OVERCOMING BARIERS TO BIG DATA ADOPTION: STRATEGIC SOLUTIONS FOR STRENGTHENING DISASTER RISK RESILIENCE IN HUMANITARIAN SUPPLY CHAINS

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ABSTRACT

This article explores the barriers to big data adoption and proposes strategic solutions for improving disaster risk resilience to overcome these barriers in humanitarian supply chains (HSCs). Its theoretical model is grounded on the resource-based view (RBV). Based on a combination of a literature review and interviews with experts from humanitarian organizations, 24 barriers to big data adoption were identified. These barriers span infrastructural, technological, managerial, financial, and human-related factors within the humanitarian supply chain. Additionally, eight strategies were defined as solutions to overcome these barriers. The study uses the Fermatean Fuzzy Analytic Hierarchy Process (FF-AHP) to obtain the weights of barriers and the Borda Social Choice Function. The findings offer valuable insights into evaluating solutions to address barriers to big data adoption. The study ranks the barriers based on their influence. The most significant barrier is the shortage of facilities to research and develop big data tools. Other critical barriers include high costs, lack of training facilities, data quality issues, and lack of government support. The results show that the most effective solutions for improving disaster risk resilience involve increasing IT infrastructure, developing strategic plans, and securing government support to overcome barriers to big data adoption. A comprehensive understanding of the barriers to big data adoption can provide policymakers and practitioners with a roadmap for enhancing disaster risk resilience and addressing challenges associated with the adoption of big data.

Keywords: disaster risk resilience; barriers to big data adoption; humanitarian supply chain; AHP; Fermatean fuzzy sets; Borda function

1. Introduction

Disasters are unpredictable; however, proactive measures can reduce social and economic damage caused by disasters (Cao et al., 2021). The disaster relief process operates in a highly complex and uncertain environment (Tomasini & Van Wassenhove, 2009). Humanitarian supply chain (HSC) operations encompass various disaster relief activities, involving but not limited to needs assessment, planning, procurement, warehousing, and the distribution of supplies to beneficiaries. Accurate needs assessment is a critical element of effective disaster management (Maghsoudi

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et al., 2018). The goal of the HSC is to deliver assistance in the form of food, water, medicine, shelter, and other essential materials to regions affected by large-scale emergencies (Balcik et al., 2008). It involves multiple stakeholders from the public or private industries, each with distinct objectives. Fontainha et al. (2017) categorized the relationships among ten key stakeholders and categorized them into three groups: the public sector, which includes government, military, and regulatory organizations; and the private sector, which consists of media, suppliers, and logistics service providers, which encompasses donors and humanitarian organizations within national and international networks.

Türkiye has a population of approximately 86 million people. It straddles Europe and Asia and ranks among the top 35 countries globally in terms of disaster frequency (ReliefWeb, 2024). According to a report from the World Health Organization, the earthquake disaster on February 6, 2023 affected nearly 15 million people in Türkiye. Similar devastating earthquakes have struck the country in the past. On August 17, 1999, a Mw = 7.6 Izmit earthquake resulted in 17,127 fatalities, 43,953 injuries, and a total of 1,358,953 affected individuals. Additionally, on October 23, 2011, a Mw = 7.1 Van earthquake caused 604 deaths, 4,152 injuries, and impacted 32,938 people (ReliefWeb, 2023). A key challenge in managing humanitarian operations during disasters is arranging various activities to ensure that services are delivered promptly to those in need (Singh et al., 2018). Given the constraints in resources, infrastructure, and facilities, Türkiye faces infrastructure, technological, managerial, financial, and human-related challenges within its HSC, which contributes to its unpredictability. The most effective tool to solve this problem is big data technology.

Big data analytics is important in HSC implementation because it allows the decision makers to gain insight and make decisions based on big data on disaster management. Due to the explosive growth in the significance of big data over the past few years, big data adoption has played a strategic role in the effectiveness of disaster resilience management. Big data represents a recent technological framework and methodology for enhancing disaster resilience. Adopting big data may decrease risks and enhance a fast and effective response after disasters. However, several challenges hinder the full utilization of this technology in the disaster management process. Limited finance, capital, and personnel resources create technological, financial, managerial, infrastructural, and human-related barriers influencing big data adoption in organizations involved in disaster management. Therefore, it is imperative to determine the relative importance of these barriers to systematically enhance the utilization of big data. The literature on the barriers to big data adoption in the HSC is limited. This study is the first to empirically test a Fermatean Fuzzy Analytic Hierarchy Process (FF-AHP) and Borda Social Choice Function along with conceptual evidence to evaluate the challenges of big data adoption and discuss disaster management strategies in Türkiye.

