

# Supply chain resilience in mindful humanitarian aid organizations: the role of big data analytics

Supply chain  
resilience

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## Abstract

**Purpose** – The purpose of this paper is to understand the nomological network of associations between collective mindfulness and big data analytics in fostering resilient humanitarian relief supply chains.

**Design/methodology/approach** – The authors conceptualize a research model grounded in literature and test the hypotheses using survey data collected from informants at humanitarian aid organizations in Africa and Europe.

**Findings** – The findings demonstrate that organizational mindfulness is key to enabling resilient humanitarian relief supply chains, as opposed to just big data analytics.

**Originality/value** – This is the first study to examine organizational mindfulness and big data analytics in the context of humanitarian relief supply chains.

**Keywords** Supply chain, Resilience, Big data analytics, Mindfulness, Humanitarian aid

**Paper type** Research paper

## 1. Introduction

The frequency and impact of natural and human-induced disasters has highlighted the critical need for resilient humanitarian aid operations during a crisis response (Flynn *et al.*, 2020; de Camargo Fiorini *et al.*, 2021; Queiroz *et al.*, 2020). Natural disasters encompass geophysical (earthquake), hydrological (flood), meteorological (storm), climatological (drought) and biological (disease pandemics). Human-induced disasters include armed conflict, terrorism and hazardous accidents (World Health Organization, 2019). Disaster response is characterized as knowledge-intensive, time-sensitive, of short duration, high urgency and extreme uncertainty (Scholten *et al.*, 2019a, b; Gutjahr and Nolz, 2016). Disaster response entails operations and supply chain management (OSCM) challenges such as planning, procurement, warehousing and rapid mobilization and deployment of supplies (Maghsoudi



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*et al.*, 2018; Pedraza-Martinez and Van Wassenhove, 2016). Supply chains (SCs) in the context of disaster response are referred to as “humanitarian relief supply chains,” which are arranged within a short timeframe by aid organizations (Ben-Tal *et al.*, 2011; Van Wassenhove, 2006).

Emerging technologies are considered important in enabling an efficient and effective response to a disaster (Beydoun *et al.*, 2018; Queiroz *et al.*, 2021). However, there is a need to understand how emerging technologies can address the various challenges (delays, congestion) faced by humanitarian relief SCs (Rodríguez-Espíndola *et al.*, 2020; Kumar and Singh, 2021).

Recent studies on emerging technologies such as blockchain (Fosso Wamba and Queiroz, 2020), artificial intelligence (Dwivedi *et al.*, 2019), big data analytics (Kinra *et al.*, 2020), internet of things (Boehmer *et al.*, 2020) and three-dimensional (3D) printing (Roscoe *et al.*, 2019) have demonstrated their important role in the context of commercial SCs. However, commercial SCs are usually proactive, whereas humanitarian relief SCs are primarily reactive (Dubey *et al.*, 2021; Bhattacharya *et al.*, 2014). Furthermore, demand and the likelihood of a disruption are relatively stable in commercial SCs (Stewart and Ivani, 2019).

In this study, these concerns are addressed by using organizational mindfulness (OMIN) as a theoretical frame to advance knowledge of SCRE in the context of humanitarian aid. Understanding the role of OMIN in this context is important, as mindfulness can address important organizational challenges such as attention overload and multi-tasking, as well as provide a foundation for better-quality information processing (Reb *et al.*, 2020; Cheung *et al.*, 2020).

Although a few studies (Papadopoulos *et al.*, 2017; Dubey *et al.*, 2021; Min, 2019) have examined the impact of emerging technologies on SCRE in the context of disaster response, there remains much scope for further research, specifically with a view to enhancing SCRE (Singh *et al.*, 2018). SCRE is defined as “the adaptive capability of a SC to prepare for and/or respond to disruptions, to make a timely and cost-effective recovery, and therefore progress to a post-disruption state of operations – ideally, a better state than prior to the disruption” (Tukamuhabwa *et al.*, 2015, p. 8).

Big data is an emerging technology that is viewed as a critical factor in generating new capabilities to optimize SCs (Queiroz and Telles, 2018; Frederico *et al.*, 2019). The focus on big data analytics capabilities (BDACs) enables us to provide novel, yet important contributions to the OSCM, by better understanding SCRE in the context of humanitarian relief SC (Van der Vegt *et al.*, 2015). However, finding optimal solutions for the management of humanitarian relief SCs should not be approached solely from the perspective of resource optimization (Abualkhair *et al.*, 2020; Chandes and Paché, 2010). The effective management of humanitarian relief SCs is also dependent on the individuals involved in the crisis response initiative, also known as the “soft side” of organizations (Dubey and Gunasekaran, 2015). Yet, there is limited knowledge about the soft side of managing humanitarian relief SC (Dubey *et al.*, 2021) since existing research largely focuses on the non-human aspects of disaster response operations (Siawsh *et al.*, 2019). This study aims to address this gap by answering the following research question (RQ):

RQ. What is the role of BDAC and OMIN in developing resilient SCs in a disaster response context?

This paper is organized as follows: a review of literature pertinent to this study is followed by the research methodology. Then, key findings and analysis lead to a discussion, the implications, future research and the conclusion.

## 2. Theoretical background

### 2.1 Supply chain resilience

SCRE is essentially a system’s ability to have adaptable capabilities that can absorb interruptions (Folke, 2006; Tendall *et al.*, 2015). SCRE capabilities include flexibility,

redundancy, agility, efficiency, visibility, adaptation, anticipation, recovery, collaboration and security (Ivanov, 2020; Kamalahmadi and Parast, 2016). This study adopts the three main phases of disruption relevant to SCRE (readiness, responsiveness and recovery) (Ponomarov and Holcomb, 2009) and adds an additional phase (adaptive strategy), as suggested by Stone and Rahimifard (2018) to form the basis for grouping the core capabilities required in a resilient system.

