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Pervaiz Akhtar[a], Victoria-Sophie Osburg[b], Gaurav Kabra[c], Subhan Ullah[d], Haseeb Shabbir[e], Sushma Kumari[f]

[a] Management Science, Kent Business School, University of Kent,
[a] IESEG School of Management, France
[b] Marketing, Sheffield University Management School, University of Sheffield, UK
[c] National Institute of Industrial Engineering (NITIE), Mumbai, India
[d] Accounting, Nottingham University Business School, University of Nottingham, UK
,[e] Marketing, Faculty of Business, Law and Politics, University of Hull, UK
,[f] Logistics, Faculty of Business, Law and Politics, University of Hull, UK

[a] Professor Pervaiz Akhtar is now associated with the University of Aberdeen Business School, University of Aberdeen, and Imperial College London, UK. He is the corresponding author and can be contacted through:

pervaiz.akhtar@abdn.ac.uk
pervaiz.akhtar20@imperial.ac.uk
pervaiz_khan972@hotmail.com

Coordination and collaboration for humanitarian operational excellence: Big data and modern information processing systems

Abstract

Humanitarian operational excellence depends on effective coordination and collaboration not only between supply chain partners but also among other actors such as host government, local and international non-government organizations (NGOs), and donors. Importantly, effective coordination and collaboration are facilitated by big data and modern information processing (BDMIP) systems that are complex and interlocked with contemporary information and communication technology (ICT). This study simplifies BDMIP systems by using a comprehensive methodology (literature review and a multi-criteria decision-making approach, called the analytic network process) and explores its key determinants and other interconnected factors. The data were collected from humanitarian managers, working in horizontally (e.g., governments, local and international humanitarian organizations) and vertically (e.g., supply chain partners) collaborated organizations. Three systems (manual, semi-automated, and fully automated) are investigated, which depend on various determinants for operational excellence interlinked with modern big data technology and its components. The results indicate that dynamic compatibility is the most important determinant for such systems to support operational excellence, followed by real-time response, cost, end-to-end visibility, and operational service quality. The implementation of fully automated systems is less cost-effective. This attributes to contemporary dimensions and enablers (e.g. the internet of things, big data collection and analytics, effective data and information sharing, modern unmanned aerial vehicles (called drones), skills for mining structured and unstructured data, among others). Semi-automated systems are also imperative for certain enablers (e.g. data accuracy, data reliability, and personalized data exchange). This study concludes by discussing these findings and their implications for practitioners; how they can combine these technical and operational foundations to execute humanitarian operational excellence and to build effective coordination and collaboration among involved parties. It further provides suggestions for future research.

Keywords: Coordination and collaboration, humanitarian operational excellence, ICT and big data applications in humanitarian operations, big data and information processing systems, analytic network process

1. Introduction

Humanitarian organizations need be coordinated and collaborated in order to achieve operational excellence, particularly when they deal with unexpected internal failures and external challenges. They often involve in horizontal (e.g., between governments and non-government organizations, NGOs) and vertical coordination (e.g., between supply chain partners) to achieve operational excellence by using modern technology (Kabra et al. 2017, Akhtar, Marr, and Garnevska 2012), particularly big data technology (Akhtar et al. 2017, Papadopoulos et al. 2017, Gölzer and Fritzsche 2017). These attributes together with their operational determinants (e.g., capabilities, service quality) assist them to be more effective operationally. Research shows that organizations differ in their capabilities to build resilience against uncertain challenges, and those with strong governance and effective operational strategies are more successful over time, emphasizing on coordinated responses (Carmeli and Markman 2011, Akhtar, Marr, and Garnevska 2012). In other words, coordination and collaboration mainly depend on contemporary technical capabilities (e.g. data and information systems) that help them to strengthen their operational excellence and be resilient (Kossek and Perrigino 2016, Akhtar et al. 2018, Akhtar et al. 2017, Lamba and Singh 2017, Gölzer and Fritzsche 2017).

Big data and modern information processing (BDMIP) systems play a crucial role in dealing with unanticipated operational challenges in disasters, emergencies, and catastrophic events (Müller, Koslowski, and Accorsi 2013, Sakurai and Kokuryo 2014, Vecchiola et al. 2013, Manyena 2006, Papadopoulos et al. 2017, Gölzer and Fritzsche 2017; Akhtar et al., 2019). BDMIP systems help to combat changes effectively by building reliable technological capabilities. Such systems provide end-to-end operational visibility that helps to respond promptly, contributing to service quality as well as saving people and infrastructures. These systems also provide the measures of persistency with the ability to effectively absorb changes and quickly recover from difficult circumstances to sustain their functionalities (Holling 1973, Sakurai and Kokuryo 2014, Cohen and Money 2017). More precisely, in the information system context, such systems refer to a fast regaining of fundamental capabilities to manage disasters and to return to the full operational capabilities straight after disasters (Sakurai and Kokuryo 2014). Their resilience therefore describes a systematic capability to cope with emergency situations and unplanned disruptions (Müller, Koslowski, and Accorsi 2013, Vecchiola et al. 2013, Manyena 2006). Even in the light of structural damages, these modern systems must be able to operate and regain as quickly as possible (Wang, Gao, and Ip 2010, Cooper, Flint-Taylor, and Pearn 2013, Fiksel 2015). Humanitarian operational teams and coordinated organizations may not overcome challenging situations without BDMIP systems that can present opportunities for operational excellence (i.e., improving dynamic capabilities, real time response, operational service quality, end-to-end operational visibility, and decreased cost) (Morash 2001, Christopher, 2011, Anjomshoae et al. 2017, Akhtar et al. 2017; Botchie, Damoah, and Tingbani, 2019). For example, involved organizations can learning analytical, technologies and data mining skills from each other and effectively utilize insights for relevant decision making and performance (Sartal et al., 2017; Sartal and Vázquez 2017; Akhtar et al. 2018; 2019). Such systems may further help to build resilience at three stages: 1) advance (i.e., mitigation and preparedness), 2) initial response, and 3) recovery stage. These stages are crucial since they lessen the chances of failures by providing guidelines for preparing actions and responding to threats simultaneously (Sakurai and Kokuryo 2014).

Nevertheless, it is impossible to design systems that never fail. BDMIP systems are therefore important to quickly recover critical operational capabilities at least, helping to respond to disasters or catastrophic events effectively and enabling operational excellence for manufacturing (Sakurai and Kokuryo 2014; Sartal and Vázquez 2017). However, such systems might face many challenges. For instance, failures may not only emerge due to incorrect data entries and retrievals but also within internal communication and coordination processes (Ash, Berg, and Coiera 2004). Nonetheless, if effectively run, these systems are associated with numerous benefits such as helping in providing real-time responses, improving service quality, and reducing communication and coordination problems (Raghupathi and Umar 2008, Wang, Qiu, and Guo 2017), although this requires that BDMIP systems are reliably operated at any given time. They also help to regain fundamental capabilities in the case of both, natural and human-made disasters (Park, Sharman, and Rao 2015). They also ensure safety and the provision of essential services, for example, in the case of unexpected disasters such as severe weather conditions, earthquakes, and tsunamis (Ash, Berg, and Coiera 2004, Dalziell and McManus 2004, Park, Sharman, and Rao 2015). Furthering, the reliable and up-to-date big data and information systems provide important operational tools for managers to act against disasters and catastrophic events (Katsikas 2000, Kivinen and Lammintakanen 2013, Wang, Qiu, and Guo 2017).

Organizations undoubtedly need to be coordinated and collaborated for operational excellence by utilizing big data technology in coping with the situational changes. A smooth run of BDMIP systems is crucial; they depend on data and information that the systems store and provide actionable insights for evidence-based decision making, contributing to performance dimensions and operational excellence (Ahmadian, Nejad, and Khajouei 2015, Ash, Berg, and Coiera 2004, Mäenpää et al. 2009, Raghupathi and Umar 2008, Papadopoulos et al. 2017, Mishra et al. 2017). However, existing studies do not examine the contemporary data and information systems (Akhtar et al. 2018, Akhtar et al. 2017), particularly in humanitarian operations (Kabra et al. 2017). The BDMIP systems for operational excellence have been insufficiently investigated, despite these systems play a key role in coordination and keeping involved organizations connected. Although there are various advantages associated with BDMIP systems, research has not paid enough attention to them, hence, it is stated that "the paradox of relying on complex systems composed of unreliable components for reliable outcomes is rarely acknowledged in theoretical discussions of information system operations, designs, and management" (Butler and Gray 2006, 211). This particularly applies to humanitarian organizations and their operations (Park, Sharman, and Rao 2015, Mikalef and Pateli 2017, Prasad, Zakaria, and Altay 2016), this is an emerging field of research.