The study aims to achieve the following objectives:

1) Classify and prioritize the challenges to big data adoption in HSCs.
2) Analyze the contextual relationships among the barriers and their hierarchical relevance to HSCs.
3) Explore strategic solutions for improving disaster risk resilience to overcome the identified barriers.

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In this context, the Resource-Based View (RBV) can provide a better explanation for investigating the challenges to big data adoption and present solutions for improving disaster risk resilience to overcome the identified barriers.

2. Literature review

2.1. Barriers to big data adoption in the humanitarian supply chain

Big data refers to massive data sets whose size is so complicated that this cumulative data encompasses all types of data gathered from various sources, necessitating the development of advanced tools and techniques to manage it, including powerful processors, algorithms, and software (Sharma et al., 2021). Conventional data processing systems are unable to manage such large volumes of data. The existing literature categorizes big data definitions into five key aspects: volume, velocity, variety, veracity, and value. Volume refers to the rapidly increasing amounts of big data. Velocity describes the speed at which data is collected, processed, and analyzed in real time. Variety highlights the different types of data collected within big data environments, while Veracity refers to the trustworthiness of the data sources. Finally, Value represents the benefits of big data in areas like transactions, strategies, and information (Bahrami & Shokouhyar, 2022). Big Data Analytics (BDA) can be described as a comprehensive approach to administrating and analyzing the 5Vs of big data, which can create value and enhance disaster resilience of relief actors by ensuring practical insights.

In parallel with all its dimensions and aspects, the concept of big data adoption strengthens the resilience for managing HSC challenges. Jeble et al. (2020) investigated how big data and predictive analytics can address the challenges of inaccurate data in performance measurement. Big data adoption presents better situational awareness and augments relief actors' ability to make sense of rapidly changing situations while assisting in the identification and administration of the allocation of critical resources in a disaster. Having precise information about the disaster locations, intensity, extent of damages, and estimates of casualties or affected individuals, along with their needs, is crucial (Moshtari & Gonçalves, 2017). Therefore, it would help humanitarian organizations to transform into data-driven organizations capable of dynamically adapting to changing conditions (Iftikhar et al., 2022). This would result in the sharing of streamlining processes by clearing the way for collaboration, transparency, and traceability among HSC members (Dubey et al., 2019).

RBV is an appropriate theoretical framework because it can improve the overall functioning of relief organizations with big data technology, which plays a crucial role in investigating huge amounts of data or data sets to unveil hidden information, different patterns, and related meaningful statistics in disaster management. This theory can be utilized to facilitate the big data adoption of the linkages between the internal and external dimensions of HSC, including local governments, non-governmental organizations (NGOs), community leaders, and international donors. Furthermore, it may minimize the costs of usage of big data and develop the capabilities to anticipate HSC requirements (Bag et al., 2023).

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A literature review was conducted to identify key barriers to the adoption of BDA in HSC, which were then discussed with twelve experts in the field. Based on their responses, the 24 identified barriers were categorized into five dimensions for further analysis. These barriers are presented in Table 1 and are subsequently discussed.

