An Investigation of Information Alignment and Collaboration as Complements to Supply Chain Agility in Humanitarian Supply Chain

Rameshwar Dubey*
Liverpool Business School
Liverpool John Moore's University
Liverpool, Merseyside L3 5UG
UK
E-mail: r.dubey@ljmu.ac.uk

David J. Bryde
Liverpool Business School
Liverpool John Moore's University
Liverpool, Merseyside L3 5UG
UK
E-mail: D.J.Bryde@ljmu.ac.uk

Cyril Foropon
Montpellier Business School
Montpellier Research in Management
2300 Avenue des Moulins
34185 Montpellier France
E-mail: c.foropon@montpellier-bs.com

Manisha Tiwari
Liverpool Business School
Liverpool John Moore's University
Liverpool, Merseyside L3 5UG
UK
E-mail: Manishalive786@gmail.com

Yogesh Dwivedi
School of Management, Swansea University, Bay Campus
Fabian Bay, Swansea, SA1 8EN, Wales, UK.
E-mail: y.k.dwivedi@swansea.ac.uk

Sarah Schiffling
Liverpool Business School
Liverpool John Moore's University
Liverpool, Merseyside L3 5UG
UK
E-mail: S.A.Schiffling@ljmu.ac.uk

* corresponding author

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Abstract

Our study examines the relationship between information alignment (IA), collaboration (CO) and supply chain agility (SCAG) under the moderating effects of artificial intelligence driven big data analytics capability (AI-BDAC) and intergroup leadership (IGL). We have grounded our theoretical model in the resource based view (RBV) and contingency theory and further tested our research hypotheses using multi-informant data collected using a web-based pre-tested instrument from 613 individuals working in 193 humanitarian organisations drawn from 24 countries located on various continents across the globe. We tested our research hypotheses using variance based structural equation modelling (PLS-SEM). Our study offers interesting results which help to advance the theoretical debates surrounding technology-driven supply chain agility in the context of humanitarian settings. We further provide some directions to managers engaged in disaster relief operations, who are contemplating using emerging technologies to enhance collaboration and supply chain agility. Finally, we have outlined the limitations of our study and offer some future research directions.

Key-words: Information Alignment, Artificial Intelligence, Big Data Analytics, Intergroup Leadership, Supply Chain Agility, Humanitarian Supply Chain, Humanitarian Operations, Pandemics, Empirical Study

1. Introduction

The humanitarian supply chains providing disaster relief are often compromised due to lack of visibility, an absence of information sharing, a lack of trust among disaster relief workers and poor collaboration (Swanson and Smith, 2013; Nurmala et al. 2018; Larson and Foropon, 2018; Dubey et al. 2019a,b; Duong and Chong, 2020). Indeed, in their recent studies, scholars found that from the Indian Ocean Tsunami, the Haiti Earthquake, the Ebola outbreak in West Africa, through to the recent COVID-19 pandemic, the disaster relief workers on the ground commonly identify a lack of visibility, poor information sharing and poor leadership as important constraints to effective operations (Altay and Pal, 2014; Dubey et al. 2019a; Salem, 2019; Ivanov, 2020a,b; Ivanov and Dolgui, 2020 a,b). In the dynamic and highly uncertain environment, enhancing the collaboration among the disaster relief workers holds great promise in terms of resolving issues that may hinder disaster relief workers' abilities to productively share their strategic resources in the form of activities and information (see, Balcik et al. 2010; Jahre and Jensen, 2010; McLachlin and Larson, 2011; Akhtar et al. 2012; Altay and Pal, 2014; Kabra and Ramesh, 2015; Prasanna and Haavisto, 2018; Dwivedi et al. 2018; Schiffling et al. 2020a). The long term impacts of theses disasters may be attributed to the poor information exchange and lack of collaboration among the disaster relief workers, who are dealing with situations that are often characterised by highly dynamic and uncertain task environments (Chen et al. 2013; Fan et al. 2019; Dubey et al. 2020a; Dolgui et al. 2020b; Queiroz et al. 2020a; Ivanov, 2020b; Dubey et al. 2020; Fosso Wamba and Queiroz, 2020; Schiffling et al. 2020b).

The existing academic literature focusing either on the role of IT or ICTs capabilities in the context of disaster relief efforts or on the management of humanitarian supply chains (see, Ragini et al. 2018; Fosso Wamba et al. 2019; Akter et al. 2019; Sharma et al. 2020; Rodríguez-Espíndola et al. 2020) has gained significant attention. Chan and Reich (2007) further argue that the level or degree of alignment between IT capabilities and business strategy often differentiates successful organisations from less successful ones (Ivanov et al. 2020; Fragapane et al. 2020). However, despite a growing rich body of literature, empirical studies focusing on the criticality of information alignment (IA) and collaboration (CO) among disaster relief workers for supporting coordinated task performance in complex operational environments are scant (Li et al. 2011; Chen et al. 2019). Agility in humanitarian supply chains is considered a vital capability for disaster relief operations (see, Charles et al. 2010; Day et al. 2012; Dubey and Gunasekaran, 2016; Altay et al. 2018; Stewart and Ivanov, 2019). Moreover, collaboration is also considered as an important element in an agile supply chain network (Lee, 2004). It is further noted that the integration, change, competence, partnership and welfare have been considered determinants of supply chain agility (Jain et al. 2008). Whilst Moshtari (2016, p. 1542) argues that "*collaboration may occur over one or more tasks within humanitarian setting, for example information sharing, capacity planning, needs assessment, resource allocation, joint procurement, warehousing, transportation and last mile delivery*". Hence, we argue that collaboration (CO) is an important element of supply chain agility (SCAG). Following Alvesson and Sandberg (2011) arguments, we attempted to address our research gaps of our study. However, the existing literature on humanitarian supply chain management remains silent in respect of the relationships between information alignment (Tan et al. 2010; Ng et al. 2013; Tarafdar and Qrunfleh, 2017; Dolgui et al. 2018), collaboration and supply chain agility. To address this research gap, we posit our first research question (RQ1) as: *What are the distinct and joint effects of LA and CO on SCAG?*

Artificial Intelligence driven Big Data Analytics Capability (AI-BDAC) is an all-encompassing term for techniques destined to handle big data characterised in terms of high volume, velocity and variety (Queiroz and Telles, 2018; Dubey et al. 2020b), as well as encompassing challenges related to capture, storage, transfer & sharing, search, analysis, and visualisation of such data. Amongst the various challenges, especially critical ones are data capture, storage, transfer & sharing related to system architecture, and search, analysis, and visualisation related to data analytics methods (Srinivasan and Swink, 2018). The applicability of Big Data has been demonstrated to represent dynamic populations (Deville et al., 2014) and to understand population flows (Wang et al., 2018). The use of big data analytics in crisis situations has been advocated in literature (Akter and Wamba, 2019). However, it is evident that we lack standards and proper methods of data anonymisation and data fusion – such as utilising Artificial Intelligence (AI) to enrich and summarise the spatial data using different data sources – in order to use the full potential of Big Data at varying temporal and spatial scales and to get this information into practice. Improved scientific solutions enable the development of models of mobility flows, contacts between people and subsequent analyses revealing the societal and economic impact of a crisis, which are needed to monitor the recovery process (Poom et al. 2020). We note this as a research gap. Hence, to address this we posit as our second research question as (RQ2) as: *What are the effects of AI-BDAC on the paths connecting LA/CO and SCAG?*