Given that the previous research neglected the role of BDMIP systems and their links with operational excellence through coordination and collaborations among diverse organizations such as government bodies, local NGOs, international NGOs, donors, and private companies (the whole supply chains with different actors), the first contribution of this study is to develop a theoretical framework. This framework investigates the literature on the key determinants of operational excellence (e.g. dynamic capabilities, real-time response, operational characteristics, and costs) for BDMIP systems, dimensions (e.g. the internet of things, big data collection and analytics, and information sharing), and enablers (e.g. relevant infrastructure, types of data, and relative pre-requisite expertise). Our framework contributes to the literature by integrating insights on underlying factors linked with operational excellence and modern data-driven support for coordination and collaboration. Data and information systems have been changed dramatically, particularly in the last few years due to big data technologies (Akhtar et al. 2018; 2019). Our study develops a framework based on recent technological advancements that have not been investigated. As research in humanitarian domains is limited and emerging, the second contribution of this study is to borrow the multidisciplinary literature from other industries and build BDMIP systems based on the inputs provided by humanitarian experts. For this purpose, a multi-decision making approach (analytic network process, ANP) is utilized. Also, existing studies (Agarwal, Shankar, and Tiwari 2006, Ayağ and Samanlioglu 2016, Jharkharia and Shankar 2007) do not provide sufficient details to conduct such analysis (see Table 1 for details), consequently, scholars from many general management domains (including scholars working in general business areas) are unable to apply such valuable methodological techniques. To help them and address this knowledge gap, we are providing detailed step-by-step procedures—so non-technical scholars can also utilize such valuable techniques. This can also assist them to promote multidisciplinary methodologies when they want to address complex problems interlinked with other social science arenas.

The remainder of this paper is structured as follows. Section 2 provides theoretical background and framework, and Section 3 highlights its methodological approach. It then presents a step-by-step procedure and results. The final section offers discussion, implications and conclusion.

2. Theoretical background and framework

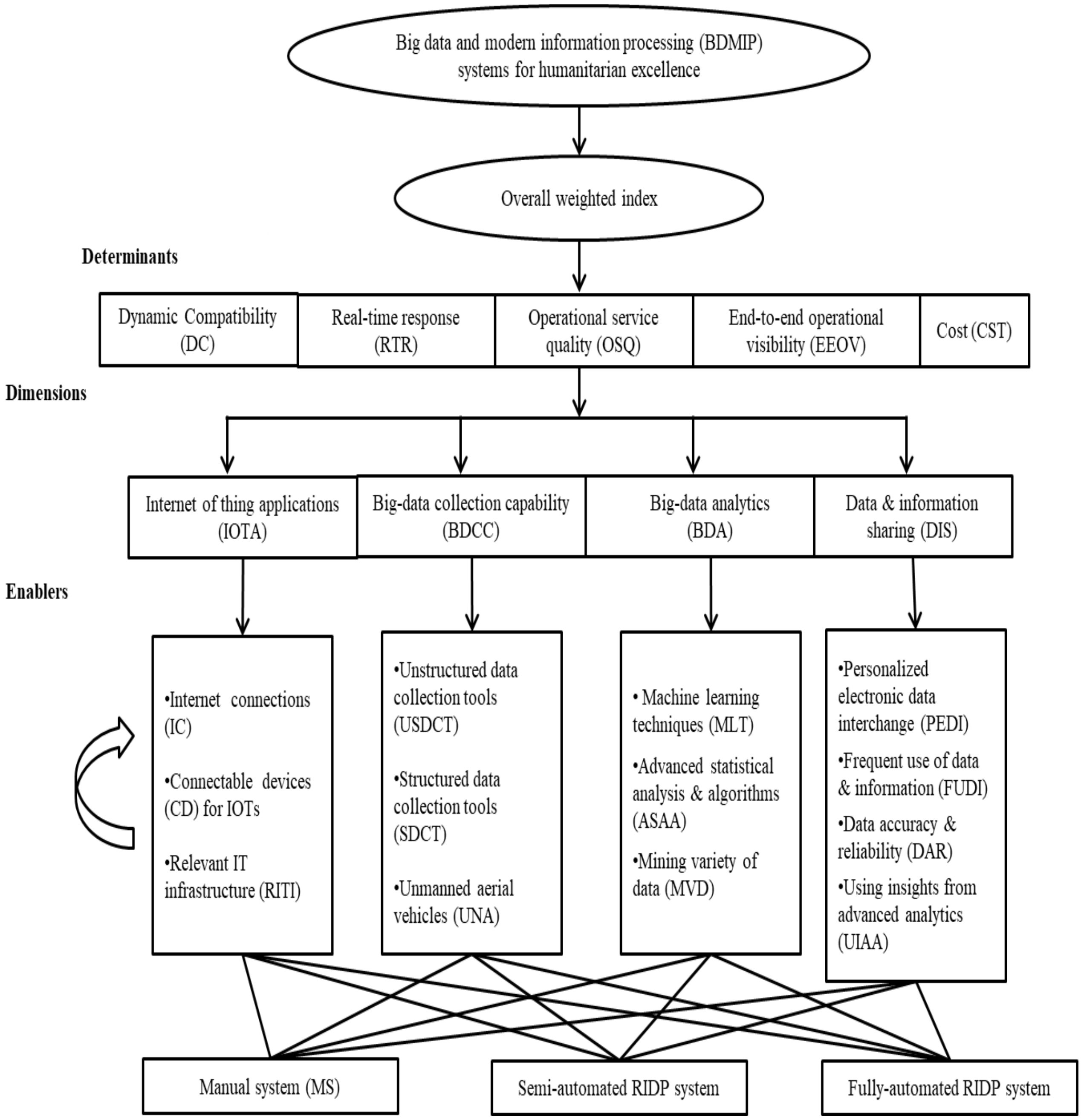
Unexpected humanitarian challenges and events lead to stressful and unpredictable situations, which require managing operational changes through coordination. In disastrous situations, organizational coordination and collaboration among different players are crucial. Such coordinated and collaborated mechanisms are defined as "*the relationships and interactions among different actors operating within the relief environment*" (Balcik et al. 2010, p. 23). These interactions can occur horizontally and vertically. Horizontally, different organization work at the same levels such as two NGOS or governments. Vertically, supply chain partners from upstream and downstream interact with each others and work together for mutual benefits. The purpose of such interactions is to serve the affected people through operational excellence (Akhtar, Marr, and Garnevska 2012), which is often supported through a provision of a technical infrastructure (Williams and Shepherd 2016, Kabra and Ramesh 2016, Kabra et al. 2017). BDMIP systems humanitarian operations may need to focus on three aspects: reducing system vulnerability, minimizing the impact of failures, and reducing the recovery time, which could be part of operational excellence (Dalziell and McManus 2004, Park, Sharman, and Rao 2015). A smooth run of the system is often challenged by the vast number of people being involved in operating and accessing the system (Ash, Berg, and Coiera 2004). However, excellence in case of unexpected disasters is also a measure to increase the perceived usefulness and trust of the system users (Kivinen and Lammintakanen 2013, Park, Sharman, and Rao 2015). This becomes even more important because trust is also linked to humanitarian operational teams that encourage coordination and collaboration among different actors involved in humanitarian operations. Consequently, BDMIP systems are beneficial in strengthening organizational communication systems that ultimately strengthen their coordination and collaboration for operational excellence that integrate factors such as quick responsiveness/real-time response, reliability capabilities, resilience, relationships among supply chain actors and cost (Christopher, 2011; Akhtar 2012).

BDMIP systems need to be accessible independent of time and space, and the relative consistency and reliability are essentials for these systems (Junglas and Watson 2006). Such systems therefore aim at enabling secure data and information flows, supporting operational activities (Mäenpää et al. 2009). This also applies when unexpected disturbances occur, which can come from both, external and internal sources (Riolli and Savicki 2003). Current information security approaches are often designed based on the assumption of a stable environment, thereby underestimating the role of unexpected disturbances (Müller, Koslowski, and Accorsi 2013). Nevertheless, it is essential that such systems react productively to unanticipated events (Home and Orr 1997), which implies that the system ultimately adopts new conditions (Riolli and Savicki 2003, Cooper, Flint-Taylor, and Pearn 2013). Previous research underlines the importance of a common understanding and shared knowledge in case of failures ultimately lead to overcome and learn from the challenging situation. This philosophy of understanding and knowledge sharing can be strongly supported by contemporary technological capabilities (e.g. Internet of Things and machine learning), as such capabilities provide a learning platform for coordination as well as for operational excellence (Akhtar et al. 2018, Mikalef and Pateli 2017, Akhtar et al. 2017).