Table 1
Barriers to big data adoption

Dimensions	**Barriers to big data adoption**	**Supporting literature**
Technological barriers	Lack of specific big data tools (TB1)	Vogt et al. (2011), Patil et al. (2021), Gavidia (2017), Sharma et al. (2021), Kabra et al. (2023).
	Complexity of data integration (TB2)	
	Data quality (T3)	
	Security and privacy (TB4)	
	Performance and scalability (TB5)	
Human-related barriers	Lack of skilled IT personnel (HB1)	Delmonteil & Rancourt (2017), Agarwal et al. (2019), Sharma et al. (2021), Kabra et al. (2023), Behl & Dutta (2019), Balcik et al. (2010).
	Mindset concerned to big data (HB2)	
	Lack of freedom to share, enhance, and create knowledge (HB3)	
	Time constraints (HB4)	
Financial barriers	High costs (FB1)	Delmonteil & Rancourt (2017), Sharma et al. (2021), Tomasini and Van Wassenhove (2009), Kabra et al. (2023), Wakolbinger and Toyasaki (2014), Gavidia (2017), Aflaki & Pedraza-Martinez (2016), Oloruntoba & Gray (2009).
	Lack of funding (FB2)	
	Competition for funding (FB3)	
	Fundraising expenses (FB4)	
Managerial barriers	Apathy towards employing new technology (MB1)	Kabra et al. (2023), Oloruntoba & Gray (2009), Patil et al. (2021), Balcik et al. (2010), Sharma et al. (2021), Behl & Dutta, (2019).
	Policy to apportion data among organizations (MB2)	
	Lack of transparency in utilization of funds (MB3)	
	Conflicting short-term focus goals-oriented culture (MB4)	
	Lack of policy to adopt technology (MB5)	
	Lack of support from government (MB6)	
	Lack of supply chain understanding (MB7)	
	Lack of trust among organizations (MB8)	
Infrastructural barriers	Lack of infrastructure facilities (B1)	Sharma et al. (2021), Kabra et al. (2023), Delmonteil and Rancourt, (2017)
	Lack of training facilities (IB2)	
	Shortage of facilities to research and develop big data tools (IB3)	

Lack of specific big data tools (TB1): Big data is composed from various sources, including websites, social media platforms, multimedia content, and GPS systems, creating difficulties for data analysts and humanitarian organizations to administrate effectively.

Complexity of data integration (TB2): The diversity of data from various sources increases complexity. Managing and analyzing different data formats can exceed the

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capabilities and expertise of many humanitarian organizations. Furthermore, integrating multiple legacy systems with the adoption of big data presents significant challenges.

Data quality (T3): Data quality varies depending on the types of data sources and the storage capacity. Due to the chaotic conditions and overwhelmed volunteers, the data gathered during a crisis tends to be of lower quality.

Security and privacy (TB4): Private and sensitive information is more vulnerable, making it essential to protect individuals' privacy. Data protection and privacy have become significant challenges in disaster management, as neglecting these issues can result in legal or ethical complications.

Performance and scalability (TB5): BDA requires immense performance and scalability, which presents a considerable challenge when using BDA tools. As a result, the lack of a clear definition for the impact of relief work reduces humanitarian performance measurement.

Lack of skilled IT personnel (HB1): A key challenge for organizations attempting to implement big data is the shortage of relief workers with the necessary analytical skills. Volunteers and relief workers often lack knowledge of big data adaptation and the experience required to use the appropriate software for extracting valuable insights from both structured and unstructured data, which are vital for enhancing operational performance.

Mindset concerned to big data (HB2): If relief workers and volunteers are generally not motivated to incorporate big data into their work, negative perceptions can contribute to their reluctance to adopt big data applications.

Lack of freedom to share, enhance, and create knowledge (HB3): The lack of benchmarking and familiarity with big data creates resistance to adopting and sharing new ideas, as relief workers are unsure about the effort required to acquire the knowledge needed for big data systems.

Time constraints (HB4): Time plays a crucial role in BDA projects, as these are seldom one-time investments with predefined start and end dates. Time limitations also pose a significant challenge in relief work when launching new operations. A minimal response time is essential in disaster situations, as it can mean the difference between life and death.

High costs (FB1): Standard commercial software packages do not meet the requirements of humanitarian operations. On the other hand, customized disaster response applications are often unavailable or extremely costly. Developing BDA tools often requires substantial financial investment for data storage and management in disaster management. Kapucu et al. (2013) also emphasized that effectively utilizing IT requires increased investment in infrastructure and advanced technology.

Lack of funding (FB2): A major challenge is the lack of funding for the advancement of big new data software and hardware. While donors' financial support is essential for relief efforts, it has been noted that donors are typically more inclined to provide funding after a disaster rather than during the preparedness phase. There is often hesitation to allocate resources for adopting big data technologies or for upgrading the infrastructure needed to effectively implement these technologies.

Competition for funding (FB3) The growing number of organizations dedicated to alleviating human suffering after disasters has led to increased competition for funding. Many relief organizations receive only in-kind donations, like food and clothing, instead of the financial support needed to invest in big data infrastructure.

Fundraising expenses (FB4): Creating BDA tools typically demands significant financial resources for data storage and management. Funding involves numerous stakeholders with varying goals in HSC. Furthermore, the costs related to securing funds from varied agencies and donors are considerable within the context of disaster management.