Despite increasing disaster relief efforts, it is noted that international humanitarian organisations' (IHO) efforts reach less than half of the estimated affected populations and the beneficiaries' needs are not met effectively (Clarke and Campbell, 2018). Salem et al. (2019) argue that leadership is pivotal for improved humanitarian operations. In fact, operations management literature has recognised the need for effective leadership to achieve desired success (de Koster et al. 2011). However, the humanitarian operations management literature has remained silent on this front (Salem et al. 2019). As a result, the role of leadership on the use of emerging technologies for improving information alignment and collaboration among disaster relief workers is also not well understood. Hence, we suggest that in the context of disaster relief, "*intergroup leadership theory*" may offer useful insights to explain collaboration among members in humanitarian supply chains (Salem et al. 2019). Gooty et al. (2010) describe leadership as the process of directing and influencing the task-related activities of group members. Salem et al. (2019) further argue that leadership plays a crucial role during pre and post disaster relief operations. Kent (2004) found that leadership has an important role to play in any organisational initiatives, through belief and participation. Although, we understand the role of effective intergroup leadership in humanitarian operations (Salem et al. 2019), it is not clear how intergroup leadership influences the effects of IA and CO on SCAG. We note this as a clear research gap. To address this research gap, we posit our third and final research question (RQ3): *what are the effects of intergroup leadership on the paths joining IA/CO and SCAG?*

We have organised our paper as follows. In section 2, we provide a brief synopsis of the underpinning theories of our study, namely: RBV and contingency theory/intergroup leadership, the theoretical model and research hypotheses. In section 3, we discuss our hypo-deductive research strategy, including our sampling design and data collection strategy, which resulted in data from questionnaires completed by 613 individuals working in 193 NGOs, UN agencies and other service providers involved in humanitarian disaster relief activities. We also report the results of non-response bias testing. In section 4, we present our data analysis, which involves using PLS-SEM to test our theoretical framework, with Warp PLS 6.0 utilised to address criticism of traditional PLS-SEM methods. We also report the results of testing the hypotheses in this section. Next, in section 5, we present a discussion of our results, focusing on the implications for theory and practice. In relation to theory development, we describe three main contributions of our study. We then set out implications for managers engaged in disaster relief, including how assumptions about the importance of interdependency and relationship duration to achieving agility, derived from research in other contexts, might not hold true in humanitarian supply chain settings. Finally, in section 6, we draw our conclusions, finishing by stressing how our study provides enhanced understanding of relationships between critical elements in humanitarian supply chains which can contribute to better management of disaster relief activities.

2. Theoretical Development and Hypotheses Formulation

There is increasing use of organisational theories to explain complex management situations (see, Ketchen and Hult, 2007; Gunasekaran et al. 2018). There are many popular organisational theories: resource based view; resource dependence theory; institutional theory; relational view; contingency theory; organisational information processing theory and many more. Ketchen and Hult (2007) emphasise the importance of organisational theories in the operations and supply chain management field. However, despite a rich body of literature on humanitarian operations management, the use of organisational theories to explain some complex phenomena has received less attention in comparison to established management fields (Gunasekaran et al. 2018). Even, some scholars like Madhok (2002) have attempted to use a combination of one or more organisational theories in theory driven empirical studies. In the current study, we try to answer our research questions using a combination of two organisational theories: resource based view and contingency theory.

The RBV logic helps to understand how resources/ capabilities can be utilised to gain competitive advantage (Rumelt, 1984; Barney, 1991; Sirmon et al. 2011; Hitt et al. 2016). Resources can be classified as physical capital, human capital, technological capital, and reputational capital, being either tangible (e.g. infrastructure) or intangible (e.g. information or knowledge sharing) (Größler and Grübner, 2006). The bundling of different types of resources helps to generate competitive advantage (Newbert, 2007). Bundling has been defined by scholars (e.g., Grant, 1991; Sirmon et al., 2008) as resource integration to allow capability building, subsequently allowing for exploiting opportunities or mitigating threats (Sirmon et al. 2008). Whereas resources refer to the tangible and intangible assets, capabilities are subsets of a firm's resources which are non-transferable and aim at enhancing the productivity of other resources (Makadok, 1999). Hence, capabilities are identified as an absolute necessity for an organisation to prosper (Hitt, 2011). They depend on the environmental conditions in which an organisation operates (Brandon-Jones et al. 2014; Gunasekaran et al. 2017). Wu et al. (2006) argue that the utilisation of capabilities may help organisations to achieve or sustain competitive advantage, and, specifically in relation to supply chains, Wong and Karia (2010) identify the logistics resources acquired and bundled by logistics service providers to achieve competitive advantage.

Few studies have investigated the effect of the combination of resources and capabilities on performance (Brandon-Jones et al. 2014; Gunasekaran et al. 2017). Those which have include Ravichandran and Lertwongsatien (2005), who examined the influence of information resources and capabilities on organisational performance. In addition, Brandon-Jones et al. (2014) tested the impacts of supply chain connectivity and supply chain information sharing as resources and supply chain visibility as capability on the resilience and robustness of supply chains when developing inter-organisational relationships. Furthermore, Dubey et al. (2018) examined the effects of intra-organisational resources, in particular top management support and IT, on leveraging capabilities, e.g. for supply chain integration (see, Themistocleous et al. 2004).

In this study, we use RBV to conceptualise AI-BDAC as an organisational capability that impacts information alignment and collaboration. However, despite its popularity among operations management scholars (Hitt et al. 2016), the RBV has never looked beyond the properties of the resources and the resource markets to explain firm heterogeneity (Oliver, 1997). Ling-Yee (2007) further argues that RBV suffers from "context insensitivity". Context insensitivity suggests that the RBV fails to provide a better explanation or identify the conditions in which resources or capabilities may be most valuable (Brandon-Jones et al. 2014). Eckstein et al. (2015) argue that contingency theory offers an alternative theoretical lens to examine the contingent conditions under which resources and capabilities can generate better value. Donaldson (2001) use contingency theory to explain how organisations must adapt depending on the environmental conditions in which they operate. Sousa and Voss (2008) discuss how contingency factors, including national context and culture, firm size, strategic context and other organisational variables, have been analysed in operations and supply chain literature. The factor of top management commitment has been identified as a key contingent factor (Dubey et al. 2018). Whilst some scholars have integrated contingency theory and RBV to address the limitations of the static nature of the RBV (see, Aragon-Correa and Sharma, 2003; Brandon-Jones et al. 2014; Eckstein et al. 2015; Dubey et al. 2018), it is well recognised within operations and supply chain literature that contingent perspectives of RBV are still underdeveloped (see, Brandon-Jones et al. 2014).

