *Journal of Operations Management*, Vol. 25 No. 2, pp. 512-527.

Muhtaroglu, F.C.P., Demir, S., Obali, M. and Girgin, C. (2013), "Business model canvas perspective on big data applications", *2013 IEEE International Conference on Big Data, IEEE, October*, pp. 32-37.

Nguyen, T., Li, Z.H.O.U., Spiegler, V., Ieromonachou, P. and Lin, Y. (2017), "Big data analytics in supply chain management: a state-of-the-art literature review", *Computers & Operations Research*.

Panchmatia, M. (2015), "Use big data to help procurement 'make a real difference", available at: www.4cassociates.com (accessed August 8, 2016).

Peng, D.X. and Lai, F. (2012), "Using partial least squares in operations management research: a practical guideline and summary of past research", *Journal of Operations Management*, Vol. 30 No. 6, pp. 467-480.

Pettit, T.J., Fiksel, J. and Croxton, K.L. (2010), "Ensuring supply chain resilience: development of a conceptual framework", *Journal of Business Logistics*, Vol. 31 No. 1, pp. 1-21.

Podsakoff, N.P. (2003), "Common method biases in behavioral research: a critical review of the literature and recommended remedies", *Journal of Applied Psychology*, Vol. 88 No. 5, pp. 879-903.

Ponomarov, S. (2012), "Antecedents and consequences of supply chain resilience: a dynamic capabilities perspective", PhD dissertation, University of Tennessee.

Ponomarov, S.Y. and Holcomb, M.C. (2009), "Understanding the concept of supply chain resilience", *The International Journal of Logistics Management*, Vol. 20 No. 1, pp. 124-143.

Prajogo, D., Oke, A. and Olhager, J. (2016), "Supply chain processes: linking supply logistics integration, supply performance, lean processes and competitive performance", *International Journal of Operations & Production Management*, Vol. 36 No. 2, pp. 220-238.

Ramanathan, U., Subramanian, N. and Parrott, G. (2017), "Role of social media in retail network operations and marketing to enhance customer satisfaction", *International Journal of Operations & Production Management*, Vol. 37 No. 1, pp. 105-123.

Roßmann, B., Canzaniello, A., von der Gracht, H. and Hartmann, E. (2017), "The future and social impact of big data analytics in supply chain management: results from a Delphi study", Technological Forecasting and Social Change, Vol. 130, May, pp. 135-149.

Sambamurthy, V., Bharadwaj, A. and Grover, V. (2003), "Shaping agility through digital options: reconceptualizing the role of information technology in contemporary firms", *MIS Quarterly*, Vol. 27 No. 2, pp. 237-263.

Schoenherr, T. and Speier-Pero, C. (2015), "Data science, predictive analytics, and big data in supply chain management: current state and future potential", *Journal of Business Logistics*, Vol. 36 No. 1, pp. 120-132.

Sheffi, Y. (2015), "Preparing for disruptions through early detection", *MIT Sloan Management Review*, Vol. 57 No. 1, pp. 31-42.

Stich, V., Jordan, F., Birkmeier, M., Oflazgil, K., Reschke, J. and Diews, A. (2015), "Big data technology for resilient failure management in production systems", in Umeda, S., Nakano, M., Mizuyama, H., Hibino, N., Kiritsis, D. and von Cieminski, G. (Eds), *Advances in Production Management Systems: Innovative Production Management towards Sustainable Growth. IFIP Advances in Information and Communication Technology*, Vol. 459, Springer, Cham, pp. 447-454.

Stonebraker, P.W., Goldhar, J. and Nassos, G. (2009), "Weak links in the supply chain: measuring fragility and sustainability", *Journal of Manufacturing Technology Management*, Vol. 20 No. 2, pp. 161-177.

Swafford, P.M., Ghosh, S. and Murthy, N. (2006), "The antecedents of supply chain agility of a firm: scale development and model testing", *Journal of Operations Management*, Vol. 24 No. 2, pp. 170-188.

Talluri, S. and Narasimhan, R. (2004), "A methodology for strategic sourcing", *European Journal of Operational Research*, Vol. 154 No. 1, pp. 236-250.

Tan, K.H., Zhan, Y., Ji, G., Ye, F. and Chang, C. (2015), "Harvesting big data to enhance supply chain innovation capabilities: an analytic infrastructure based on deduction graph", *International Journal of Production Economics*, Vol. 165, pp. 223-233.

Tang, C.S. (2006), "Robust strategies for mitigating supply chain disruptions", *International Journal of Logistics: Research and Applications*, Vol. 9 No. 1, pp. 33-45.

