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Impact of artificial intelligence-driven big data analytics culture on agility and resilience in humanitarian supply chain: A practice-based view

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ABSTRACT

This study attempts to understand the role of artificial intelligence-driven big data analytics capability in humanitarian relief operations. These disasters play an important role in mobilizing several organizations to counteract them, but the organizations often find it hard to strike a fine balance between agility and resilience. Operations Management Scholars' opinion remains divided between responsiveness and efficiency. However, to manage unexpected events like disasters, organizations need to be agile and resilient. In previous studies, scholars have adopted the resource-based view or dynamic capability view to explain the combination of resources and capabilities (i.e., technology, agility, and resilience) to explain their performance. However, following some recent scholarly debates, we argue that organizational theories like the resource-based view or dynamic capability view are not suitable enough to explain humanitarian supply chain performance. As the underlying assumptions of the commercial supply chain do not hold true in the case of the humanitarian supply chain. We note this as a potential research gap in the existing literature. Moreover, humanitarian organizations remain sceptical regarding the adoption of artificial intelligence-driven big data analytics capability (AI-BDAC) in the decision-making process. To address these potential gaps, we grounded our theoretical model in the practice-based view which is proposed as an appropriate lens to examine the role of practices that are not rare and are easy to imitate in performance. We used Partial Least Squares (PLS) to test our theoretical model and research hypotheses, using 171 useable responses gathered through a web survey of international non-governmental organizations (NGOs). The findings of our study suggest that AI-BDAC is a significant determinant of agility, resilience, and performance of the humanitarian supply chain. Furthermore, the reduction of the level of information complexity (IC) on the paths joining agility, resilience, and performance in the humanitarian supply chain. These results offer some useful theoretical contributions to the contingent view of the practice-based view. In a way, we have tried to establish empirically that the humanitarian supply chain designs are quite different from their commercial counterparts. Hence, the use of a resource-based view or dynamic capability view as theoretical lenses may not help capture true perspectives. Thus, the use of a practice-based view as an alternative theoretical lens provides a better understanding of humanitarian supply chains. We have further outlined the limitations and the future research directions of the study.

1. Introduction

An efficient response to a disaster involves providing the right relief materials at the right time to victims and this is the most important aspect of the humanitarian supply chain (Vanajakumari et al., 2016). Humanitarian crises have forced disaster relief organizations to develop abilities that combine speed, flexibility, robustness, and the ability to restore normalcy (Gupta et al., 2016; Altay et al., 2018; Altay and Narayanan, 2022). To tackle humanitarian crises, the humanitarian supply chain should be agile and resilient (Ivanov and Das, 2020;

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Mandal and Dubey, 2021; Queiroz et al., 2020, 2021; Stewart and Ivanov, 2019). Altay et al. (2018) further argue that despite the rich body of literature on agility and resilience, most of the studies have examined these two important attributes of the humanitarian supply chain in isolation. To date, except for a few studies, most of the literature has largely remained silent on the relationship between these two attributes. We note this as a clear research gap. To address this research gap, we state our first research question (RQ1): *What are the effects of agility and resilience on humanitarian supply chain performance?*

The significant rise in disasters has further accelerated the need for the adoption of AI-driven technologies. These will shape global response strategies to tackle the world's most difficult challenges, especially in the humanitarian sector (Pizzi et al., 2020). Besiou et al. (2021) argue that the adoption of data analytics, AI, and other emerging technologies will further help human progress and contribute to achieving UN sustainable development goals. Hence, we argue that the use of digital technology in humanitarian assistance has played a significant role in saving numerous lives and properties (Sandvik et al., 2014; Gupta et al., 2016; Lawson-McDowall et al., 2021; Besiou et al., 2021; Queiroz et al., 2022).

However, the adoption of advanced technology, workforce adoption, and capability building is uniquely challenging because of the scope of humanitarian missions and the multifaceted nature of its stakeholders (Sandvik et al., 2014; Dubey et al., 2019a). Brock and Von Wangenheim (2019) and Watson et al. (2021) provide empirical insights based on leaders' perceptions of how their organizations will shape corporate strategy in the AI and big data analytics era. Existing studies though only offer anecdotal evidence and findings from empirical studies investigating the role of AI-driven big data analytics culture (AI-BDAC) on agility and resilience in the humanitarian supply chain remain scant. We note this as a research gap. To address this research gap, we posit our second research question (*RQ2): What are the effects of AI-driven big data analytics culture (AI-BDAC) on agility and resilience in the humanitarian supply chain?*

Effective coordination among the different humanitarian supply chain actors depends on the ability of the individual actors to process the acquired information (Altay and Pal, 2014; Mishra et al., 2020). However, Rao and Jarvenpaa (1991) argue that the need to communicate among the group members often distracts the information processing capabilities of the group members. Hence during humanitarian relief operations, the different actors engaged in humanitarian relief operations often need to process large information within a short time (Day et al., 2009). Hence, these demands may lead to information overload. This phenomenon of processing voluminous amounts of information, resulting in information overload, is termed information complexity (Day et al., 2009; Paul and Nazareth, 2010).

Information complexity is considered a key area of managerial concern (Rao and Jarvenpaa, 1991) and a critical factor moderating the various relations between actual practice and performance (Liu, 2015; Champion et al., 2019). Information complexity often leads to confusion and further depletes the trust formed among the humanitarian actors. This often leads to a rise in opportunistic behavior (Dubey et al., 2019a; Tatham and Kovács, 2010). Hence a reduction of information complexity using emerging technologies may enhance the positive effects of agility and resilience on humanitarian supply chain performance. In previous research, such effects of information complexity have not been addressed or empirically tested. Therefore, we state our third research question (RQ3): *What are the effects of the information complexity on the paths joining agility, resilience, and humanitarian supply chain performance?*

To address the three research questions, the main objectives of our research *are:*

a. To develop a theoretical framework that helps explain the role of AI-driven big data analytics capability (AI-BDAC) to enhance agility, resilience, and performance in the humanitarian supply chain.
b. To then empirically validate the theoretical framework.

Most management scholars have conceptualized agility and resilience as dynamic capabilities (Brusset, 2016; Altay et al., 2018; Yu et al., 2019). However, in this study, we question the suitability of the dynamic capability view (DCV) for humanitarian operations management research on multiple fronts.

Firstly, Teece et al. (1997), grounded their arguments in strategic management, with a focus on how the organization's dynamic capability can help sustain competitive advantage. However, the focus of humanitarian supply chain management is to alleviate the suffering of the victims by providing the right relief materials, at the right time in the right place. Hence, the competitive advantage notion, which applies to the business or firm, may not easily translate to humanitarian operations management research.

Secondly, DCV argues that dynamic capabilities are the organization's ability to integrate, build and reconfigure internal and external competencies, to tackle dynamic and turbulent environments (Teece et al., 1997; Lee and Rha, 2016; Fosso Wamba et al., 2020). Yet humanitarian relief efforts are carried out by multiple actors, each of them being guided by their missions, interests, capacity, and supply chain expertise (Balcik et al., 2010).

Following Bromiley and Rau (2016a) arguments we posit that the practice-based view (PBV) is a simpler and a far more comprehensive alternative option to the DCV, with which to examine agility and resilience. Practices that help humanitarian relief actors to provide aid to victims affected by disasters include providing food, medicines, and medical support to ensure a quick recovery.

We also note there is a clear research gap in the operations management literature of studies, underpinned by theory besides DCV in understanding the relationships between agility, resilience, and humanitarian supply chain performance. Hence, by empirically validating our theoretically derived framework with data gathered from 171 international humanitarian non-governmental organizations, our study offers two major contributions to theory. Firstly, the integration of two theoretical perspectives: PBV (Bromiley and Rau, 2016a) and contingency theory (see, Lawrence and Lorsch, 1967; Sousa and Voss, 2008). This helps to examine the extent to which agility and resilience in the humanitarian supply chain contribute to supply chain performance. Secondly, by recognizing the role of information complexity in the humanitarian supply chain network.

The remaining part of our paper is organized as follows. In the next section, we have presented the literature review. In the third section, we have discussed our theoretical framework and research hypotheses. In the fourth section, we have set out our mixed-methods research design, involving the collection of data through interviews of managers working for global Non-Governmental Organizations (NGOs) (n = 17) followed by an online survey of such managers (n = 171). This section also contains information on how we operationalized our constructs, using multi-item scales derived from the literature and how we then analyzed the data. In the fifth section, we have presented the results obtained through statistical analyses. In the sixth section, we discuss the findings, highlighting the relevance of the PBV and contingency theory to explain relationships in the unique context of humanitarian supply chain operations. This is followed by a discussion of our theoretical contributions. We follow this with some thoughts on the implications for managers, specifically around the evidence justifying investment in, and a focus on, AI-driven technologies, to drive enhanced performance. We then acknowledge the limitations of our study, specifically around the online survey, and outline some future research directions. In doing this we call for more work around the applicability of the PBV in this context. Finally, we draw our main conclusions regarding the complex and nuanced relationships between antecedents and moderators of HSCP, encompassing technology factors, culture, organizational agility, resilience, and communications between actors involved in humanitarian disaster relief operations.