The *readiness phase* refers to an organization's anticipation of a disruption either by preparing for it or by avoiding it (Fahimnia and Jabbarzadeh, 2016; Leat and Revoredo-Giha, 2013). This phase involves identifying and monitoring changes in the environment as well as those elements that need to be developed early to be utilized in other stages (Stone and Rahimifard, 2018). Flexibility is also required as it enhances resilience in the SC, which in turn enables an organization to respond and recover from disruptions (Stevenson and Spring, 2007).

The *responsiveness phase* refers to the pre-planned elements that mitigate the impact of a disruption, and at the same time, enable the system to remain functional (Fahimnia and Jabbarzadeh, 2016; Stone and Rahimifard, 2018). Information-sharing by partners across the SC is key to enabling the most effective response (Ivanov, 2020).

The *recovery phase* refers to both the repair of loss and the minimization of the time that it takes to return to the original or desired state (Fahimnia and Jabbarzadeh, 2016; Leat and Revoredo-Giha, 2013).

The *adaptive strategy phase* refers to the capability of a system to adjust operations in response to certain eventualities by using emergent technologies and learning from the disruption experience (Hohenstein *et al.*, 2015).

## 2.2 Supply chain resilience and the role of organizational mindfulness

SCRE and crisis management initiatives have largely focused on recovery and adaptability in emergency situations while facing unpredicted challenges (Ambulkar *et al.*, 2015; Craighead *et al.*, 2007). Organizations that succeed in crisis management and resilience planning are viewed as "high reliability organizations" (HROs), a term that implies that organizations can successfully overcome turbulent conditions, with a minimum number of failures (Weick *et al.*, 2008). Reliability in HROs reflects cognitive and behavioral attributes that can sustain resilience in times of crises (Weick *et al.*, 1999; Weick and Sutcliffe, 2006). A shared characteristic of HROs is OMIN (Sutcliffe, 2011; Weick *et al.*, 2008). Weick *et al.* (2008) argue that due to the criticality of errors and their consequences in HROs, learning by "trial and error" is intolerable and the reliability of HROs is grounded on highly standardized routines. The challenges facing humanitarian organizations can be considered within the ever-changing processes following "trial-and-error" approaches and the limited standardization of fixed routines (Larson and Foropon, 2018). Therefore, the approaches to HROs cannot be applied in humanitarian organizations *per se*; they need to be tailored to the specifics of the humanitarian operations.

While HROs often imply a commercial venture that relies on a variety of tools for quality and process improvement, the humanitarian organizations hold the same goals as HROs but in a more fluid setting. What distinguishes a humanitarian organization from an HRO is the dynamic nature of humanitarian supply and demand, the changing stakeholders as well as a high level of uncertainty (Kovacs and Spens, 2007). Unlike commercial organizations, where the focus is primarily on "costs," humanitarian organizations focus on "time," due to life-and-death disaster scenarios (Day *et al.*, 2012). Essentially, SCs must be efficient, flexible and responsive to unpredictable events (Larson and Foropon, 2018).

Weick and Sutcliffe (2006) propose that OMIN is a combination of ongoing scrutiny of existing expectations with the capability to invent new expectations that make sense of unprecedented events.

A mindful organization advocates the “big picture” of operations and “act[s] thoughtfully” by rewarding the reporting of failures, reducing assumptions and establishing measures to increase sensing capabilities of their employees (Weick *et al.*, 2008). Situational awareness encompasses the cognition and comprehension of the current situation as well as its projection to the future, implying organizational learning behaviors (Levinthal and Rerup, 2006; Vogus and Sutcliffe, 2012). Weick *et al.* (1999) introduced the term “collective mindfulness” in relation to organizations and safety. In this study, mindfulness is explored in the context of humanitarian organizations since the effective adoption of its characteristics can lead to improved outcomes (Weick *et al.*, 2005). Maitlis and Christianson (2014) highlight the necessity of mindfulness in organizations, as it allows resilience practices to emerge and creates a sense of urgency to take corrective actions in response to unexpected events. This approach marks the common ground shared by humanitarian organizations and HROs as persistence in the face of adversity leads to the resilience, which is a goal for both types of organizations (Ogliastri and Zuniga, 2016). Mindfulness in humanitarian organizations is defined in the following terms: situational awareness, development of an environment of “safety,” sensitivity to operations, commitment to resilience and urgency for corrective actions, which are linked to mindfulness studies where organizations adopt technological interventions to remain resilient (Ramiller and Swanson, 2009).

### *2.3 Supply chain resilience in mindful organizations enforcing big data capability*

As mindful organizations follow resilience practices for their SCs, they have to continuously reconfigure their resources in times of crises, to achieve the responsiveness and adaptability of the SC (Burnard *et al.*, 2018; Weick *et al.*, 2008). Mindful organizations focus on the practice of resilience to proactively prepare for disruptions through appropriate contingency planning (Mandal, 2019). SCRE provides the essential awareness in advance of a disaster situation through real-time communication and information-sharing (Fosso Wamba and Akter, 2019).

To build resilient SCs, organizations need to critically assess their technological capabilities to assist in the recovery of their SC from interruptions, as well as to cope with future interruptions (Dubey *et al.*, 2021; Giannakis *et al.*, 2019). Data-driven technological approaches, such as big data capability in organizations, could draw on unstructured data to explain disaster resilience (Dubey *et al.*, 2021). Data-driven approaches are enforcing new organizational capabilities focusing on technology for collection and analysis of real-time data, termed as BDAC (Mikalef *et al.*, 2019). BDAC is an emergent technological capability that refers to the organization’s ability to capture and analyze data to generate insights by effectively deploying its resources to enable effective decision-making (Mikalef *et al.*, 2020; Dubey *et al.*, 2021).

## **3. Hypothesis development and research model**

### *3.1 Big data analytics capabilities and supply chain resilience*

The frequency and impact of disruptions to SCs has prompted researchers and practitioners to adopt an approach toward resilience (Remko, 2020). SCRE refers to how SC stakeholders contain and control a disturbance within the system, by developing strategies to mitigate its impacts (Kamalahmadi and Parast, 2016).

