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Big data analytics in sustainable humanitarian supply chain: barriers and their interactions

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Abstract

Big data analytics research in humanitarian supply chain management has gained popularity for its ability to manage risks. While big data analytics can predict future events, it can also concentrate on current events and support preparation for future events. Big data analytics-driven approaches in humanitarian supply chain management are complicated due to the presence of multiple barriers. The current study aims to identify the leading barriers; further categorize them and finally develop the contextual interrelationships using the Fuzzy Total Interpretive Structural Modeling (TISM) approach. Sustainable humanitarian supply chain management research is in nascent stage and therefore, Fuzzy TISM is used in this study for theory building purpose and answering three key questions-what, how and why. Fuzzy TISM shows some key transitive links which provides enhanced explanatory framework. The TISM model shows that the fifteen barriers achieved eight levels and decision-makers must aim to remove the foundational barriers to apply big data analytics in sustainable humanitarian supply chain management. Fuzzy TISM were synthesized to develop a conceptual model and this was statistically validated considering a sample of 108 responses from African based humanitarian organizations. Findings suggest that organizational focus is required on implementing modern management practices; second, more emphasis is required on infrastructure development and lastly, improvement is required on quality of information sharing as these variables can influence sustainable humanitarian supply chain management. Finally, the conclusions and future research directions were outlined which may help stakeholders in sustainable humanitarian supply chain management to eliminate the BDA barriers.

Keywords Barriers · Big data analytics · Fuzzy total interpretive structural modeling · Humanitarian supply chain management · Sustainability

1 Introduction

Disasters cause massive losses and disruptions to normal life (Altay and Green 2006; O'Brien et al. 2006; Behl and Dutta 2019). Disasters can be created by humans or nature with slow

Extended author information available on the last page of the article onset or sudden onset (Jabbour et al. 2017). There has been increasing focus on the preparadeness stages to manage disaster situations (Behl and Dutta 2019) with a particular emphasis on using data and analytics to support decision-making (Prasad et al. 2018; Gupta et al. 2019). Given how successesful big data analytics (BDA) applications have been in commercial supply chains (Wamba et al. 2015; Hazen et al. 2016a, b; Mishra et al. 2018; Papadopoulos et al. 2017a; Gunasekaran et al. 2017; Wamba et al. 2018), the relatively recent and slow uptake of BDA applications in humanitarian relief operations appear to suggest significant barriers to application in this area.

Humanitarian supply chain (HSC) processes include planning, implementation, and managing goods and information from origin and firms to where these goods are consumed to reduce suffering of helpless families and individuals facing the disaster (Field 2012). There are a range of actors through HSC, such as donors, military relief forces, governments, trade bodies, and ultimately the end-users (Van Wassenhove 2006; Dubey and Gunasekaran 2016). HSC organizations such as supranational aid agencies, government agencies, and small and big NGOs get involved in different stages of disaster relief; e.g., preparedness and prevention, response, as well as the consequential reconstruction work that all saves lives and minimizes loss (Jabbour et al. 2017).

The primary attributes of HSC are the stochastic nature of demand combined with vagueness poor visbility (Kovács and Spens 2007; Balcik et al. 2010; Charles et al. 2010; van der Laan et al. 2016). The urgency, uncertainty, and coordination difficulties of HSCs' differ from traditional supply chain challenges (Behl and Dutta 2019).

If the flow of information is impacted by any barrier during the early stage of humanitarian response, then it creates problems during later stages of the HSC cycle. When there is too much information or less relevant information, HSC actors may make poor decisions (Altay and Labonte 2014).

Ambiguity, equivocality, uncertainty, and sense-making are mainly generated from HSC complexities and impact humanitarian decision making. HSC complexity also impacts actual planning and preparation in humanitarian coordination (Altay and Labonte 2014).

Dubey et al. (2018) presented evidence that BDA can improve visibility and coordination in HSC and significantly improve performance. In HSCs' every moment, a variety of data is generated from various sources (e.g., mobile phones, transactions and purchasing records, and social media posts) and various formats are used, which poses challenges for the humanitarian organizations (Alharthi et al. 2017; Sharma and Joshi 2019).

Further humanitarian organizations lack data analytics experts having the ability to process the voluminous amount of data to extract further valuable information. Insufficient training and education in the field of data science are the key reasons for skill gaps (Sarkis et al. 2012). Moreover, traditional mind-set of employees in humanitarian organizations is leading to inadequate focus on the data skills related developmental aspects among employees (Kabra et al. 2017). The traditional organizational culture among humanitarian organizations is another reason for the lack of focus in instilling world-class data management practices (Alharthi et al. 2017). Therefore, it is clear that management and workers must have trust in the BDA potential to extract its benefits (Dubey et al. 2018). Developing reliable human resources with BDA capabilities is essential for aligning analytics capability with strategic goals (Akter et al. 2016). Given this reliance on people and strategic alignment, there may be additional challenges in HSC scenarios where the environmental instability makes alignment more challenging. Low level of public–private partnerships (Papadopoulos et al. 2017b) and incapability to attract funding (Jahre and Heigh 2008) can potentially influence the economic aspects in HSC, and eliminating these barriers can help in the development of information technology infrastructure for BDA applications (Kabra and Ramesh 2015).

Humanitarian organizations are doing a noble job of saving lives under various degrees of resource constraints and complexities. These organizations require information to run their HSC management sustainably. BDA has gained popularity in the field of operations management, and humanitarian organizations can leverage the benefits presented by BDA progression after eliminating the BDA impediments (Ma and Zhang 2017; Gupta et al. 2019).

Various past research works conducted previously explored various aspects of predictive aspects of BDA in HSC, such as enhancing visibility and coordination (Dubey et al. 2018); review of BDA in HSC (Gupta et al. 2019); analyze coordination in HSC and what drives or prevents coordination (Kabra and Ramesh 2015); and a recent study of challenges of using BDA in HSC (Sharma and Joshi 2019). However, none of the studies identified the barriers faced by humanitarian organizations while using BDA in the preparedness stage. Therefore, this research address three questions. First, what are the barriers to BDA adoption in HSC management? Secondly, how are these barriers interconnected? Thirdly, can a conceptual model be developed and statistically validated to extend the HSC knowledge base?

The above research questions helped us to frame the research objectives (RO):

RO1: To identify barriers to BDA in sustainable HSC management.
RO2: To understand the interrelationships among the BDA barriers.
RO3: To develop a conceptual model and further statistically validate the model.

Literature review will aid to identify the BDA barriers in sustainable HSC management. A fuzzy TISM approach helps to structure and further develop an understanding of the core barriers to generate a conceptual model. Next, a survey validates the framework and suggests the strength of the interrelationships.

This research is important as while BDA holds great promise, but it is challenging to implement in the increasingly important HSC environments (Moshtari and Gonçalves 2017). When we better understand what the core barriers are in practice and which are closely connected, managers and planners will be better able to develop more robust and effective strategies for developing approaches to incorporate BDA applications to enhance HSC management. In particular, we identify how the BDA human and organizational barriers are related within the HSC context. The ability to overcome these BDA barriers should support enhanced HSC performance.

BDA can improve decision making within many organizations and enhance humanitarian coordination between organizations and actors. It is increasingly important to improve decisions and coordination given the growing size and impact of disasters (Dubey et al. 2018). The period from 2001 to 2018 was influenced by significant disaster events resulting in huge death and losses, such as the Indonesia earthquake, Nepal earthquake, Gujarat earthquake, Dresden floods, European heatwave, Bam earthquake, South Asian tsunami, Kashmir earthquake, Mumbai floods, Hurricane Katrina, Java earthquake, Haiti earthquake, and Japan earthquake. This can impact the social, environmental and economic aspects of sustainable development (GAR 2019). Due to increased number of disasters and changing funding mechanisms, the global humanitarian relief spending rose rapidly after 2005 (Taylor et al. 2012) and the number of field personnel rose approximately 27% from 2013 to 2017 (Clarke et al. 2018). The effective use of BDA would enable better use of resources and support sustainable HSC management.

The rest of the paper is structured as follows. In Sect. 2, we present our literature review that highlights the background concepts. In Sect. 3, we explain the research methods. Section 4 provides an overview of the Fuzzy TISM modeling. In Sect. 5, detailed discussions of statistical testing have been laid out. The final section covers the discussion drawn from study followed by unique contribution and future research directions.

2 Literature review

This section presents the contributions of BDA in HSC and also provides the barriers that will be further used as an input in Fuzzy TISM in next section.

2.1 Application of big data analytics in humanitarian supply chain management

The aim of conducting the review of prior studies is to understand the progress of BDA application in the field of HSC and further identify the leading barriers influencing the HSC operations. HSC management consist of highly complex activities and are a slow and costly exercise. Moreover, it involves human lives, which emphasizes the need for improving the quality of decision makings and efficiency of resource usage (Knezic and Mladineo 2006).

Big data differs from traditional analytics as it involves handling data characterized by not only big volumes but also higher velocities and a greater variety of the types of information assets used. BDA calls for economic and unique ways of information processing to gain rich insights for high quality of decisions. Big data does not have value in isolation; while its value can be unlocked only when it is used for making decisions. Data management and analytics are part of big data management process. While data management comprises all the processes and associated technologies for storage of big data; the analytics part involves various techniques applied to examine big data and extract key information from it (Gandomi and Haider 2015).

Interestingly, BDA in HSC management has proven to be a useful tool for reducing vulnerabilities in disaster situations (Akter and Wamba 2019). BDA can create visibility to actors involved in HSC operations through access to real-time information critical for reducing disaster risks (Dubey et al. 2018). BDA can be useful for preventing disasters by detecting disasters in advance, and the information can be used for shifting the people in the affected community to safer zones and plan relief aids and logistics in a better fashion (Mehrotra et al. 2013; Wang et al. 2016a, b, 2018). In particular, during the early recovery period after a disaster, the aid delivery amount, water, sanitation and hygiene, and health services are most important (Jana et al. 2019); reaching the victims has proven challenging in terms of transport and logistics (Zhu et al. 2018; John et al. 2019). Timely and accurate information can be used for expediting urgent matters, prevention of follow-up hazards after a disaster occurrence and coordination of logistics for timely deliveries to the site (Papadopoulos et al. 2017b).