2. Literature review

2.1. Practice-based view (PBV)

The practice-based view (PBV) is a relatively new perspective proposed by Bromiley and Rau (2014) as an alternative approach to the resource-based view (RBV) (see, Barney, 1991; Peteraf, 1993). The PBV stems from the logic that even small day-to-day activities of any firm or organization influence their performance. The RBV and the DCV, seek to explain how the resources or the capabilities of the firm generate superior performance for the organization or help to sustain superior performance (Bag et al., 2021). Nevertheless, Bromiley and Rau (2014, 2016a) argue that the theory of competitive advantage is only applicable to a few selected firms in an industry and that average firms, which are making small but significant progress, do not meet the eligibility criteria for the application of the RBV/DCV.

Moreover, the RBV or DCV focuses on the explanatory variables that result in competitive advantage (Kovács and Tatham, 2009). However, humanitarian relief efforts involve actors from various organizations to help victims by providing them with necessary relief items and shelter. In such cases, humanitarian operations management scholars need to focus on those common practices that may improve humanitarian supply chain performance.

There is a common belief among scholars that the management of humanitarian supply chains is a simple application of practices derived from the management of commercial supply chains. Yet some scholars advocate that despite some commonalities, these two types of supply chain are significantly different in terms of objectives (Holguín-Veras et al., 2012). Hence, it requires different kinds of skills to manage humanitarian supply chains efficiently and effectively (e.g., Charles et al., 2010; Holguín-Veras et al., 2012).

Compared with a commercial supply chain, loss in a humanitarian supply chain is not measured in terms of increased distribution cost or poor on-time delivery (Tatham and Kovács, 2010). A lack of effectiveness or inefficiencies can cause huge losses in terms of the negative impact on the lives of vulnerable people who are stuck in disaster-affected areas. Therefore, to explain humanitarian supply chain performance, the theories of RBV or DCV do not seem appropriate. For instance, the idea of RBV stems from the assumption that those resources that help generate or sustain competitive advantage must be valuable, rare, not easy to imitate and are non-substitutable (V, R, I, N) (Barney, 1991; Peteraf, 1993). However, it is hard to imagine such resources that may help generate a commercial competitive advantage are equally applicable in the context of humanitarian relief efforts. The humanitarian supply chain is often formed rapidly, and the actors involved are working voluntarily (Tatham and Kovács, 2010). Thus, the PBV is far more applicable as it focuses on common practices and performance.

Similarly, the DCV also focuses on the ability to integrate, build and reconfigure internal and external competencies. To create capabilities that help the organization sustain competitive advantage in a highly dynamic or turbulent environment. However, to create such kinds of capabilities organizations need to pursue this as a long-term project, which requires significant investment. Nevertheless, the humanitarian supply chain mostly involves short-lived projects which require an immediate response. Again, instead of DCV, it is the PBV that makes more sense.

2.2. Contingency theory (CT)

"*As operations management (OM) best practices have become mature, research on practices has begun to shift its interest from the justification of the value of those practices to the understanding of the contextual conditions under which they are effective—OM practice contingency research (OM PCR)*" (Sousa and Voss, 2008, p.697). Eckstein et al. (2015) argue that CT is considered a mid-range theory that aims at identifying the situations within the firm's settings that influence performance. CT posits that the organization should adapt its structure and practices to suit the environmental context in which the organization is operating (Donaldson, 2001). CT explains under what contextual situations operations management practices enhance the performance of the organization.

Kunz and Gold (2017) argue that humanitarian operations aim at alleviating the suffering of disaster-affected victims in the shortest time, with limited resources. In this context, it is very important to keep in mind that while moving disaster relief materials to the affected victims, the disaster relief workers should consider the local environment. Humanitarian supply chain design needs to align not only to the relief organization's structure but also to the local population's long-term requirements, as well as to any socio-economic and governmental contingency factors (Salam and Khan, 2020). Hence following the tenets of the CT, we argue that the practices of humanitarian organizations, under specific conditions, may provide a better explanation to enhance humanitarian supply chain performance.

2.3. Artificial intelligence-driven big data culture (AI-BDAC)

In recent times we have witnessed a significant rise in the use of the "big data" term. However, in the next few years, such a term may make no sense due to the rapid changes in computing technology and capabilities i.e., the scale of big data today may appear to be small in the next few years (Akter and Wamba, 2019). Moreover, without the application of artificial intelligence (AI) big data will have no usage (Akter et al., 2021; Kankanamge et al., 2021 O' Leary, 2013).

Big data is enabling commercial as well as non-profit making organizations to move away from intuitive to data-driven decision-making (Duan et al., 2019). Organizations will use big data to help create value by tackling complex issues and problems in less time, at a relatively low cost (Dwivedi et al., 2021). As a result, the critical role of AI is to generate value by providing organizations with intelligent insights from large data sets (Dubey et al., 2020) and to help capture structured interpretations of large unstructured data sets which constitute nearly 85% of the total volume of big datasets.

Sandvik et al. (2014) argue that humanitarian sectors have enormous opportunities to improve their actions using digital technology. In recent disaster relief efforts, the use of mobile phones, social media platforms, geospatial technologies, and various forms of crowdsourcing tools have redefined the way humanitarian crises are identified and tackled, and how information is gathered, analyzed and shared among the various humanitarian actors (Behl and Dutta, 2020; Fan et al., 2021; Kankanamge et al., 2021; Papadopoulos et al., 2017; Sandvik et al., 2014). This has led to attempts to tackle the challenges of humanitarian relief efforts using multidisciplinary approaches, see, for example, Fan et al. (2021).

Despite increasing optimism related to the application of digital technology in the humanitarian space. Literature on the role of AI-driven big data analytics on agility and resilience practices to improve humanitarian supply chain performance is still in the infancy stage. Humanitarian organizations are relatively slow to appreciate the importance of this technology to improve their decision-making abilities (Behl et al., 2021). One of the main causes for the slow adoption of AI-driven big data analytics in the humanitarian sector is the lack of proper understanding of the technology. Together with an absence of the complex skills needed to use it to tackle humanitarian challenges.

The lack of an AI-BD-AC may be one of the factors contributing to the poor adoption of emerging technologies to improve humanitarian relief efforts (Pizzi et al., 2020). Gupta and George (2016) and Dubey et al. (2019a, b) argue that a "big data" culture has a significant impact on technology's adoption. The role of culture in the field of operations management has been extensively studied by various scholars (see, Altay et al., 2018; Dubey et al., 2019a, b; Gupta and Gupta, 2019; Prasanna and Haavisto, 2018; Zanon et al., 2021). Based on the preceding arguments, it is well-understood that the promotion of better coordination practices, knowledge sharing, and the use of artificial intelligence can foster a data-driven decision-making culture within a humanitarian setup (Pizzi et al., 2020; Sandvik et al., 2014).

2.4. Humanitarian supply chain agility (HSCA)

Supply chain agility has gained significant attention in recent years due to the high degree of supply and demand uncertainties (Lee, 2002). Agility is often defined as a capability of the supply chain that firstly, enables the organization to respond to changes in the shortest possible time. Secondly, being highly responsive in reacting to unpredictable and dynamic changes in the external environment. Thirdly, being flexible in adjusting capabilities to tackle the situation with the support of hard and soft technologies, human resources, and information to beat competitions (Gunasekaran et al., 2019). However, the literature reveals some inconsistencies in conceptualizing the term (Charles et al. 2010). Sometimes, supply chain agility is confused with other similar, but different, concepts, such as adaptability, flexibility, and resilience (Charles et al., 2010). Despite diverse conceptualizations, overall research into supply chain agility shows a rise in consensus emphasizing the ability to deal with and take advantage of uncertainties and volatilities. Through sensing and responding to changes rapidly and flexibly (Eckstein et al., 2015; Fosso Wamba and Akter, 2019; Gligor et al., 2019; 2019).

In recent times we have witnessed a significant rise in crises resulting from disasters, including recently, the COVID19 pandemic. This trend has reinvigorated the humanitarian operations management community's focus on agility (Ivanov, 2020; Dubey et al., 2021). Many of the fatalities that have occurred due to the pandemic are primarily due to the lack of adequate resources (i.e., hospital ICU capacity) to deal with the sudden rise in severe cases resulting from people catching the virus (Altay and Pal, 2022). Such humanitarian crises call for agility in the supply chain, to meet the immediate medical needs of those infected. In response to this need Charles et al. (2010, p. 727) identified the following characteristics of humanitarian supply chain agility:

- *"Agility is the vital need of humanitarian supply chain actors for preparedness and this constitutes an additional argument to motivate donors to increase their level of cooperation in terms of donation of funds for disaster preparedness"*

  And.