Figure 1 provides the summary of the framework for BDMIP systems and Table 1 highlights relevant studies that assist to develop the parameters of our framework. Our BDMIP system consists of its key determinants for operational excellence, relative dimensions, and enablers. The determinants include dynamic capabilities, real-time response, operational service quality, end-to-end operational visibility, and cost. The dimensions and enablers also encompass multiple factors that are discussed in the following sections, starting from the key determinants:

[Insert Table 1 here]

Figure 1. Framework of big data and modern information processing (BDMIP) systems for humanitarian excellence



2.1. Key determinants for operational excellence:

2.1.1. Dynamic Compatibility

Dynamic capabilities can be defined as the organizations' ability to integrate, strengthen, and reshape human and non-human competencies to cope with frequently changing internal and external environments (Teece 2014, 2007, Mikalef and Pateli 2017). Modern technological systems such as BDMIP systems help top operational teams to better engage in unexpected situations. Dynamic competencies are considered as the key determinants for achieving operational objectives (Kivinen and Lammintakanen 2013, Mikalef and Pateli 2017). In this context, it is worthwhile to note that the implementation of dynamic information systems timely processes data and information for humanitarian operations. Such systems are particularly effective when unforeseen disturbances occur (Berg 2001), and the reliability of their infrastructure is an important prerequisite for building BDMIP systems (Sakurai and Kokuryo 2014). Although these systems often operate based on limited resources, it is essential that humanitarian organizations jointly overcome incompatibilities and optimize data and information processing for proactive actions against catastrophic events (Junglas and Watson 2006, Mikalef and Pateli 2017, Park, Sharman, and Rao 2015).

Additionally, automated data and information processing capabilities (Ash, Berg, and Coiera 2004), the ease of use of systems (Kivinen and Lammintakanen 2013, Pai and Huang 2011), producing actionable insights (IBM 2013, Barnaghi, Sheth, and Henson 2013, Akhtar et al. 2018), data and information quality (Hazen et al. 2014), and relative human expertise (Cohen et al. 2009, Prasad, Zakaria, and Altay 2016, Akhtar et al. 2018) contribute to the overall dynamic capabilities for building BDMIP systems, supporting operational excellence. Moreover, universally available and multifaceted devices may be used in the case of catastrophic events, which rely on minimal resources (Sakurai and Kokuryo 2014). Mindfulness is needed in the sense that organizations have to identify relevant information cues and act accordingly (Butler and Gray 2006). When systems fail, back up components need to be activated, which have similar capabilities to the failed components (NIST 2011). Finally, coordination among the relevant entities is fundamental to ensure compatibility (Sakurai and Kokuryo 2014), and effective coordination may depend on the different system characteristics (Pai and Huang 2011). Succinctly, BDMIP systems help organizations to coordinate and collaborate effectively, which is particularly vital in the case of disasters (Williams and Shepherd 2016).

Organizations and their teams are often not well prepared for unpredictable changes, particularly due to contemporary skills and capabilities require for agile operations (Carmeli, Friedman, and Tishler 2013, Akhtar et al. 2018). A particular challenge is that information systems are frequently embedded in turbulent and fast-changing environments, which often require global interdependencies subject to security issues (Dalziell and McManus 2004, Müller, Koslowski, and Accorsi 2013, Riolli and Savicki 2003). It is therefore essential to maximize the system protection, while minimizing its vulnerability and costs at the same time (Riolli and Savicki 2003). Hence, there is common agreement that the security of information systems deserves more attention (Müller, Koslowski, and Accorsi 2013). Since infrastructure and organizations are becoming more and more connected, this risks system security issues (Dalziell and

McManus 2004). Although global or organizational interdependencies (where organizations collaborate) can represent an asset, they are also associated with safety and reliability issues (Müller, Koslowski, and Accorsi 2013). The concept of information assurance (Ezingeard, McFadzean, and Birchall 2007, Park, Sharman, and Rao 2015) therefore needs to be reviewed, so it can be ensured that data and information are reliable, secure, accurate, and accessible. Given the sensitivity of the stored information, confidentiality of data must be ensured—particularly when personalized data is used for humanitarian assistance (Katsikas 2000, Park, Sharman, and Rao 2015). Additionally, the nature of unexpected threats to information systems continuously broadens and this makes it increasingly unpredictable. Thus, a well-elaborated security management system is essential, which exceeds the dynamic compatibility of organizations (Müller, Koslowski, and Accorsi 2013, Mikalef and Pateli 2017). Additionally, appropriate relative training courses for people operating information systems and their expertise are important to maintain BDMIP systems (Katsikas 2000, Mikalef and Pateli 2017). Furthermore, information system security management implies that the system should be continuously evaluated for further improvements that contribute to dynamic capabilities (Ahmadian, Nejad, and Khajouei 2015).

2.1.2. Real-time response and operational service quality

The immediate and reliable information access may help to overcome many unexpected events, because it allows to better structure operational processes and response to disasters accordingly. The real-time response of information systems contributes to the success of humanitarian operations, contributing to operational excellence. It also ensures how fast information can be exchanged between involved organizations (Kivinen and Lammintakanen 2013, Mäenpää et al. 2009). Through fast responses, information systems may also increase operational service quality, which is a key determinant for operational excellence in humanitarian operations (Pai and Huang 2011, Park, Sharman, and Rao 2015). The data that is collected during catastrophic events also need to be processed as fast as possible. This can further increase visibility for operational effectiveness (Sakurai and Kokuryo 2014).

As real-time responses also define an information system success (Berg 2001), this feature is required during unexpected challenges. The crucial element of information system resilience is the capability to cope with unforeseen disturbances and uncertainties, whenever they occur (Butler and Gray 2006, Park, Sharman, and Rao 2015). Delays in responding to these unforeseen events are particularly accompanied by severe consequences for a networked system (Wang, Gao, and Ip 2010). It is therefore beneficial if a system can quickly adapt to new situations (Dalziell and McManus 2004). Also, creative, automated and prompt responses are particularly essential when BDMIP systems are used for disaster management (Sakurai and Kokuryo 2014).

Additionally, the continuous documentation of BDMIP systems for efficient monitoring and improving services is important (Barrote et al. 2014, Kivinen and Lammintakanen 2013, Mäenpää et al. 2009). This can reduce the occurrence of human-made errors (Ahmadian, Nejad, and Khajouei 2015, Melin and

Axelsson 2014). By following the philosophy of continuous improvement, BDMIP systems may tap its full potential that contribute to operational service quality (Pai and Huang 2011). It is thereby dependent on both, the quality of BDMIP systems as well as on data and information reliability and accuracy that are interrelated and influence the (perceived) usability and effectiveness of BDMIP systems (Kivinen and Lammintakanen 2013, Pai and Huang 2011).

BDMIP systems may further strengthen certain levels of robustness towards emergency situations and respond to them effectively and efficiently (Vecchiola et al. 2013). As humanitarian organizations often rely on networked systems, collective responses are important predictors of operational service quality since these are more vulnerable than a single system due to the large number of external interfaces and the threat of cascading failures (Katsikas 2000, Wang, Gao, and Ip 2010). Hence, a BDMIP system ensures that information systems can realize their target, which is the enhancement of service quality (Ahmadian, Nejad, and Khajouei 2015). This implies that BDMIP systems allow both, actionable insights and timely information sharing for better service quality (IBM 2013, Barnaghi, Sheth, and Henson 2013, Kivinen and Lammintakanen 2013).

2.1.3. End-to-end operational visibility and cost

The effectiveness of BDMIP systems further depends on end-to-end operational visibility that is linked with coordination and cooperation between different groups or organizations (Chiasson et al. 2007, Pai and Huang 2011). In such organizations, BDMIP systems provide a stable foundation and information platform for mastering challenging situations. The achieved visibility through BDMIP systems facilitates communication and information exchanges between different entities including suppliers, intermediaries, and end-users (Ahmadian, Nejad, and Khajouei 2015). Whilst these entities represent both individuals and organizations (Melin and Axelsson 2014), it is essential that they regularly communicate and share necessary data and information for better coordination to tackle unexpected events. Additionally, BDMIP systems support information integration so that diverse data and information from different channels can be combined. This can also reduce the total cost of managing the system (Vecchiola et al. 2013). Although information exchange is clearly an asset, it represents a disadvantage for individual entities if the system fails; hence, demonstrating the relevance of developing BDMIP systems that can keep them connected (Dalziell and McManus 2004, Park, Sharman, and Rao 2015).

In addition to end-to-end operational visibility, an appropriate acceptance and the utilization of information systems by all involved organizations is crucial to support the system (Park, Sharman, and Rao 2015, Raghupathi and Umar 2008). Similarly, a system can fail during unexpected events because of both, technical problems and social aspects (Berg 2001, Fiksel 2015); therefore, requiring compliance and commitment of all involved organizations or individuals. It is also essential that relevant data and information can be accessed from suppliers (e.g. donors and material suppliers) to consumers (e.g. disaster affected people) (Ash, Berg, and Coiera 2004). Similarly, data and information completeness matters since incomplete data and information may impede operational service quality, and increase costs (Mäenpää et al. 2009). Efficient BDMIP systems based on minimal resources can be useful as long as they help to achieve main goals (Watson, Kunene, and Islam 2013). As catastrophic events are characterized by limited resources, cost-effective BDMIP systems may contribute to operational efficiencies (Sakurai and Kokuryo 2014).