2.1 Theoretical Model

Our theoretical model has two key elements: RBV and contingency theory, with a specific use of intergroup leadership in respect of the latter of the two elements (see Figure 1). Building on this tradition, we seek to use RBV to explain how information alignment, collaboration and AI-BDAC impact supply chain agility. The alignment of information is recognised as a critical factor that supports the coordination of task performance in complex operational environments (Caldwell et al. 2008). Moreover, contingency theory provides an explanation as to how contingent factors like intergroup leadership influence the effects of the information alignment and collaboration on supply chain agility. Thus, based on these two theories: RBV and contingency theory (intergroup leadership), we develop our theoretical model.

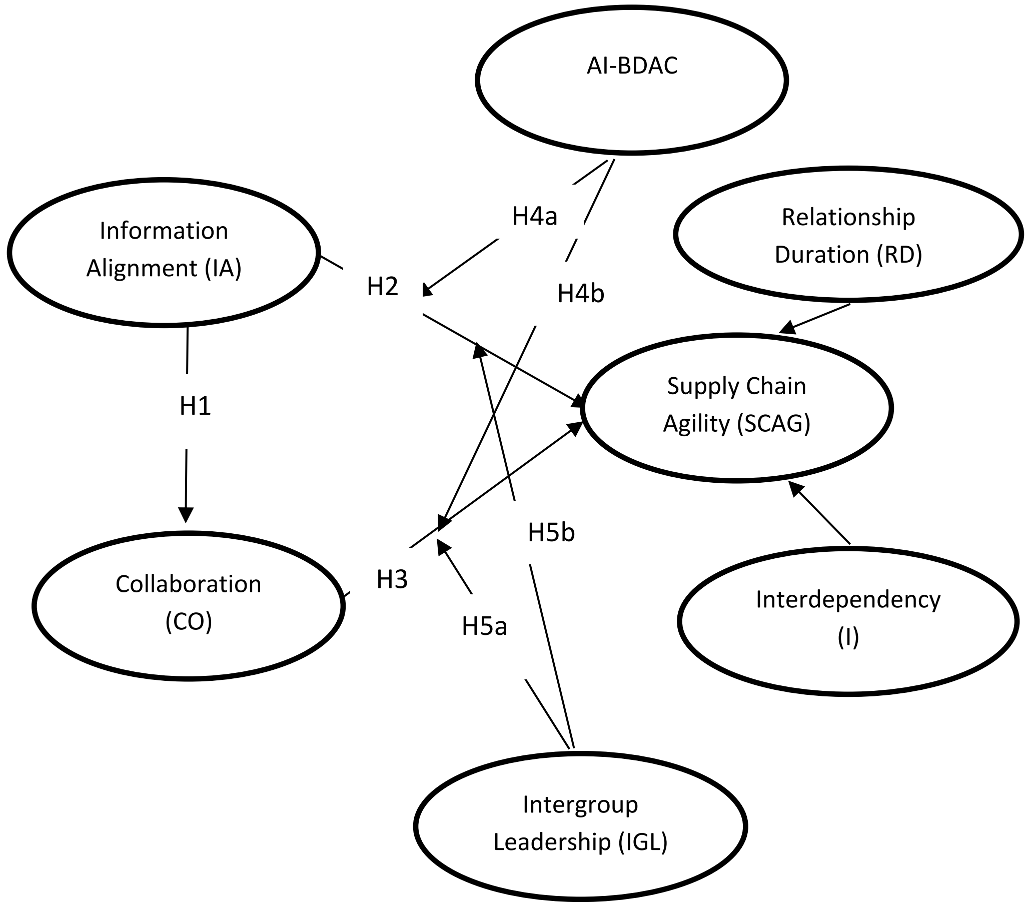

Figure 1: Theoretical Model

2.2 Research Hypotheses

2.2.1 Impact of Information Alignment on Collaboration

In complex environments like humanitarian operations, information sharing among disaster relief workers is often considered critical for better collaboration (Wentz, 2006; Altay and Pal, 2014; Altay and Labonte, 2014). Furthermore, organisations involved in humanitarian efforts that have high levels of transparency and effective information-sharing capabilities are significantly well positioned to develop and deploy systems and processes for supporting analytics capabilities (Prasad et al. 2019). In addition, organisations that invest in developing artificial intelligence driven big data analytics capabilities are likely to invest in supply chain visibility because visibility provides data upon which analytics systems and processes operate (Dubey et al. 2019a; Akhtar et al. 2019; Dubey et al. 2020b). Tatham and Rietjens (2016) argue that for effective collaboration it is important to understand the roles, relationships, capabilities, motivations, and information-sharing needs in complex environments. Based on the existing literature on collaboration among humanitarian workers and IT-business alignment, we argue that the extent to which information communication technology (ICT) capabilities improve information transparency and real-time data/information exchange depends on the severity of the disasters and their effects on victims (Fan et al. 2019). Reich and Benbasat (2000, p. 82) define information alignment as "*the degree to which the information technology mission, objectives and the plans support and are supported by the business mission, objectives and plans*". Kearns and Lederer (2003) argue that information alignment is a key predictor of IT investment profitability. In the context of supply chains, Tan et al. (2010, p. 378) define information alignment as "*the alignment of information flows and the use of compatible information systems between the buyer and supplier consistent with meeting strategic goals and customer requirements*". We note that the literature focuses on resource (e.g., IT applications), operational enabler (e.g., business process reengineering), and strategic weapon (e.g., a deliberately planned contract that sets specific alignment targets) as the most important factors for achieving IT and operational integration (Chi et al. 2020). Chi et al. (2020) further argue that in order to maximise the benefit of relationship-specific IT investment, appropriate policies and procedures should be put in place to guide and govern IT-enabled collaborative activities. Thus, we can argue that information alignment improves collaboration (Simatupang and Sridhar, 2005; Li et al. 2011; Chi et al. 2020). Following these arguments, this study focuses on exploring how information alignment between humanitarian workers engaged in disaster responses impacts collaboration among the disaster relief workers. Hence, we expect organisations involved in humanitarian activities, such as disaster relief, to understand the connections between information alignment and collaboration. We hypothesise these connections as:

H1: Information alignment has positive and significant effect on collaboration.

2.2.2 Impact of information alignment and collaboration on agility

In recent years, information technology alignment has remained a top priority for humanitarian relief organisations (L' Hermitte et al. 2016). Information alignment has a positive influence on agility (Tallon and Pinsonneault, 2011). Whether information alignment helps or hurts agility in humanitarian contexts is an unresolved issue (Fawcett and Fawcett, 2013). In this study, we intend to examine the relationship between information alignment and agility in humanitarian supply chains. Humanitarian organisations are expected to make relationship-specific investment and reconfigure business processes to align not only with their internal business models but also with other organisation models to create a seamless disaster response mechanism. Information should flow freely between collaborative partners to streamline operations. Finally, humanitarian workers should also govern and formalise the relationship with explicit rules and procedures. Lee (2004) argues that collaboration is an essential element of supply chain agility and Moshtari (2016) posit that where there is diversity between disaster relief workers' characteristics i.e. in goals, motivations, the success of collaborative relationships often depends on the workers' level of understanding about each other's objectives, operations and values. Dubey et al. (2019a) found that emerging technology like big data analytics plays a significant role in improving collaboration in context to civil-military partnerships. Hence we argue that information alignment and collaboration are crucial elements of agility. We hypothesise these relationships as:

H2: Information alignment has positive and significant effect on agility.