- *"To provide humanitarian supply chain actors with effective ways of collaborating with other stakeholders to enhance mutual understanding and organizational learning"*.

Following Bromiley and Rau's (2014, 2016b) arguments, we assume sensing ability, speed and flexibility as the processes that constitute agility as a practice that is imitable by organizations involved in providing humanitarian relief in response to disasters.

2.5. Humanitarian supply chain resilience (HSCR)

Supply chain resilience is a characteristic that enables the restoration of normalcy following any disruption resulting from unexpected events (Bhamra et al., 2011). The term resilience gained its popularity following the work of Holling (1973) titled "*Resilience and Stability of Ecological Systems*". Since then, resilience has gained its footing in various disciplines. In the last few decades, the entire world has experienced severe disruptions resulting from terrorist attacks, tsunamis, earthquakes, floods, hurricanes, and in recent health crises on a global scale, pandemics).

Unfortunately, many organizations were not prepared for these disasters. As a result, companies have faced severe economic losses (Ivanov and Dolgui, 2020; Shen and Sun, 2021). Sheffi and Rice (2005) argue that risk management should be a strategic initiative, as it helps enhance the competitive advantage for the company in the long term. Pettit et al. (2010) further argue that a resilient supply chain should include elements such as supply base strategy, collaborative planning, visibility and the factoring in of risk consideration into decision-making processes. Folke et al. (2002) further identified three properties of resilience:

- The amount of change that a supply chain network can undergo while retaining the same controls on structure and function.
- The degree to which the system can organize itself without disorganization or force from external factors.
- The degree to which a system develops the capacity to learn and adapt in response to disturbances.

Nevertheless, the resilience of a humanitarian supply chain is far more complex than that of a commercial supply chain (Dennehy et al., 2021). The information sharing and coordination required are more complex due to the unique nature of the humanitarian supply chain, due to the chaotic post-disaster environment, the high variety of public and private actors and the lack of adequate resources. Most of the studies on resilience are from a commercial supply chain perspective and humanitarian supply chain resilience (HSCR) is a relatively recent concept and a less-studied topic (see, Altay et al., 2018; Dennehy et al., 2021). In this study, we conceive humanitarian relief activities, through the lens of a supply chain as a practice rather than a capability. Hence our notion of resilience, in this context, is viewed through the prism of PBV rather than RBV or DCV.

3. Summary

Fig. 1 illustrates the theoretical model. In Table 1 we summarize the definitions of the constructs used in the theoretical model.

4. Theory and hypotheses development

Our theoretical framework (see Fig. 1) is grounded in the practice-based view (PBV) and contingency theory (CT). We argue that AI-BD-AC is an explanatory variable that drives agility and resilience as two practices. In contrast to previous scholars i.e., Altay et al. (2018) and Polater (2020) we refer to agility and resilience as two practices that are imitable and can be easily transferred to other similar organizations. The AI-BD-AC reflects the belief that data-driven insights may help humanitarian relief organizations to move the right relief materials in the right quantity at the right place and at the right time (Pizzi et al., 2020).

The humanitarian space is characterized by a chaotic environment. Hence, decision-making is often a complex task. The RBV logic rules out the possibility of the adoption of the processes that make the humanitarian supply chain agile and resilient. Moreover, the RBV and DCV are rooted in the commercial competitive advantage of the firm which is not the aim of any humanitarian organization. Hence, we argue that AI-BD-AC drives the agile and resilient practices of humanitarian organizations, which ultimately helps enhance humanitarian supply chain performance. Moreover, following the arguments of CT, we believe that a reduction in information complexity has a moderating influence on the paths joining agility/resilience and performance. Thus, our research hypotheses are informed by two theories: PBV and CT.

In the next section, we derive the seven hypotheses H1-H6b shown in Fig. 1.

4.1. The impact of AI-driven big data analytics culture (AI-BDAC) on humanitarian supply chain agility (HSCA)

Lee (2004) argues that the best-performing organizations do not only care about speed and cost; crucially they respond to unexpected changes in demand and supply in their external markets. Building on Lee's arguments, humanitarian scholars have advocated for agility in the humanitarian supply chain due to its complex and rapidly changing nature

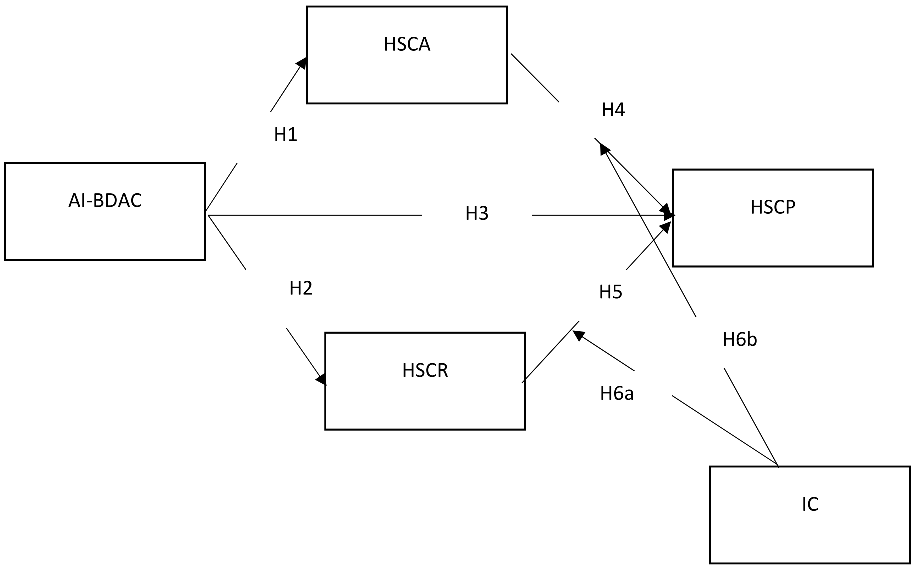

Fig. 1. Theoretical Framework. Notes: AI-BDAC, Artificial Intelligence-driven big data analytics culture; HSCA-humanitarian supply chain agility; HSCR-humanitarian supply chain resilience; IC-information complexity; HSCP-humanitarian supply chain performance.

Table 1
Definitions of the main constructs.

Constructs	Definition
AI-driven Big Data Analytics Capability (Dubey et al., 2020; Akter et al., 2021)	*The AI that reflects human intelligence helps extract useful information from big data sets which is distinct from other machine learning techniques. Hence, the AI-driven Big Data Analytics capability is defined as an organizational capability that helps generate competitive advantage.*
Humanitarian supply chain agility (HSCA) (L' Hermitte et al., 2016, p. 174)	*Humanitarian supply chain agility is the ability to develop and maintain operational responsiveness and flexibility to manage sudden and short-term logistics and supply chain risks and uncertainties. Thus responsiveness (the ability to sense and identify operational risks and to swiftly draw up suitable responses) and flexibility (the ability to act promptly and to adjust logistics operations rapidly) are seen as two essential components of agility.*
Humanitarian Supply Chain Resilience (HSCR) (Scholten et al., 2014	*Humanitarian supply chain resilience can be defined as the adaptive capability that helps prepare the organization for unexpected events, respond to disruptions and recover from them. Through maintaining continuity of the operations at the desired level of connectedness and control over the structure and function.*
Humanitarian Supply Chain Performance (HSCP) (Abidi et al., 2014)	*Humanitarian supply chain performance is defined as a set of metrics that help quantify the efficiency or effectiveness of humanitarian relief action.*
Information Complexity (Champion et al., 2019, p. 343, p. 343)	*Information complexity is defined as poor data integration, quality and timely access to information that can impair the implementation of information artifacts.*

(see, Altay et al., 2018; Oloruntoba and Gray, 2006).

However, building agility in the humanitarian supply chain is far more complex in comparison to the commercial supply chain (Oloruntoba and Kovacs, 2015; L'Hermitte et al., 2017). This may be attributed to the design of the humanitarian supply chain which is often created to address the short-term crisis. Moreover, the actors engaged in the humanitarian supply chain are quickly brought together, typically from diverse backgrounds, which often leads to trust and coordination issues (Dubey et al., 2019a, 2021; Tatham and Kovács, 2010).

Balcik et al. (2010) further argues that effective and efficient coordination among humanitarian actors, necessary for improved humanitarian supply chain performance, requires a high level of information integration among these actors (Dubey et al., 2021). White et al. (2005) argue that the high levels of integration may reduce the ability to make rapid changes in the relationship, which is often considered an important aspect of supply chain agility. Whilst Fosso Wamba and Akter (2019) describe how organizations may improve supply chain agility through data analytics capability.