2.2 Dimensions and enablers for operational excellence

The term "the internet of things" (IoTs) is used for devices that can send or receive data and information by utilizing network connections (Atzori, Iera, and Morabito 2010, Ma 2011). It is an emerging area in technological domains that plays a vital role to enhance the effectiveness of operations (Wortmann and Flüchter 2015). Massive data and information produced through IoTs is utilized to improve operational visibility that ultimately helps to monitor and control interconnected operational flows for coordination. Organizations using such capabilities are more agile due to the applications of actionable insights they produce from data and evidence-based decision making linked with IoT implications (Lou et al. 2011, No, An, and Park 2015). The significance of such developments has been evidenced by many IT and business experts. For instance, Microsoft believes that "*the internet of things can make a difference to your business by beginning with the things in your business that matter the most. It's really the internet of your things, and it starts by building on the infrastructure you already have in place, using familiar devices and services in new ways, and incorporating the right technology to ultimately help you use data to create insights and make more informed business decisions*" (Edson 2014, 4). Consequently, IoT devices are expected to increase by 26 billion units in 2020. This represents "*an almost 30-fold increase from 0.9 billion in 2009*" and it may generate incremental revenue "*exceeding $300 billion*" (Gartner 2013, 1). Furthermore, the Vodafone IoT Barometer suggests that 76% of organizations indicate that the IoTs will be critical for future developments and operational excellence. This report also found that 90% of the surveyed organizations have already integrated IoT data into their existing operations and 63% of adopters have gained more than 20% revenue growth due to IoT applications, supporting their BDMIP systems (Forbes 2016, Vodafone 2016). It clearly demonstrates that the IoTs assist to build effective data and information systems as well as contribute to dynamic capabilities that strengthen internal and external operational activities linked with the dimensions of operational excellence (e.g., operational agility) (Teece 2007, 2014, No, An, and Park 2015, Akhtar et al. 2017).

Additionally, big data collection and big data analytics play an important role to build BDMIP systems. Big data, which is linked with business intelligence and artificial intelligence (Chen, Chiang, and Storey 2012, Davenport 2006), is defined as a combination of technologies that produce structured (e.g. large quantitative datasets) and unstructured data (e.g. images and text data), and analyzing such data to produce actionable insights is called big data analytics. Some researchers enclose big data with 3Vs—volume, variety and velocity (APICS 2012, Lamba and Singh 2017). Big data collection depends on various advanced technological applications such as deploying unmanned aerial vehicles (also called drones) and building smart websites that can automatically collect data. A variety of advanced mathematical/statistical techniques (e.g. machine learning techniques and advanced multivariate analysis) are used to analyze big data, which can provide information that is shared across internal and external departments for proactive actions (Qiu and Antonik 2017, Lytras, Raghavan, and Damiani 2017, Roden et al. 2017).

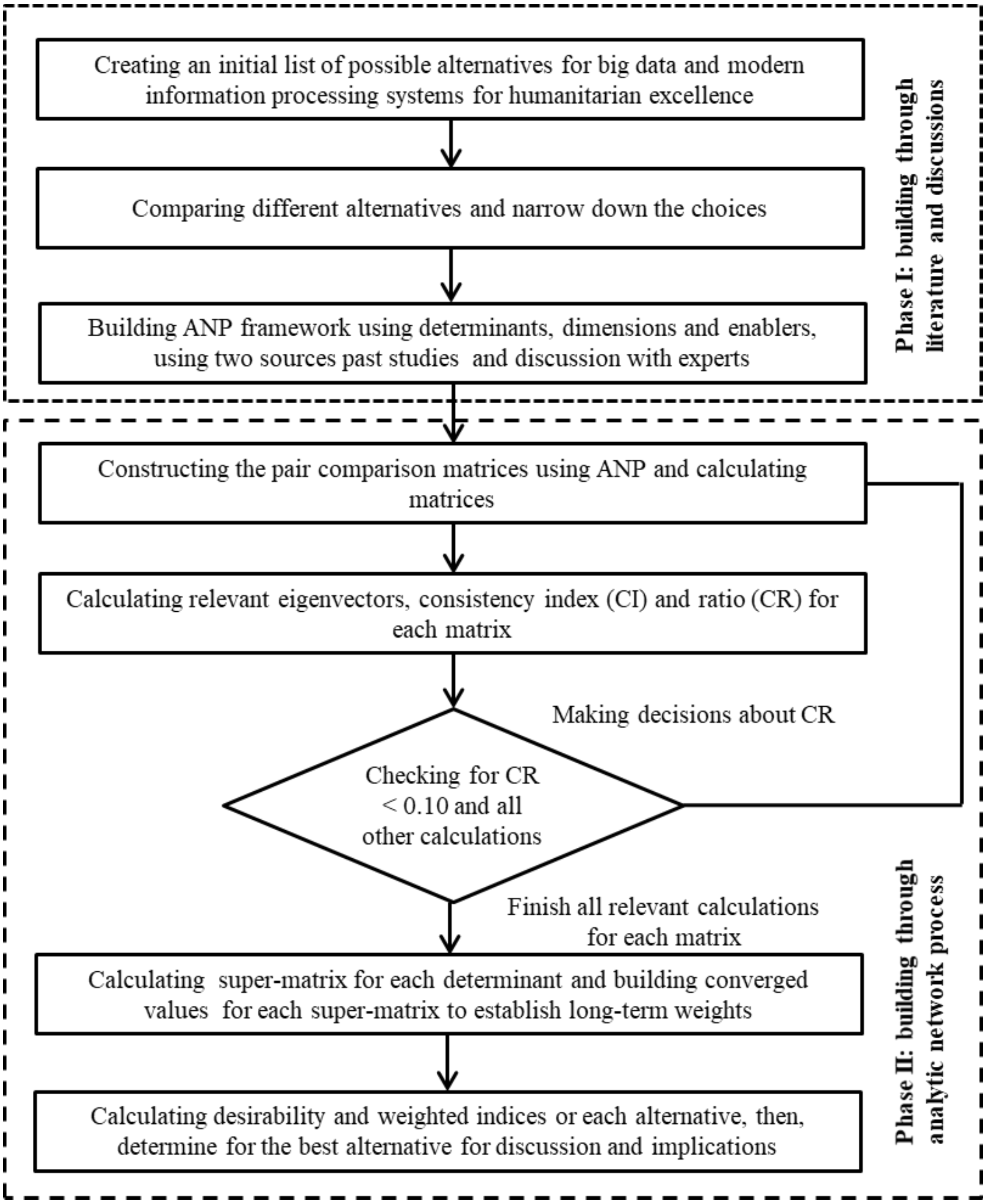
Structured and unstructured data help in building BDMIP systems for actionable information that can be valuable for operational activities as well as for network partners who work collaboratively for common goals (Malhotra 2000, 2005, Del Giudice and Straub 2011, Gubbi et al. 2013). This data and information is shared through various connected devices supporting to build BDMIP infrastructure (Atzori, Iera, and Morabito 2010, Barnaghi, Sheth, and Henson 2013, Roden et al. 2017). Organizations invest in such infrastructure (e.g. IoTs and big data technologies) to improve their IT capabilities that transfer valuable insights to improve operational performance and excellence (Gubbi et al. 2013, Lou et al. 2011, Uckelmann, Harrison, and Michahelles 2011; Sartal et al., 2017). Actionable information and insights are produced using advanced technology and statistical tools, playing a vital role for massively connected organizations. Such organizations handle huge amount of structured and unstructured data, and timely processing data and information can affect their whole network (Chen and Zhang 2014). Thus, collecting, sensing, analyzing, and using data and information can reconfigure operational processes and capabilities to enhance operational excellence. The reliability and accuracy of data is also vital to build effective coordination systems that can strengthen operational excellence (Xu, Frankwick, and Ramirez 2016, Xiang et al. 2017, Akhtar et al. 2017).

3. Methodological approach

3.1. Proposed Methodology

The proposed methodology, shown in Figure 2, provides a platform to evaluate alternative resilient data and information processing (BDMIP) systems in two phases: I) conducting literature review and investigating an initial screen of BDMIP systems applied by different organizations, and II) applying the analytic network process (ANP) method to quantify the framework. In the first phase, it is important to identify the research participants who have relevant expertise and skills to evaluate the procedure adopted for this study.

Figure 2. A two-phased methodology



First, this study identifies different experts (supply chain data scientists, operational analysts, IT managers, operations/supply chain/procurement/logistics/project managers) from those medium and large-sized non-government humanitarian organizations (NGOs) with a focus on end-to-end supply chain operations. We have selected healthcare and food sectors, as these sectors are potentially linked with basic needs during natural disasters and relevant organizations engaging in providing supplies play crucial roles. Managers in these organizations provide interesting insights about organizational resilience, as they deal with the issue of resilience on continuously. Furthermore, the severity and impact of natural disasters vary, therefore these organizations have a critical understanding of organizational resilience while dealing with different types of disasters in different times. Humanitarian organizations are also the first line of contact for other organizations/societies in the event of natural calamities, hence they have a good understanding of organizational resilience in a much broader context. Table 2 lists the details of these participants. These experts have in-depth knowledge and expertise to build BDMIP systems. The participants also have experiences from other industries, which assists to investigate how good practices applied in private organizations can be implied in humanitarian operations. This first step thus helps to establish a team of experts who can build a BDMIPS, contributing to the compatibility of whole systems adopted by humanitarian organizations. Our survey participants have experiences in other industries as well. We thus believe our findings could be applied in general business settings and should not be narrowly interpreted in the context of humanitarian and food/healthcare organizations.