Apathy towards employing new technology (MB1): HSC organizations frequently do not have access to technological solutions designed to tackle their unique challenges.

Policy to apportion data among organizations (MB2): There is a lack of effective data sharing between humanitarian organizations. Relief workers often function independently and infrequently exchange information during disaster preparedness. The reluctance to share information creates challenges in creating effective strategies within organizations.

Lack of transparency in utilization of funds (MB3): Donors and volunteers generally prioritize the transparent and scalable allocation of funds. Organizations are responsible for providing transparency in how donor funds are utilized. However, numerous organizations face challenges in establishing the necessary systems to prove effective fund use at a micro-level. Stewart et al. (2009) argued the transparency surrounding the distribution and use of donated relief materials and resources. Also, they point out the level of mutual respect between the partners in disaster management.

Conflicting short-term focus goals-oriented culture (MB4): HSC organizations typically operate only during the disaster response phase and show little interest in long-term improvements during the disaster preparedness phase. Donors and volunteers are focused on short-term goals, such as funding a specific disaster, causing humanitarian organizations to adopt strategies that are primarily operational, addressing only the immediate crisis.

Lack of policy to adopt technology (MB5): There is a lack of organizational policies that support the adoption of information and digital technologies in disaster management. HSCs often operate in isolation, seldom sharing information with other relief organizations during the disaster preparedness process. This reluctance to share information frequently hinders the development of effective policies at the organizational level.

Lack of support from the government (MB6): Relief organizations are often unaware of government policies that promote the adoption of information and digital technologies. This lack of awareness also extends to available support for funding, training, and knowledge acquisition.

Lack of supply chain understanding (MB7): The HSC is essential to any relief operation, regardless of the disaster's scale or geographic location. However, HSC

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organizations have a limited understanding of the role of supply chain management and its connection to big data technology.

Lack of trust among organizations (MB8): Stakeholders lack trust in relief organizations to utilize BDA tools due to the significant investment required and the uncertainty surrounding the additional effort involved.

Lack of infrastructure facilities (IB1): Poor IT infrastructure and improper organizational structure to share and enhance knowledge have a high degree of influential power on disaster risk resilience. However, existing technological infrastructures need to be upgraded to address the requirements of the current environment. This involves the need for well-educated IT staff and updating hardware and software systems.

Lack of training facilities (IB2): The adoption of BDA may be impeded by inadequate staff training. Effective information transfer and the development of real-time decision-making skills require personnel training, which is crucial for continuous improvement and the support of information and digital technology adoption. However, relief workers frequently face inadequate training opportunities to advance their skills.

Shortage of facilities to research and develop big data tools (IB3): There are limited facilities to address existing disaster management issues and in developing big data tools.

2.2. Strategic solutions for strengthening disaster risk resilience in humanitarian supply chains

Disaster resilience is considered a crucial ability for managing and developing responses to both disasters and post-disasters (Sarker et al., 2020). Disaster resilience refers to the ability of relief organizations and systems to withstand and respond to the adverse impacts of hazards. Understanding resilience to disaster is an integral part of evaluating capacities to overcome potential disasters and enforcing risk reduction measures (Brown et al., 2017). Researchers and disaster managers have paid attention to disaster risk resilience solutions as a crucial factor influencing the effectiveness of disaster operations. Natural disasters like earthquakes or conflicts such as wars disrupt a region’s physical infrastructure, creating challenges in route planning and delivery systems. Similarly, security concerns arising from complex emergencies such as natural disasters or famines during war time impact questions of inventory control (Altay & Pal, 2014). Disaster risk resilience solutions are a comprehensive plan designed to decrease the impacts of disasters, improve preparedness, enhance response efforts, and ensure quick recovery. These solutions focus on strengthening infrastructure systems and humanitarian organizations to withstand and recover from natural or human-made hazards (Saja et al., 2019). RBV theory helps guide the strategic management of resources required to implement effective disaster risk resilience solutions (Dubey et al., 2022).