H3: Collaboration has positive and significant effect on agility.

2.2.3 Moderating Role of Artificial Intelligence driven Big Data Analytics Capability (AI-BDAC)

Artificial Intelligence (AI) and Machine Learning (ML) offer new opportunities to use the big data that we already have, as well as unleash a whole lot of new uses with new data types (Akter et al. 2020; Ivanov and Dolgui, 2020; Dolgui et al. 2020a,b). Srinivasan and Swink (2018) argue that analytics capability enables firms to increase their information processing capability. Dwivedi et al. (2019) identify several positive impacts on extracting useful information from big data that AI driven big data analytics capability has, which includes trust building, more coordination in uncertain environment and better decision making. Akter et al. (2016) highlight the role played by BDAC in improving alignment between various functional strategies and organisational level strategy to achieve better performance in highly dynamic environment. Dubey et al. (2019a) found a positive association between big data analytics capability and collaboration among civil-military organisations engaged in disaster relief operations. Achieving a shared vision, managing shared expectations, facilitating collaboration, and sharing information are crucial for disaster relief operations (Altay and Labonte, 2014). However the moderating role of AI-BDAC on the paths joining information alignment/collaboration and the agility is an unresolved issue. Hence, we hypothesise it as:

H4a: AI-BDAC has positive and significant effect on the path joining information alignment and agility.

H4b: AI-BDAC has positive and significant effect on the path joining collaboration and agility.

2.2.4 The Moderating Role of Intergroup Leadership

Following the tenet of intergroup leadership (Hogg et al. 2012) we argue that managing disaster relief subgroups of diverse backgrounds to achieve desired levels of collaboration requires leaders to recognise and respect each disaster relief subgroup's identities. In order to achieve desired levels of collaboration among distinct subgroups engaged in disaster relief operations, effective leaders engage in subgroup leadership, which refers to leading distinct subgroups. Such leaders understand that maintaining a positive subgroup identity requires a successful relationship with the respective subgroup (Hogg et al. 2012; Salem et al. 2019). Balcik et al. (2010) reveal that disaster relief environments generally engage international non-governmental organisations (NGOs), host governments, the military, local and regional relief organisations and third party logistics service providers (3PLs), each having different interests, mandates, capacity and logistics expertise. Specifically, in such cases where there is high level of diversity amongst these organisations, intergroup leadership is often considered beneficial as it does not invoke identity crises among these organisations. Rather, it respects the identity of each organisation and welcomes diversity as an important characteristic for effectively managing disaster relief efforts. Following intergroup leadership theory (see, Hogg et al. 2012; Rast III et al. 2018), we argue that leaders cultivate unique and beneficial traits via team meetings, personal conversations or after-work occasions, which build special bonds amongst diverse groups engaged in disaster relief operations. These traits often help leaders to resolve conflicts that are a result of a lack of transparency. In this way, we view intergroup leadership as complementary to information alignment, collaboration and supply chain agility. Hence, we hypothesise the following as:

H5a: Intergroup leadership has positive and significant effect on the path joining information alignment and agility.

H5b: Intergroup leadership has positive and significant effect on the path joining collaboration and agility.

3. Research Design

We tested our hypotheses in the context of organisations involved in disaster relief humanitarian activities. We gathered our data from numerous and diverse participants (see Appendix A) drawn from various countries across Asia, Europe, Africa, North America, and South America (this is an extension of a previous study by Dubey et al. (2019a)). The collaboration amongst various humanitarian organisations focuses on partnerships. Hence, we used constructs to study the information alignment, collaboration among various humanitarian organisations and the agility in the supply chains. Following Ketokivi and Schroeder's (2004) guidelines, we used measures based on multiple respondents, who were expected to have in depth understanding about partnerships during disaster relief operations and supply chain agility.

Our target respondents were project directors, deputy directors, and managers from NGOs, UN specialized agencies, as well as service providers and contractors, as they are the people with direct responsibility for managing and monitoring disaster relief operations. We conducted our study with the help of the United Nations Office for the Coordination of Humanitarian Affairs (OCHA), who provided contact information of the international NGOs and the military forces involved in the disaster relief operations. We have completed several prior studies with the assistance of OCHA, which as an organisation offers different services that reduces the specific category effects (Moshtari, 2016; Dubey et al. 2019a, 2020a).

3.1 Survey Instrument Development

We adopted a two stage process of construct definition and identification of measurement items (Eckstein et al., 2015; Dubey et al. 2019a) (see Appendix B). Firstly, we undertook an extensive review of literature drawn from operations management and organisational studies' streams of management. Extant literature provided us with the construct's definitions and the initial list of items used for measuring each construct. Secondly, we adapted the constructs and their associated items to humanitarian settings (see, Moshtari et al., 2016; Dubey et al., 2019a; Dubey et al. 2020a). The items were measured on a five-point Likert scale, with anchors ranging from strongly disagree (1) to strongly agree (5). This scale assures high statistical variability amongst responses gathered using our structured survey-based instrument (see, Moshtari, 2016; Srinivasan and Swink, 2018; Dubey et al. 2019a; Salem et al. 2019; Dubey et al. 2020a) (see Appendix B).

We undertook two steps to pre-test our instrument, to ensure that respondents would not face any difficulties in understanding the items when completing the survey (Hensley, 1999; Boyer and Pagell, 2000). In the first step we invited five experienced researchers to complete the survey in order to elicit their critical opinion on the wording of the questions, specifically analysing them for ambiguity, clarity, and appropriateness of items (DeVellis, 1991). Following Dillman's (2011) suggestions, we further analysed the feedback of these researchers to understand whether our questions are appropriately set in the context of humanitarian settings. We then utilised all the opinions of the five researchers to modify the questions if necessary or to delete some questions which were deemed not relevant to the setting of disaster relief humanitarian activities (Chen and Paulraj, 2004). In the second step, we e-mailed our questionnaire to eight senior managers drawn from various NGOs who had extensive experience of managing complex disaster relief operations and who had in depth understanding of the subject matter. We requested these managers to provide their critical input on structure, readability, ambiguity, and completeness of the questions asked in the survey. Taking their feedback on board we finalised our survey instrument ready for data collection.