AI-BD-AC enables humanitarian organizations to quickly collate and process complex information from diverse sources. Thereby producing solutions that may guide the humanitarian organizations involved in managing the logistics of the disaster relief materials i.e., to redirect shipments from alternate warehouses to reach the victims and thus help save lives. Those organizations that develop visibility in the humanitarian supply chain are well-positioned to invest and develop systems that foster AI-BD-AC (Dubey et al., 2019a).

We, therefore, argue that those organizations that are interested in creating transparency and improving better information alignment to foster collaboration among humanitarian actors are likely to benefit from an AI-BD-AC (Ragini et al., 2018; Qadir et al., 2016). Visibility and collaboration are often regarded as a prerequisite for supply chain agility in the humanitarian supply chain (Dubey et al., 2021). So, following the arguments above, we hypothesize the following:

H1. The AI-BDAC has a positive effect on the HSCA.

4.2. The impact of AI-driven big data analytics culture (AI-BDAC) on humanitarian supply chain resilience (HSCR)

In recent times supply chain disruptions resulting from disasters have increased significantly (Gupta et al., 2019; Queiroz et al., 2022). These often have severe and long-term economic effects (Hendricks and Singhal, 2005a, b; Ketchen and Craighead, 2021). To mitigate the risk from such events, organizations invest in building their supply chain resilience (Brandon-jones et al., 2014; Li and Zobel, 2020). The recurrent, protracted, and complex nature of many disasters and humanitarian crises further necessitates the need for long-term interventions that help tackle developmental challenges.

HSCR refers to the ability to cope, adapt and recover quickly from disruptions caused by crises. In recent years the importance of emerging technologies in enhancing such resilience within the humanitarian sector has gained significant attention (see, Florez et al., 2015; Dennehy et al., 2021; Dubey et al., 2020; Papadopoulos et al., 2017; Rodríguez-Espíndola et al., 2020). Although humanitarian organizations are relatively slow and sceptical about the application of emerging technologies in humanitarian relief efforts (Pizzi et al., 2020). Some studies suggest a significant and positive effect of the big data analytics capability of humanitarian organizations on supply chain resilience (Dennehy et al., 2021). The growing interest of humanitarian organizations in the use of AI-driven data analytics tools to tackle complex challenges may have a positive and significant effect on building resilience in the humanitarian supply chain (Florez et al., 2015; Rodríguez-Espíndola et al., 2020). Hence, we hypothesize:

H2. The AI-BDAC has a positive effect on the HSCR.

4.3. The impact of AI-driven big data analytics culture (AI-BDAC) on humanitarian supply chain performance (HSCP)

AI-BDAC is like any other technological revolution, has its own cultural and social fabrics (Barlow, 2013). McAfee and Brynjolfsson (2012) identify five obstacles for organizations becoming data-driven organizations: 1) poor leadership, 2) lack of talent management, 3) dated technology, 4) inadequate decision-making and 5) a negative company culture. The fifth obstacle, culture, is an integral and critical component of the success of big data adoption (Davenport and Bean, 2018).

The world has witnessed the transition from vacuum tubes to the convergence of cloud, mobile and social networking systems. With the technological journey going through and needing a series of accompanying cultural adjustments, individuals and organizations often faced severe challenges in capturing the value generated from technology (Barlow, 2013).

Davenport and Bean (2018) found that the new organizations are generally positive towards, and show a great deal of enthusiasm for, embracing the potential of AI-driven big data analytics. Nevertheless, long-established organizations face severe challenges in integrating, newly acquired talent into existing organizational structures and creating new structures that may enable data-driven managers to search for better and innovative solutions. Pizzi et al. (2020) argue that despite slowness in embracing AI into practice, humanitarian organizations are showing a high level of interest in adopting AI-driven big data analytics to improve their decision-making capabilities.

The pandemic resulting from the outbreak of the COVID-19 virus, in many ways, has prepared humanitarian organizations to deal with future global crises with the help of emerging technologies like AI-enabled big data analytics. Various organizations have leveraged AI and big data analytics capability to control the spread of the virus through pandemic surveillance (Singh et al., 2020). Hence, we hypothesize:

H3. The AI-BDAC has a positive effect on HSC performance (HSCP).

4.4. Impact of humanitarian supply chain agility (HSCA) and humanitarian supply chain resilience (HSCR) on humanitarian supply chain performance

Altay et al. (2018) argue that agility and resilience are complementary to each other and, in the case of humanitarian relief operations, a single and mutually exclusive strategy i.e., agility or resilience, may not be useful. Agility refers to the practices undertaken by humanitarian organizations to respond quickly and cost-effectively to highly unpredictable crises.

Yet having resilience at the same time enables the humanitarian relief supply chain to cope with the disruptions and return to normalcy. To better explain how agility and resilience in the humanitarian supply chain may work together to enhance the humanitarian supply performance, we use an ambidexterity logic.

Simsek (2009) argues that in recent times organizational scholars are increasingly using ambidexterity theory to explain how organizations are maintaining a high level of balance between exploitation and exploration. Blome et al. (2013) note hat supply chain ambidexterity is an organizational strategic choice that allows organizations to pursue both exploitation (efficiency) and exploration (flexibility) practices.

Following Gibson and Birkinshaw's (2004) arguments, we see that humanitarian organizations need to respond rapidly to save lives (agility). Whilst at the same time, engaging with the affected people and communities at a structural level to enable their immediate survival and their ability to live in dignity in evidently deteriorating conditions (resilience). The preparedness of the humanitarian supply chain actors is often regarded as a critical aspect of disaster relief operations.

Agility is seen through the better coordination of disaster assistance, with related community support services and long-term recovery efforts and better disaster planning to recover from crises. Resilience involving recovery is an important phase of a disaster. It is the restoration of all aspects of the disaster's impact on a community and the return of the local economy to some sense of normalcy.

The recovery phase can be broken down into two periods. The short-term phase typically lasts from six months to one year. It involves the delivery of immediate services to victims in the form of medical aid, food, drinking water, building materials to construct damaged infrastructure, clothing, and other necessary materials. Communities must access and deploy a range of public and private resources to enable long-term recovery. Altay et al. (2018) found a positive association between HSCAG and HSCR and humanitarian supply chain performance. Thus, we hypothesize it as:

H4. The HSCAG has a positive effect on HSC performance.

H5. The HSCR has a positive effect on HSC performance.

4.5. The moderating effect of the information complexity (IC)

The actors belonging to different organizations involved in disaster relief carry their own set of beliefs, values and practices when acting in the supply chain. The diversity often makes sharing of information and coordination of work extremely complex (Balcik et al., 2010; Tatham and Kovács, 2010). Information sharing is often considered a critical aspect of the coordination among humanitarian actors (Altay and Pal, 2014) and poor coordination leads to the wastage of resources (Altay and Labonte, 2014). For example, the failures of the Haiti disaster relief efforts in 2010 were partly attributed to nformation-related issues among humanitarian agencies involved in the response, which revealed a variety of impediments to information flow considerably hindered coordination (Altay and Labonte, 2014).

The processing and the sharing of information are important for effective coordination (Ruesch et al., 2021). Rao and Jarvenpaa (1991) argue that information complexity is a matter of concern that moderates the relationship between practices and performance (Liu, 2015). Moreover, information complexity often leads to chaos and results in a lack of trust among the actors involved in disaster relief operations (Day et al., 2009). Such situations often lead to competition among humanitarian agencies for scarce resources (Dubey et al., 2021; Ruesch et al., 2021). Hence, we hypothesize that:

H6a. Information complexity will have a negative moderating effect on the path joining HSCA and the HSC performance

H6b. Information complexity will have a negative moderating effect on the path joining HSCR and the HSC performance.

5. Research methods

Our study adopted a two-stage sequential mixed-methods approach (Boyer and Swink, 2008; Schilke, 2014). In stage one we conducted qualitative field interviews to learn about the practices relevant to humanitarian organizations engaged in disaster relief operations and their effects on performance. As well as to pre-test the survey questionnaire used in stage two. In this second stage, we conducted a cross-sectional survey. This survey gathered data for testing the hypotheses, independent variables, and the dependent variable from the same organizations that had completed a similar survey two years previously.

5.1. Interviews

We conducted 17 semi-structured interviews (see Appendix A) in July 2017 with high-level managers of the global NGOs who were involved in the relief activities following the 2015 Nepal earthquake and the Chennai Flood. Each interview lasted between 60 and 75 min. The interview was organized into two stages (see Appendix B). Firstly, we asked the managers to share their views on the use of emerging technological tools in their disaster relief works. The AI-driven technology to examine the visual images obtained through satellite, geo-spatial, telecom, and many other images from social media platforms, turned out to be among the most common responses.

In the second stage, we further validated our initial research hypotheses by asking how critical the use of AI-driven big data analytics was to improve ways to identify damage. Further to guide the disaster relief workers to provide desired humanitarian aid to the victims in the shortest possible time. Thereby improving recovery and reducing the time that it usually takes to restore back to normalcy.