Several studies that investigated the link between big data analytics and SCM highlight the need for organizations to develop a data-driven culture (LaValle *et al.*, 2011) and also note that big data analytics have a positive effect on SC performance (Trkman *et al.*, 2010; Waller and Fawcett, 2013). However, the process through which organizations employ big data analytics in the wake of SC disruptions has not received adequate attention (Fan *et al.*, 2016). We follow the recommendation that resilience studies should be grounded on dynamic

capabilities (Teece *et al.*, 1997), by adopting the concept of big data analytics capability to understand SCORE. Studies have shown that there is a complementary relationship between SC analytics and SC visibility and flexibility (Srinivasan and Swink, 2018), and that BDAC has a direct positive effect on SCORE (Dubey *et al.*, 2021). Following on from this discussion, the following hypotheses are proposed:

*H1.* There is a positive relationship between BDACs and SCORE.

### *3.2 Big data analytics capabilities and organizational mindfulness*

The multiplicity of disruptive events in the local and global SCs is forcing organizations to adopt resilient practices. Research shows that SC disruptions have significant economic impacts (Adobor McMullen, 2018) that can be very costly to organizations (Vanpoucke and Ellis, 2019). Studies also show that SC disruptions decrease firm stock prices by an average of 10% (Hendricks and Singhal, 2005) and may take several years to recover (Wildgoose *et al.*, 2012). To ensure SCORE, aid organizations should adopt the features of HROs as embodied in OMIN. The key features of OMIN include flexibility and commitment to resilience (Weick *et al.*, 2008). Technology infrastructure is an integral part of core organizational capabilities for mindfulness and performance (Dernbecher and Beck, 2017). Redman (2014) demonstrates that BDAC enables the enhancement of adaptive capabilities to deal with uncertainty.

*H2.* There is a positive relationship between BDACs and OMIN.

### *3.3 Big data analytics capabilities, organizational mindfulness and supply chain resilience*

SC are complex adaptive systems (CAS) that consist of several active agents that interact with each other according to a set of rules (Wycisk *et al.*, 2008). Since CAS adapts by interacting with their environments and co-evolve to create dynamic emergent realities, SCORE has been described as an adaptive phenomenon (Shastri *et al.*, 2014). Being an adaptive phenomenon, SCORE with features such as avoidance, redundancy, collaboration, agility and flexibility replicates the key principles of HRO (Sawyer and Harrison, 2019). High-performing organizations have been described as mindful organizations (Weick and Sutcliffe, 2006) as they operate under precariously complex conditions (Linnenluecke, 2017) but have the ability to avoid failures by achieving reliability through human processes and relationships (Weick and Sutcliffe, 2006). The pursuit of reliability and avoidance of accidents by HROs make them congruous to SCs that seek resilience through avoidance of disruptions and recovery and adaptability after disruptions (Sawyer and Harrison, 2019).

*H3.* There is a positive relationship between OMIN and SCORE.

The adoption of emerging technologies like big data analytics can be prone to bandwagon effects, by adopting a technology due to pressure from other organizations that have already adopted it (Abrahamson and Bartner, 1990). To resist such bandwagon effects, organizations should assess technological innovations based on their usefulness to the organization's needs (Abrahamson, 1991). Mindful organizations are able to deal with the bandwagon phenomenon, especially in turbulent environments (Wolf *et al.*, 2012). Mindfulness, as an organization's cognitive processes of revealing and redirecting new events and their erroneous consequences (Weick and Sutcliffe, 2006), is relevant in this study as aid organizations operating in turbulent times characterized by change, complexity and uncertainty (Dernbecher and Beck, 2017). OMIN enhances the recognition of organizational circumstances demanding an innovative approach and fostering the capabilities to effectively execute a timely response (Swanson and Ramiller, 2004). With regard to achieving time-sensitive organizational performance, there exists an association between mindful use of technological innovations and organizational resilience (Gardner *et al.*, 2017).

H4. OMIN mediates the relationship between BDACs and SCRE.

In this study, the conceptualization of BDAC is grounded on the dynamic capabilities view (Teece *et al.*, 1997), which relates to actions and behaviors that are learned and institutionalized within organizations and are oriented toward their supplier relationships (Mitrega *et al.*, 2017). These actions and behaviors are moderated by the organizational makeup, which consequently impacts organizational attitudes (Henneberg *et al.*, 2010). This study adopts OMIN to represent the attitudes held by organizations regarding big data analytics. From a theoretical perspective, it has been demonstrated that mindfulness can moderate the relationship between theoretical constructs like BDAC and SCRE (Dernbecher and Beck, 2017). While in H4, OMIN has been theorized as mediating the relationship between BDAC and SCRE, we also explore a possible moderating role for OMIN. This attempt is motivated by the fact that the role of mindfulness is not adequately addressed in SCRE research. This is the view of Preacher *et al.* (2007), who asserted that in special cases, a variable can act both as a mediator and a moderator. This leads to the fifth hypothesis:

H5. OMIN moderates the relationship between BDACs and SCRE.

Drawing on the OMIN view of the firm, this study proposes the research model shown in Figure 1. Note that H4 is derived indirectly through the mediation analysis procedure.

#### 4. Research methodology

##### 4.1 Survey administration and data collection

This study adopted the questionnaire-based survey method as it enables the identification of associations between variables and generalizability of findings (Pinsonneault and Kraemer, 1993). All constructs and respective items were operationalized on a five-point Likert scale, a well-accepted practice in empirical research (Kumar *et al.*, 1993).

Following best practice, which recommends involving up to 50 people to test a survey (Sudman, 1983), a pretest was conducted with 50 humanitarian aid practitioners using Qualtrics. Qualtrics is a cloud-based platform for creating and distributing Web-based surveys that are General Data Protection Regulation-compliant. The pretest enabled us to examine survey design issues (Vanpoucke and Ellis, 2019). Several respondents known to the authors were contacted after completion of the pretest phase to discuss survey design issues.