[Insert Table 2 here]

To select the respondents, purposive sampling was used to select those experts (respondents) who meet the study requirements, mainly working in humanitarian healthcare and food operations and have relevant information about the constructs under our investigation. A pilot survey was conducted to check the suitability of our participants. A total 50 experts (respondents) were invited to participate in the study. After several reminders and in-person motivation efforts, 20 experts (40%) agreed to participant in the study, who represented different domains controlling for single-informant bias. Additionally, we did not find any differences between different groups based on experience or education.

Second, the key objectives such as effective real-time responses, improved operational service quality, end-to-end visibility across horizontal (between organizations) and vertical operations (between supply chain partners), system security, and efficiency are clearly defined. These objectives are built based on two sources, namely literature reviews and in-depth discussions with selected experts. To examine the effectiveness of these objectives, the involved organizations are regularly audited for what disaster (e.g. earthquake) affected people expect to receive in terms of supplies, what actually is delivered and how BDMIP systems associated with the dimensions of contemporary technology and analytics (IoT infrastructure, big data collection facilities, big data analytics, sharing insights for actions, and evidence-based decisions making) supporting humanitarian operations. These dimensions dependent on enablers (e.g. internet availability, connectable devices, using different data types, among others) that support BDMIP systems depicted in Figure 1.

3.2. Analytic Network Process

The analytic network process (ANP) method is a comprehensive decision-making tool that is used for complex frameworks. According to Saaty (2004), decision making process involves certain criteria and alternatives to be chosen from. The ANP is a systematic decision making process, involving comparisons and human judgements. This approach is a method of measurement of a particular complex social phenomena and it is a decision making framework involving certain human attributes e.g., emotions and feelings. Involved determinants, dimensions, and enablers create more complexities and the ANP methodology facilities to simplify this, compared to other methods such as structural equation modelling and regression. We utilized this methods due to the complex structure of our framework, involving a number of determinants, dimensions and enablers. We believe understanding this method would be useful for readers in the supply chain literature as the method is related with the role of information in human decision making. To overcome the technical difficulties of the method for management scholars, we have provided a step-by-step procedure that non-technical researchers can utilize and existing studies do no provide sufficient details (Agarwal, Shankar, and Tiwari 2006, Ayağ and Samanlioglu 2016, Jharkharia and Shankar 2007). It allows encompassing all underlying determinants, dimensions, and enablers to reach decision to select a suitable BDMIP system based on rigorous calculations and measures built through rankings, using a nine-point scaling system and their relevant reciprocals, eigenvectors, super-decision matrices and weighted indices. The method was introduced by (Saaty 1996) and it links with the analytic hierarchy process (AHP) firstly utilized in the 1980s (Saaty 1980a). The ANP approach has the capability to integrate interdependencies and feedback loops that are often necessary for complex decision making. The relative weights are based on pair-wise comparisons as in the standard AHP. The weights are then utilized in the super-matrix that indicates the interrelationships of components (elements). A score of 1 in the scaling process for pair-wise comparisons indicates equal importance of two underlying components and a score of 9 represents extreme importance. The reciprocal values are then also assigned to the underlying components. Table 3 shows the details of these scales.

[Insert Table 3 here]

The idea of ANP is described as a system of N components (part of a cluster), forming a network in which every component (C_n) can interact with itself or other components. The network (N) equals where L= {{C_a, C_a}, {C_a, C_b},{C_a, C_c},...,{Cn, Cn}} and represents the set of pair-wise linkages within or between components. Pair-wise comparisons in the ANP are made in the framework of matrices and local priority vectors are calculated by using equation 1 (Ayağ and Samanlioglu 2016, Niemira and Saaty 2004, Saaty 1980b).

$$A \times w = \lambda_{max} \times w \quad (1)$$

Where A is the matrix of pair-wise comparison, w is the eigenvector, and λ_{max} is the largest eigenvalue of A.

The eigenvector is obtained by fixing the mean value and identifying the maximum eigenvalue, and the consistency index (the measure of inconsistency) is calculated by:

$$CI = (\lambda_{max} - n)/n\text{-}1 \quad (2)$$

The consistency ration (CR) is finally used to estimate the consistency of pair-wise comparisons, and it is computed by dividing CI with random consistency index (RI):

$$CR = CI/RI \quad (3)$$

Where RI is the average index for randomly generated weights.

Additionally, the local priorities are synthesized by utilizing the following three-step procedure; 1) summing up the values in each column of the pair-wise comparison matrix, 2. Dividing each components in a column by the sum of its respective column, so the normalized pair-wise comparison matrix can be produced, and 3) summing up the components in each row of the normalized pair-wise comparison matrix, and divide the sum by the n components in the row. These final numbers provide estimates of the relative priorities (Chung, Lee, and Pearn 2005, Niemira and Saaty 2004, Saaty 1980b).

For global priorities, the ANP extends the AHP method to incorporate dependencies/feedback loops by using super-matrix (W). In this process, the local priority vectors are entered in the appropriate columns of the super-matrix in which each matrix segment represents a relationship between two components. The super-matrix, W, is a complete matrix of components, {Ca, Cb, Cc. ..., Cn}, and their linkages or weights, $W_{ij}C_i = \{e_{i1}, e_{i2}, \ldots, e_{in}\}$ are the subcomponent elements of the criterion component i. If there is no link between two components, then, the W for those two components will be zero. In other words, there is no dependence between those two components (Chung, Lee, and Pearn 2005, Niemira and Saaty 2004, Saaty 1980b).

$$\mathbf{W} = \begin{array}{c} \\ C_a \\ C_b \\ \vdots \\ \\ \\ C_n \end{array} \begin{array}{c} \begin{array}{cccc} C_a & C_b & \cdots & C_n \end{array} \\ \begin{bmatrix} \mathbf{W}_{aa} & \mathbf{W}_{ab} & \cdots & \mathbf{W}_{an} \\ \mathbf{W}_{ba} & \mathbf{W}_{bb} & \cdots & \mathbf{W}_{bn} \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ \mathbf{W}_{na} & \mathbf{W}_{nb} & \cdots & \mathbf{W}_{nn} \end{bmatrix} \end{array}$$

After the super-matrix and relative analysis, the desirable index is computed for alternatives that are based on determinants, dimensions, and enablers. The equation of desirable index, Dia, is calculated as follows (Agarwal, Shankar, and Tiwari 2006, Ayağ and Samanlioglu 2016, Jharkharia and Shankar 2007, Meade and Sarkis 1999):

$$\mathrm{Dia} = \sum_{j=1}^{J} \sum_{k=1}^{Kja} \mathrm{Pja}\ A^{D}\mathrm{kja}\ A^{I}\mathrm{kja}\ \mathrm{Sikja} \quad (4)$$

Where, the notation Pja is the relative importance of dimension j in influencing the determinant a. $A^{D}kja$ is the relative importance of an enabler k in influencing the determinant a through dimension j for the dependency (D) relationships. $A^{I}kja$ is the stabilized importance weight of the enabler k in the dimension j and determinant a for interdependency (I) relationships. These values are taken from the converged super-matrix. $Sikja$ is the relative impact of alternative i on enabler k of dimension j for determinant a. Kja is the index set of enablers for dimension j of determinant a, and J is the index set for dimension j (Agarwal, Shankar, and Tiwari 2006, Ayağ and Samanlioglu 2016, Jharkharia and Shankar 2007, Meade and Sarkis 1999).

Finally, the overall weighted indices (OWIi) for alternative BDMIP system are calculated by summing up the products of the normalized desirability indices (DiaN) and the relative importance weights of the determinants (C_n). The normalized values ensure that the sum of OWI values is equal to one, OWIi are mathematically represented by:

$$OWIi = \quad D_{iaN}C_n \qquad (5)$$

4. Step-by-step procedure and results

The model shown in Figure 1 was first built through the literature and a series of discussions with practitioners, working in non-governmental humanitarian organizations (NGOs), which handle humanitarian healthcare and food operations. This implies that the framework for big data and modern information processing (BDMIP) systems could be considered by managers and practitioners in making a decision using a relative measurement model. In other words, healthcare and food handling organizations have the flexibility to apply this framework in choosing the best available options from a set of BDMIP systems. The applied ANP approach is suitable in modelling complex decision problems linked with criteria, sub-criteria and available alternatives. The ranking of alternatives (manual, semi-automated, fully automated BDMIP systems) do not only depend on the weighting of criteria, the given alternatives and interdependencies also influence them.