There was a high degree of agreement that the use of AI-driven analytics helped to interpret tweets, Facebook posts or other kinds of social media feeds following the disasters. The quick interpretation of these social media feeds further guided the disaster relief workers to respond quickly to the affected areas with humanitarian aid. Also, to help them to provide shelter to displaced people who were forced to be homeless.

Information sharing among disaster relief workers was now far more convenient and this further enhanced the effectiveness of the cluster approach in providing humanitarian aid to victims. However, some managers were sceptical about the application of AI-driven big data analytics in disaster relief operations. Reflecting different perspectives in the academic literature, some managers suggested that, in any circumstance, the use of AI-driven big data analytics will enhance the organizational practices and their effects on disaster relief performance. On the other hand, some managers suggested that despite the use of emerging technologies, government organizations are reluctant to share satellite images or data with the NGOs, although they might provide useful information.

In the final and second stages of the interviews, we requested some of the managers to fill out the initial version of the questionnaire to be used in the final survey. We could then determine whether they understood the questions and if we needed to improve the clarity of the wording in the questionnaire. Based on the feedback from the interviewees, we reworded some of the questionnaire items or dropped those questions deemed as not relevant to humanitarian supply chains.

5.2. Sampling design and data collection

The empirical setting of our study is international NGOs involved in disaster relief operations in Nepal and India. The unit of the analysis is that of international NGOs and the questionnaire was designed for completion by a single respondent. Previous research indicates that this unit of analysis (international NGOs) provides a detailed understanding of the adoption of emerging technologies and the supply chain practices that influence the performance of disaster relief operations (Dennehy et al., 2021; Dubey et al., 2019b; Moore et al., 2003).

We obtained contact details of 1340 NGOs with the assistance of the National Institute of Disaster Management (NIDM), which is an apex body of the Government of India (see, Altay et al., 2018). Then we further examined the details of each NGO through a google search and finally identified 640 NGOs that are using emerging technologies in disaster relief operations and have a presence in multiple countries.

Hence, our study population consisted of 640 NGOs. The target respondents comprised the senior managers in the NGOs who are knowledgeable about the use of emerging technologies in post-disaster relief operations. We sent e-mail invitations to the 640 NGOs during July 2019. By the end of November 2019, after three waves of reminders, we finally received 171 useable responses - representing a response rate of approximately 26.72%. This response rate is consistent with comparable studies utilizing survey-based research (e.g., Salem et al., 2019). Table 2 provides the demographic profiles of the respondents. As shown in the table, 23.39% of the respondents were executive directors, 9.94% were communication managers, 33.33% were program managers, and the remaining 33.33% were CTOs, chief procurement managers, or logistics managers.

We then tested for non-response bias in two ways. Firstly, we examined non-response by comparing the early with late respondents (see, Armstrong and Overton, 1977). The results of the student's t-test yielded no significant differences ($p > 0.1$) across the means for each measuring item between them. Secondly, following Wagner and Kemmerling (2010) suggestions, we contacted 45 randomly selected non-respondents and asked them to answer one item for each construct of our theoretical model. The resultant *t*-test yields no significant differences between respondents and non-respondents ($p > 0.1$). These results provide evidence that non-response bias is not a major concern. We also performed Kruskal Wallis H tests on responses from four different information groups: 1) executive director 2) communication manager 3) program manager and 4) others. We observed no significant differences in responses.

5.3. Measures

We used multi-item scales to measure the constructs used in the theoretical model (see Fig. 1). The measurement items used for the operationalization of constructs are listed in Table 3. As shown in the table, we have adapted measures from existing research. We further refined the measurement scales through in-depth interviews with 17 experts - see description in sub-section 4.1 above - following the recommendations of DeVellis and Thorpe (2021). Item sorting and pre-testing were carried out, based on the protocol of Anderson and Gerbing (1991), with seven scholars with knowledge of the field. We undertook further pre-testing of the questionnaire with 32 managers engaged in disaster relief operations. Finally, we triangulated the information shared by the managers with complementary data sources.

In addition to the main constructs of our study, we included some relevant control variables to account for the main differences among various NGOs. Following Bernerth and Aguinis (2016) suggestions we included theoretically and statistically relevant variables i.e., absorptive capacity (Cohen and Levinthal, 1990) and organizational compatibility (Liang et al., 2007). The learning perspective indicates that the use of emerging technologies like AI or big data analytics can be further enhanced if organizations have previous experience with them.

This perspective is grounded in absorptive capacity theory (see, Cohen and Levinthal, 1990), which is well understood in the context of

Table 2
Sample composition.

Position of respondent	Sample in t = 1	Sample in t = 2	Sample in t = 3	%
Executive Director	12	15	13	23.39
Communication Manager	6	5	6	9.94
Program Manager	12	18	27	33.33
Others (e.g. CTO, Chief Procurement, Manager, Logistics Manager, etc.)	20	26	11	33.33
Totals	50	64	57	171

Table 3
Measurement scales.

Construct	Item	Statement	Source
AI-BDAC	AI-BDAC1	We use cognitive computing tools to examine the unstructured data in the form of tweets and images obtained from various sources.	Davenport (2014); Kankanamge et al. (2021)
	AI-BDAC2	We use cognitive interpretations of the information derived using big data analytics to make decisions related to the movement of the right relief materials to the disaster-affected areas.	
	AI-BDAC3	We use AI-driven technologies to recognize damages and detect socioeconomic recovery.	
	AI-BDAC4	We often use AI-driven technologies to help evacuate the people stuck in disaster-affected areas.	
	AI-BDAC5	We believe that the use of AI-driven big data analytics tools may help predict disasters and their consequences in advance.	
HSCA	HSCA1	We are flexible enough to accommodate any changes in the disaster relief materials or mode of delivery to help disaster-affected people.	Altay et al. (2018); Charles et al. (2010)
	HSCA2	We quickly respond to the disaster-affected areas to evacuate people or provide necessary relief items.	
	HSCA3	With the help of technology, we have developed sensing capabilities to predict disasters and prepare ourselves for relief operations.	
HSCR	HSCR1	We quickly restore the flow of food and water supply with the help of AI-driven technologies.	Altay et al. (2018); Papadopoulos et al. (2017)
	HSCR2	We would be able to provide necessary relief materials during unexpected disruptions with the help of information gathered using AI-driven technology.	
	HSCR3	We maintain a buffer stock of important relief items to tackle demand and supply uncertainties.	
	HSCR4	We quickly repair the damages caused to the basic property, schools, and other important centers.	
IC	IC1	We sometimes face difficulty accessing the original data which delays our relief operations.	Day et al. (2009)
	IC2	Sometimes we face challenges with inadequate data or unnecessary information that mislead relief operations.	
	IC3	We sometimes face trust issues with other participating organizations as they do not share adequate information.	
	IC4	We sometimes face reliability issues related to the provided information.	
HSCP	HSCP1	We believe that with the help of AI-driven technology we can quickly respond to the needs of disaster-affected victims and save more lives of people.	Altay et al. (2018); Pizzi et al. (2020)
	HSCP2	With the help of AI-driven technology, we can discover and repair the damages caused to public properties.	
	HSCP3	With the help of AI-driven technology, we can improve coordination among the disaster relief team and save the wastage of resources.	
	HSCP4	With the help of AI-driven technology, we can predict and stock the necessary relief materials in advance to improve the responsiveness of disaster relief efforts.	
AC	AC1	We had extensive training for our people to use emerging technologies	Liang et al. (2007)
	AC2	We know well within our organization who can extract useful information from the complex data set.	
	AC3	We can provide some additional training to our people to acquire complex data analytics and machine learning skills.	
OC	OC1	Created emotional stress among our people in the workplace at first.	Liang et al. (2007)
	OC2	Decreased work productivity at first due to time to learn.	
	OC3	Required a complete change in the organization's values, norms, and attitude.	

Notes: AI-BDAC, Artificial Intelligence-driven big data analytics culture; HSCA-humanitarian supply chain agility; HSCR-humanitarian supply chain resilience; IC-information complexity; HSCP-humanitarian supply chain performance; AC-absorptive capacity; OC-organizational compatibility.

large commercial organizations' efforts to adopt innovative technologies (see, Liang et al. 2007). We posit that in the case of humanitarian organizations absorptive capacity may influence the intention to use these technologies. To account for this variation, we controlled for the differences among the organizations in terms of their absorptive capacity.

We also recognize that the managers of the organizations must have assessed their compatibility issues with various dimensions of the organization, such as objectives, work practices, and organizational culture (Liang et al. 2007). Since humanitarian organizations often operate in different contexts, the organizational criteria for assessment might have changed. Any change in conditions might likely hinder the use of emerging technologies. Hence, we controlled for this variable as due to incompatibility issues, it may influence the results.