3.2 Data Collection

We started our data collection on 22nd February, 2019 and completed it on 23rd November, 2019. We collected data from various international NGOs, UN specialised agencies and service providers, as an extended part of a previous study (Dubey et al., 2019a). We sent our questionnaire via e-mail to nearly 1800 potential respondents from 600 organisations and followed-up with two e-mail reminders. We assured potential respondents that their information would remain anonymous and the data gathered would only be used for academic purposes. After careful examination of each response, we eliminated cases which failed to meet our selection criteria. This resulted in usable responses from 193 organisations (see Appendix A), an effective rate of 27.16%, with at least three participants from each individual organisation (a total of 613 multiple responses). Since we have gathered our data at one point of time, i.e. cross-sectional data using a survey based instrument, we needed to analyse if those respondents who did not return their survey may have affected our findings. This kind of bias is termed as non-response bias (Armstrong and Overton, 1977). To test for this bias we performed ANOVA analysis on our data split into two parts: early wave and late wave (see, wave analysis recommended by Armstrong and Overton, 1977). The test yielded no significant difference between early-wave and late-wave groups of respondents (p=0.32). Hence, we conclude that non-response bias is not a concern in our study.

4. Data Analysis and Results

We have used PLS-SEM technique to test our theoretical model. Following Kock's (2019) arguments we have used Warp PLS 6.0 to address criticisms of traditional PLS-SEM methods due to them being composite-based, not factor-based. Recently, scholars have attempted to bridge the gap between factor-based and composite-based structural equation modelling (SEM) techniques (Kock, 2019). That is, in traditional PLS-SEM methods, latent variables are estimated as weighted aggregations of indicators without the inclusion of measurement errors (Henseler et al., 2014; Kock, 2019). Kock (2019) noted that traditional PLS-SEM ignore the measurement errors, which often leads to some known sources of bias; thus weakening the path coefficients with respect to their corresponding true values.

4.1 Multiple Rater Agreement Measures

As we have used multiple respondents in our study we need to assess the validity of the views of three or more respondents from one organisation. Following Ketokivi and Schroeder (2004) protocol we have performed inter-rater agreement analysis using four different methods: the percentage method (Boyer and Verma, 2000; Ketokivi and Schroeder, 2004), the ratio method (James et al., 1984; Boyer and Verma, 2000; Ketokivi and Schroeder, 2004), the inter-class correlation coefficient (Boyer and Verma, 2000) and paired t-test (Boyer and Verma, 2000; Ketokivi and Schroeder, 2004) (see, Appendix C). We therefore conclude, based on the results shown in Appendix C, that the inter-rater agreement in the data is acceptable.

4.2 Measurement Model Reliability and Validity

We adopted a two step process to validate our model (see Figure 1) as suggested in existing literature (see, Peng and Lai, 2012; Moshtari, 2016; Dubey et al. 2019a; Salem et al. 2019; Kock, 2019). Firstly, we examined the reliability and validity of our model with reflective constructs (Fornell and Larcker, 1981). Table 1 shows the result of confirmatory factor analysis (CFA) [i.e. the range of factor loadings (λi), the scale composite reliability (SCR), and average variance extracted (AVE)]. As shown in Table 1, factor loadings of each item are greater than 0.5 and significant at the 0.01 level, SCR of each construct is greater than 0.7 and AVE of each construct is greater than 0.5, indicating sufficient convergent validity at indicator and construct levels (Fornell and Larcker, 1981).

Table 1: Measurement Properties of Constructs (Convergent Validity) (N=193)

Constructs	Items	Factor Loadings (λi)	Variance (λi²)	Error (1-λi²)	SCR	AVE
IA	IA1	0.66	0.43	0.57	0.83	0.56
	IA2	0.70	0.49	0.51		
	IA3	0.88	0.77	0.23		
	IA4	0.74	0.55	0.45		
CO	CO1	0.82	0.68	0.32	0.83	0.55
	CO2	0.69	0.47	0.53		
	CO3	0.74	0.55	0.45		
	CO4	0.71	0.50	0.50		
SCAG	SCAG1	0.74	0.55	0.45	0.78	0.54
	SCAG2	0.75	0.57	0.43		
	SCAG3	0.71	0.50	0.50		
AI-BDAC	AI-BDAC1	0.78	0.61	0.39	0.86	0.60
	AI-BDAC2	0.81	0.65	0.35		
	AI-BDAC3	0.81	0.65	0.35		
	AI-BDAC4	0.70	0.49	0.51		
IGL	IGL1	0.69	0.48	0.52	0.86	0.52
	IGL2	0.60	0.36	0.64		
	IGL3	0.73	0.53	0.47		
	IGL4	0.72	0.52	0.48		
	IGL5	0.77	0.59	0.41		
	IGL6	0.79	0.63	0.37		
I	I1	0.80	0.65	0.35	0.78	0.65
	I2	0.80	0.65	0.35		

Notes: IA, Information Alignment; CO, Collaboration; SCAG, Supply Chain Agility; AI-BDAC, Artificial Intelligence driven big data analytics capability; IGL, Intergroup Leadership; I, Interdependency.

Secondly, we examined the divergent validity of measures used in our structural model (see Figure 1) via two methods: Fornell and Larcker's criterion and HTMT (hetrotrait-monotrait ratio of correlations). Following Fornell and Larcker (1981), we further examined the entries of the leading diagonal matrix (see Table 2), with the inter-correlation values in the given rows and columns. We observed that the square root values of each entries of leading diagonal, i.e. square root of AVE of construct, are greater than the inter-correlation values in each row and column in the matrix. Thus we conclude that our constructs possess sufficient divergent validity.

Table 2: Construct Correlations (Divergent Validity) (N=193)

	IA	CO	SCAG	AI-BDAC	IGL	I
IA	**0.75**					
CO	0.27	**0.74**				
SCAG	0.25	0.37	**0.73**			
AI-BDAC	-0.01	0.09	0.05	**0.77**		
IGL	0.26	0.23	0.21	0.15	**0.72**	
I	0.02	-0.02	-0.04	-0.07	0.01	**0.81**

Notes: IA, Information Alignment; CO, Collaboration; SCAG, Supply Chain Agility; AI-BDAC, Artificial Intelligence driven big data analytics capability; IGL, Intergroup Leadership; I, Interdependency.

In addition, we assessed the discriminant validity among constructs via HTMT criterion test. The HTMT values (see, Table 3) between reflective constructs are below 0.90, suggesting that adequate discriminant validity exist for all the constructs (Henseler et al. 2015).

Table 3: HTMT Values

	IA	CO	SCAG	AI-BDAC	IGL	I
IA						
CO	0.364					
SCAG	0.263	0.376				
AI-BDAC	0.157	0.162	0.211			
IGL	0.286	0.749	0.843	0.186		
I	0.223	0.617	0.667	0.114	0.812	

Notes: IA, Information Alignment; CO, Collaboration; SCAG, Supply Chain Agility; AI-BDAC, Artificial Intelligence driven big data analytics capability; IGL, Intergroup Leadership; I, Interdependency.