Early explorations of the role of BDA in HSC management have been done (e.g., Knezic and Mladineo 2006; Hristidis et al. 2010; Monaghan and Lycett 2013; Comes 2016; Prasad et al. 2018; Akter and Wamba 2019; Dubey et al. 2018, 2019a; Papadopoulos et al. 2017a, b; Griffith et al. 2019). In general, the focus has been on prevention, mitigation, and management of HSC operations based on the knowledge and innovation to build resilience against the growing number of disasters over the years (Akter and Wamba 2019). The loss of life and property can be reduced to a great extent by using BDA tools (Papadopoulos et al. 2017b). BDA can be used to exploit the next generation technologies for emergency responses during the disaster management phases. Timely and accurate information can empower humanitarian organizations to work in a more planned manner, which can be helpful to save costs and also enable quick responses. It is important how the data is efficiently generated, stored safely and analyzed properly to get quality information (Hazen et al. 2014). The sources of these types of 'unstructured data' include news, articles, and blogs from websites and social networks; multimedia data consisting of images and videos; business reports and satellite imagery data (Hristidis et al. 2010). Information given using social networking platforms by HSC emergency teams can be immensely helpful to improve levels of situational awareness. It can also help people in disaster-affected areas to identify emergency food, water, accommodation and evacuation route (Akter and Wamba 2019).

Besides the number of benefits of BDA, there are also associated challenges that disable humanitarian organizations/central humanitarian operations centre to apply BDA. The high volume of data generated from disaster-related events does not fit in the traditional data storage and processing systems, suggesting a need to develop infrastructure to fit big data in the system for processing and visualization (Akter and Wamba 2019).

Hristidis et al. (2010) also mentioned in his studies that a few challenges related to BDA applications in HSC such as many organizations that create and use information; both static and constantly changing (streamed) data and heterogenous data formats; the varying trustworthiness of fast-changing sources of information; non-standarized terminology; and, the highly time-sensitive nature of shared information. These circumstances create a necessity for data integration and ingestion for assisting HSC executives in quick decision makings during emergency operations. However, enabling automation and virtual integration for data management appears to be an outstanding challenge for designing of HSC-based data management system.

The biggest challenge faced by HSC executives is that they have rich data but fail to unlock its value (Griffith et al. 2019). Every data source can consist of a mix of data elements from social networks, remote sensing data, multimedia data, and videos from the disaster affected regions. To enable self-service analytics capabilities, it is necessary to streamline the entire system including data gathering process to feed the data in BDA platform. However, challenges remain in managing BDA processes due to the volume of data generated from many disparate data sources, thus creating difficulty for centralization (Griffith et al. 2019).

Increasingly, efforts have been made to provide more useful managerial support in HSC based on data. Griffith et al. (2019) proposed a self-service analytic tool that can aid planners in allocating scarce resources. The selection of a logistics partner in HSC involves three subdimensions: economic, technical and social (Kim et al. 2018). Tools and decision-support mechanisms exist to streamline the selection of partners in HSC operations (Venkatesh et al. 2019) and how data-driven approaches can improve decision-making and reduce managerial biases (Wood et al. 2017). Knezic and Mladineo (2006) combined GIS and MCDM techniques to develop a system that can set priority efficiently of humanitarian demining and minimizing risks. BDA is opening up new opportunities in the area of HSC but more empirical research is required to make progress in this field (Prasad et al. 2018).

Next, an attempt has been made to classify barriers to BDA in sustainable HSC management. In this case the barriers were identified based on recently published literature and further refined through the workshop sessions with five HSC experts. The review and workshop enabled us to synthesize the fifteen barriers which falls under categories (refer Table 1). As per suggestion of the experts we have changed the wording of the barriers to make it more relavant in context to South Africa.

2.2 Barriers of big data analytics in sustainable HSC operations

The leading barriers are detailed further under. These barriers are influencing BDA use in sustainable HSC operations.

2.2.1 Poor management of data generated from multiple sources

Big data is generated from multiple sources such as websites, social networks platforms, multimedia data, and GPS data, which make it challenging to be managed by data analysts and humanitarian agencies (Alharthi et al. 2017). The overflow of information can cause delay in decision making and crisis response. HSC operations happen under a time constrainted situation where data scientist/analyst can only process a certain part of data, to avoid delays in crisis response (Sharma and Joshi 2019).

2.2.2 Multiple formats of data

The big data collection and organizing involves multiple formats which makes it too much complicated for data processing and interpretation (Alharthi et al. 2017). The data generated from various sources comprises of both structured and unstructured data; and also in different languages at a given point in time which further makes batch analysis difficult (Sharma and Joshi 2019).

2.2.3 Lack of skills for proper data processing and correct interpretation

BDA calls for special skills and knowledge, which is vital for analysis and correct information generation. Kunz and Gold (2017) argued that humanitarian organizations need to develop capabilities (routines, established processes, knowledge, experience, skills) for sustainable HSC management. Big data skills include knowledge of techniques are statistics, machine learning, data mining and optimization (Waller and Fawcett 2013; Choi et al. 2018).

However, these skills and knowledge are lacking in the African context and are thus considered a barrier to BDA application in HSC management (Alharthi et al. 2017).

2.2.4 Insufficient training and education

There is a lack of on-going professional development to proper training and education for the existing workforce for BDA. The lack of development and training results in poor performance among data analysts. Continuous education is essential for upgrading knowledge in this dynamic environment (Sarkis et al. 2012).

2.2.5 Complexity

Technological complexity is a barrier to BDA application in sustainable HSC management. BDA is not an user friendly process as it involves application of data integration techniques, advanced data analysis and data visualization techniques which are relatively difficult to apply in disaster relief HSC context. It increases system-related complicatedness and challenges in use of data for decision making (Alharthi et al. 2017).

2.2.6 Fear of new technology

Fourt industrial revolution has ushered a wave of advanced technologies that can be useful in both the manufacturing and services industry. HSC management is not an exception but these new technologies require new set of skills and new processes to be adopted for unlocking the value. BDA application involves system changes, process changes, recruit persons having BDA skills which naturally raises fear on the mind of employees (Alharthi et al. 2017).

2.2.7 Infrastructure un-readiness

Infrastructure un-readiness is one of the barriers to BDA application in sustainable HSC operations. Both physical systems and software must be implemented and are crucial for smoothly running the BDA programs. Collecting data, storing and processing data itself is a challenge due to infrastructure un-readiness (Alharthi et al. 2017).

2.2.8 The traditional mind-set of existing employees

Traditional thinking acts as a barrier to BDA application in HSC operations, and it is essential to change the mind-set of employees working in HSC agencies for accepting the changes. It is really important to have motivated employees in the humanitarian organizations to drive the BDA projects (Alharthi et al. 2017).

2.2.9 Difficulty in changing organizational culture across the entire organization

Cultural changes in the organization will help in developing an environment for better application of BDA in HSC operations. Literature indicates that data driven culture in the organisation is important to drive BDA projects (Alharthi et al. 2017; Dubey et al. 2019b).

2.2.10 Low focus on new employee development

Some organizations have insufficiently developed human resource (HR) functions that do not fully develop the potential of the workforce. Developing an HR system that embeds the BDA skill sets among new employees is essential for long term sustainability in HSC management (Alharthi et al. 2017).

2.2.11 Lack of focus in instilling modern management practices

World-class practices help in better management of BDA in the humanitarian organization (Alharthi et al. 2017). However, many humanitarian organizations have failed to adopt new practices and lack continuous improvement in the areas of warehouse management and inventory tracking. HSC management can be improved by adopting modern management practices and further motivate use of data driven decision making (Balcik et al. 2010).

2.2.12 Poor infrastructure

Poor infrastructure leads to low level of resilience and further disruption of normal life in the society. High degree of resilience of HSC would be less seriously affected by a disaster (Papadopoulos et al. 2017b).

2.2.13 Poor quality of information sharing

This acts as a barrier to sustainable HSC operations, which leads to untimely and poor decision making (Papadopoulos et al. 2017b).

2.2.14 Low level of public–private partnership

This acts as one of the barriers to BDA application in sustainable HSC management. Attracting more public–private partnerships will change the current scenario and will enable building resilience in HSC (Papadopoulos et al. 2017b).

2.2.15 Failure to attract funds

This is one the reason for poor BDA infrastructure and lack of proper system across the HSC network. Managing resources efficiently in HSC is the crucial to disaster relief. Therefore, it is important that humanitarian organizations try arranging funds from government and international agencies for utilising it in HSC management using BDA (Jahre and Heigh 2008).

3 Research design

Mixed methods are rarely used and empirical evidence in HSC publications is limited, thereby undermining both the rigor and the relevance of humanitarian logistics research (Kovacs et al. 2019). Roadmap for higher research quality in HSC was proposed by Kovacs and Moshtari (2019). To ensure our research method yields high quality research output; therefore, we opted for mixed methods research. We provide an outline of the methodology and data collection strategy we adopted. To address our research questions, we used a two-stage research process. First, we identified a fuzzy total interpretive structural modeling technique as a suitable method as it has greater flexibility than in traditional interpretive structural modelling (Sushil 2012). Fuzzy TISM can aid in the development of theory by answering three important questions (what, how and why) (Sushil 2016). The Fuzzy TISM results are presented in Sect. 4. Fuzzy TISM were synthesized to develop a conceptual model which is the main contribution of this work. Dubey et al. (2015) has used similar approach to build sustainable manufacturing framework.

Second, we collected survey data from HSC experts and professionals to validate our conceptual model and determine how the barriers are related in practice. For this step, we used an online survey to collect data and a structural equation modeling (SEM) process to understand the relationships between barriers. The survey and the consequent conceptual model after testing is presented in Sect. 5.