6. Data analysis

6.1. Measurement validation

We report the Cronbach's alpha (α), the factor loadings of the construct items (λi), the scale composite reliability (SCR), and the average variance extracted (AVE) values for the multi-item constructs in Table 4. According to Fornell and Larcker (1981), the multi-item constructs are reliable and valid if each item's factor loadings (λi) are greater than 0.5, the SCR values of each construct are greater than 0.7 and the AVE of each construct is greater than 0.5. In our case, our multi-item constructs satisfy all these criteria.

We also checked the discriminant validity of the constructs (see Table 5). We found that the inter-correlation values of each construct are less than the square root of the AVEs of each construct in each row and column (see Fornell and Larcker, 1981). We performed the confirmatory

Table 4
Measurement scales.

Construct	Item	Factor Loadings	Variance	Error	SCR	AVE
AI-BDAC (Mean = 4.27; S. D = 0.67) (α = 0.96)	AI-BDAC1	0.96	0.92	0.08	0.97	0.86
	AI-BDAC2	0.95	0.91	0.09		
	AI-BDAC3	0.81	0.65	0.35		
	AI-BDAC4	0.96	0.93	0.07		
	AI-BDAC5	0.94	0.89	0.11		
HSCA (Mean = 4.51; S.D = 0.64) (α = 0.88)	HSCA1	0.83	0.70	0.30	0.93	0.82
	HSCA2	0.95	0.90	0.10		
	HSCA3	0.93	0.86	0.14		
HSCR (Mean = 4.61; S.D = 0.60) (α = 0.97)	HSCR1	0.97	0.95	0.05	0.98	0.92
	HSCR2	0.96	0.91	0.09		
	HSCR3	0.95	0.91	0.09		
	HSCR4	0.96	0.92	0.08		
IC (Mean = 4.03; S. D = 0.62) (α = 0.77)	IC1	0.96	0.92	0.08	0.98	0.95
	IC2	0.98	0.97	0.03		
	IC3	0.98	0.95	0.05		
HSCP(Mean = 3.95; S.D = 0.95) (α = 0.79)	HSCP2	0.88	0.77	0.23	0.91	0.76
	HSCP3	0.90	0.81	0.19		
	HSCP4	0.84	0.71	0.29		
AC (Mean = 3.96; S.D = 0.94; α = 0.68)	AC1	0.7	0.49	0.51	0.73	0.48
	AC2	0.65	0.42	0.58		
	AC3	0.72	0.52	0.48		
OC(Mean = 3.71; S.D = 1.02; α = 0.71)	OC1	0.79	0.62	0.38	0.74	0.59
	OC2	0.74	0.55	0.45		

Notes: AI-BDAC, Artificial Intelligence-driven big data analytics culture; HSCA-humanitarian supply chain agility; HSCR-humanitarian supply chain resilience; IC-information complexity; HSCP-humanitarian supply chain performance; AC-absorptive capacity; OC-organizational compatibility.

Table 5
Discriminant validity.

	AI-BDAC	HSCA	HSCR	IC	HSCP	AC	OC
AI-BDAC	**0.93**						
HSCA	0.60	**0.91**					
HSCR	0.28	0.34	**0.96**				
IC	−0.09	−0.09	0.01	**0.97**			
HSCP	−0.39	−0.31	−0.04	−0.03	**0.87**		
AC	0.34	0.30	0.29	0.15	−0.30	**0.85**	
OC	−0.38	−0.24	−0.31	0.07	0.48	−0.44	**0.86**

Notes: values in bold placed at diagonal are the square root of the AVEs.

factor analysis (CFA) test using the variance structural equation modeling software (WarpPLS 7.0). We further checked the measures of the goodness of fit which is satisfactory in our case [average R-squared (ARS) = 0.45, $p < 0.001$; Tenenhaus (GoF) = 0.61].

6.2. Common method bias

We recognize that our data, which was collected using a single-respondent survey, could suffer from common method bias (CMB) (Podsakoff et al., 2003). Following MacKenzie and Podsakoff's (2012) recommendations, we adopted some procedural remedies to reduce the undesirable effects of collecting data from a single source.

There are many sources of the biases resulting from the questionnaire design. Some of these sources are from overly complex or abstract questions (Doty and Glick, 1998). For instance, such questions might increase the difficulty of the comprehension of the respondents.

We therefore conducted qualitative interviews to assess the difficulty level in comprehending questions and based on the feedback we reworded some of the questions asked in the questionnaire. Another source of CMB is item ambiguity (Podsakoff et al., 2003), which may increase the level of difficulty in retrieving relevant information or making judgments (Krosnick, 1991).

To minimize the discomfort level of the respondents, we tried to use clear and concise language. We avoided using syntax or providing an explanation so that the respondents did not face any level of difficulty in comprehending the questions. Double-barrelled questions are one of the major sources of biases (Krosnick, 1991; Bradburn et al., 2004). They often present respondents with a dilemma as to whether they answer the first part first or the second part, or both parts. We have avoided the double-barrelled questions. Finally, retrospective questions increase the difficulty of accurate retrieval of information, which put lots of strain on respondents (Krosnick, 1991). Hence, we have asked questions in a way that measures the current state, so that the respondents can answer questions instantly.

In addition to procedural remedies, we performed a conservative single factor Harman's test. Scholars find the single factor Harman's test, particularly useful in the case of single informant reported data, not a useful method to assess the common method variance (CMV) (see, Podsakoff et al., 2003; Hulland et al., 2018). Therefore, we used the correlation marker technique to assess CMB (Lindell and Whitney, 2001).

We followed Williams et al. (2010) review, in which most scholars were found to have used the unrelated variable to separate the correlations induced by the CMB. Then we further determined the significance of the correlations using the equations provided by Lindell and Whitney (2001). Noting the minimal differences between adjusted and unadjusted correlations. From our results from these tests, we argue that the potential impacts caused by the CMV are non-significant. Furthermore, we considered the moderating effect of the IC on the paths joining HSCA/HSCR and HSC performance. Siemsen et al. (2010) argue that the moderating effects of the variable in a study are less likely to be affected by CMB.

We recognize that the endogeneity bias often leads to inaccurate estimates and incorrect inferences, which may result in wrong conclusions (Guide and Ketokivi, 2015; Ullah et al., 2018). Endogeneity has been a long-standing problem in the operations management literature (Guide and Ketokivi, 2015). Following Kock's (2017) suggestions, we have reported NLBCDR (nonlinear bivariate causality direction ratio), which estimates the causality. For instance, it helps understand whether the proposed directions (see Fig. 1) are far more stable in comparison to the reverse direction.

In our case, the NLBCDR = 0.86 (approximately) is sufficiently high in comparison to the suggested cut-off value (i.e., 0.7). The 0.86 value of NLBCDR shows that for at least 86% of the paths in the model, the reversed hypotheses linkage is weak or not supported. All the reverse linkages in our model were weak or not significant. Hence, we can argue that causality is not a major concern.

6.3. Hypotheses testing

We tested our research hypotheses using PLS-SEM (WarpPLS 7.0). The PLS estimates the standard errors using the bootstrapping method. The PLS path coefficients and p-values for the proposed theoretical model are reported in Table 6. Our final model is presented in Fig. 2 based on our hypothesis testing. We found support for H1 (AI-BDAC→HSCA) ($\beta = 0.88$, $p < 0.01$), H2 (AI-BDAC→HSCR) ($\beta = 0.69$, $p < 0.01$), and H3 ($\beta = 0.57$, $p < 0.01$).

Therefore AI-BDAC explains nearly 78% of the variance in the HSCA ($R^2 = 0.78$) and 47% of the variance in the HSCR ($R^2 = 0.47$). Our study empirically supports prior research which found that AI-driven big data analytics decision-making culture offers significant guidance to the disaster relief team, enhancing responsiveness, resilience, and effectiveness (Florez et al., 2015; Rodríguez-Espíndola et al., 2020; Pizzi et al., 2020).

Furthermore, the hypotheses H4 (HSCA→HSCP) ($\beta = 0.69$; $p < 0.01$) and H5 (HSCR→HSCP) ($\beta = 0.38$; $p < 0.01$) were supported, lending

Table 6
Structural estimates.

Hypothesis	Impact of	Impact on	β	p-value	Supported/not supported
H1	AI-BDAC	HSCA	0.88	<0.01	supported
H2	AI-BDAC	HSCR	0.69	<0.01	supported
H3	AI-BDAC	HSCP	0.57	<0.01	supported
H4	HSCA	HSCP	0.69	<0.01	supported
H5	HSCR	HSCP	0.38	<0.01	supported
H6a	HSCA*IC	HSCP	−0.69	<0.01	supported
H6b	HSCR*IC	HSCP	−0.56	<0.01	supported
control variables					
	AC	HSCP	0.13	<0.05	supported
	OC	HSCP	0.27	<0.01	supported

weight to the claim that agility and resilience in the humanitarian supply chain are highly desirable characteristics (Altay et al., 2018; Ivanov, 2020). The HSCA and HSCR, together with the control variables, explain nearly 19% of the total variance in the HSCP ($R^2 = 0.19$). Hence, we conclude that HSCA and the HSCR are significant predictors of HSCP.