To test the research model, a Web-based survey was sent to practitioners working with humanitarian aid organizations (Table 1) as the unit of analysis was at the organizational level. Author 1 had previously worked with both national and international non-governmental organizations (NGOs) in Kenya for several years. Author 5 had over 15 years' experience with aid agencies throughout Africa and also lectures on the international

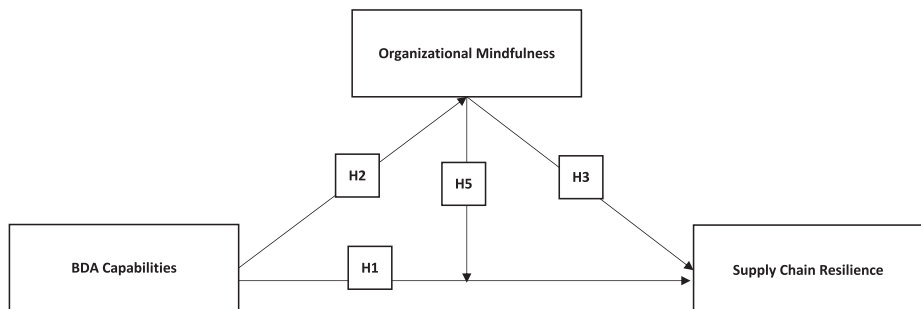


Figure 1.  
Research model

<i>Factors</i>	Sample (n = 135)	Proportion (%)
<i>Gender</i>		
Female	78	58
Male	57	42
<i>Years of experience in humanitarian aid</i>		
1–5 years	77	57
6–10 years	12	9
11–15 years	11	8
16–20 years	28	21
21+ years	7	5
<i>Main place of work</i>		
Asia	2	2
Africa	68	50
Europe	64	47
North America	1	1
<i>Highest qualification</i>		
PhD	3	2
Postgraduate (master's, higher diploma)	50	37
Primary degree	42	31
Other (certificate, diploma, A-levels)	40	30
<i>Respondent's position</i>		
Manager (regional, country, office, warehouse)	38	28
Field operative	18	13
IT and data analytics	16	12
Administrator	14	10
Public health care and social services	12	9
Medical (doctor, nurse)	11	8
Operations and supply chain logistics	8	6
Finance	4	3
C-level manager (CEO, director, founder)	4	3
Legal and public relations	4	3
Program evaluation and development	3	2
Security and maintenance	3	2
<i>Type of organization</i>		
NGO	94	70
Registered charity	43	32
Government development department	8	6
Think tank/consultancy	4	3
<i>Headquarters</i>		
Africa	65	48
Europe	62	46
North America	8	6
<i>Years with current organization</i>		
<5 years	34	25
6–10 years	16	12
11–15 years	23	17
16–20 years	25	19
20+ years	37	27
<i>Number of employees</i>		
1–50	48	36
51–100	42	31
101–500	23	17
501–1,000	9	7
1,000+	13	9

**Table 1.**  
Sample characteristics

development degree program at a university. This experience provided access to NGOs (Concern, Goal, Trócaire) funded by Irish Aid, the Government of Ireland's international aid program, as well as access to alumni who had roles in organizations such as the United Nations. In addition, Author 2 lives in Kenya and has access to a network of aid organizations operating in East Africa. Individuals at these organizations were contacted by email informing them of the study's objective and offering a report of the aggregate findings, if requested. An email invitation with the survey link was then sent to individuals who agreed to participate; a follow-up email reminder was sent one week after the invitation. The data collection process took approximately ten weeks (September to mid-November 2020), and on average, the survey completion time was 9 min. The final sample comprised 204 responses, of which 135 were complete and retained for analysis. Further, 69 responses were deemed not suitable for further analysis as 19 were incomplete and 50 were from the pretest.

#### *4.2 Measurements scales*

The scales used to measure the various constructs in this study were adapted from extant literature where they were previously tested. To ensure that the scales were relevant to the study, they were rephrased to fit the context of humanitarian relief SCs. The study variables, SCORE, OMIN and BDACs, were specified as first-order reflective constructs (cf. Urbach and Ahlemann, 2010). Reflective indicators are commonly used when the latent variables exist separately at a deeper level than its indicators. Modelling latent variables as reflective indicators is a common practice in organization-oriented studies (Vanpoucke and Ellis, 2019). Furthermore, constructs are not inherently formative or reflective in nature but are modeled based on the researcher's definition of the conceptual construct (MacKenzie et al., 2011). The mean of the survey items for each indicator was used as the final measure of the indicator. A Likert-type scale ranging from 1 (strongly disagree) to 5 (strongly agree) was used to capture the responses for the survey items. Table 2 is a summary of the study's items, their indicators, the survey items and the sources from which the measures were adapted.

#### *4.3 Non-response bias and common method bias*

The potential for non-response bias was assessed by comparing responses from early and late respondents on selected indicators from each latent variable following Armstrong and Overton (1977). It is assumed that late respondents are most similar to non-respondents because their replies required more nudging and took the longest time (Clotey and Grawe, 2014). Assessing non-response bias comparison of early and late respondents is widely used in OSCM research (Ateş and Memiş, 2021; Vanpoucke and Ellis, 2019). A sample of the first 50 early responders and the last 50 late responders was used for the comparison based on one indicator picked from every latent variable: OMIN2, BDAC2 and SCORE2. Mean differences for the three indicators were not significant ( $p = 0.625$ ,  $p = 0.449$ ,  $p = 0.465$ , respectively), indicating that non-response bias was not a threat in this study.