4 Data analysis and findings

4.1 Fuzzy TISM

The fuzzy TISM modeling technique is used for building the interrelationships among the barriers. Fuzzy TISM removes the limitations associated with simple ISM while providing enhanced suppleness in understanding the intensity of power among the variables (Sushil 2012, 2016). The steps suggested by Khatwani et al. (2015) are followed in this study.

We obtained data from five HSC experts to create five SSIM matrices, following Khatwani et al. (2015) and the guidelines they provide. The data that we used for analysis in the fuzzy TISM was collected from HSC practicioners based in Africa. The first expert whom we

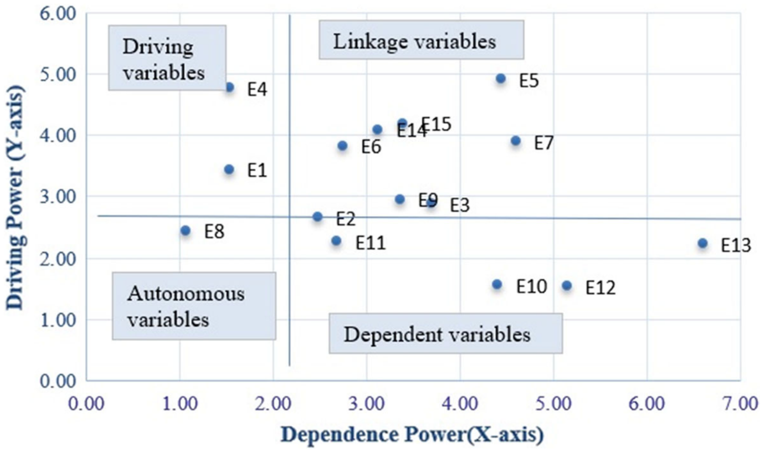

Fig. 1 Driving power and dependence matrix (MICMAC) based on fuzzy reachability matrix of Table 10. *Source*: Authors' compilation

selected had an experience in the logistics function of South African military forces. With prior appointment, a workshop was conducted for 2 h to gather the data for developing the interrelationships between the barriers. After this data collection was done and we also collected data from four HSC practicioners who are associated with "The South African Red Cross Society"; "Southern Africa Trust"; "The Food and Agriculture Organization in South Africa"; "United Nations Educational, Scientific and Cultural Organization".

We engaged them in similar workshop sessions with these four experts. From the data generated at the five workshops with HSC experts, we developed five SSIM matrices (Tables 3, 4, 5, 6, 7). All of these five HSC experts were selected using convenience sampling and have more than 20 years of experience in HSC and exposure to BDA applications, which gave us confidence in the quality of data that is obtained during the workshop. These participants were previously informed about this research work, which is intended for academic purposes, and they were happy to participate in the brainstorming session and share their real-life experiences. No incentives were provided for participation.

This section presents fuzzy TISM modeling. An analysis is provided in the "Appendix". Table 1 (refer to "Appendix") presents the leading barriers which were identified during the literature review and further refined through the workshop sessions with five HSC experts. The review and workshop enabled us to synthesize the core barriers and categories (Table 1). The data analysis using fuzzy TISM is further continued; Tables 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22 ("Appendix") provides a step-by-step analysis and presentation of results.

In Fig. 1, we can see the driving power and the dependence matrix (MICMAC), which is based on the fuzzy reachability matrix, and in Fig. 2, we can observe the driving power and dependence matrix (MICMAC) based on the defuzzified reachability matrix.

The defuzzified TISM digraph is derived from Table 12 and provided in Fig. 3.

4.2 Conceptual framework and statistical validation

The amalgamation of TISM and MICMAC analysis, including in Fig. 3, allowed us to develop our conceptual model (Fig. 4). In phase II of this study, the conceptual model has been statis-

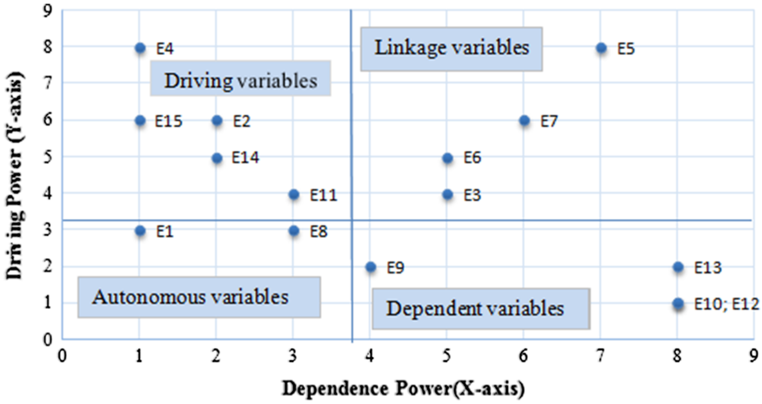

Fig. 2 Driving power and dependence matrix (MICMAC) based on defuzzified reachability matrix of Table 12. *Source*: Authors' compilation

tically validated using 108 responses from African based humanitarian organizations. Shibin et al. (2018) has employed similar mixed methods research methodology for developing the conceptual model using TISM and MICMAC analysis and, thereafter, empirically tested the conceptual model using survey based primary data. The details of constructs are provided in Table 26 (refer to "Appendix").

5 Empirical data analysis

In this study, we used WarpPLS Version 6.0, the PLS (Partial Least Squares) based SEM. PLS-SEM is a suitable technique for this exploratory study as we are not seeking confirmation of the results of past research (Hair et al. 2014). Using PLS-SEM maximizes the R^2, making it valuable for exploratory analysis. By developing an understanding of the conceptual relationships, it supports superior conceptual model development and the predictive power of the models. In this way, using PLS is more suited than covariance-based structural equation modelling (CB-SEM) (Hair et al. 2014) for our study.

5.1 Data collection

HSC practitioners involved with disaster relief operations were selected to participate. The list of such organizations was identified from a website named "reliefweb." Organizations based in Africa were selected for participation. A convenience sampling technique was used to select potential respondents and further gather responses through an online survey. The questionnaire pre-testing was conducted with the HSC experts who initially participated in the workshop and helped us to develop the SSIM matrix. This pre-test enabled evaluation of the questionnaire design; based on HSC experts' feedback, we made minor modifications of the questionnaire wording on seven items to improve more clarity. The survey used a five-point Likert-type scale; 1 represents strongly disagree, 2 is disagree, 3 is neutral, 4 is agree, and 5 is strongly agree. Survey distribution was to 250 executives working in Non-Government Organizations, Non-Profit Organizations, and Government agencies involved in humanitarian supply chain management. The questionnaire was sent to two persons from the same

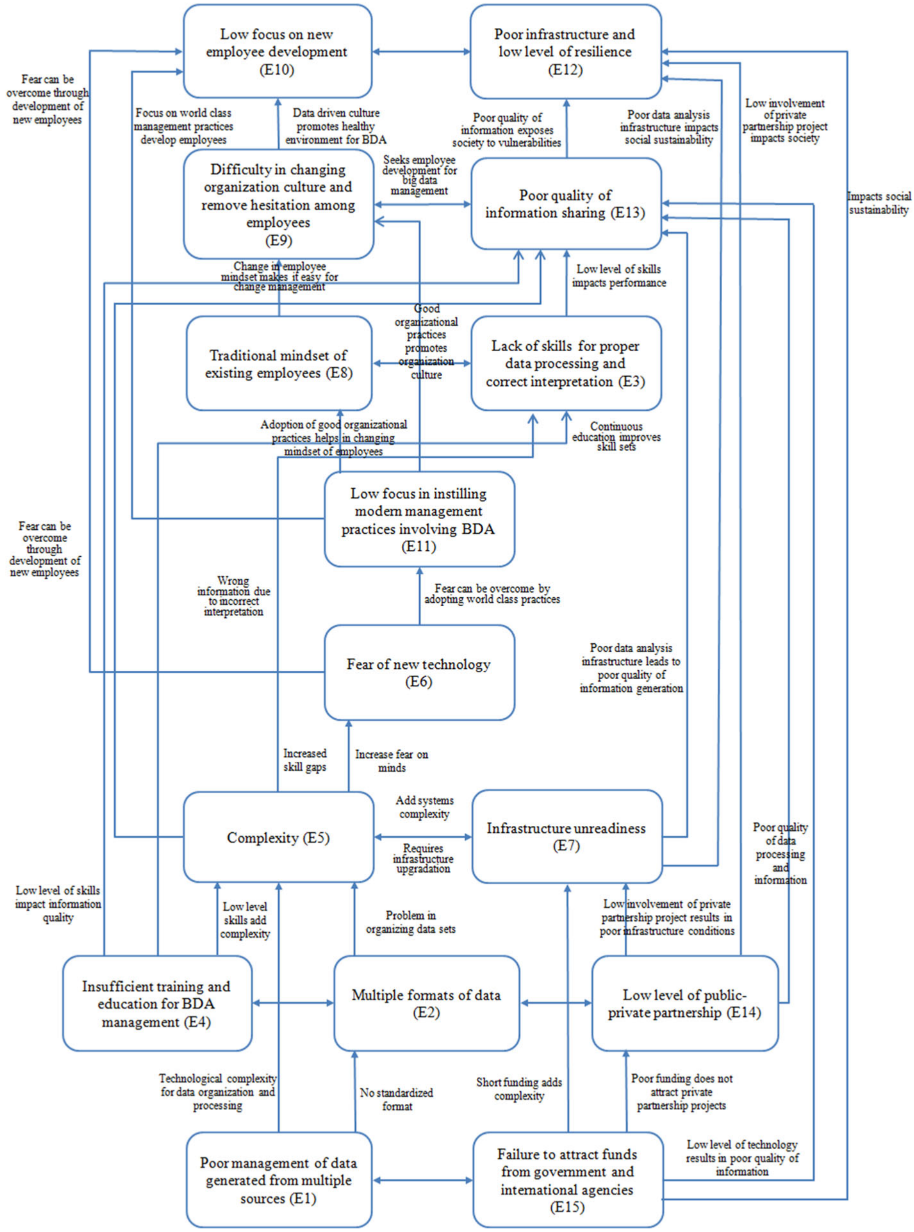

Fig. 3 The TISM digraph, drawing on fuzzy linguistic terms with a very high influence (VH) and high influence (H) as 1 with the others as 0

organization. We closed survey after doing one round of online follow-ups. No incomplete submissions were received as the online survey format only allowed complete submissions. In total, we received 108 responses, a 43% response rate. Respondents' demographic data and experience are provided in Table 23.