It was also ensured that all participants have experiences from private industries as well. There were two reasons to include this criterion. First, advanced and emerging IT applications (e.g. IoTs and big data analytics) are limited in NGOs and experiences/good practices from private industries may help to adopt suitable BDMIP systems by utilizing contemporary tools and techniques (e.g. mining unstructured data and machine learning methods). Second, the in-depth domain knowledge and expertise of BDMIP experts (research participants) provide effective assessments for selecting a suitable BDMIP system. These experts are selected from seven medium and large-sized NGOs (healthcare and food), which use different levels of BDMIP systems (i.e., manual systems, semi-automated systems and fully-automated systems). Once these requirements and criteria are satisfied, the ANP model is applied using a nine-step procedure that is explained in the following sections.

Step 1: Model Development and Problem Formulation

After reviewing the literature and developing initial thoughts from discussions, it becomes possible to categorize various determinants, dimensions, and enablers (depicted in Figure 1). The determinants are first placed at the top level as they represented higher or strategic criteria, which play an imperative role in developing BDMIP systems and their relevant decision making. These determinants encompass dynamic capabilities, real-time response, operational service quality, end-to-end operational visibility, and cost. Practitioners strongly supported this classification by showing unanimity with the literature (Kivinen and Lammintakanen 2013, Mikalef and Pateli 2017, Teece 2014). Similarly, the next level criteria (dimensions) are examined, which support the top level (determinants). Additionally, these dimensions (IoT applications, big data collection capabilities big data analytics, and data and information sharing) are individually dependent on enablers such as IT infrastructure, internet connections, unstructured and structured data collection tools, using a variety of advanced statistical tools and producing actionable insights for practical implications. These enablers support respective dimensions as well as show interlinks among them. These interlinks (or interdependencies) are show in Figure 1 by including an arc on the left side of Figure 1. Finally, BDMIP systems that depended on overall weighted indices are placed at the bottom of Figure 1.

The opinions of the experts are obtained using pair-wise matrices that are used to calculate e-vectors. In the interest of space, we illustrate a complete procedure for one determinant, called dynamic compatibility. However, the relevant results for all determinants are utilized to calculate the overall weighted indices.

Step 2: Pair-Wise Comparison of Determinants.

The second step provides the relative importance of underlying determinants. A ration scale of 1-9 is used to obtain importance; 1 represented equal importance of two factors and 9 indicated extreme importance of one factor on another relative factor (See Table 3). Then, the relative reciprocals (e.g. 9 corresponding to 1/9) are used to highlight the comparative weaker impacts. This then helps to group the rankings to calculate local priority vectors (Eigen-vector or e-vector), presented in Table 4. The results show that dynamic compatibility is the most important determinant, followed by real-time response and cost. End-to-end visibility (i.e., visibility between upstream and downstream) and operational service quality are equally important.

[Insert Table 4 here]

Step 3: Pair-Wise Comparison of Dimensions

The relative rankings of each dimension linked with the determinants are next acquired. The matrix for dynamic compatibility is first calculated, as listed in Table 5. The e-vectors from Table 4 are used as Pja in Table 9. Similarly, the pair-wise comparison matrices and e-vectors for other determinants are obtained and Pja values are calculated to compute desirability indices (Dia). The results reveal that big-data analytics is the most important dimension for building BDMIP systems for humanitarian excellence, followed by data and information sharing, big-data collection capability, and the internet of thing applications—which also facilitate coordination and collaboration among involved organizations.

[Insert Table 5 here]

Step 4: Pair-Wise Comparison of Enablers

Table 6 provides the example of the pair-wise comparison of enablers (e.g. internet of things). The question for experts is framed as what is the relative impact on the internet of thing applications by enabler IC when you compare it to enabler CD in building dynamic compatibility between the BDMIP systems for humanitarian excellence. The e-vector computed in Table 5 is carried as $A^D kja$ for calculating desirability indices (Dia). Similarly, other questions are designed and completed among the underlying enablers within the given clusters and are imported in relative tables.

[Insert Table 6 here]

Step 5: Pair-Wise Comparison matrices for interdependencies

This step captures the interdependencies among the enablers studied in this research. An example of such comparison is shown in Table 7 that presents the result of the cluster DC-IOTA with internet connections (IC) as the controlling factor over other underlying enablers. The question for this enabler is asked as when you consider IC in connection to enhance dynamic compatibility, what is the relative impact of CD when you compare it to RITI. The e-vectors from Table 6 are used to develop the super-matrix, which is converged by raising the super-matrix to power 2^{k+1} (Jharkharia and Shankar 2007, Saaty and Vargas 2013). Likewise, pair-wise comparison matrices and relative e-vectors are computed for other enablers.

[Insert Table 7 here]

Step 6: Evaluation of BDMIP Systems

Table 8 shows an example of the final set of pair-wise comparisons for the relative impact of alternative BDMIP systems (i.e. manual system, semi-automated system and fully-automated system). The example shown in Table 9 examines the impact of these alternative systems on the enablers IC in influencing the determinant DC. The corresponding e-vectors from this comparison are utilized in the second row (corresponding to the IC enabler) of columns 6-8 for computing desirability indices (Dia) in Table 10. Similarly, pair-wise comparisons and relative e-vectors are calculated for other enablers linked with other alternative BDMIP systems and determinants.

[Insert Table 8 here]

Step 7: Super-matrix Formation

The super-matrices are used for the resolutions of interdependencies among the factors. As depicted an example in Table 9, the super-matrix presents the results of relative importance for the enablers linked with the dynamic compatibility determinant. The e-vectors from Table 7 and other relative set of pair-wise comparison matrices are first converged before developing Table 9.

Step 8: Selection of the best BDMIP system for a determinant

The selection of the best BDMIP system is dependent on the set of desirability index values, which indicate the relative importance of alternative BDMIP systems linked with the underlying determinants for humanitarian excellence. An example of desirability indices (Dia) and their normalized values (DiaN) for the dynamic compatibility determinant is shown in the last two rows of Table 10. These are calculated using equation 4 explained in the methodology section ($\mathrm{Dia} = \sum_{j=1}^{j} \sum_{k=1}^{Kja} \mathrm{Pja}\ \mathrm{A^{D}kja}\ \mathrm{A^{I}kja}\ \mathrm{Sikja}$). The first row of Table 9 clearly explains where these values are imported from and how the row values are calculated. The last three columns show the weight values of alternative BDMIP systems. Once they are calculated, the relative row-wise summation of the last three columns provides desirability indices (Dia) that are shown in the second last row, and they are then normalized.

[Insert Table 9 here]

[Insert Table 10 here]

Step 9: Calculation of Overall Weighted Index

Overall weighted indices (OWIs) for the alternative BDMIP systems are calculated using equation 5 (OWIi = DiaNCn). These indices are shown in Table 11. An example of such a calculation is illustrated below:

OWIi for DC = {(0.3802*0.1453) + (0.2813*0.2287) + (0.1002*0.2580) + (0.1019*0.2350) + (0.1364*0.5756) = 0.2479

[Insert Table 11 here

5. Discussion, implications and conclusion

5.1 Summary of Results

This study examines big data and modern information processing (BDMIP) systems for humanitarian operational excellence integrated with coordination and collaboration among involved parties (e.g., government agencies, NGOs, and private companies). The complexity of three underlying systems (manual system, MS; semi-automated system, SAS; and fully-automated system, FAS) is simplified by using a multi-criteria decision-making approach, the analytic network process (ANP). This approach quantifies the experts' judgments that evaluate these complex decision making systems. The results show that dynamic compatibility plays the most important role in building effective BDMIP systems for humanitarian operational excellence, followed by real-time response, cost, visibility, and service quality. The overall results indicate that a fully-automated system (with a 0.4286 weighted index) is the first choice for experts to implement an effective BDMIP system. This mainly attributes to dynamic capabilities (DiaN = 0.5716) that strengthen organizations to apply such systems that are more flexible and sustainable (Kivinen and Lammintakanen 2013, Mikalef and Pateli 2017). However, implementing such systems is costly, with an overall index of 0.1713 compared to other underlying systems (SAS = 0.2531; MS = 0.5756) (Sakurai and Kokuryo 2014). Although manual systems are cost-effective, they cannot handle big data and modern information and data process promptly, which is the key to provide real-time responses that contribute to humanitarian service quality, being part of humanitarian operational excellence and effective coordination. The second favourite choice for experts is semi-automated applications for building BDMIP systems (Mikalef and Pateli 2017). Apart from the cost determinant, this choice dominates extant manual operating systems. While the overall indices provide an indication for the preferred system (i.e., FAS), it is not necessary that other systems are not useful (Sakurai and Kokuryo 2014). For instance, a semi-automated system (SAS) has clearly more importance in certain areas. A semi-automated system (SAS) could overcome some of the limitations associated with each of the two alternative BDMIP systems. As highlighted in Table 10 (column seven) for dynamic capabilities, such systems are more important for structured data collection (0.4934), personalized data interchange (0.5278), and obtaining data accuracy and reliability (0.4934) for building BDMIP systems for humanitarian operational excellence.