To reduce the threat of common method bias, precautionary measures were taken during the survey design and administration. First, as mentioned previously, a pretest eliminated ambiguous terms in the survey. Second, anonymity of respondents was ensured to reduce desirability bias. Third, the order of the questionnaire items for the predictor and criterion variables were counterbalanced to mitigate the effects of priming as recommended by Podsakoff et al. (2003). To test for common method bias, we applied the Harman's single-factor test (Podsakoff et al., 2003). When implemented using a factor-based partial least squares structural equation modeling (PLS-SEM) test (Kock, 2021), the average variance extracted (AVE) was 0.558 against the commonly suggested threshold of 0.5. While the Harman's test indicated some levels of common method bias, the method is indicative and not confirmatory (Yu et al., 2019).



(continued)

Construct	Indicators (Reflective)	Items (5-point Likert-type scale) (1 – strongly disagree, 2 – somewhat disagree, 3 – neither agree nor disagree, 4 – somewhat agree, 5 – strongly agree)	References
SCORE	Responsiveness (SCORE1)	(1) Quick response to SC disruption (2) Ability to respond in a timely manner when a disruption happens	Ambulkar <i>et al.</i> (2015), Chowdhury and Quaddus (2016), Kamalahmadi and Parast (2016), Ponomarov and Holcomb (2009), Sheffi and Rice (2005)
	Adaptability (SCORE2)	(3) Ability to reactivate in the occurrence of a disruption (1) Adapting operations to the new circumstances after disturbance (2) Modifying operations to match new circumstances (3) Ability to return to the original state after being disturbed (4) Ability to move to a new, more desirable state after being disturbed	
	Resistance (SCORE3)	(1) Ability to withstand systemic discontinuities in case of a disruption (2) In the occurrence of a disruption, we can tolerate disturbances (3) In the occurrence of a disruption, we can mitigate the impact of the disruption	
	Resource reconfiguration (SCORE4)	(1) Reconfigure resources and processes in response to the environmental changes (2) Restructure resource base to react to the changing business environment (3) Realignment of resources to fit changes in operating environment	
	Readiness (SCORE5)	(1) Sensing and forecasting SC events (2) Tracking and monitoring SC operations (3) Layered defense mechanisms for both our physical and systems resources (4) Multiple supplier locations (5) Backup sites for IT systems	
	Recovery (SCORE6)	(1) Ability to recover in a short time in case of disruption (2) Ability to absorb huge losses resulting from disruption (3) Ability to reduce impact of loss resulting from disruption (4) Ability to recover from crisis at a less cost	

**Table 2.** Summary of constructs, their indicators and source

Construct	Indicators (Reflective)	Items (5-point Likert-type scale) (1 – strongly disagree, 2 – somewhat disagree, 3 – neither agree nor disagree, 4 – somewhat agree, 5 – strongly agree)	References
OMIN	Preoccupation with failure (OMIN1)	(1) Focus more on employees' successes than failures (2) Treating near misses and errors as information about the health of a system and learning from them (3) Inclination to report mistakes that could have significant consequences even if nobody notices (4) Employees feel free to talk to superiors about problems (5) Employee are rewarded for identifying problems, mistakes, errors or failures	Dembecher <i>et al.</i> (2014), Ray <i>et al.</i> (2011), Sutcliffe (2011), Weick <i>et al.</i> (1999), Weick and Sutcliffe, (2006), Wolf <i>et al.</i> (2009)
	Reluctance to simplify operations (OMIN2)	(1) Encouraging employees questioning (2) Encouraging employees to express their views regarding operations (3) Carefully listening to everyone's views without ignoring	
	Sensitivity to operations (OMIN3)	(1) Share operational information with each other (2) Availability of experts to handle problems when they arise (3) Interaction among employees to build a clear picture of the current situation (4) Our employees have access to (additional) resources if unexpected situations occur (5) Communication of operational anomalies as they occur	
	Commitment to resilience (OMIN4)	(1) Committed to solve any problem that arises (2) Limiting of any negative consequences so that the firm can continue operations in cases of disruption (3) Employees use their knowledge in novel ways (4) Employees have several informal contacts that they sometimes use to solve problems (5) Employees are given tasks from which they can learn more about different aspects of the operational processes	

(continued)

Construct	Indicators (Reflective)	Items (5-point Likert-type scale) (1 – strongly disagree, 2 – somewhat disagree, 3 – neither agree nor disagree, 4 – somewhat agree, 5 – strongly agree)	References
BDAC	Deference to expertise (OMIN5)	(1) Employees know who has the expertise to respond to problems as they arise	Dubey <i>et al.</i> (2021), Fosso Wamba and Akter (2019), Mikalef <i>et al.</i> (2018, 2019), Papadopoulos <i>et al.</i> (2017)
		(2) Employees are comfortable asking others with more expertise for help	
		(3) People most qualified to make decisions can make the decisions	
		(4) Employees value expertise over hierarchical rank or position	
		(5) Employees value experience over hierarchical rank or position	
BDAC	Tangible (BDAC1)	(1) Access to technologies for collecting and storing large volumes of data	
		(2) Deployment of analytics to extract and analyze data	
		(3) Presence of big data projects aimed at capturing all types of data	
		(4) Presence of big data projects for collecting data from all sources	
BDAC	Intangible (BDAC2)	(5) Curation of all data collected into a central data warehouse	
		(6) Budgets for big data analytics projects	
		(1) Employees are open to learning big data analytics skills	
		(2) Organization supports employees to learn new emerging technologies	
		(3) Organization has a data-driven culture	
		(4) Top management commitment to the use of big data analytics	
BDAC	Human skills (BDAC3)	(5) Top management makes decisions based on intelligence derived from big data analytics	
		(1) Employees have skills in big data management	
		(2) Employees have big data analytics skills	
		(3) Availability of employees who understand the data analytics life cycle	
		(4) Employees who understand ethics and governance of big data analytics	
		(5) The managers use big data analytics results to make decisions	
		(6) Big data analytics is guided by business objectives	

Table 2.