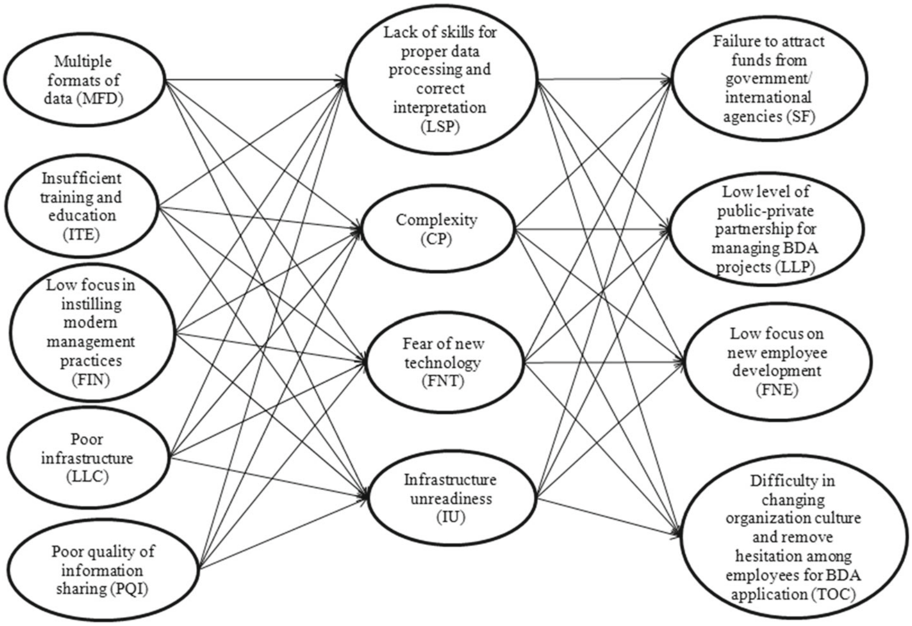

Fig. 4 Conceptual model

5.2 Common method bias

We selected key informants to respond, ensuring they were aware that the survey was for scholarly purposes and confidentiality would be maintained, enabling us to capture correct and accurate information. The respondents are senior management team members with extensive humanitarian service-based experience, and they were presented with constructs on separate pages to minimize the item-priming effect. Due to their position and roles, they could assess and answer all survey questions, matching the typical Type I design (Flynn et al. 2018). We followed Podsakoff et al. (2003) and used Harman's single factor test. The test results indicated that no single factor was representative of the majority of the total variance; the highest loading was 24.36% on the first factor, which is far lower than the suggested limit of 50%. For these reasons, we are confident that our study has no common method bias issue.

5.3 Non-response bias

The online-based survey method has been criticized for issues relating to non-response of participants and the bias it creates. If responses from survey participants vary considerably than those who did not respond, there may be problems in generalization of results. Completeness of data and the data collection method also plays a vital role in reducing non-response bias (Armstrong and Overton 1977). To examine the issue, we split our responses to those received before the follow-up and those received after. We did not find any significant variation between the waves of responses. As later responses were similar to earlier responses, we concluded that non-response bias was not an issue with our data, based on the established guidelines (Armstrong and Overton 1977). Further, Levene's homogeneity of variance test was performed (Table 24). The test passing criteria is that if there is no difference between values, which means they are not different. The results show no difference between both waves, suggesting that non-response bias issues are not present in our data.

5.4 Model estimation and analysis

The combined Loadings and cross loadings are presented in Table 27 (Refer to "Appendix"). Guidelines indicate that each indicator loading should exceed 0.50 and be significant (*p* value less than 0.05) (Hair et al. 1992).

To test the discriminant validity, the correlations between variables were compared to the square root of the average variance extracted. To satisfy the test, the AVE value should exceed correlations linked to the latent variable (Table 28, Refer to "Appendix"). The results were acceptable.

The results of latent variable coefficients are presented in Table 29 (Refer to "Appendix"). Composite reliability and Cronbachs' alpha enable us to assess the model reliability. As they exceed 0.70, they are acceptable. We used the variance inflation factors (VIF) to assess multicollinearity; as all VIF values were below 5, we found it satisfactory.

Finally, we ran established checks on model fit, quality indices, and causality assessment (Tables 30, Table 31, in the "Appendix"). The results suggest the model has good fit.

5.5 Tested model

The final model (Fig. 5) shows that associated factors contributed for a 9% variance in complexity, a 32% variance in fear of new technology, and a 10% variance in infrastructure un-readiness. It also shows that associated factors contributed to a 9% variance in failure to attract funding, a 13% variance in the low level of public–private partnership and a 24% variance in difficulty in changing organizational culture. Several variables and many relationships were not found to be significant and have not been shown in Fig. 5.

The acceptance of the research hypothesis is undertaken based on the *p* value (Table 25). We have used an alpha value of 0.05 (5%) as the significance threshold.

6 Discussion

As indicated previously, there are past research works available that explored various aspects of BDA in HSC, such as how it can enhance inter-organizational visibility and coordination (Dubey et al. 2018). However, Sharma and Joshi (2019) highlighted challenges of using BDA in HSC, which can be compared with our findings. They summarized the challenges that can impact HSC due to over-dependence on BDA tools. However, our study focuses on identifying the barriers to BDA application in sustainable HSC management and explaining how these are related. Therefore, our study is unique compared to previous studies related to BDA in HSC. We have categorized the barriers under informational, human, technological, organization, social, and economical. The categorizations add depth to the analysis of responses and enable more effective management of barriers; our approach embraces the suggestion to take a socio-technical approach (Alharthi et al. 2017). In contrast, Sharma and Joshi (2019) have cautioned HSC executives to be careful while using BDA in humanitarian missions for reasons including the digital divide amongst the population, imperfections in data collection technologies, challenges faced due to nature of big data, volunteer-related problems, ethical and data security challenges, high costs at the initial stage of digital setups, cultural, and

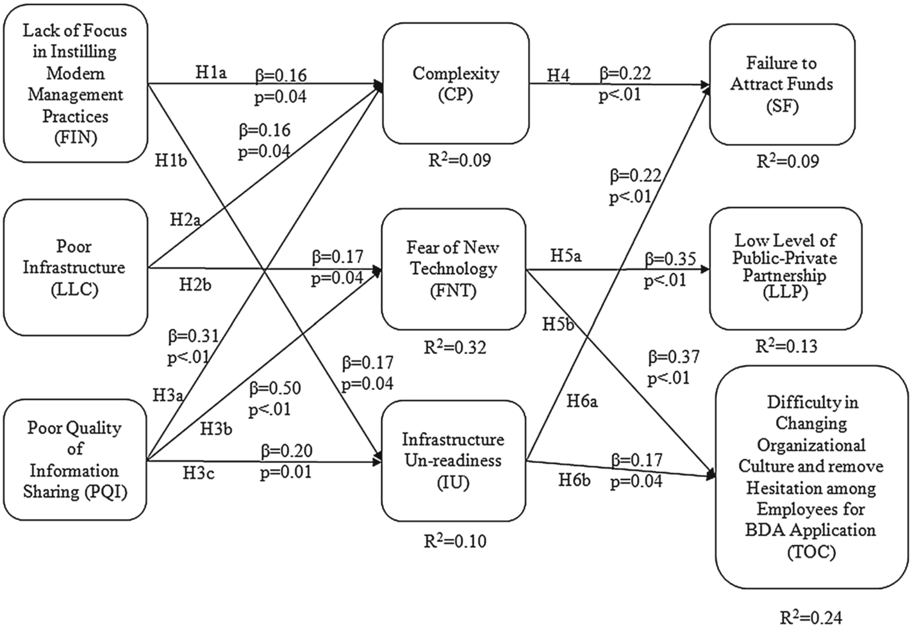

Fig. 5 Conceptual model after PLS-SEM. (Only the statistically significant relationships and variables have been shown to improve the readability of the image, although all relationships shown in Fig. 4 were tested)

language induced errors and statistical errors. Further, we present pathways and connections between the barriers, in a way that a manager is better able to develop a plan to overcome the barriers, more so than when presented with a categorization of barriers (e.g., Sharma and Joshi 2019). Our study corroborates with the findings of Dubey et al. (2018, 2019b), which suggested that organizational culture and learning plays a critical role in BDA application in HSC. While there is literature available on BDA and HSC management, much of the research has emphasized the mitigation and response phases. Our work emphasizes the preparedness phase, outlined as one of the areas where more work should be completed (Akter and Wamba 2019).

Our results add context to more general or broad research on BDA use in the commercial sector; for example, while studies such as Akter et al. (2016) and Alharthi et al. (2017) emphasize commercial factors, our model also includes elements that will be more relevant to HSC and other public-sector and non-profit organizations, such as difficulty in attracting funding and public–private partnerships. In this way, we extend the analysis of barriers to other sectors and provide greater context for studying BDA applications in HSC management. This suggests that suggestions for future research, such as provided in Mishra et al. (2018), also need to account for the distinctiveness of HSCs and BDA approaches; just as they list applications in healthcare as an area for future study, our results suggest that sustainable HSC management is also a distinct area requiring further attention.

6.1 Theoretical implications

While there is a rich body of literature on HSC; however, research on theory building in sustainable HSC is limited. Either qualitative and quantitiative methods were used by researchers in the past to devlop theory in HSC. We have used mixed methods research design to ensure scientific rigor in our study. The conceptual model was developed using Fuzzy TISM. Although interpretive structural modeling technique was widely used in HSC research; however, with a few exceptions, past researchers have failed to use this technique in building theory. In the current study Fuzzy TISM methodology was applied to build the conceptual model which is a unique contribution to HSC literature.