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Table 2
Strategic solutions for strengthening disaster risk resilience

Strategic solutions	Authors
Enhancing IT infrastructure	Saja et al., 2019; Van Wassenhove, 2006; Fontainha et al., 2017; Pettit & Beresford, 2009; Yadav & Barve, 2015; Dubey & Gunasekaran, 2016; Grange et al., 2020; Sarker et al., 2020; Hunt et al., 2022
Skilled IT personnel	Pettit & Beresford, 2009; Singh et al., 2018; Van Wassenhove, 2006; Wild & Zhou, 2011
Preparation of a strategic plan	Singh et al., 2018; Yadav & Barve, 2015; Jahre, 2017; Pettit & Beresford, 2009; Sarker et al., 2020; Kumar & Singh, 2022
Improving government support	Singh et al., 2018; Wild & Zhou, 2011; Yadav & Barve, 2015; Dubey & Gunasekaran, 2016; Van Wassenhove, 2006; Fontainha et al., 2017
Strengthening public and private collaboration	Fontainha et al., 2017; Pettit & Beresford, 2009; Jahre, 2017; Singh et al., 2018; Van Wassenhove, 2006; Wild & Zhou, 2011; Dubey & Gunasekaran, 2016; Sarker et al., 2020
Increasing incentives and financial support	Van Wassenhove, 2006; Santarelli et al., 2015; Sarker et al., 2020; Prasad et al., 2018
Making legal arrangements	Bealt et al., 2016; Sarker et al., 2020; Yadav & Barve, 2015; Jahre, 2017
Preparation for training programs to develop technical knowledge and skills	Sarker et al., 2020; Wild & Zhou, 2011; Marie-Allen et al., 2013; Kovács & Tatham, 2010; Dubey & Gunasekaran, 2016; Tint et al., 2015; Van Wassenhove, 2006

Relief personnel play a critical role in HSC management organizations. They need to possess a set of skills and competencies suited to the peculiar challenges of their work environment. Therefore, it is essential to develop education and training programs that meet their needs (Van Wassenhove, 2006). Training should cover practical skills for using BDA tools and platforms, such as data analysis software or more specialized tools (Dubey & Gunasekaran, 2016). It could involve teaching employees how to apply machine learning, data mining, and predictive analytics in disaster scenarios. This will allow them to uncover trends, make informed decisions, and optimize workflows (Marie-Allen et al., 2013). Kovács and Tatham (2010) highlighted the significance of training programs for growing functional logistics skills in the HSC.

Strategy 1: Preparation of training programs to develop technical knowledge and skills on big data applications.

BDA tools facilitate data sharing among humanitarian organizations and their partners, which helps accelerate the restoration of infrastructure, reduces human casualties, ensures transparency, and improves decision-making (Kabra et al., 2023). Enhancing infrastructure is crucial, as it involves creating a centralized system that integrates data from various sources, including logistics providers, suppliers, and volunteers, to offer a real-time view of the humanitarian supply chain (Yadav & Barve, 2015).

Strategy 2: Enhancing infrastructure for big data applications.

Disaster management encompasses a series of actions that provide the effective implementation of relief operations, starting with the design of strategic processes. The strategic planning phase involves setting policies that prevent any potential losses from inadequate preparation (Yadav & Barve, 2015). It focuses on long-term decisions that help organizations become ready for emergencies, including needs assessments, coordination planning, sourcing and transportation of aid materials, supplier selection strategies, and partnerships with other relief organizations (Pettit & Beresford, 2009). For example, assessment and planning for the Asian tsunami and Türkiye earthquake crisis were inadequate within many organizations which led to huge difficulties in the execution of an effective response.

Strategy 3: Preparation of a strategic plan for big data applications.

Big data can streamline operations, optimize resource allocation, create cost savings, and more effectively deliver at a low cost (Prasad et al., 2018). Santarelli et al. (2015) developed a measurement system for evaluating the impact of financial support on disaster resilience. Burkart et al. (2016) established humanitarian funding models based on physical donations, such as food banks distributing excess food to those in need, a concept known as the 'Resource Recycler' model.

Strategy 4: Increasing incentives and financial support for BDA applications.

Governments should be able to respond to developing the necessary infrastructure to support big data initiatives, including cloud storage, data processing capabilities, and secure communication networks in disaster management. Vogt et al. (2011) emphasized that policymakers must recognize the benefits of big data in HSC. Singh et al. (2018) argued that governments need to have a backup plan for data storage and communication, including satellite phones and radio networks, especially in areas prone to natural disasters.

Strategy 5: Increasing government support for big data applications.