**5. Data analysis**

*5.1 Measurement model evaluation*

The model was evaluated for reliability and validity before testing the hypotheses. For the construct to explain more than 50% of its indicators' variance, a loading of 0.708 is recommended to provide acceptable item reliability (Hair *et al.*, 2019). Given that the latent variables of the study, which include BDAC, OMIN and SCRE, were measured using reflective indicators, the evaluation metrics recommended by Urbach and Ahlemann (2010) were conducted. Internal consistency reliability was evaluated using composite reliability (CR) and Cronbach's alpha (CA) with the threshold value of 0.700 and above, which indicates satisfactory reliability values (Hair *et al.*, 2019). Convergent validity for each of the construct's measure was evaluated through the AVE. An acceptable value of AVE is 0.50 or higher, which indicates that the construct accounts for at least 50% of the variance of its items (Latan and Ghozali, 2012). The indicator reliability which measures how much of the indicators variance is explained by the corresponding latent variable was evaluated using cross loadings with a threshold value of 0.700 or slightly lower for exploratory studies (Chin, 1998). To ensure that no indicator inadvertently loaded highly on a different construct, cross-loadings were obtained by correlating the component scores of each latent variable to all the other variables. The loading of each indicator is higher for its designated construct than for any other constructs and each of the construct loads highest within its own items as recommended by Latan and Ghozali (2012). The values for the cross-loadings, CA, CR and AVE are presented in Table 3.

To assess the discriminant validity, which is the extent to which a construct is empirically distinct from other constructs, two criteria were applied as recommended by Voorhees *et al.* (2016). The first one is the Fornell-Larcker (1981) criterion, which proposes that a factor's AVE should be higher than its squared correlations with all other factors in the

	BDAC	OMIN	SCRE	BDAC*OMIN	Fornell-Larcker
<i>BDAC: CA = 0.892, CR = 0.933, AVE = 0.822</i>					0.907
BDAC					
BDAC1	0.910	0.526	0.695		
BDAC2	0.899	0.644	0.722		
BDAC3	0.912	0.488	0.728		
<i>OMIN: CA = 0.898, CR = 0.925, AVE = 0.711</i>					0.613
OMIN	(0.673)		(0.675)	(0.573)	
OMIN1	0.474	0.846	0.54		
OMIN2	0.428	0.859	0.515		
OMIN3	0.53	0.871	0.599		
OMIN4	0.555	0.807	0.631		
OMIN5	0.568	0.831	0.638		
<i>SCRE: CA = 0.914, CR = 0.933, AVE = 0.701</i>					0.789
SCRE	(0.864)	(0.765)		(0.374)	
SCRE1	0.685	0.585	0.871		
SCRE2	0.638	0.691	0.877		
SCRE3	0.466	0.496	0.711		
SCRE4	0.677	0.593	0.819		
SCRE5	0.814	0.597	0.897		
SCRE6	0.635	0.547	0.836		
<i>BDAC*OMIN: CA = 1.00, CR = 1.00, AVE = 1.00</i>					0.255
BDAC*OMIN	(0.267)		(0.374)		
BDAC*OMIN	-0.255	-0.543	-0.354		

**Table 3.** Reliability and validity of the measurement model

**Note(s):** HTMT measures in brackets

model. All the latent variables met the Fornell–Larcker criterion (Table 3). Although the Fornell–Larcker metric is largely used to assess discriminant validity, recent research shows that it does not perform very well, especially when the indicator loadings on a construct differ slightly (Henseler *et al.*, 2015). As a result, Henseler (2017) proposed the heterotrait-monotrait ratio of correlations (HTMT), which estimates the upper boundary factor correlation and should be significantly smaller than 1 to discriminate between two factors. All factor correlations (Table 3) were below the threshold (0.900), as recommended by Franke and Sarstedt (2019).

5.2 Structural model evaluation

The model was evaluated through several metrics. The first standard evaluation criterion to be checked was collinearity. Collinearity was assessed through the variance inflation factor (VIF). The VIF (inner model) indicates how much of a construct’s variance is explained by the other constructs and thus redundant. The VIF values for the inner paths were all less than 3 (BDAC → SCRE = 1.625, BDAC → OMIN = 1.000, OMIN → SCRE = 2.155 and BDAC\*OMIN → SCRE = 1.439), indicating that there were no collinearity issues among the constructs. Since collinearity was not an issue, we moved to examine the  $R^2$  of the endogenous constructs.  $R^2$  measures the variance that is accounted for in each of the endogenous constructs and is therefore considered a measure of the model’s explanatory power (Hair *et al.*, 2019). The rule of thumb considers  $R^2$  values of 0.750 as substantial, 0.50 as moderate and values below 0.25 are considered weak (Henseler *et al.*, 2015). The  $R^2$  for OMIN was 0.376, while that of SCRE was 0.698, indicating weak and moderate explanatory power, respectively.

After checking the model’s explanatory power through  $R^2$ , the statistical significance and relevance of the path coefficients were assessed. A path coefficient estimates the variability in an endogenous variable accounted for by a unit change in an exogenous variable, *ceteris paribus*. A path coefficient needs to be assessed for direction, magnitude, significance (Urbach and Ahlemann, 2010) and indirect effects such as mediation (Nitzl, 2016). The path coefficients of the model were greater than 0.100, except BDAC\*OMIN (Table 4). Path coefficients that are greater than 1.00 are considered to be of substantial impact on the model (Urbach and Ahlemann, 2010). The significance of the path coefficients was examined through the bootstrapping algorithm (Hair *et al.*, 2019) using 500 subsamples from the original dataset with 300 iterations to generate the *t*-statistics and *p*-values. In addition to assessing the  $R^2$  value, the effect size, which evaluates the extent to which an omission of a particular exogenous construct leads to a change in  $R^2$ , was calculated using Cohen’s  $f^2$ . To calculate the value of  $f^2$ , Cohen’s (1988) guidelines for exogenous variables were used. Specifically, values of between 0.020 and 0.150, between 0.150 and 0.350, and those exceeding 0.350 indicate that an exogenous latent variable has a small, medium and large effect, respectively, on an endogenous latent variable. The Cohen’s  $f^2$  was estimated by means of bootstrapping and the results. The values of Cohen’s  $f^2$  were as follows: BDAC → SCRE = 0.686, BDAC → OMIN = 0.602, OMIN → SCRE = 0.167 and BDAC\*OMIN → SCRE = 0.002. The results indicate that the exogenous variable BDAC had a