4.3 Common Method Bias (CMB)

As we use a survey based instrument to collect data there is a possibility that common method bias (CMB) may contaminate our results (Podsakoff and Organ, 1986; Podsakoff et al., 2003). Whilst we do not claim to have completely eliminated the chance of CMB occurring, following the suggestions of Ketokivi and Schroeder (2004) we aim to reduce its effects by using multi-informant data. Further, we have examined CMB in multiple ways. Firstly, we performed traditional one factor Harman's test (single factor explained nearly 21.21% of the total variance). Secondly, we examined for CMB via correlation marker technique (Lindell and Whitney, 2001). We adopted an unrelated variable to partial out correlations caused by CMB. Additionally, we determined the significant values of correlations, as suggested by Lindell and Whitney (2001). We noted minimal differences between the adjusted and unadjusted correlations. Therefore, based on these statistical results, we conclude that CMB is not a major issue in our study.

Following Kock's (2017) recommendations, we also calculated nonlinear bivariate causality direction ratio (NLBCDR). The NLBCDR measures the extent to which bivariate nonlinear coefficients of association provide support for the hypothesized directions of the causal links in the proposed theoretical model (Kock, 2012, p.52-53). The acceptable value should be ≥ 0.7. In our study we found NLBCDR=0.88 (approx.), which is greater than the critical value of 0.7. We therefore conclude that causality is not a major issue. We have further provided the values for model fit and quality indices supporting this conclusion in Appendix D.

4.4 Hypotheses Testing

Table 4 provides the results of PLS-SEM analysis. The hypotheses H1-H3 examine the linkage between information alignment, collaboration and supply chain agility. Firstly, we found support for H1 (IA→CO) (β=0.28; p<0.001). This finding is consistent with previous literature (see, Chi et al. 2020). Next, we found support for H2 (IA→SCAG) (β=0.38; p<0.001). This findings is also consistent with our previous studies (Tallon and Pinsonneault, 2011; Fawcett and Fawcett, 2013). Addressing, H3 (CO→SCAG), we found support (β=0.75; p<0.001), which is consistent with previous arguments (see, Lee, 2004).

We have further tested the interaction effects of AI-BDAC and intergroup leadership on the paths joining IA/CO and SCAG (H4a/b & H5a/b). We found support for H4a (β=0.38; p<0.001) and H4b (β=0.33; p<0.001). Similarly, we found support for H5a (β=0.27; p<0.001) and H5b (β=0.36; p<0.001). Our findings paint an interesting picture. Our findings further extend the Salem et al. (2019) findings by examining the moderating influence of intergroup leadership. However, we did not find support for control variables interdependency (I) (β=0.002; p>0.1) and relationship duration (RD) (β=-0.010; p>0.1). We interpret these observations as demonstrating that the interdependency (i.e. the degree to which partners are dependent on each other) and relationship duration (i.e. the age of collaborative relationship between disaster relief groups) does not produce significant effects on supply chain agility.

Table 4: Structural Estimates (N=193)

Hypothesis	*Effect of*	*Effect on*	*β*	*p-value*	*Results*
H1	IA	CO	0.28	<0.001	supported
H2	IA	SCAG	0.38	<0.001	supported
H3	CO	SCAG	0.75	<0.001	supported
Interaction effects					
H4a	IA*AI-BDAC		0.38	<0.001	supported
H4b	CO*AI-BDAC		0.33	<0.001	supported
H5a	IA*IGL		0.27	<0.001	supported
H5b	CO*IGL		0.36	<0.001	supported
	Control variables				

	I	SCAG	0.02	>0.1	Not-supported
	RD	SCAG	-0.010	>0.1	Not-supported

To further examine the explanatory power of our theoretical model (see Figure 1) we analysed the explanatory power (R^2) of the endogenous constructs as shown in Appendix E. The IA explains nearly 32% of the total variance in CO (R^2=0.32) and the IA and CO explain nearly 83% of the total variance of SCAG (see Figure 2). We further determined the effect size (f^2) value of CO using Cohen's f^2 formula. Consequently, the effect size of IA on CO is 0.21 and on SCAG is 0.27 and CO on SCAG is 0.72. We additionally examined the predictability of the model. Stone-Geiser's Q^2 values of endogenous constructs are CO (0.18) and SCAG (0.88) (see Appendix E), which are greater than zero. With these results, we find that the AI-BDAC has significant predictive capability (Peng and Lai, 2012). Figure 2 shows the validated conceptual framework after SEM analysis.

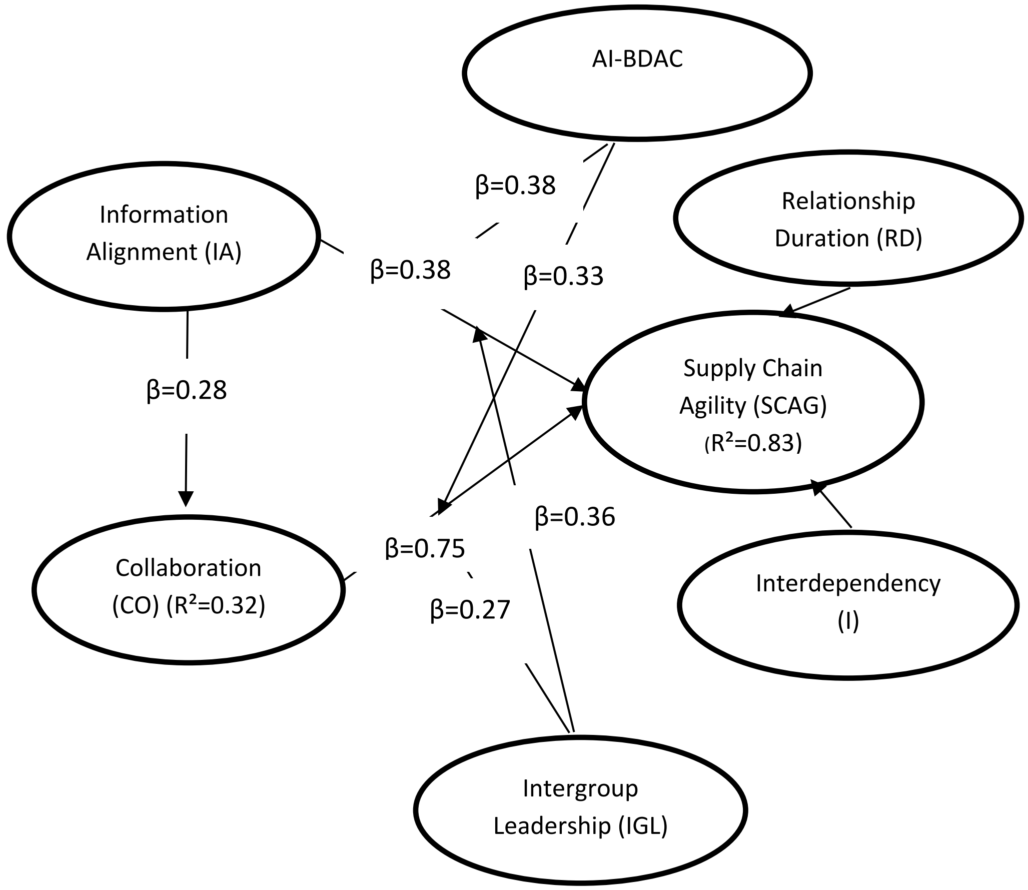

Figure 2: Final Model

5. Discussion

Our results paint an interesting picture of associations amongst information alignment, collaboration and supply chain agility from resources and capability perspective. They reveal how agility in humanitarian supply chains is enhanced within collaborative relationships developed via artificial intelligence driven big data analytics capability and intergroup leadership. The results, derived via statistical analysis, use empirical data gathered from a pretested instrument. They highlight how the interplay between tangible and intangible resources further help to enhance collaboration amongst the disaster relief operations partners and supply chain agility. Furthermore, the moderating effects of AI-BDAC and IGL on the paths joining IA/CO and SCAG provide nuanced understanding of how artificial intelligence driven big data analytics capability and intergroup leadership influences the supply chain agility in humanitarian supply chains. Collectively, these findings offer some useful contributions to theory and some interesting directions for the managers engaged in disaster relief operations. Furthermore, the findings raise potential research questions that help to advance future research.