6.2 Practical implications

Several key insights can be obtained from the tested model. First, humanitarian supply chain practitioners must focus on instilling modern management practices to remove the system related bottlenecks and technological complexity. World-class practices will help to create the infrastructure ready for BDA applications. Second, attention must be given towards building critical infrastructure resilience. It is quite essential to remove the technological complexity and fear among employees for application of BDA enabled technologies. Third, emphasis must be given towards a high quality of information sharing to remove the technological complexity. Timely sharing of relevant and correct information will create BDA awareness, which can eliminate fear from the minds of people related to new BDA enabled technologies. Quality information can help to get the infrastructure ready for the application of BDA in HSC. Fourth, technological complexity is a barrier in the way of BDA, which must be removed to attract more funding. Fifth, fear of new BDA enabled technologies must be addressed to attract private–public partnership on BDA related HSC projects. Such fear of new technologies can be removed by managing the changes in the organization and moving away from traditional organization culture. Finally, infrastructure readiness on BDA applications is found to attract more funds, and BDA projects implementation can also change the traditional mind-set of people. Employees will gain trust and accept technological advancements after seeing the results of BDA applications. We conclude that BDA applications in sustainable HSC management are at a nascent stage in the African continent. However, BDA can be exploited to reap huge benefits and can also help to meet sustainability goals.

7 Conclusion and future research directions

The study aspires to find barriers related to BDA adoption in sustainable HSC management and, secondly, identify the interrelationships among these barriers and, thirdly, statistically validate the conceptual model. The study is conducted in two phases. First, the literature review was used to identify barriers, and the barriers were refined by five HSC experts before fuzzy TISM was used to identify interrelationships between the barriers. The barriers are multiple sources of data, multiple formats of data, lack of skills for proper data processing and correct interpretation, insufficient training and education, complexity, fear of new technology, infrastructure un-readiness, traditional mind-set of existing employees, difficulty to change organizational culture across the entire organization, low focus on new employee development, lack of focus in instilling new management practices, low level of critical infrastructure resilience, poor quality of information sharing, low level of public–private partnership and difficulty to attract funding. These fifteen barriers are further divided into six categories, such as informational, human, technological, organization, social, and economical. Fuzzy TISM technique enabled us to assess barrier interrelationships and depicted these in the TISM model. The TISM based model shows that multiple sources of data and difficulty to attract funding are the bottom level barriers. The top-level barriers are low focus on new employee development and low level of critical infrastructure resilience. Elimination of bottom level barriers can help to apply BDA in sustainable HSC management.

In the second phase of the study, the conceptual model, which is primarily derived from the application of Fuzzy TISM methodology is further tested using survey data to validate the model statistically. Based on the testing, few links that are not supported with the survey data are eliminated. The final refined version of the model is presented for a clear understanding of readers. The analysis shows that focus in instilling modern management practices have a positive relationship with complexity and infrastructure un-readiness. Secondly, poor infrastructure is found to have a positive relationship with complexity and fear of new technologies. Thirdly, poor quality of information sharing is found to have a positive relationship with complexity, fear of new technologies and infrastructure un-readiness. Fourth, complexity is found to have a positive relationship with difficulty to attract funding. Fifth, fear of new technologies have appositive relationship with low levels of public–private partnerships and difficulty to change organization culture. Finally, infrastructure un-readiness is found to have a positive relationship with difficulty to attract funding and difficulty to change organization culture.

We believe this research is unique as it aims to identify the contextual interrelationships among barriers to BDA application in sustainable HSC management. Finally, the model has been statistically validated in the African context and provides meaningful insights. With this process, we have extended knowledge base in the domain of sustainable HSC management. Like other research work, this study also suffers from few limitations. The first limitation of this study is that the sample size for data collection in Fuzzy TISM data collection is limited to five experts based in Africa. Second, the sample size considered for the empirical survey is smaller (108) in size. Future research can consider larger sample size and samples from other continents to generalize the results. Information sharing and technology implementation in HSC is an important area and requires attention from future researchers. Future research could also explore the effect of integrating BDA and blockchain in HSC. Performance measures and metrics in sustainable HSC management also need additional focus from future researchers. Finally, this exploratory research has focused on the preparedness phase of disaster relief HSCs, and the results may not be fully generalizable to other phases and so further investigation over each of the phases should be conducted in the future.

Appendix

See Tables 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30 and 31.

Table 1 Barriers to big data usage in sustainable HSC management, based on the literature review and workshopping with five HSC experts

Categories	Barriers	Source
Informational refers to big data generation in real-time which can be used in sustainable humanitarian operations to build resilience	Poor management of data generated from multiple sources	Alharthi et al. (2017)
	Multiple formats of data	Alharthi et al. (2017)
Human refers to data scientists involved in big data analysis and interpretation	Lack of skills for proper data processing and correct interpretation	Alharthi et al. (2017)
	Insufficient training and education	Sarkis et al. (2012)
Technological refers to technology and systems necessary for exploiting big data in sustainable humanitarian operations	Complexity	Alharthi et al. (2017)
	Fear of new technology	Alharthi et al. (2017)
	Infrastructure un-readiness	Alharthi et al. (2017)
Organizational refers to agencies involved in sustainable humanitarian operations	The traditional mind-set of existing employees	Alharthi et al. (2017)
	Difficulty in changing organizational culture across the entire organization and remove hesitation among employees for BDA application	Alharthi et al. (2017)
	Low focus on new employee development	Alharthi et al. (2017)
	Lack of focus in instilling modern management practices	Alharthi et al. (2017)
Social (implications for communities)	Poor infrastructure	Papadopoulos et al. (2017b)
	Poor quality of information sharing	Papadopoulos et al. (2017b)
Economic (financial implications)	Low level of public–private partnership	Papadopoulos et al. (2017b)
	Failure to attract funds from government and international agencies	Jahre and Heigh (2008)

Table 2 Linguistic scales for the influence. *Source*: Khatwani et al. (2015)

Linguistic terms	Linguistic values
Very high influence (VH)	(0.75, 1.0, 1.0)
High influence (H)	(0.5, 0.75, 1.0)
Low influence (L)	(0.25, 0.5, 0.75)
Very low influence (VL)	(0, 0.25, 0.5)
No influence (No)	(0, 0, 0.25)

Table 3 SSIM matrix of expert 1

Barriers	E15	E14	E13	E12	E11	E10	E9	E8	E7	E6	E5	E4	E3	E2
E1	O (No)	O (No)	V (VL)	O (No)	O (No)	O (No)	O (No)	O (No)	O (No)	O (No)	V (H)	O (No)	O (No)	V (VH)
E2	O (No)	O (No)	V (L)	O (No)	O (No)	O (No)	O (No)	O (No)	O (No)	O (No)	V (H)	O (No)	O (No)	
E3	O (No)	O (No)	V (H)	O (No)	O (No)	V (H)	O (No)	O (No)	O (No)	A (L)	A (H)	A (VH)		
E4	O (No)	O (No)	V (H)	O (No)	O (No)	O (No)	O (No)	O (No)	V (L)	V (L)	V (H)			
E5	O (No)	V (VL)	V (H)	V (L)	O (No)	O (No)	O (No)	O (No)	X (H)	V (H)				
E6	O (No)	V (L)	O (No)	O (No)	V (H)	V (H)	O (No)	O (No)	O (No)					
E7	A (VH)	A (VH)	V (VH)	V (H)	O (No)	O (No)	O (No)	O (No)						
E8	O (No)	O (No)	O (No)	O (No)	A (VH)	O (No)	V (VH)							
E9	O (No)	O (No)	O (No)	O (No)	A (VH)	V (H)								
E10	O (No)	O (No)	O (No)	O (No)	A (H)									
E11	O (No)	O (No)	O (No)	O (No)										
E12	A (VH)	A (VH)	A (H)											
E13	A (VH)	A (H)												
E14	A (VH)													

Table 4 SSIM matrix of expert 2

Barriers	E15	E14	E13	E12	E11	E10	E9	E8	E7	E6	E5	E4	E3	E2
E1	O (No)	O (No)	V (VL)	O (No)	O(No)	O (No)	O (No)	O (No)	O (No)	O (No)	V (H)	O (No)	O (No)	V (VH)
E2	O (No)	O (No)	V (L)	O (No)	O (No)	O (No)	O (No)	O (No)	O (No)	O (No)	V (H)	O (No)	O (No)	
E3	O (No)	O (No)	V (H)	O (No)	O (No)	V (H)	O (No)	O (No)	O (No)	A (L)	A (H)	A (VH)		
E4	O (No)	O (No)	V (H)	O (No)	O (No)	O (No)	O (No)	O (No)	V (L)	V (L)	V (H)			
E5	O (No)	V (VL)	V (H)	V (VL)	O (No)	O (No)	O (No)	O (No)	X (H)	V (H)				
E6	O (No)	V (L)	O (No)	O (No)	V (H)	V (H)	O (No)	O (No)	O (No)					
E7	A (VH)	A (H)	V (VH)	V (H)	O (No)	O (No)	O (No)	O (No)						
E8	O (No)	O (No)	O (No)	O (No)	A (VH)	O (No)	V (VH)							
E9	O (No)	O (No)	O (No)	O (No)	A (VH)	V (H)								
E10	O (No)	O (No)	O (No)	O (No)	A (H)									
E11	O (No)	O (No)	O (No)	O (No)										
E12	A (VH)	A (VH)	A (H)											
E13	A (VH)	A (H)												
E14	A (VH)													