#	Hypothesis	Path coefficient	<i>t</i> -statistic	<i>p</i> -values (alpha < 0.001)	Comment
H1	BDAC → SCRE	0.580	10.663	0.000	Supported
H2	BDAC → OMIN	0.632	9.789	0.000	Supported
H3	OMIN → SCRE	0.330	4.778	0.000	Supported
H4	BDAC → OMIN → SCRE	0.202	3.941	0.000	Supported
H5	(BDAC*OMIN) → SCRE	−0.018	0.418	0.685	Not supported

**Table 4.**  
Hypothesis testing  
using PLS-SEM

large effect on the endogenous variables SCORE and OMIN, while OMIN had a moderate effect on SCORE. The interaction effect (BDAC\*OMIN) had a minimal effect on SCORE.

Another important structural model validity criterion that assesses the model's predictive accuracy is the  $Q^2$  value, which is calculated by performing the Stone–Geisser's test through the blindfolding procedure. The blindfolding procedure removes single points in the data matrix and then imputes the removed points with the mean to estimate the model parameters (Sarstedt *et al.*, 2014). Since  $Q^2$  combines synthetic data points with the sample data points, it provides a hybrid prediction based on in-sampling and out-sampling. During blindfolding, omission distance was set to 7 as the model dataset had 135 observations ( $n = 135$ ). This follows the recommendation of Hair *et al.* (2014, p. 167) that the omission distance ( $d$ ) should be between 5 and 7, provided that the quotient of the total number of observations ( $n = 135$ ) and the omission distance ( $n = 7$ ) are not an integer. The  $Q^2$  values of the model's endogenous variables, OMIN = 251 and SCORE = 479, were above 0 ( $Q^2 > 0$ ) threshold, suggesting that they all had explanatory and predictive relevance (Hair *et al.*, 2019).

In this study, the exogenous latent variables, BDAC and OMIN were used to explain the endogenous latent variable SCORE. In explanatory models, controlling for endogeneity is crucial when testing hypotheses (Papies *et al.*, 2017). While endogeneity may have several causes, it generally stems from omitted variables that correlate with one or more independent variable(s) and the dependent variable(s) in the regression model (Rossi, 2014). Failing to account for endogeneity may lead to biased parameter estimates, which undermines the validity of the findings obtained from regression-type analysis of observed data (Sande and Ghosh, 2018). There are a number of approaches used to treat endogeneity problems such as the control variables approach (Germann *et al.*, 2015) and the control function approach (De Blander, 2010). We tested for endogeneity on the latent variable SCORE because it had both direct (BDAC, OMIN) and an indirect predictor (BDAC) using the instrumental variable approach. We adopted this approach as it is widely used in PLS-SEM (Sande and Ghosh, 2018). An interval variable, *iv\_SCORE*, was created and added to the model as a predictor of SCORE to test for endogeneity through its path coefficient and significance (Kock, 2017) using WarpPLS 6.0. The path coefficient (*iv\_SCORE*) was  $B = 0.02$  and  $p = 0.41$ , showing that the endogeneity effect was minimal and non-significant.

### 5.3 Hypothesis testing

To assess the validity and reliability of the research model, PLS-SEM analysis was applied. PLS-SEM was chosen for this study for three pertinent reasons. First, it is considered an appropriate methodology for exploratory research and shares the modest distributional and sample size requirements of ordinary least squares regression (Hair *et al.*, 2011). Second, PLS-SEM is appropriate when estimating the relationships among latent variables (Urbach and Ahlemann, 2010). Specifically, the software package SmartPLS (v.3) was used to conduct all analyses. Finally, as the proposed research model builds more on exploratory theory-building, rather than theory-testing, PLS-SEM is a better alternative than covariance-based SEM (Hair *et al.*, 2017).

The effect of BDAC on SCORE was positive and significant ( $\beta = 0.580, p < 0.001$ ). Therefore, H1 that BDAC influences SCORE is supported. The effect of BDAC on OMIN was positive and significant ( $\beta = 0.631, p < 0.001$ ), indicating that H2 is supported. The results for the estimation of the effect of OMIN on SCORE showed a positive and significant relationship ( $\beta = 0.330, p < 0.001$ ). H3 was, therefore, supported. The mediating role of OMIN on the relationship between BDAC and SCORE was estimated as  $\beta = 0.202, p < 0.001$ . This implies that the indirect role of OMIN as expressed in H4 (BDAC  $\rightarrow$  OMIN  $\rightarrow$  SCORE) was positive and significant and therefore supported. H5, which captured the interaction effect between OMIN and BDAC on SCORE, was negative and not significant. The small and insignificant effect of

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OMIN on the relationship between BDAC and SCRE may be attributed to the ceiling effect as there is already a strong and significant effect of BDAC on SCRE (Table 4).

## 6. Discussion, implications and future research

Drawing on the contemporary literature, we frame both the theoretical and empirical contributions of this study. The most salient theoretical contribution of this research is the use of OMIN as a lens to study humanitarian relief SCs. This is an important contribution as studies linking OMIN and BDAC to SCM remain under-researched (Frederico *et al.*, 2019). By investigating the moderating role of OMIN in SCRE, this study advances knowledge on the application of BDAC in the management of resilient SC (Bag *et al.*, 2020; Khanra *et al.*, 2020). Specifically, the effect of BDAC on OMIN is positive and significant, which reveals that BDAC is an antecedent of OMIN. This is an important revelation as previous studies have focused mainly on OMIN as a predictor but not on the antecedents of OMIN. Also, the moderating role of OMIN on the relationship between BDAC and SCRE is very small and not significant. This could be due to the fact that BDAC and OMIN explain almost 70% of SCRE.