5.2 Implications

Implications arising from this study are multifold. First, BDMIP systems play a crucial rule to provide a real-time response, contributing to operational excellence. Particularly, healthcare services and food supplies are major challenges in disasters and linking upstream with downstream through modern data processing and information sharing that assist organizations to save lives. Timely big data processing and information sharing further helps to identify those areas that are most affected, so the priorities can be set for certain areas. Once such areas are identified, modern logistic solutions (drones) can be used to provide medical services and food supplies. This does not only help to provide a timely response but also improves service quality that is a key performance indicator for humanitarian operational excellence (Park, Sharman, and Rao 2015, Mikalef and Pateli 2017, Prasad, Zakaria, and Altay 2016). Service quality is further improved when organizations have better visibility in their supply chain operations. This helps them to monitor their supplies from international warehouses or suppliers to local affected areas. Visibility particularly contributes to frontline services. For instance, humanitarian managers and local representatives can plan their operations in advance when they know where their supplies are in the pipeline and they can also inform upstream players (e.g. donors and manufacturers) about how much further assistance is required in a particular area. Second, the resources needed in humanitarian operations often vary—depending on daily, weekly, and monthly requirements, thus, timely and accurate information sharing among supply chain players may help to optimize requirements such as manpower (e.g. medical doctors, nurses, cooks, among others) and transportation. Third, another key performance indicator in humanitarian operations is a fair distribution of scarce resources. It may be possible that the most deserving people could not get supplies due to the unfair distribution of relief goods (Tzeng, Cheng, and Huang 2007). Personalized data and information sharing through modern IT infrastructure can help to reduce this factor. For example, if personalized information is available (e.g. pregnant women in the area, number of kids, types of diseases in certain group of people, destroyed houses, among others), humanitarian representatives can directly focus on these people and areas without involving locals who may favor their relatives and ignore the most deserving people around those areas. This can also help to provide personalized healthcare services for individuals (Park, Sharman, and Rao 2015). To collect personalized information, semi-automated BDMIP systems may work better due to following reasons: a) when people and technology both are involved in collecting such data, it can create more trust that the personalized data may not be used for other than humanitarian assistance b) semi-automated systems can help to collect and analyze big data by investigating online activities in which people are involved. This combination can also enhance the reliability and accuracy of big data by applying cross checks on different types of data collected from different sources (e.g. online resources, images, videos, surveys, and unmanned aerial vehicles). Our study also provides a robust framework for building modern systems in organizations. By using analytics and information produced from BDMIP systems, humanitarian organisations can make their risk assessments for better managing and responding to natural disasters, even quantifying risk effectively. The concept of risk assessments has recently attracted the attention of policy makers, particularly after the global financial crisis. Companies around the world are increasingly disclosing in their annual reports about the different types of risks they are facing and how these risks are minimized or mitigated. An effective BDMIP system can thus enhance an organizational resilience strategy against risk arising from different events. The framework therefore can also be used by other organizations, particularly which share similar characteristics and facing risk from major disturbances.

Although effective BDMIP systems significantly contribute to humanitarian operational excellence and coordination, there are a number challenges to implement such systems. Firstly, building dynamic compatibility consisting of advanced IT systems and relevant experts is the key hurdle for small and medium-sized humanitarian organizations. Particularly, there is a lack of humanitarian data scientists who can play a key role in building such systems. It is thus crucial for such organizations to build stronger alliances with leading (large-sized) humanitarian organizations, government agencies and private organizations (called public-private partnerships). This could not only provide them with learning opportunities but they together can also better respond to large-sized disasters. Secondly, IT infrastructure may be damaged due to disasters. This can create another challenge in local areas. If it is not rebuilt on time, the utilization of BDMIP systems can be limited. However, such systems may be built in a way that they can automatically collect and analyze all data that could not be collected when the system was down. This automation can lead to evidence-based decision-making that may be used to improve operational visibility, contributing to humanitarian operational excellence, coordination and collaboration linked with BDMIP systems.

5.3 Limitations and Future Research

Since studies investigating the explicit role of building BDMIP systems for humanitarian operational excellence, coordination, and collaboration are in its infancy, there are several specific domains in which future research might be conducted. While this study underpins the theoretical grounds together with empirical data from humanitarian experts and the ANP approach, future research may examine in-depth case studies to unpack the interactions between BDMIP systems and the further dimensions of operational performance or excellence. A mix-method approach can provide more insights. Since this study is based on two specific areas (e.g., healthcare and food), future research may benefit from follow-up studies in other areas (e.g. building infrastructure) that are also important for humanitarian organizations and long term sustainability.

What key challenges large humanitarian organization are facing in implementing BDMIP systems can also be an interesting arena for researchers. Furthermore, the use of unmanned aerial vehicles (also called drones) is an emerging topic and investigating it can provide useful insights. Such vehicles have particular applications in those areas (e.g. mountainous areas, damaged infrastructure, and risky roads), where traditional logistics (e.g. trucks and vans) cannot reach easily. Thus, supplying food and medical services in those areas through drones may tackle relative challenges. Additionally, conducting case studies on how humanitarian data scientists utilize a variety of data and advanced techniques (e.g. spatial analysis, machine learning techniques, and combining unstructured and structured data) can provide actionable insights for decision makers. Additionally, the role of BDMIP systems may vary in the future due to advances in technology and mathematical techniques for data analysis. Assessing relevant technical skills and how they help to produce automated analysis for evidence-based decision-making can significantly contribute to emerging humanitarian domains and operational excellence linked with coordination and collaboration among involved organizations.

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Table 1. Key studies and their characteristics to develop the parameters of our framework.

Author	Year	Design	Sample	Dependent Variable	Results
Dynamic capabilities, data and IT					
Teece	2007	Theoretical paper	N/A	Business performance	Strong dynamic capabilities relate to entrepreneurial enterprises; lead to long-term organizational success
Teece	2014	Theoretical paper	N/A	Enterprise performance	Dynamic capabilities in combination with good

					strategy lead to superior performance (esp. in changing environments)
Mikalef and Pateli	2017	Quantitative study (SEM and fsQCA)	274 international firms	Competitive performance	IT-enabled dynamic capabilities influence competitive performance via organizational agility
Akhtar et al.	2018	Quantitative study (SEM)	205 respondents	Operational agility	Dynamic data and information processing capabilities mediate the relationship between IoTs use and operational agility
Akhtar et al.	2019	Quantitative study (SEM)	240 respondents	Business performance	Business performance depends on big data-savvy teams' skills, big data-driven actions
Real-time response and operational service quality (part of operational excellence)					
Dalziell and McManus	2004	Conceptual paper	N/A	System failure	Adaptive capacity (e.g., system speed) has a core driver of system resilience
Wang et al.	2010	Measurement development	N/A	Resilience	Resilience depends on enterprise information systems' prompt recovery ability
Pai and Huang	2011	Quantitative study (SEM)	366 respondents	Intention to use	Service quality influences usage intention via perceived usefulness and perceived ease-of-use
Ahmadian et al.	2015	Systematic literature review	N/A	Evaluation methods for health information systems	Service quality and time reduction among the most important aspects for system evaluation
End-to-end operational visibility and cost (part of operational excellence)					
Ash et al.	2004	Qualitative study	Separate studies in 3 countries	Unintended consequences of IT	Errors can appear along the whole chain, and due to communication problems, thus, requiring transparency and awareness
Dalziell and McManus	2004	Conceptual paper	N/A	System failure	Connection, transparency and redundancy as influencers of system resilience
Ahmadian et al.	2015	Systematic literature review	N/A	Evaluation methods for health information systems	Information accessibility and cost reduction among the most important aspects for system evaluation

Watson et al.	2013	Case studies	2 cases	Frugal IS	Public data and process simplification as design elements for successful frugal IS

Table 2. Respondents' characteristics.

Job titles	Operations/industry	Experience	Education	Numbers
Supply chain data	Healthcare/food	3-5 years	Bachelor and masters	3
Operational analysts	Food	5-10 years	Masters	2
IT managers	Healthcare	10-15 years	Bachelor	2
Data and information processing managers	Healthcare/food	5-10 years	Bachelor	3

Operations, supply chain, procurement, logistics, and project	Healthcare/food	15-20 years	PhD and masters	10 (2 each)

Table 3. ANP scales.

Scale intensity	Meaning	Explanation
1	Equal Importance	Two components contributing equally to the selection
2	Weak	Slightly favoring one component over another
3	Moderate Importance	
4	Moderate Plus	Strongly favoring one component over another
5	Strong Importance	
6	Strong Plus	
`7	Very Strong Or Demonstrated Importance	Very strongly favoring over another; its dominance is demonstrated in practice
8	Very, Very Strong	Favoring one component over another is of the highest possible order of affirmation
9	Extreme Importance	
Reciprocals	If component i has one of the above nonzero numbers given to it when it is compared with component j, then, j has the reciprocal value.	