Table 5 SSIM matrix of expert 3

Barriers	E15	E14	E13	E12	E11	E10	E9	E8	E7	E6	E5	E4	E3	E2
E1	O (No)	O (No)	V (VL)	O (No)	O (No)	O (No)	O (No)	O (No)	O (No)	O (No)	V (H)	O (No)	O (No)	V (VH)
E2	O (No)	O (No)	V (L)	O (No)	O (No)	O (No)	O (No)	O (No)	O (No)	O (No)	V (H)	O (No)	O (No)	
E3	O (No)	O (No)	V (H)	O (No)	O (No)	V (H)	O (No)	O (No)	O (No)	A (L)	A (H)	A (VH)		
E4	O (No)	O (No)	V (H)	O (No)	O (No)	O (No)	O (No)	O (No)	V (L)	V (L)	V (H)			
E5	O (No)	V (VL)	V (H)	V (L)	O (No)	O (No)	O (No)	O (No)	X (H)	V (H)				
E6	O (No)	V (L)	O (No)	O (No)	V (H)	V (H)	O (No)	O (No)	O (No)					
E7	A (H)	A (VH)	V (VH)	V (H)	O (No)	O (No)	O (No)	O (No)						
E8	O (No)	O (No)	O (No)	O (No)	A (VH)	O (No)	V (VH)							
E9	O (No)	O (No)	O (No)	O (No)	A (VH)	V (H)								
E10	O (No)	O (No)	O (No)	O (No)	A (H)									
E11	O (No)	O (No)	O (No)	O (No)										
E12	A (VH)	A (VH)	A (H)											
E13	A (VH)	A (H)												
E14	A (VH)													

Table 6 SSIM matrix of expert 4

Barriers	E15	E14	E13	E12	E11	E10	E9	E8	E7	E6	E5	E4	E3	E2
E1	O (No)	O (No)	V (VL)	O (No)	O (No)	O (No)	O (No)	O (No)	O (No)	O (No)	V (H)	O (No)	O (No)	V (VH)
E2	O (No)	O (No)	V (L)	O (No)	O (No)	O (No)	O (No)	O (No)	O (No)	O (No)	V (H)	O (No)	O (No)	
E3	O (No)	O (No)	V (H)	O (No)	O (No)	V (H)	O (No)	O (No)	O (No)	A (L)	A (H)	A (VH)		
E4	O (No)	O (No)	V (H)	O (No)	O (No)	O (No)	O (No)	O (No)	V (L)	V (L)	V (H)			
E5	O (No)	V (VL)	V (H)	V (L)	O (No)	O (No)	O (No)	O (No)	X (H)	V (H)				
E6	O (No)	V (L)	O (No)	O (No)	V (H)	V (H)	O (No)	O (No)	O (No)					
E7	A (VH)	A (VH)	V (VH)	V (H)	O (No)	O (No)	O (No)	O (No)						
E8	O (No)	O (No)	O (No)	O (No)	A (VH)	O (No)	V (VH)							
E9	O (No)	O (No)	O (No)	O (No)	A (VH)	V (H)								
E10	O (No)	O (No)	O (No)	O (No)	A (H)									
E11	O (No)	O (No)	O (No)	O (No)										
E12	A (VH)	A (VH)	A (H)											
E13	A (VH)	A (H)												
E14	A (VH)													

Table 7 SSIM matrix of expert 5

Barriers	E15	E14	E13	E12	E11	E10	E9	E8	E7	E6	E5	E4	E3	E2
E1	O (No)	O (No)	V (VL)	O (No)	O (No)	O (No)	O (No)	O (No)	O (No)	O (No)	V (H)	O (No)	O (No)	V (VH)
E2	O (No)	O (No)	V (L)	O (No)	O (No)	O (No)	O (No)	O (No)	O (No)	O (No)	V (H)	O (No)	O (No)	
E3	O (No)	O (No)	V (H)	O (No)	O (No)	V (H)	O (No)	O (No)	O (No)	A (L)	A (H)	A (H)		
E4	O (No)	O (No)	V (H)	O (No)	O (No)	O (No)	O (No)	O (No)	V (L)	V (L)	V (H)			
E5	O (No)	V (VL)	V (H)	V (L)	O (No)	O (No)	O (No)	O (No)	X (H)	V (H)				
E6	O (No)	V (L)	O (No)	O (No)	V (H)	V (H)	O (No)	O (No)	O (No)					
E7	A (H)	A (VH)	V (H)	V (H)	O (No)	O (No)	O (No)	O (No)						
E8	O (No)	O (No)	O (No)	O (No)	A (VH)	O (No)	V (VH)							
E9	O (No)	O (No)	O (No)	O (No)	A (VH)	V (H)								
E10	O (No)	O (No)	O (No)	O (No)	A (H)									
E11	O (No)	O (No)	O (No)	O (No)										
E12	A (VH)	A (VH)	A (H)											
E13	A (VH)	A (H)												
E14	A (VH)													

Table 8 Aggregated SSIM matrix

Barriers	E15	E14	E13	E12	E11	E10	E9	E8	E7	E6	E5	E4	E3	E2
E1	O (No)	O (No)	V (VL)	O (No)	O (No)	O (No)	O (No)	O (No)	O (No)	O (No)	V (H)	O (No)	O (No)	V (VH)
E2	O (No)	O (No)	V (L)	O (No)	O (No)	O (No)	O (No)	O (No)	O (No)	O (No)	V (H)	O (No)	O (No)	
E3	O (No)	O (No)	V (H)	O (No)	O (No)	V (H)	O (No)	O (No)	O (No)	A (L)	A (H)	A (VH)		
E4	O (No)	O (No)	V (H)	O (No)	O (No)	O (No)	O (No)	O (No)	V (L)	V (L)	V (H)			
E5	O (No)	V (VL)	V (H)	V (L)	O (No)	O (No)	O (No)	O (No)	X (H)	V (H)				
E6	O (No)	V (L)	O (No)	O (No)	V (H)	V (H)	O (No)	O (No)	O (No)					
E7	A (VH)	A (VH)	V (VH)	V (H)	O (No)	O (No)	O (No)	O (No)						
E8	O (No)	O (No)	O (No)	O (No)	A (VH)	O (No)	V (VH)							
E9	O (No)	O (No)	O (No)	O (No)	A (VH)	V (H)								
E10	O (No)	O (No)	O (No)	O (No)	A (H)									
E11	O (No)	O (No)	O (No)	O (No)										
E12	A (VH)	A (VH)	A (H)											
E13	A (VH)	A (H)												
E14	A (VH)													

Table 9 Fuzzy reachability matrix based on aggregated fuzzy SSIM matrix

Barriers	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11	E12	E13	E14	E15
E1		VH	No	No	H	No	No	No	No	No	No	No	VL	No	No
E2	No		No	No	H	No	No	No	No	No	No	No	L	No	No
E3	No	No		No	No	No	No	No	No	H	No	No	H	No	No
E4	No	No	VH		H	L	L	No	No	No	No	No	H	No	No
E5	No	No	H	No		H	H	No	No	No	No	L	H	VL	No
E6	No	No	L	No	No		No	No	No	H	H	No	No	L	No
E7	No	No	No	No	H	No		No	No	No	No	H	VH	No	No
E8	No	No	No	No	No	No	No		VH	No	No	No	No	No	No
E9	No	No	No	No	No	No	No	No		H	No	No	No	No	No
E10	No	No	No	No	No	No	No	No	No		No	No	No	No	No
E11	No	No	No	No	No	No	No	VH	VH	H		No	No	No	No
E12	No	No	No	No	No	No	No	No	No	No	No		No	No	No
E13	No	No	No	No	No	No	No	No	No	No	No	H		No	No
E14	No	No	No	No	No	No	VH	No	No	No	No	VH	H		No
E15	No	No	No	No	No	No	VH	No	No	No	No	VH	VH	VH	

Table 10 Final fuzzy reachability matrix ~Z of 5 experts with fuzzy and crisp values of driving power and dependence of criteria

Barriers	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11	E12	E13	E14	E15	Driving power	Crisp value
E1	(1, 1, 1)	(0.75, 1, 1)	(0, 0, 0.25)	(0, 0, 0.25)	(0.5, 0.75, 1)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0.25, 0.5)	(0, 0, 0.25)	(0, 0, 0.25)	(2.25, 3, 6.25)	3.44
E2	(0, 0, 0.25)	(1, 1, 1)	(0, 0, 0.25)	(0, 0, 0.25)	(0.5, 0.75, 1)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0.25, 0.5, 0.75)	(0, 0, 0.25)	(0, 0, 0.25)	(1.75, 2.25, 5.75)	2.66
E3	(0, 0, 0.25)	(0, 0, 0.25)	(1, 1, 1)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0.5, 0.75, 1)	(0, 0, 0.25)	(0, 0, 0.25)	(0.5, 0.75, 1)	(0, 0, 0.25)	(0, 0, 0.25)	(2, 2.5, 6)	2.88
E4	(0, 0, 0.25)	(0, 0, 0.25)	(0.75, 1, 1)	(1, 1, 1)	(0.5, 0.75, 1)	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0.5, 0.75, 1)	(0, 0, 0.25)	(0, 0, 0.25)	(3.25, 4.5, 7.75)	4.77
E5	(0, 0, 0.25)	(0, 0, 0.25)	(0.5, 0.75, 1)	(0, 0, 0.25)	(1, 1, 1)	(0.5, 0.75, 1)	(0.5, 0.75, 1)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0.25, 0.5, 0.75)	(0.5, 0.75, 1)	(0, 0.25, 0.5)	(0, 0, 0.25)	(3.25, 4.75, 8.25)	4.91
E6	(0, 0, 0.25)	(0, 0, 0.25)	(0.25, 0.5, 0.75)	(0, 0, 0.25)	(0, 0, 0.25)	(1, 1, 1)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0.5, 0.75, 1)	(0.5, 0.75, 1)	(0, 0, 0.25)	(0, 0, 0.25)	(0.25, 0.5, 0.75)	(0, 0, 0.25)	(2.5, 3.5, 7)	3.82
E7	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0.5, 0.75, 1)	(0, 0, 0.25)	(1, 1, 1)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0.5, 0.75, 1)	(0.75, 1, 1)	(0, 0, 0.25)	(0, 0, 0.25)	(2.75, 3.5, 6.75)	3.90
E8	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(1, 1, 1)	(0.75, 1, 1)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(1.75, 2, 5.25)	2.45
E9	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(1, 1, 1)	(0.5, 0.75, 1)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(1.5, 1.75, 5.25)	2.95
E10	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(1, 1, 1)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(1, 1, 4.50)	1.56