OSCM studies (e.g. Dutta and Bose, 2015; Fossa Wamba *et al.*, 2015) highlight the benefits of big data analytics (better decision-making, enhanced SC capabilities). Although emerging technologies have the potential to revolutionize OSCM (Roh *et al.*, 2019), they remain understudied in the context of humanitarian relief SCs. By adopting an interdisciplinary perspective, this study supports research calls to break down existing walls between OSCM and other disciplines (Liberatore and Luo, 2010). By theorizing about the phenomena of BDAC in the context of humanitarian relief SCs, this research project makes important contributions to OSCM (Van der Vegt *et al.*, 2015), specifically to the field of supply chain management, an emerging discipline (Harland *et al.*, 2006).

As this study focuses on the intersection between BDAC and OMIN, in the context of resilient humanitarian relief SCs, it makes an empirical contribution (Han *et al.*, 2020) as the findings demonstrate that OMIN is key to enabling SCRE, as opposed to just the BDAC itself (Reina and Kudesia, 2020). Specifically, the mediating role of OMIN is significant.

This study makes a methodological contribution by developing and testing the model in the context of humanitarian relief SCs, and therefore, it supports calls to move beyond traditional SCM (Scholten and Fynes, 2017). In doing so, we also extend the generalizability of OMIN and provide novel insights about SCRE that have not been reported previously. Specifically, BDAC had a strong effect on SCRE with an effect size ( $f$ -squared) of 0.686. This implies that BDAC had a strong explanatory power on SCRE compared to OMIN and BDAC\*OMIN.

### 6.1 Implications for research

This study has implications for OSCM research. First, despite the differences between humanitarian and commercial SC, much can be learned by understanding how commercial SC techniques and research can be applied to humanitarian relief SC (Stewart and Ivanov, 2019). Second, while the outcome of this study reduces the gap between the understanding of SCM in academic literature and that in practice (Abualkhair *et al.*, 2020; Remko, 2020), there remains a lack of scientific reasoning in disaster management when multiple disasters occur repeatedly “in the same space” (Alem *et al.*, 2021).

Finally, the study provides empirical evidence to challenge the assumption that big data analytics will itself lead to a resilient humanitarian relief SC. This assertion leads to an important implication for OSCM research, as much of the claimed benefits about big data analytics lack theoretical validity as they have been provided by consultants (Gupta and George, 2016), who may be biased to the claims. Also, the study of SCs in the context of humanitarian relief operations is a relatively new field of research (Stewart and Ivanov, 2019).

### 6.2 Implications for practice

The findings of this study present several interesting implications for OSCM and disaster response. First, this study highlights the value and importance of an organization's mindfulness, and therefore, managers need to develop and implement mindfulness strategies that can contribute to embedding an organizational resilient mindset to realize the potential benefits of big data analytics.

To develop BDAC, funding agencies need to allocate funding for sector-wide adoption of big data analytics. This may contradict the traditional funding model (Dennehy *et al.*, 2013) where humanitarian organizations are constrained by cost minimization measures (Dubey *et al.*, 2017). Another implication is the need to assess the time to acquire and develop key resources and the expected return on investment of big data analytics (Mikalef *et al.*, 2020). Such an assessment is critical as there are claims that a high percentage of organizations have not realized the potential of their big data investment (Ross *et al.*, 2013). Further, many of the individuals managing humanitarian relief SCs are not specialists in OSCM and therefore are not experts in the technologies that could be used to address SC disruptions (Ergun *et al.*, 2009).

Finally, managers need to be aware that big data analytics is not a "silver bullet" to develop resilient SCs, and that fostering a data-driven mindful organizational culture is critical to generate value from big data analytics. The importance of organizational change has been highlighted by Vidgen *et al.* (2017), who provide guidelines on how to develop BDAC.

### 6.3 Limitations and future research

As with all research, however, we acknowledge this study has two limitations, which also offer directions for future research. The first relates to endogeneity (Guide and Ketokivi, 2015). We did test for endogeneity on the latent variable SCORE (Hair *et al.*, 2019), and since the effect of endogeneity was minimal and non-significant, it was not necessary to control for it (Papias *et al.*, 2017). The second limitation relates to survey-based research as the knowledge-intensive and time-sensitive activities of humanitarian aid may not always be captured (Scholten *et al.*, 2019a, b). Future research could engage with a specific aid organization and seek organization-wide support to ensure that staff involved in disaster response initiatives complete the survey as this would improve internal validity and provide insights unique to the organization in terms of its state of mindfulness toward big data analytics. Future research could also focus on contextual factors such as the role of organizational culture (Dubey *et al.*, 2020) and national culture (Gupta *et al.*, 2019), as these have not been adequately explored in the context of humanitarian relief SCs and big data analytics. Despite these limitations, this study provides direction for future research in the OSCM field, which has been criticized for not engaging with emerging technologies (Vidgen *et al.*, 2017; Mortenson *et al.*, 2015).

## 7. Conclusion

This study was largely motivated by the urgent need to advance understanding about the role played by emerging technologies in developing and managing resilient humanitarian relief SCs. While valuable contributions have been made about big data analytics in commercial SCs, OSCM researchers have lagged behind in examining this aspect in humanitarian relief SCs. What studies do exist largely focus on the technology adoption, which has led to limited knowledge about the socio-technical aspects that can influence the successful use of big data analytics. This study uses OMIN and BDAC to advance knowledge to develop resilient humanitarian relief SCs. The findings demonstrate that OMIN is key to enabling resilient humanitarian relief SCs, as opposed to just big data analytics alone. In doing so, stakeholders involved in disaster response need to consider both the technical characteristics of big data analytics and the state of mindfulness of their organization.



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