Table 4. Pair-wise comparison of determinant.

Determinant	DC	RTR	OSQ	EEO	CS	e-vectors
Dynamic compatibility (DC)	1	2	5	2	3	0.3802
Real-time response (RTR)	1/2	1	3	2	4	0.2813
Operational service quality (OSQ)	1/5	1/3	1	2	1/2	0.1002
End-to-end operational visibility	1/2	1/2	1/2	1	1/2	0.1019
Cost (CST)	1/3	1/4	2	2	1	0.1364

Consistency ration = 0.0912

Table 5. Pair-wise comparison of dimensions.

Dimension	IOTA	BDC	BDA	DI	e-vectors
Internet of thing applications (IOTA)	1	1/3	¼	1/3	0.0872
Big-data collection capability	3	1	½	1/2	0.2007
Big-data analytics (BDA)	4	2	1	2	0.4279
Data & information sharing (DIS)	3	2	½	1	0.2844

Consistency ration = 0.0304

Table 6. Pair-wise comparison matrix for internet of thing applications (dimension) under the DC.

Enabler	IC	CD	RITI	e-vectors
Internet connections (IC)	1	2	½	0.3108
Connectable devices (CD)	1/2	1	½	0.1958
Relevant IT infrastructure (RITI)	2	2	1	0.4934

Consistency ration = 0.0304

Table 7. Pair-wise comparison matrix for internet of thing applications under the DC, IOTA, and internet connections.

Enabler interactions	CD	RITI	e-vectors
Connectable devices (CD)	1	1/2	0.3333
Relevant IT infrastructure (RITI)	2	1	0.6667

Table 8. Pair-wise comparison matrix for alternative systems on enabler IC in influencing the dc determinant.

Alternative systems	MS	SAS	FAS	e-vectors
Manual system (MS)	1	1/5	1/4	0.0989
Semi-automated (SAS)	5	1	1/2	0.3643
Fully-automated (FAS)	4	2	1	0.5368

Consistency ration = 0.0904

Table 9. Super-matrix M for dynamic compatibility after convergence.

	IC	CD	RITI	USDCT	SDCT	UNA	MLT	ASAA	MVD	PEDI	FUDI	DAR	UIAA
IC	0.3645	0.3645	0.3645										
CD	0.2243	0.2243	0.2243										
RITI	0.4112	0.4112	0.4112										
USDCT				0.4105	0.4105	0.4105							
SDCT				0.2090	0.2090	0.2090							
UNA				0.3805	0.3805	0.3805							
MLT							0.2286	0.2286	0.2286				
ASAA							0.3429	0.3429	0.3429				
MVD							0.4285	0.4285	0.4285				
PEDI										0.1316	0.1316	0.1316	0.1316
FUDI										0.2939	0.2939	0.2939	0.2939
DAR										0.3569	0.3569	0.3569	0.3569
UIAA										0.2176	0.2176	0.2176	0.2176

Table 10. Desirability indices for dynamic compatibility.

Dimensions	Att.	1 (Pja, from Table 4, dimensions)	2 (for IOTA from Table 5, enablers	3 (from converged super-matrix	4 (CS, from Table 7)	5 (SRIS, from Table 7)	6 (FRISI, from Table 7)	CS (1x2x3x4)	SRIS (1x2x3x5)	FRISI (1x2x3x6)
Internet of thing applications (IOTA)	IC	0.0872	0.3108	0.3645	0.0989	0.3643	**0.5368**	0.0010	0.0036	0.0053
	CD	0.0872	0.1958	0.2243	0.0974	0.3331	**0.5695**	0.0004	0.0013	0.0022
	RITI	0.0872	**0.4934**	**0.4112**	0.1570	0.2493	**0.5936**	0.0028	0.0044	0.0105
Big-data collection capability (BDCC)	USD	0.2007	0.2631	**0.4105**	0.1172	0.2684	0.6144	0.0025	0.0058	0.0133
	SDC	0.2007	0.1897	0.2090	0.1958	**0.4934**	0.3108	0.0016	0.0039	0.0025
	UNA	0.2007	**0.5472**	0.3805	0.1220	0.3196	0.5584	0.0051	0.0134	0.0233
Big-data analytics (BDA)	ML	0.4279	0.3108	0.2286	0.1311	0.2081	**0.6608**	0.0040	0.0063	0.0201
	ASA	0.4279	0.1958	0.3429	0.1897	0.2631	**0.5472**	0.0054	0.0076	0.0157
	MVD	0.4279	**0.4934**	**0.4285**	0.1265	0.1865	**0.6870**	0.0114	0.0169	0.0622
Data & information sharing (DIS)	PED	0.2844	0.1069	0.1316	0.1397	**0.5278**	0.3325	0.0006	0.0021	0.0013
	FUD	0.2844	0.3416	0.2939	0.1571	0.2493	**0.5936**	0.0045	0.0071	0.0169
	DA	0.2844	**0.3832**	**0.3569**	0.1958	**0.4934**	0.3108	0.0076	0.0192	0.0121
	UIA	0.2844	0.1683	0.2176	0.1634	0.2970	**0.5396**	0.0017	0.0031	0.0056
Desirability indices, Dia	IC							0.0486	0.0947	0.1911
Normalized desirability indices,	CD							**0.1453**	**0.2832**	**0.5716**

Table 11. Overall weighted index for alternative systems.

	DC (0.3802a)	RTR (0.2813)	OSQ (0.1002)	EEOV (0.1019)	Cost (0.1364)	OWI
MS	0.1453	0.2287	0.2580	0.2350	0.5756	0.2479
SAS	0.2832	0.3767	0.3811	0.3655	0.2531	0.3236
FAS	0.5716	0.3946	0.3609	0.3995	0.1713	0.4286

a from Table 2; b from table 10

Bios:

Pervaiz Akhtar is Associate Dean of Graduate Studies, Director of MBA and Chair (Full Professor) in Business Analytics, Big Data and Supply Chains. He is one of only 155 academics across all disciplines in the UK who earned their Professorship under the age of 35 as per HESA records and became the youngest professor from his country of origin (out of over 200 million population). Capitalizing on over 15 years of academic and industrial experiences from leading public, private, and non-profit-making organizations, he published in top-ranked journals such as *International Journal of Operations & Production Management, British Journal of Management, International Journal of Production Economics, Business Ethics*, among others.

Victoria-Sophie Osburg is a Senior Lecturer in Marketing at the University of Sheffield, UK. She holds a PhD in Marketing from the University of Göttingen, Germany, and she is experienced in teaching in several different countries. Her core research interests include topics such as sustainability, responsibility and digital transformation. She has been involved in several interdisciplinary projects exploring questions surrounding societal responsibility and organizational effectiveness. She has published many articles in leading journals such as *Journal of Business Ethics, Journal of Business Research, and Journal of Cleaner Production*.

Gaurav Kabra is working as an Assistant Professor in the area of Operations and Supply Chain Management at National Institute of Industrial Engineering (NITIE) Mumbai, Maharashtra, India. He completed his doctoral research in the area of humanitarian supply chain management from Indian Institute of Technology Roorkee, Roorkee, Uttarakhand, India. He obtained his integrated B.Tech (Information Technology) and MBA from Indian Institute of Information Technology and Management, Gwalior, Madhya Pradesh, India. His areas of interest include supply chain management, humanitarian logistics, social media analytics, and application of IT in business. He is the recipient of Emerald Literati Network Awards for Excellence – 2016. Gaurav Kabra can be contacted at kabraiiitm@gmail.com.

Subhan Ullah is Associate Professor in Accounting and Divisional Research Director at the University of Nottingham. Prior to joining Nottingham, he was a Lecturer in Accounting and Programme Director of MSc Accounting and Finance at the University of Hull. He has extensive experience of teaching in several institutions, including, Nottingham Trent University, University of Buckingham, The Open University, COMSATS University (Pakistan), and University of Peshawar (Pakistan). His research in the area of corporate governance appears in leading international journals, namely, *British Journal of Management, Industrial Marketing Management*, *Resources Policy*, and Research in International Business and Finance.

Haseeb Shabbir is a Senior Lecturer in Marketing at the University of Hull. His work has published in the *Journal of Advertising, Journal of Advertising Research, European Journal of Marketing, Industrial Marketing Management, Psychology & Marketing, and Journal of Service Research*. He has a particular interest in advertising ethics, not for profit marketing and humanitarian organizations. He can be contacted at h.shabbir@hull.ac.uk.

Sushma Kumari is a full-time Lecturer at University of Hull. Prior to that, she has worked as HR Executive in different international firms in India. She has also worked as a research assistant on numerous projects funded by Biotechnology and Biological Sciences Research Council (BBSRC), British Academy (BA), Horizon 20-20, Innovate UK, Higher Education Academy (HEA). Her research articles have been published in various renowned journals of Operations Research and Operations & Supply chain Management.