Table 10 continued

Barriers	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11	E12	E13	E14	E15	Driving power	Crisp value
E11	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0.75, 1, 1)	(0.75, 1, 1)	(0.5, 0.75, 1)	(1, 1, 1)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(3, 3.75, 6.75)	2.27
E12	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(1, 1, 1)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(1, 1, 4.5)	1.54
E13	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0.5, 0.75, 1)	(1, 1, 1)	(0, 0, 0.25)	(0, 0, 0.25)	(1.5, 1.75, 5.25)	2.23
E14	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0.75, 1, 1)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0.75, 1, 1)	(0.5, 0.75, 1)	(1, 1, 1)	(0, 0, 0.25)	(3, 3.75, 6.75)	4.09
E15	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0.75, 1, 1)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0.75, 1, 1)	(0.75, 1, 1)	(0.75, 1, 1)	(1, 1, 1)	(4, 5, 7.5)	4.19
Dependence power	(1, 1, 4.5)	(1.75, 2, 5.25)	(2.5, 3.25, 6.5)	(1, 1, 4.5)	(3, 4, 7.5)	(1.75, 2.25, 5.75)	(3.25, 4.25, 7.25)	(1.75, 2, 5.25)	(2.5, 3, 6)	(3, 4, 7.5)	(1.5, 1.75, 5.25)	(3.75, 5, 8)	(4.75, 6.75, 9.75)	(2, 2.75, 6)	(1, 1, 4.50)		

Table 11 Categorizing barriers based on Fig. 1

No.	Barriers	Dependence power (X)	Driving power (Y)	Sector	Category
E1	Poor management of data generated from multiple sources	1.53	3.44	IV	Driving
E2	Multiple formats of data	2.48	2.66	III	Linkage
E3	Lack of skills for proper data processing and correct interpretation	3.70	2.88	III	Linkage
E4	Insufficient training and education	1.53	4.77	IV	Driving
E5	Complexity	4.44	4.91	III	Linkage
E6	Fear of new technology	2.75	3.82	III	Linkage
E7	Infrastructure un-readiness	4.60	3.90	III	Linkage
E8	Traditional mindset of existing employees	1.07	2.45	I	Autonomous
E9	Difficulty in changing organizational culture across the entire organization and remove hesitation among employees for BDA application	3.36	2.95	III	Linkage
E10	Low focus on new employee development	4.41	1.56	II	Dependent
E11	Lack of focus in instilling modern management practices	2.69	2.27	II	Dependent
E12	Poor infrastructure	5.15	1.54	II	Dependent
E13	Poor quality of information sharing	6.60	2.23	II	Dependent
E14	Low level of public–private partnership	3.13	4.09	III	Linkage
E15	Failure to attract funds from government and other international agencies	3.39	4.19	III	Linkage

Table 12 Defuzzified reachability matrix with fuzzy linguistic terms

Barriers	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11	E12	E13	E14	E15	Driving power
E1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	3
E2	0	1	1*	0	1	1*	1*	0	0	0	0	0	1*	0	0	6
E3	0	0	1	0	0	0	0	0	0	1	0	1*	1	0	0	4
E4	0	0	1	1	1	1*	1*	0	0	1*	0	1*	1	0	0	8
E5	0	0	1	0	1	1	1	0	0	1*	1*	1*	1	0	0	8
E6	0	0	0	0	0	1	0	1*	1*	1	1	0	0	0	0	5
E7	0	0	1*	0	1	1*	1	0	0	0	0	1	1	0	0	6
E8	0	0	0	0	0	0	0	1	1	1*	0	0	0	0	0	3
E9	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	2
E10	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1
E11	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	4
E12	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1
E13	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	2
E14	0	0	0	0	1*	0	1	0	0	0	0	1	1	1	0	5
E15	0	0	0	0	1*	0	1	0	0	0	0	1	1	1	1	6
Dependence power	1	2	5	1	7	5	6	3	4	8	3	8	8	2	1	

*Indicates transitive links

Table 13 Categorizing barriers based on Fig. 2

No	Barriers	Dependence power (X)	Driving power (Y)	Sector	Category
E1	Poor management of data generated from multiple sources	1	3	I	Autonomous
E2	Multiple formats of data	2	6	IV	Driving
E3	Lack of skills for proper data processing and correct interpretation	5	4	III	Linkage
E4	Insufficient training and education	1	8	IV	Driving
E5	Complexity	7	8	III	Linkage
E6	Fear of new technology	5	5	III	Linkage
E7	Infrastructure un-readiness	6	6	III	Linkage
E8	Traditional mindset of existing employees	3	3	I	Autonomous
E9	Difficulty in changing organizational culture across the entire organization	4	2	II	Dependent
E10	Low focus on new employee development	8	1	II	Dependent
E11	Lack of focus in instilling modern management practices	3	4	IV	Driving
E12	Poor infrastructure	8	1	II	Dependent
E13	Poor quality of information sharing	8	2	II	Dependent
E14	Low level of public–private partnership	2	5	IV	Driving
E15	Failure to attract funds from government and other international agencies	1	6	IV	Driving

Table 14 First iteration of final fuzzy reachability matrix partition

Barriers	Reachability set	Antecedent set	Intersection set	Level
1	1, 2, 5	1	1	
2	2, 3, 5, 6, 7, 13	1, 2	2	
3	3, 10, 12, 13	2, 3, 4, 5, 7	3	
4	3, 4, 5, 6, 7, 10, 12, 13	4	4	
5	3, 5, 6, 7, 10, 11, 12, 13	1, 2, 4, 5, 7, 14, 15	5, 7	
6	6, 8, 9, 10, 11	2, 4, 5, 6, 7	6	
7	3, 5, 6, 7, 12, 13	2, 4, 5, 7, 14, 15	5, 7	
8	8, 9, 10	6, 8, 11	8	
9	9, 10	6, 8, 9, 11	9	
10	10	3, 4, 5, 6, 8, 9, 10, 11	10	I
11	8, 9, 10, 11	5, 6, 11	11	
12	12	3, 4, 5, 7, 12, 13, 14, 15	12	I
13	12, 13	2, 3, 4, 5, 7, 13, 14, 15	13	
14	5, 7, 12, 13, 14	14, 15	14	
15	5, 7, 12, 13, 14, 15	15	15	

Table 15 Second iteration of final fuzzy reachability matrix partition

Barriers	Reachability set	Antecedent set	Intersection set	Level
1	1, 2, 5	1	1	
2	2, 3, 5, 6, 7, 13	1, 2	2	
3	3, 13	2, 3, 4, 5, 7	3	
4	3, 4, 5, 6, 7, 13	4	4	
5	3, 5, 6, 7, 11, 13	1, 2, 4, 5, 7, 14, 15	5, 7	
6	6, 8, 9, 11	2, 4, 5, 6, 7	6	
7	3, 5, 6, 7, 13	2, 4, 5, 7, 14, 15	5, 7	
8	8, 9	6, 8, 11	8	
9	9	6, 8, 9, 11	9	II
11	8, 9, 11	5, 6, 11	11	
13	13	2, 3, 4, 5, 7, 13, 14, 15	13	II
14	5, 7, 13, 14	14, 15	14	
15	5, 7, 13, 14, 15	15	15	

Table 16 Third iteration of final fuzzy reachability matrix partition

Barriers	Reachability set	Antecedent set	Intersection set	Level
1	1, 2, 5	1	1	
2	2, 3, 5, 6, 7	1, 2	2	
3	3	2, 3, 4, 5, 7	3	III
4	3, 4, 5, 6, 7	4	4	
5	3, 5, 6, 7, 11	1, 2, 4, 5, 7, 14, 15	5, 7	
6	6, 8, 11	2, 4, 5, 6, 7	6	
7	3, 5, 6, 7	2, 4, 5, 7, 14, 15	5, 7	
8	8	6, 8, 11	8	III
11	8, 11	5, 6, 11	11	
14	5, 7, 14	14, 15	14	
15	5, 7, 14, 15	15	15	

Table 17 Fourth iteration of final fuzzy reachability matrix partition

Barriers	Reachability set	Antecedent set	Intersection set	Level
1	1, 2, 5	1	1	
2	2, 5, 6, 7	1, 2	2	
4	4, 5, 6, 7	4	4	
5	5, 6, 7, 11	1, 2, 4, 5, 7, 14, 15	5, 7	
6	6, 11	2, 4, 5, 6, 7	6	
7	5, 6, 7	2, 4, 5, 7, 14, 15	5, 7	
11	11	5, 6, 11	11	IV
14	5, 7, 14	14, 15	14	
15	5, 7, 14, 15	15	15	

Table 18 Fifth iteration of final fuzzy reachability matrix partition

Barriers	Reachability set	Antecedent set	Intersection set	Level
1	1, 2, 5	1	1	
2	2, 5, 6, 7	1, 2	2	
4	4, 5, 6, 7	4	4	
5	5, 6, 7	1, 2, 4, 5, 7, 14, 15	5, 7	
6	6	2, 4, 5, 6, 7	6	V
7	5, 6, 7	2, 4, 5, 7, 14, 15	5, 7	
14	5, 7, 14	14, 15	14	
15	5, 7, 14, 15	15	15	

Table 19 Sixth iteration of final fuzzy reachability matrix partition

Barriers	Reachability set	Antecedent set	Intersection set	Level
1	1, 2, 5	1	1	
2	2, 5, 7	1, 2	2	
4	4, 5, 7	4	4	
5	5, 7	1, 2, 4, 5, 7, 14, 15	5, 7	VI
7	5, 7	2, 4, 5, 7, 14, 15	5, 7	VI
14	5, 7, 14	14, 15	14	
15	5, 7, 14, 15	15	15	

Table 20 Seventh iteration of final fuzzy reachability matrix partition

Barriers	Reachability set	Antecedent set	Intersection set	Level
1	1, 2	1	1	
2	2	1, 2	2	VII
4	4	4	4	VII
14	14	14, 15	14	VII
15	14, 15	15	15	

Table 21 Eight iteration of final fuzzy reachability matrix partition

Barriers	Reachability set	Antecedent set	Intersection set	Level
1	1	1	1	VIII
15	15	15	15	VIII