Skilled professionals ensure that data is accurate, complete, and consistent across the system. Otherwise, data errors or inconsistencies in a humanitarian context could lead to inefficiencies, delays, or incorrect resource allocation. Therefore, skilled IT personnel build trust with stakeholders, including donors, governments, and beneficiaries, ensuring that resources are used appropriately and effectively (Wild & Zhou, 2011). Big data implementations generate vast amounts of information, and to extract meaningful insights, qualified personnel who can analyze and interpret complex data sets are needed. Skilled data scientists and analysts can identify patterns, trends, and key insights that help optimize disaster management (Pettit & Beresford, 2009).

Strategy 6: Skilled IT personnel for big data applications.

Big data adaptation is an effective method for managing and analyzing large datasets, allowing for the comprehensive collection of information. These advanced analytics can help generate valuable insights and enhance decision-making (Sharma et al., 20121. Hence, Jahre (2017) advocated for legal arrangement policies that promote the use of big data, such as data-sharing agreements, privacy regulations, and open data initiatives that make relevant information accessible to stakeholders.

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Strategy 7: Making legal arrangements for big data applications.

As disasters grow more complex, fostering collaboration becomes crucial—not just between governments, military, and humanitarian organizations, but also with private sector partners. However, these partnerships are challenging due to the stark differences between the two sectors: one is often bureaucratic and slow, while the other is agile and action-driven, with differing priorities. Strengthening public-private collaboration could enhance the use of big data in disaster management (Van Wassenhove, 2006). Improved management of stakeholders can enhance the effectiveness and efficiency of disaster response and humanitarian efforts (Fontainha et al., 2017).

Strategy 8: Strengthening public-private collaboration in big data applications.

3. Methodology

3.1. Fermatean fuzzy sets concept and its applications in attribute weighting

When Zadeh (1965) proposed the fuzzy set (FS) concept as a solution to the modeling uncertainties, decision scientists found it useful for presenting the vagueness and ambiguity hidden in human consciousness. In many decision problems, attributes such as dimensions, distance, weight, and cost are directly measured with a scale. These are called objective attributes. In reality, many more attributes are subjective since they are not easily measurable without human judgment because of their nature, such as comfort, opinion, and feeling. Thus, it is obvious that the subjectivity of evaluations creates a significant level of uncertainty in representing the expertise and preference of the decision-maker.

The FS concept is a tool allowing uncertainty to be accounted for in mathematical and logical operations. In the classical definition of FS, each element belongs to a set with a certain degree of membership (T), and this membership degree ranges between 0 and 1. The membership degree symbolizes the degree of optimism or level of agreement related to a particular subject when expressing personal judgments. Therefore, the membership degree carries a positive meaning. Over time, defining uncertainty parameters with different characteristics in various decision-making problems has emerged. For example, an element may belong to a set with a certain membership degree, but at the same time, the degree of non-membership should also be expressed separately. For example, in an election environment, an individual may like certain features of a candidate while not liking other features. Moreover, due to the candidates' views on certain issues, neutral thoughts might also emerge among voters. To model such uncertainties, which encompass various levels of thought and information, many extensions of FSs have been developed.

FS extensions allow for the consideration of multiple dimensions of uncertainty. Atanassov (1986) introduced the concept of intuitionistic fuzzy sets (IFS) by adding a new element to the definition of FSs: the non-membership degree (F). This element provides a certain flexibility in information representation, as it allows for the expression of negative features or judgments about a subject. In the election example, voters' dislike of certain aspects of a candidate can be expressed by the non-membership degree. The mathematical relationship between the degrees in IFSs is as follows: $0 \leq T + F \leq 1$. Moreover, Atanassov (1986) introduced an indeterminacy domain to the positive or negative features of the information. This can represent

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situations where voters remain neutral or uncertain about some particular ideas of the candidate. The mathematical measure of this situation is the indeterminacy degree, which is calculated as $\pi = 1 - T - F$. Based on this, IFS gets the capability of representing three levels of information: membership, non-membership, and indeterminacy.