Teece, D.J. (2016), "Dynamic capabilities and entrepreneurial management in large organizations: toward a theory of the (entrepreneurial) firm", *European Economic Review*, Vol. 86 No. 6, pp. 202-216.

Teece, D.J. (2017), "Dynamic capabilities and the multinational enterprise", *Globalization*, Springer, Berlin and Heidelberg, pp. 105-129.

Teece, D.J., Pisano, G. and Shuen, A. (1997), "Dynamic capabilities and strategic management", *Strategic Management Journal*, Vol 18 No. 7, pp. 509-533.

Tenenhaus, M., Vinzi, V.E., Chatelin, Y.M. and Lauro, C. (2005), "PLS path modeling", *Computational Statistics & Data Analysis*, Vol. 48 No. 1, pp. 159-205.

Tiwari, S., Wee, H.M. and Daryanto, Y. (2018), "Big data analytics in supply chain management between 2010 and 2016: insights to industries", *Computers & Industrial Engineering*, Vol. 115 No. 1, pp. 319-330.

Välikangas, L. (2010), *The Resilient Organization: How Adaptive Cultures Thrive Even When Strategy Fails*, McGraw-Hill, New York, NY.

Wallace, S.W. and Choi, T.M. (2011), "Flexibility, information structure, options, and market power in robust supply chains", *International Journal of Production Economics*, Vol. 134 No. 2, pp. 284-288.

Waller, M.A. and 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*, Vol. 34 No. 2, pp. 77-84.

Wamba, S.F., Akter, S., Edwards, A., Chopin, G. and 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*, Vol. 165 No. 7, pp. 234-246.

Wamba, S.F., Gunasekaran, A., Akter, S., Ren, S.J.F., Dubey, R. and Childe, S.J. (2017), "Big data analytics and firm performance: effects of dynamic capabilities", *Journal of Business Research*, Vol. 70 No. 1, pp. 356-365.

Wang, G., Gunasekaran, A. and Ngai, E.W.T. (2016), "Distribution network design with big data: model and analysis", *Annals of Operations Research*, pp. 1-13, available at: https://doi.org/10.1007/s10479-016-2263-8

Wang, G., Gunasekaran, A., Ngai, E.W. and Papadopoulos, T. (2016), "Big data analytics in logistics and supply chain management: certain investigations for research and applications", *International Journal of Production Economics*, Vol. 176 No. 6, pp. 98-110.

Wieland, A. and Wallenburg, C.M. (2013), "The influence of relational competencies on supply chain resilience: a relational view", *International Journal of Physical Distribution and Logistics Management*, Vol. 43 No. 4, pp. 300-320.

Wilden, R., Devinney, T.M. and Dowling, G.R. (2016), "The architecture of dynamic capability research identifying the building blocks of a configurational approach", *Academy of Management Annals*, Vol. 10 No. 1, pp. 997-1076.

Wu, K.J., Liao, C.J., Tseng, M.L., Lim, M.K., Hu, J. and Tan, K. (2017), "Toward sustainability: using big data to explore the decisive attributes of supply chain risks and uncertainties", *Journal of Cleaner Production*, Vol. 142 No. 2, pp. 663-676.

Yu, W., Chavez, R., Jacobs, M.A. and Feng, M. (2017), "Data-driven supply chain capabilities and performance: a resource-based view", *Transportation Research Part E: Logistics and Transportation Review*, Vol. 114, June, pp. 371-385.

Yu, W., Jacobs, M.A., Chavez, R. and Feng, M. (2017), "The impacts of IT capability and marketing capability on supply chain integration: a resource-based perspective", *International Journal of Production Research*, Vol. 55 No. 14, pp. 4196-4211.

Zhao, R., Liu, Y., Zhang, N. and Huang, T. (2017), "An optimization model for green supply chain management by using a big data analytic approach", *Journal of Cleaner Production*, Vol. 142 No. 2, pp. 1085-1097.

Zhong, R.Y., Newman, S.T., Huang, G.Q. and Lan, S. (2016), "Big data for supply chain management in the service and manufacturing sectors: challenges, opportunities, and future perspectives", *Computers & Industrial Engineering*, Vol. 101 No. 11, pp. 572-591.

Further reading

Hazen, B.T., Skipper, J.B., Boone, C.A. and 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, S.I.: Big Data Analytics in Operations and Supply Chain Management, available at: http://dx.doi.org/10.1007/s10479-016-2226-0

Pettit, T.J., Croxton, K.L. and Fiksel, J. (2013), "Ensuring supply chain resilience: development and implementation of an assessment tool", *Journal of Business Logistics*, Vol. 34 No. 1, pp. 46-76.

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