Next, we considered the moderation effect of IC on the model. We found a significant moderating effect on the paths joining HSCA and HSCP ($\beta = -0.69$, $p < 0.01$) and HSCR and HSCP ($\beta = -0.56$, $p < 0.01$).

From this, we conclude that IC in humanitarian settings is often considered a function of rule and strategic complexities which arise due to different factors, including the large number of disparate actors involved in the disaster relief operations. Most of the time information exchange is hindered due to the different languages spoken by the local and the international actors engaged in relief operations (Balcik et al., 2010).

Moreover, owing to the different beliefs and faith, information exchange is far more difficult. Thus, a reduction in IC may help improve the overall effects of HSCA and HSCR on HSCP. We further found that the absorptive capacity (AC) and the organizational compatibility (OC) have a significant effect on HSCP. The exact role of the AC and OC on the humanitarian supply chain performance and its further association with the other constructs remain interesting questions for future research.

7. Discussion

Our study has focused on the role of AI-driven big data analytics culture (AI-BDAC) in building HSCA and HSCR. We examined the combined effects of AI-BDAC, HSCA, and HSCR on HSCP. Our interest in this topic was triggered by two facets of humanitarian relief operations. Firstly, the role of AI-driven big data analytics decision-making culture in disaster relief operations has seen a significant rise among NGOs and government agencies. However, most of these initiatives during humanitarian relief operations are noted in the practitioner literature. Secondly, existing studies have used a resource-based view (RBV)/dynamic capability view (DCV) to explain the humanitarian supply chain performance. AI-BDAC, HSCA, and HSCR are now common practices and most organizations have been practicing them for quite some time now in the wake of the rise in disasters. Moreover, the humanitarian supply chain is designed to save the lives of the victims and alleviate their suffering through providing necessary relief materials in the right condition, at the right time at the right place. Thus, the RBV and the DCV are not appropriate theoretical lenses to examine the role of practices in the humanitarian setting. Under these circumstances, we argue that the practice-based view (PBV), as discussed earlier, is highly relevant, in comparison to the other theories, which are informed by commercial supply chain research.

To lend further support to our conceptual model, we also recognized the role of information complexity (IC) in the humanitarian setting. Hence, we have identified IC as a moderating construct. In most cases, disaster relief efforts are negatively affected by a lack of information sharing or by compatibility issues. The moderation effect of IC is useful in explaining the variability in HSCP. Of course, the rigorous test of the usefulness of the moderation effect of IC could be determined only if we have restricted our study to a few organizations to understand how the organization tackles the information complexity issue. This aspect remains an interesting question for future research.

The results of the study paint an interesting image of the associations and interactions among the variables of AI-BDAC, HSCA, HSCR, and IC. In totality, our findings have implications for theory and practice, as well as offering some new directions for future research in this area. Davenport (2014, p. 147) argues that managers must learn to differentiate between the big data culture and analytics culture as a first step toward building an AI-driven big data analytics culture and calls for further research that test this assertion.

In response, our study provides empirical support that AI-BDAC is significantly linked with HSCA, HSCR, and HSCP. The focus of research

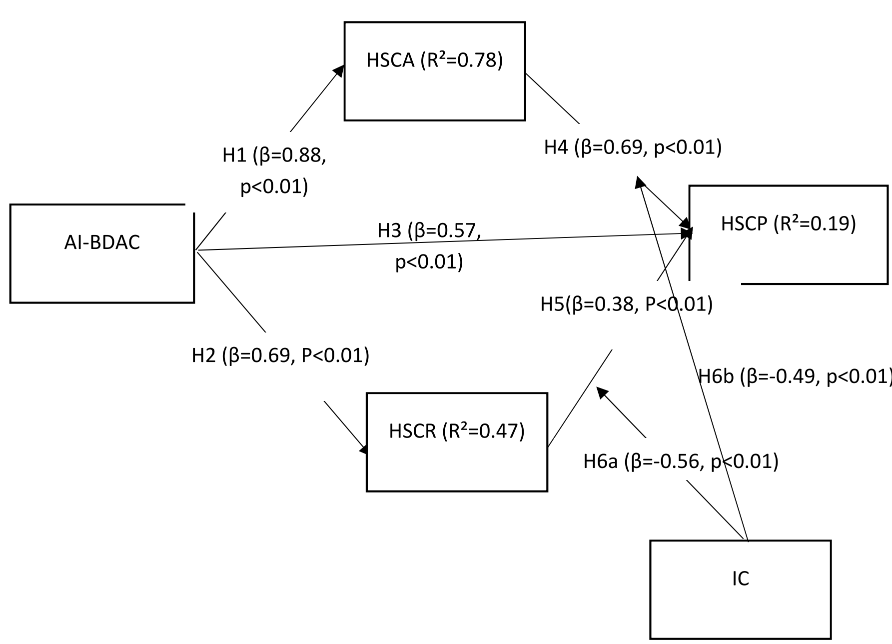

Fig. 2. Final model.

on the AI-driven big data analytics culture has been on the team and organizational level competitiveness (Ransbotham et al., 2021). Specifically, AI-driven big data analytics culture has played a significant role in improving trust and collaboration (Glikson and Woolley, 2020). Unfortunately, NGOs engaged in disaster relief efforts have been relatively slow in leveraging AI for analyzing complex data drawn from various sources. Such analysis would allow them to cope better with the humanitarian crisis (van den Homberg et al., 2020).

7.1. Theoretical contributions

The role of AI-BDAC in the context of humanitarian efforts is well discussed in the literature (van den Homberg et al., 2020). What is less understood is how the AI-BDAC affects HSCA and HSCR. This study contributes to enhancing understanding of this area using the practice-based view (PBV) theoretical lens. This is achieved in two ways. Firstly, we focus on how AI-BDAC, HSCA, and HSCR, as distinct practices that are in no way inimitable or rare, influence performance. The humanitarian supply chain practices have been conceptualized as dynamic capabilities (Altay et al., 2018; Matopoulos et al., 2014; Polater, 2020; Tabaklar et al., 2021). However, the dynamic capability view stems from the belief that the resources and capabilities of the organization generate a competitive advantage. However, we argue that humanitarian practices aim to reduce human suffering by providing relief to the affected victims during a disaster and further helping to rebuild infrastructure back to its original state. Hence, in such situations, these practices are not compatible with the RBV or DCV. So, using the PBV to explain how some of these humanitarian practices help enhance performance is far more logical.

Secondly, Bromiley and Rau (2016a) argue that due to bounded rationality, organizations are not aware of the practices that might benefit them. In such cases, despite being imitable, we argue that the AI-BDAC, HSCA, and HSCR are significant determinants of the humanitarian supply chain performance (HSCP).

The two main components of the PBV are the dependent variable and the independent variables (see, Bromiley and Rau, 2016a, p. 101). To address the first component of the PBV we derived RQ1: What are the effects of agility and resilience on the humanitarian supply chain performance? To address RQ1 we empirically tested the paths joining HSCA/HSCR and HSCP. Our findings suggest that HSCA/HSCR are significant predictors of HSCP. We also tested the direct impact of AI-BDAC on HSCP, finding that it was a strong and positive determinant. These findings further strengthen the PBV, which assumes that practices that are not necessarily rare or inimitable can help achieve desired performance. Thus, our findings of the study extend the Bromiley and Rau (2014, 2016a) PBV to explain the complex disaster relief operations. These findings further extend the work of Altay et al. (2018) and Dennehy et al. (2021). Secondly, to explain the differential results in HSCP we assumed the moderating effect of IC on the paths joining the HSCA/HSCR and HSCP. This view is grounded in contingency theory. Thus, we integrate the two perspectives: the PBV and the contingency view.

Next, to address the second component of the PBV we posited our guiding research question (RQ2): What are the effects of AI-driven big data analytics culture on agility and resilience in the humanitarian supply chain? In response to this RQ2, we empirically tested the relationship between AI-BDAC and HSCA/HSCR, which we found to be significant; a result that further strengthens the earlier work of Bromiley and Rau (2014, 2016a) relating to PBV.

Furthermore, considering that research into humanitarian practices is a relatively new discipline that has borrowed theories from established disciplines such as operations management and strategic management, it may require a different theoretical lens to explain the complex problems which are guided by completely different objectives. Hence, we argue that our findings are noteworthy. Our findings show that AI-BDAC has positive and significant effects on HSCA and HSCR. We extend Davenport's (2014) and Davenport and Bean's (2018) arguments to humanitarian organizations which are guided through different objectives.