5.1 Implications for Theory

Our study offers some important contributions to existing theoretical debates. Firstly, we demonstrate that IA and CO, as two distinct types of resources, in combination can help to generate SCAG. Prior to our study, the extant literature has not offered any clarity on the possible link between IA, CO and SCAG. Previous studies, i.e. Tan et al. (2010) and Ng et al. (2013), have argued to recognise the importance of information alignment in building partnerships. However, these studies were conducted in the context of commercial enterprises and, to date, humanitarian scholars have remained silent in terms of the interplay of resources and capabilities in generating competitive advantage.

Secondly, our study provides empirical evidence that information alignment and collaboration act as antecedents to agility in humanitarian supply chains (see Figure 2). This is one of the few studies utilising a survey based approach to test such hypothesised relationships. The existing literature has offered anecdotal evidence, with little theory driven and empirically tested results. Existing literature has often studied the interplay of resources and capabilities to examine the level of agility (Swafford et al. 2006; Braunscheidel and Suresh, 2009; Blome et al. 2013; Dubey et al. 2019d; Gligor et al. 2015). However, in the context of humanitarian operations, theory driven research, using empirical data, is scant. Hence, our study attempts to disentangle the concept of agility from its predominant commercial organisations' perspective. Although we have taken our arguments from commercial supply chain literature and organisational studies, the pretesting exercise in the context to humanitarian settings offers different and interesting perspectives.

Thirdly, building upon previous findings (see, Salem et al. 2019), we have examined the moderating role of intergroup leadership. The operations management literature has acknowledged the role of top management commitment and leadership (see, de Koster et al. 2011; Lee et al. 2011; Dubey et al. 2018), in enhancing performance. However, based on Hogg et al.'s (2012) arguments, we posit that humanitarian operations are complex in terms of the nature and characteristics of the hastily formed teams. Salem et al. (2019) have examined the relationship between intergroup leadership and humanitarian operations performance under the mediating effect of cooperation. We have further extended the arguments via testing the moderating effect of IGL on the paths joining IA/CO and

SCAG. We believe, our results paint an interesting picture about intergroup leadership theory, which may help to explain the complex interaction between technology and humanitarian groups.

Despite some interesting contributions, we believe that there is still sufficient room for further investigations. For instance, we are yet to understand how intergroup leadership may help to address the dilemma of managing the interplay between inter-organisational cultural complexities, inter-organisational learning and intergroup leadership in the context of humanitarian settings; where the COVID-19 pandemic has exposed limitations of our management of disaster relief operations. Moreover, despite the great number of emerging technologies, most of the disaster relief efforts has failed to address complexities associated with the human and technology interface. In understanding and then addressing these complexities in humanitarian settings there is an urgent need for theory driven and data driven studies.

5.2 Implications for Practice

This study offers a number of useful implications for managers engaged in managing disaster relief operations. In the past, we have witnessed significant investment in building advance technological capabilities. However, investment in these technologies alone cannot help organisations – including those involved in humanitarian endeavours – achieve the desired levels of success. Alongside utilising the right technologies, there need to be leaders with the right traits to direct the complex activities that take place in disaster relief. Our findings, which are based on arguments drawn from extant literature and data gathered using a pre-tested instrument, confirm that intergroup leadership, with the associated required traits, may play a significant role in the effective working of hastily formed organisations, as is the case for disaster relief. Previous work by Schiffling et al. (2020a) has shown how crucial personal connections are for enabling swift actions in humanitarian responses. We provide evidence for the influence of intergroup leadership in particular on supply chain agility, which is a desirable trait in many humanitarian supply chains. In addition, information alignment and collaboration can together play a significant role in explaining the presence of agility in humanitarian supply chains. Hence, managers need to understand the interplay of, and maintain a fine balance between, information alignment and collaboration, while also focusing on leadership that enables intergroup connections. This should inform training of humanitarian supply chain professionals and leaders. Furthermore, the balance between information alignment and collaboration should be an important consideration in designing and operationalising interactions between different humanitarian organisations if supply chain agility is of importance,

Finally, our results offer useful observations in relation to relationship duration and interdependency of the parties that make up humanitarian supply chains. In the past, literature has highlighted the role of relationship duration and interdependency in building agility in different organisational contexts. However, our results suggest that for managers of humanitarian efforts such a role might be difficult to establish, as we found no significant relationship between relationship duration, interdependency and agility. This may be attributable to the specific characteristics of the humanitarian organisations, such as there is very little time to build relationships, so duration is not a critical variable and swift trust is vital to many interactions. For managers, this can be an encouraging finding as agility has not been shown to depend on long-term relationships, which may often be unattainable in disaster relief contexts. Although, in respect of this observation, we caution our readers that our results must be interpreted with respect to this particular situation and the findings need further testing in different contexts; thus there is a need for careful interpretation. That said, it is clear that managers who seek greater agility in the responses of their supply chain partners, may need to look for other antecedents, besides relationship durations and interdependency, and uncovering these antecedents is a potentially fruitful avenue for future research.

5.3 Limitations and Further Research Directions

Humanitarian organisations and other aid agencies recognise the benefits of using emerging technologies to improve information alignment and collaboration. Furthermore, donors are increasingly demanding more transparency, becoming less tolerant of the inefficiencies arising during disaster relief operations, and, therefore, demanding more collaborative efforts among humanitarian organisations (Moshtari, 2016). Our study contributes to the technology-enabled collaboration, intergroup leadership and supply chain agility literature, specifically in the context of humanitarian supply chains. However, despite our efforts via using established organisational theories, as well as testing our research hypotheses using multi-informant data gathered using a pre-tested questionnaire with the help of reputable organisations, we feel that our study has some limitations.

Firstly, we have focused on the application of a few antecedents, information alignment and collaboration, to empirically investigate the interplay of these two resources and capabilities in enhancing agility in humanitarian supply chains. Hence, future studies can explore how other organisational factors may enhance agility in the technology era, including how factors might interact in negative ways, such as the misuse of technology providing an inhibitor to the interplay of IA and CO. Additionally, our current study has not considered other potentially significant variables, such as organisational culture or the attitude of those involved in humanitarian activities towards the usage of technologies.