Table 22 Level partition

No	Barriers	Level
E1	Poor management of data generated from multiple sources	VIII
E2	Multiple formats of data	VII
E3	Lack of skills for proper data processing and correct interpretation	III
E4	Insufficient training and education	VII
E5	Complexity	VI
E6	Fear of new technology	V
E7	Infrastructure un-readiness	VI
E8	Traditional mindset of existing employees	III
E9	Difficulty in changing organizational culture across the entire organization	II
E10	Low focus on new employee development	I
E11	Lack of focus in instilling new management practices	IV
E12	Low level of critical infrastructure resilience	I
E13	Poor quality of information sharing	II
E14	Low level of public–private partnership	VII
E15	Failure to attract funds from government/international agencies	VIII

Table 23 Details of respondents

Domain of work	Experience in humanitarian operations				
	Below 10 years	10–20 years	20–30 years	Above 30 years	Total
Non-government organization	3	7	9	19	38
Non-profit organizations	2	5	14	26	47
Government agencies	0	5	18	0	23
Total	5	17	41	45	108

Table 24 Levene statistics for the test of variance homogeneity

	Levene statistic	df1	df2	Sig.
TOC	.762	2	103	.470
FIN	7.206	2	103	.065
LLC	3.265	2	103	.069
PQI	0.420	2	103	.658
LLP	0.182	2	103	.834
SF	1.960	2	103	.146
CP	0.442	2	103	.644
FNT	2.644	2	103	.076

Table 25 Testing results

Research hypothesis	β and p value	Supported or not-supported
H1a: lack of focus in instilling modern management practices is positively related to technological complexity	$\beta = 0.16$ $p = .04$	Supported
H1b: lack of focus in instilling modern management practices is positively related to infrastructure un-readiness	$\beta = 0.17$ $p = .04$	Supported
H2a: poor infrastructure is positively related to technological complexity	$\beta = 0.16$ $p = .04$	Supported
H2b: poor infrastructure is positively related to fear of new technology	$\beta = 0.17$ $p = .04$	Supported
H3a: poor quality of information sharing is positively related to technological complexity	$\beta = 0.31$ $p < .01$	Supported
H3b: poor quality of information sharing is positively related to fear of new technology	$\beta = 0.50$ $p < .01$	Supported
H3c: poor quality of information sharing is positively related to infrastructure un-readiness	$\beta = 0.20$ $p = .01$	Supported
H4: technological complexity is positively related to failure to attract funds	$\beta = 0.22$ $p < .01$	Supported
H5a: fear of new technology is positively related to the low level of public–private partnership	$\beta = 0.35$ $p < .01$	Supported
H5b: fear of new technology is positively related to difficulty in changing organization culture	$\beta = 0.37$ $p < .01$	Supported
H6a: infrastructure un-readiness is positively related to failure to attract funds	$\beta = 0.22$ $p < .01$	Supported
H6b: infrastructure un-readiness is positively related to difficulty in changing organization culture	$\beta = 0.17$ $p = .04$	Supported

Table 26 Operationalization of constructs

Operationalization of constructs			
Latent variable	Indicator	Measurement constructs	Journal paper considered
Multiple formats of data	MFD1	We use various formats for data collection	Alharthi et al. (2017), Papadopoulos et al. (2017b)
	MFD2	We use multiple formats for communicating the results of data analysis	
Lack of skills for proper data processing and correct interpretation	LSP1	We use basic data analysis tools and techniques with ease	
	LSP1	We use basic data analysis tools and techniques with ease	
	LSP2	We use advanced data analysis tools and techniques with ease	
Insufficient training and education	ITE1	Our employees are engaged with continuous BDA education	
	ITE2	Our employees have undergone training to apply advanced BDA technological tools	
Complexity	CP1	Big data application and analysis in HSC operations involves technological complexity	
	CP2	BDA technological complexity involves systems complexity which is not user friendly	
Fear of new technology	FNT1	HSC professionals perceive new big data and predictive modeling techniques technologies as a major challenge	
	FNT2	HSC professionals are scared of losing job with new technology advancements	
Infrastructure un-readiness	IU1	There is lack of proper hardware systems related to BDA application in HSC operations	
	IU2	There is lack of advanced software and systems capacity to run BDA application in HSC operations	
Difficulty in changing organizational culture across the entire organization	TOC1	Traditional organizational culture is generally found among employees in HSC organizations	

Table 26 continued

Operationalization of constructs			
Latent variable	Indicator	Measurement constructs	Journal paper considered
	TOC2	There is low level of flexibility among employees in HSC organizations	
Low focus on new employee development	FNE1	HSC organizations hardly focus on new employee development through BDA awareness programs and trainings	
	FNE2	Proper BDA goal setting and focus on new employee development is missing in HSC organizations	
Lack of focus in instilling modern management practices	FIN1	Modern management practices are missing in HSC organizations	
	FIN2	Best practices and benchmarking tools are not commonly seen in HSC organizations	
Poor infrastructure	LLC1	Critical infrastructure resilience is found low among African countries	
	LLC2	Focus on building critical infrastructure resilience using BDA application is missing	
Poor quality of information sharing	PQI1	World class communication levels are missing in HSC operations	
	PQI2	Prompt response and transparency in information sharing is lacking	
Low level of public–private partnership	LLP1	Public–private partnership can lead to sustainable HSC operations	
	LLP2	HSC projects are not attracting public–private partnership involving BDA applications to mitigate risks	
Failure to attract funds from government/international agencies	SF1	Short funding can create financial crisis during emergency HSC operations	
	SF2	Short funding can lower sustainability levels in HSC operations	

Table 27 Combined loadings and cross-loadings

	FIN	LLC	PQI	CP	FNT	IU	SF	LLP	TOC
FIN1	0.873	– 0.029	– 0.048	0.019	0.096	– 0.062	– 0.019	0.056	– 0.056
FIN2	0.955	– 0.138	– 0.137	– 0.012	0.087	0.017	0.057	– 0.024	– 0.28
LLC1	– 0.14	0.906	0.036	0.359	– 0.449	0.067	– 0.135	0.091	0.075
LLC2	0.056	0.764	0.017	0.164	– 0.122	0.046	– 0.028	– 0.121	– 0.094
PQI1	0.638	– 0.084	0.795	– 0.195	0.298	– 0.006	– 0.024	0.002	– 0.544
PQI2	– 0.254	0.013	0.892	0.048	– 0.280	0.086	0.072	0.094	– 0.061
CP1	– 0.054	0.061	0.051	0.769	– 0.625	– 0.123	– 0.005	0.024	0.085
CP2	0.254	– 0.209	– 0.216	0.759	0.544	– 0.044	– 0.024	– 0.066	– 0.174
FNT1	– 0.164	0.017	– 0.047	– 0.225	0.,878	– 0.17	0.032	– 0.172	– 0.058
FNT2	0.534	– 0.096	– 0.207	– 0.539	0.670	0.043	– 0.243	– 0.154	– 0.397
IU1	0.009	0.014	0.002	0.054	– 0.10	0.992	– 0.049	– 0.001	0.006
IU2	0.089	– 0.056	– 0.007	0.01	– 0.026	0.957	– 0.079	– 0.056	– 0.037
SF1	– 0.514	– 0.016	0.219	– 0.143	– 0.084	0.172	0.644	– 0.075	0.109
SF2	0.155	– 0.073	– 0.29	– 0.084	0.323	– 0.053	0.809	– 0.072	– 0.054
LLP1	– 0.347	– 0.037	– 0.047	0.076	– 0.078	0.017	0.007	0.656	0.251
LLP2	0.153	– 0.065	– 0.078	– 0.039	0.005	0.029	– 0.075	0.822	– 0.108
TOC1	– 0.072	0.001	– 0.028	0.215	– 0.382	0.040	– 0.136	0.110	0.863
TOC2	– 0.685	0.244	– 0.39	0.014	0.259	– 0.241	– 0.082	– 0.156	0.631

Table 28 Correlations among latent variables with square root of AVEs

	FIN	LLC	PQI	CP	FNT	IU	SF	LLP	TOC
FIN	0.915								
LLC	0.581	0.838							
PQI	0.624	0.301	0.845						
CP	0.063	0.013	0.343	0.764					
FNT	0.357	0.304	0.531	0.676	0.781				
IU	0.203	0.06	0.21	0.378	0.549	0.975			
SF	0.255	0.337	0.149	0.098	0.098	0.085	0.731		
LLP	0.178	0.252	0.104	0.229	0.351	0.072	0.172	0.744	
TOC	0.774	0.381	0.691	0.131	0.429	0.291	0.161	0.082	0.756

Table 29 Latent variable coefficients

Coefficients	FIN	LLC	PQI	CP	FNT	IU	SF	LLP	TOC
R-squared coefficients	–	–	–	0.09	0.325	0.099	0.089	0.126	0.239
Adjusted R-squared coefficients	–	–	–	0.064	0.312	0.082	0.072	0.117	0.225
Composite reliability coefficients	0.911	0.824	0.833	0.737	0.754	0.974	0.700	0.71	0.723
Cronbach's alpha coefficients	0.918	0.834	0.828	0.713	0.77	0.983	0.700	0.700	0.730
Average variances extracted (AVE)	0.837	0.703	0.714	0.584	0.61	0.95	0.534	0.553	0.572
Variance inflation factors (VIF)	3.542	1.835	2.54	2.162	3.552	1.605	1.19	1.262	3.274

Table 30 Model fit and quality indices

Average path coefficient (APC)	0.250, $p = .002$
Average R-squared (ARS)	0.161, $p = .021$
Average block VIF (AVIF)	1.205, acceptable if ≤ 5, ideally ≤ 3.3

Table 31 Causality assessment indices

Simpson's paradox ratio (SPR)	0.917, acceptable if ≥ 0.7, ideally $= 1$
R-squared contribution ratio (RSCR)	0.959, acceptable if ≥ 0.9, ideally $= 1$
Statistical suppression ratio (SSR)	1.000, acceptable if ≥ 0.7

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