By performing a moderating test, we addressed our third research question (RQ3): what are the effects of the information complexity on the paths joining agility/resilience and the humanitarian supply chain performance? Our findings suggest how PBV, and contingency further explain the differential effects due to humanitarian supply chain practices, to improve humanitarian supply chain performance. These findings extend the work of Bromiley and Rau (2014, 2016a) on PBV and further help explain the coordination required amongst the various humanitarian actors engaged in disaster relief operations. That is needed to tackle a complex humanitarian crisis operating under different constraints. Communication challenges often hinder coordination. Our study findings further strengthen such an assertion made by various scholars in the past (see, Altay and Pal, 2014; Altay and Labonte, 2014; Balcik et al., 2010; Ruesch et al., 2021). Our contribution is noteworthy in this context. The finding that IC hinders the joint effects of the HSCA and HSCR on HSCP further extends the works of Altay and Labonte (2014) and Altay et al. (2018).

7.2. Managerial implications

This study offers some useful directions to those humanitarian supply chain managers engaged in disaster relief operations. Firstly, humanitarian supply chain managers must appreciate the role of both agility and resilience for performance benefits. In this case, we found that agility and resilience are both desirable properties of the humanitarian supply chain which have a significant impact on humanitarian supply chain performance.

Secondly, we found that AI-driven big data analytics capability has a significant effect on the agility and resilience of the humanitarian supply chain. Those humanitarian supply chain managers who make decisions based on an AI-driven big data analytics capability are likely to be more flexible in terms of their delivery of disaster relief materials or in responding to changes of destination.

In the past, humanitarian organizations face significant challenges in delivering humanitarian aid at the right time, to the right people at the right place. These challenges are due to a lack of proper information exchange among various humanitarian actors which often led to poor coordination (Altay and Labonte, 2014). AI is useful, as it is a complex system that can imitate the intelligence of human beings. Hence, the information derived using AI-driven technology may offer those involved in humanitarian relief guidance, extra capability to locate victims and sort out issues as fast as possible.

In this way, a disaster relief team can minimize suffering and restore normalcy. Thus, NGOs engaged in disaster relief efforts may find our research findings encouraging and encourage them to work towards improving their exploitation of AI-driven big data analytics capability. It may also encourage them to further explore possible ways to improve better coordination among the various relief actors to actors, tackle complex challenges, and avoid costly mistakes.

Thirdly effective, and efficient coordination among disaster relief actors is crucial for the success of disaster relief efforts. However, despite several efforts, information complexity often leads to mistrust amongst humanitarian actors resulting in negative consequences. Such as a rise in opportunistic behavior, that may reduce the effectiveness of agility and resilience and subsequently impact negatively on humanitarian supply chain performance. Our findings recommend managers work on improving the authenticity and reliability of the data generated during disaster relief operations.

Whilst we also recommend humanitarian organizations to actively embrace an AI-BDAC, we acknowledge that NGOs face various implementation challenges. As they need to be able to shift their operation base, in response to humanitarian crises and to different geographical locations. Most of the time they recruit local people based on their understanding of the local environment. However, this often leads to communication and compatibility issues that hinder effective coordination amongst disaster relief actors or various agencies involved in the relief efforts. To mitigate these issues, umbrella organizations, such as the United Nations and national governments, need to work together, share information and act in transparent ways, to enhance trust amongst disaster relief teams and provide effective joint responses to affected victims.

7.3. Limitations and future research directions

We have suggested that humanitarian organizations now understand the true implications of AI-BDAC and the need to enhance trust and coordination between different disaster relief actors. The stakeholders, like donors, are increasingly demanding high accountability and transparency in the actions of humanitarian relief organizations (Rodríguez-Espíndola et al., 2020). The donors are far more impatient and less tolerant of the inefficiencies in the contemporary digital era.

Our study contributes to understanding the relationships between AI-BDAC and humanitarian practices like HSCA and HSCR. The empirical findings help clarify key humanitarian practices and contingencies that influence humanitarian supply chain performance. These findings point to the striking difference in the practices-performance relationship between settings characterized by information complexity.

Nonetheless, several limitations to our study need to be acknowledged, which may further open the door for future research opportunities. The sample is representative of the international NGO population, but it does not fully represent the true population of agencies involved in a disaster. For instance, the dataset included international NGOs, and, as such, care should be exercised cautiously in terms of the generalizability of the results. We suggest that future research should include more actors i.e., military organizations, government agencies, and commercial organization, to ensure a higher level of variance of information complexity in the dataset. Future study is also needed to determine whether the moderating role of information complexity between HSCA/HSCR and HSCP extends to other characteristics such as the nature of the organizations and the stage of the evolution of their adoption of AI-BDAC (e.g., early or later adopter).

Secondly, we have developed a theoretical model and tested our hypotheses using a survey-based instrument. Although we insured, as far as possible, that the constructs we used were reliable and valid, we acknowledge the limitations of survey-based data. We have used a questionnaire designed for the single informant. Then tried to minimize the level of common method bias (CMB) by adopting several procedural remedies. However, we understand CMB cannot be eliminated totally, which is a weakness of any survey-based research design. Future studies could collect data from multiple sources, which would give rich insights. Although such an approach is challenging, due to the difficulty of getting some organizations to be open and transparent and share data.

Thirdly, our study adopted a rather narrow definition of humanitarian practices, which focused on experience-based, rather static routines and which did not include more flexible forms of organizational change. We believe a strand of research, grounded in the interpretivism philosophy (i.e., qualitative research design), would be useful to explore in greater detail the interplay between humanitarian practices and information complexity. Finally, we encourage work to clarify the differences between resources, practices and capabilities, to provide better clarity and to further establish the usefulness, of the practice-based view (PBV). That can be applied to explain the different and complex aspects of managing humanitarian supply chains.

8. Conclusion

In conclusion, our findings, presented in this paper, suggest that humanitarian practices have far more complicated performance effects than previously studied. These range from AI-driven big data analytics to an artificial intelligence culture, humanitarian supply chain agility, resilience, and resolving any communication challenges. We believe that the findings of our study, and the unanswered questions that our study has raised, can spur further empirical research to help us understand the subtle difference in strategic resources, dynamic capabilities, and practices. That exists in humanitarian settings. Also, to appreciate further the relevance of the PBV and its utility in understanding how to address complex supply chain problems, with minimum efforts, to achieve better coordination and improve the performance of humanitarian relief operations.

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Appendix A. Sample for interviews

Participant	Nationality	Gender	Experience (years)	Position
1	Indian	M	10	Operations manager
2	British	F	7	Operations manager
3	French	F	12	Field officer
4	Italian	M	10	Field officer
5	Indian	M	15	Country head
6	Bangladesh	M	10	Operations manager
7	Sri Lanka	M	8	Field officer
8	Bangladesh	M	12	Field officer
9	Turkish	M	15	Operations manager
10	Irish	F	9	Field manager
11	British	F	8	Operations manager
12	American	F	7	Field officer
13	Indian	M	13	Operations head
14	Polish	F	12	Field officer
15	Dutch	M	14	Operations manager
16	British	M	11	Operations manager
17	Indian	M	17	Country director

Appendix B. Interview Guidelines

Research questions: "*Our main question is, to understand how the use of digital technologies such as big data analytics tools, AI-driven technologies, social media, distributed ledger technology, geo-positioning systems images, etc., are useful in disaster relief operations and what the main challenges do they face while making a decision based on digital technologies*".

"*Thank you for accepting our invitation to participate in my study. This study is about non-governmental agencies involved in various disaster relief operations and the use of digital technologies in disaster relief operations. All data and answers will be treated anonymously and confidentially. Before we start, could you please provide me with some information about yourself?*"

- ✓ *Age, education, nationality*
- ✓ *Job history & current job role*
- ✓ *What is your personal goal for your job? What motivates you most to be in this extremely challenging field?*
- ✓ *Could you please briefly explain the organization you are working for, its main goal, and the organizational culture?*
- ✓ *Are you familiar with the kind of digital tools used by your organization in disaster relief operations?*
- ✓ *If yes, then can you name some of the frequently used tools for disaster relief operations or decide based on the information extracted using these tools for improving disaster relief efforts?*

Part 1: Use of Digital Technologies in Disaster Relief Operations.

1. How important are digital technologies to your organization? How does it compare to five years ago?
2. How important are AI-driven technologies or big data & predictive analytics to your organization? How the information extracted using these technologies are useful in decision making?
3. Which other digital tools are used by your organization in disaster relief operations?

Part 2: Implications of AI-BDAC on Humanitarian Supply Chain.

1. How important is the information obtained using AI-driven big data analytics capability in disaster relief operations in terms of responsiveness, flexibility, and effective and efficient coordination?
2. How important is the information obtained using AI-driven big data analytics capability in preparing for the crises in terms of procuring necessary disaster relief materials, allocating resources to the affected areas, and gaining normalcy?

"Thank you for your time and for providing valuable insights. So far, all my questions have been answered. Is there anything else that you would like to add or share with me in context to this study?"

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