Secondly, disparities of power amongst partners may yield different outcomes. Although, we have partially recognised the potential influence of disparity in power structures and their effects on collaboration by introducing the concept of intergroup leadership to iron out such differences, still our understanding of the interplay of intergroup leadership in complex humanitarian context remains limited. Although Salem et al. (2019) offers a comprehensive perspective, still lot of questions relating to intergroup leadership in the context to humanitarian settings need answering.

Finally, we have utilised cross-sectional survey data to test our research hypotheses. Hence, with the help of cross-sectional data, the cause and effects relationship between constructs may not be understood. Thus, to address such limitations, we recommend further research involving the collection of panel data. However, we recognise the challenges in obtaining such panel data in humanitarian settings and hence a possible solution could be the collection of multi-level data (see, Dubey et al. 2019a).

6. Conclusions

Our study examined the interplay between information alignment and collaboration in order to improve supply chain agility in the context of humanitarian settings. To further substantiate our arguments, we introduced the moderating role of AI-BDAC and intergroup leadership to explain how emerging technology and different traits of leadership help complex humanitarian organisations to achieve significant results. We have grounded our arguments in established resource based view (RBV) and contingency theory, as we have recognised the need for such theories to explain the differential effects of emerging technologies and intergroup leadership on agility in humanitarian settings. To test our research hypotheses we used multi-informant survey data, as suggested by Ketokivi and Schroeder (2004). In this way, we have tried to address previous concerns raised by a majority of the operations and supply chain management scholars. Our results offer some useful insights to future scholars and managers. Further, we have noted some limitations of our study that may help shape future research agendas and, thus, we hope that our study may offer enough ingredients for further research that will in turn add to the ongoing debate. Finally, we hope our study provides insight into understanding the relationships between critical elements of humanitarian supply chains, which may be utilised to better manage the disaster relief efforts.

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Appendix A: Profile of the responding organisations (N=193)

Organisations	Frequency	Percentage
Developed-country government aid agencies	59	30.57
International NGOs	63	32.64
Volunteer, university and faith-based teams and individuals	54	27.98
Service providers and contractors	17	8.81
Nationality	**Frequency**	**Percentage**
Asia		
Afghanistan	4	2.07
Bangladesh	5	2.59
China	17	8.81
DPR Korea	6	3.11
India	13	6.74
Indonesia	3	1.55
Japan	13	6.74
Myanmar	4	2.07
Thailand	5	2.59
Europe		
Belgium	3	1.55
Denmark	6	3.11
France	11	5.70
Finland	7	3.63
Ireland	3	1.55
Netherlands	6	3.11
United Kingdom	8	4.15
Africa		
Cameroon	7	3.63
Egypt	3	1.55
South Africa	6	3.11
North America		
Canada	16	8.29
United States	15	7.77
Mexico	3	1.55
South America		
Argentina	12	6.22
Brazil	13	6.74

Appendix B: Operationalisation of Constructs

Construct and Derivation	**Types**	**Measures**
Artificial Intelligence driven Big Data Analytics Capability (AI-BDAC) (Adapted and modified from Dubey et al. 2019a)	Reflective	We use artificial intelligence guided advanced analytical techniques (e.g. simulation, optimisation, regression) to improve decision-making related to joint disaster relief operations (AI-BDAC1) We use multiple data sources to improve collaboration during disaster relief efforts (AI-BDAC2) We use data visualisation techniques (e.g. dashboards) to assist users to decision-maker in understanding complex information (AI-BDAC3) We use dashboards to display information to undertake cause analysis and continuous improvement (AI-BDAC4)
Information Alignment (IA) (Chan and Reich, 2007; Tan et al. 2010)	Reflective	We use informal information sharing agreements among participating humanitarian organisations (IA1) We regularly communicate our future strategic needs to our service providers (IA2) We regularly communicate our future strategic needs among participating partners in disaster relief operations (IA3) We create compatible information systems among various humanitarian organisations (IA4)
Collaboration (CO) (Krishnan et al. 2006; Moshtari, 2016)	Reflective	The objectives for which the collaboration was established are being met (CO1) Our organisation is satisfied with the overall performance of the collaboration (CO2) Our association with these partners has been a successful one (CO3) These partners seem to be satisfied with the overall performance of the collaboration (CO4)
Supply Chain Agility (SCAG) (Altay et al. 2018)	Reflective	Our organisation can quickly detect changes in our environment (SCAG1) Our organisation can quickly sense threats in its environment (SCAG2) We make quick decisions to deal with changes in environment (SCAG3)

Intergroup Leadership (IGL) (Hogg et al. 2012; Salem et al. 2019)	Reflective	The field manager interacts frequently with both, local and expatriate employees (IGL1) The field manager puts lots of effort into strengthening the relationship between the local and expatriate group (IGL2) The field manager is a good example of the relationship between the local and expatriate group (IGL3) The field manager is an embodiment of the connection between the local and expatriate group (IGL4) The field manager stresses that local and expatriate employees work together while maintaining their distinct and separate group identities (IGL5) The field manager argues that the local and expatriate employees are two separate groups that need to work together collaboratively (IGL6)
Interdependency (I) (Brown et al. 1995)	Reflective	It would be costly for our organisation to lose its collaboration with the partner (I1) This partner would find it costly to lose the collaboration with our organisation (I2)
Relationship Duration (RD) (Moshtari, 2016)	Formative	Time in years

Appendix C: Measures of inter-rater agreement

Constructs	Percentage method (%)	Ratio method	Inter-class correlation coefficient	Paired t-test
AI-BDAC	88	0.79	0.38	Not-significant
IA	85	0.76	0.43	Not-significant
CO	87	0.82	0.38	Not-significant
SCAG	84	0.83	0.33	Not-significant
IGL	83	0.73	0.29	Not-significant
I	91	0.79	0.32	Not-significant

Notes: AI-BDAC, Artificial Intelligence driven big data analytics capability; IA, Information Alignment; CO, Collaboration; SCAG, Supply Chain Agility; IGL, Intergroup Leadership; I, Interdependency.

Appendix D: Model fit and quality indices (N=193)

Model fit and quality indices	Value from analysis	Acceptable if	Reference
APC	0.31, $p<0.001$	$p<0.05$	Rosenthal and Rosnow (1991)
ARS	0.512, $p<0.001$	$p<0.05$	
AVIF	3.504, $p<0.001$	$p<0.05$	Kock (2012)
Tenenhaus GoF	0.612	Large if ≥ 0.36	Tenenhaus et al. (2005)

Appendix E: R^2, Prediction and Effect Size (N=193)

CONSTRUCT	R^2	Q^2	F^2 IN RELATION TO		
			IA	CO	SCAG
IA					
CO	0.32	0.18	0.21		
SCAG	0.83	0.88	0.27	0.72	

Notes: AI-BDAC, Artificial Intelligence driven big data analytics capability; IA, Information Alignment; CO, Collaboration; SCAG, Supply Chain Agility