IFS may be insufficient in the mathematical representation of some complex decision situations. For example, if the level of participation in a topic is 0.5 and the level of non-participation is 0.4, this idea can simply be expressed as IFS (T, F) = (0.5, 0.4). But, if the membership degree is 0.5 and the non-membership degree is 0.6, their sum would be 1.1, thus exceeding the limit of 1 and making it impossible to be represented as an IFS. To mathematically express such situations in decision models, several extensions have been proposed. Yager (2014) proposed the Pythagorean fuzzy set (PFS) concept, which is a more extensive form of IFS. In PFS logic, the mathematical constraint of the parameters is defined as the sum of the squares of the membership and non-membership degrees: $0 \leq T^2 + F^2 \leq 1$. Thus, the indeterminacy domain is computed by $\pi = \sqrt{1 - T^2 - F^2}$.

To handle cases that may not fit these constraints, Senapati and Yager (2020) extended the representation domain of IFS and PFS by relaxing the boundary and setting the cubic sum of the degrees within the unit interval: $0 \leq T^3 + F^3 \leq 1$. This new fuzzy concept is called Fermatean fuzzy set (FFS). Accordingly, the indeterminacy degree is defined as $\pi = \sqrt[3]{1 - T^3 - F^3}$. The geometric representations of IFS, PFS, and FFS are demonstrated in Figure 1. As seen, the domain of definition expands from IFS to PFS and to FFS. Therefore, FFS is the more inclusive one. For example, (0.85, 0.70) cannot be modeled as IFS and PFS since their sum is 1.55 (>1) and their squared sum is 1.21 (>1). But this set can be defined in FFS because the sum of the cubes is 0.96 (<1).

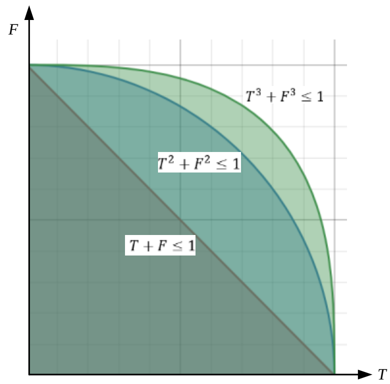

Figure 1 Domains of IFS, PFS, and FFS (Camci et al., 2022)

Basic definitions and operations of FFS are explained below (Senapati & Yager, 2020; 2019a; 2019b).

Definition 1. Let X be a universal set. Then, FFS A in X has the following structure:

$$A = \{(x, T(x), F(x)) \mid x \in X\} \tag{1}$$

where T and F are defined in [0,1]. For $\forall x \in X$, $T(x)$ is named as membership degree and $F(x)$ is the non-membership degree. The only condition that must be satisfied is:

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$$0 \leq \left(T(x)\right)^3 + (F(x))^3 \leq 1, \forall x \in X \quad (2)$$

Accordingly, $\pi(x) = \sqrt[3]{1 - \left(T(x)\right)^3 - (F(x))^3}$ is called the indeterminacy (hesitancy) degree.

Definition 2. Let $X = (T_1, F_1)$, $Y = (T_2, F_2)$ and $Z = (T, F)$, the operations are listed as follows:

$$X \oplus Y = (\sqrt[3]{(T_1^3 + T_2^3 - T_1^3 T_2^3}, F_1 F_2 \quad (3)$$

$$A \otimes B = (T_1 T_2, \sqrt[3]{(F_1^3 + F_2^3 - F_1^3 F_2^3})\quad (4)$$

$$kZ = (\sqrt[3]{(1 - (1 - T^3)^k}, F^k) \quad (5)$$

$$Z^k = (T^k, \sqrt[3]{(1 - (1 - F^3)^k}) \quad (6)$$

$$Z^c = (F, T) \quad (7)$$

Definition 3. Let $Z = (T, F)$ be a FFS, then the score and accuracy functions are as follows:

$$sc(Z) = T^3 - F^3 \quad (8)$$

$$acc(Z) = T^3 + F^3 \quad (9)$$

Definition 4. Let $X = (T_1, F_1)$ and $Y = (T_2, F_2)$ be FFSs, then their rankings can be obtained by the following rules:

i. If $sc(X) < sc(Y)$, then $X < Y$

ii. If $sc(X) > sc(Y)$, then $X > Y$

iii. If $sc(X) = sc(Y)$, then

   a. If $acc(X) < acc(Y)$, then $X < Y$
   b. If $acc(X) > acc(Y)$, then $X > Y$
   c. If $acc(X) = acc(Y)$, then $X \approx Y$

FFSs have caught the interest of researchers and have been integrated with other MADM methods. This article uses a FFS version of the well-known AHP method for weighting the attributes. Therefore, the literature that utilized FFS for attribute weighting is summarized in Table 3. As seen, SWARA (Stepwise Weight Assessment Ratio Analysis) is the most utilized method with an FFS version utilized in six of the 14 articles. Both the BWM (Best-Worst Method) and DEMATEL (Decision-Making Trial and Evaluation Laboratory) were modified for FFS in three articles. Finally, two articles used the same version of the AHP for interval valued FFS. In addition to these 14 journal articles, an FFS version of the AHP which is based on Fermatean

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fuzzy geometric mean aggregation operation using eigenvector calculation, was developed by Camci et al. (2022). This article utilizes this FF-AHP version for dealing with the uncertainty included in the expert's judgments.

Table 3
Attribute weighting under FFS conditions

Authors	Weighting method	Integrated method	Application	Real Appl.
Aydoğan & Ozkir, 2024	FF-SWARA	FF-TOPSIS	(i) Ranking Turkish research universities for performance assessment; (ii) Selecting the optimal facility location for a company in the beverage industry in Türkiye	+
Gao et al., 2024	FF-BWM	FF-VIKOR	Selecting health care waste treatment technology in Jinan, China	+
Alkan & Kahraman, 2023	IVFF-AHP	-	Prioritization of supply chain digital transformation strategies	+
Bouraima et al., 2023	IVFF-AHP	IVFF-TOPSIS	Assessing the causes of accidents in the construction industry in Africa	+
Deveci et al., 2023	FF-SWARA	-	Evaluating the risks impeding sustainable mining in Greece	+
Görçün et al., 2023	IVFF-SWARA	IVFF-COPRAS	Selecting sustainable logistics service providers for medical waste disposal treatment in the healthcare industry in Türkiye	+
Moktadir & Ren, 2023	IVFF-DEMATEL	-	Assessing interactions among Industry 4.0 implementation challenges in a circular economy context for new energy systems towards carbon neutrality in Bangladesh	+
Seikh & Mandal (2023)	IVFF-SWARA	IVFF-PROMETHEE II	Choosing the most capable organization to manage biomedical waste in India	+
Zeng et al., 2023	FF-BWM	FF-EDAS	Evaluating a green supplier	-
Ayyildiz, 2022	FF-SWARA	-	Prioritizing indicators to achieve sustainable development goal-7 (accessible and clean energy) in İstanbul, Türkiye	+
Gonzales et al., 2022	FF-DEMATEL	Maximum mean de-entropy	Modeling the Barriers to Implementing Education 4.0 in the Philippines	+
Karuppiah et al., 2022	FF-DEMATEL	-	Evaluating the critical factors in green economy practices	+
Korucuk et al., 2022	FF-SWARA	FF-COPRAS	Assessing green approaches and digital marketing strategies for twin transition in İstanbul, Türkiye	+
Wei et al., 2022	FF-BWM	FF-CoCoSo	Evaluating a green supplier	-

3.2. FF-AHP for attribute weighting

The AHP, developed by Thomas L. Saaty in the 1970s, focuses on the prioritization of decision elements. It requires experts to make pairwise comparisons, concentrating

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on two attributes at a time (Bozbura et al., 2007). A benefit of the AHP is that experts remain unaffected by external influences when comparing attributes and possess in-depth knowledge to carry out these comparisons. Beyond its individualistic approach, the AHP is a useful tool for MADM in group settings. However, certain adjustments are necessary for group decisions to ensure a sufficient level of consistency among the integrated decision elements (Saaty, 1990).

Throughout the years, the AHP has been extended into different fuzzy concepts. For example, Xu and Liao (2014) designed an intuitionistic fuzzy version of the AHP (IF-AHP) with the development of a consistency check and applied it in a global supplier selection problem. Karasan et al. (2019) extended the AHP into PFS (PF-AHP) and implemented it in a landfill site selection problem for the city of Istanbul in Türkiye. Interested readers can see Yesilcayir et al. (2024), Deepika (2023), Lahane and Kant (2023), Ortiz-Barrios et al. (2023), Sun et al. (2023), Duleba et al. (2022), Bakioğlu and Atahan (2021), Shete et al. (2020), Ilbahar et al. (2018) for different and interesting applications of IF-AHP and PF-AHP.

Since the FF-AHP, developed by Camci et al. (2022), provides a broader decision domain for handling the linguistic uncertainty of the decision makers, it was chosen for this study. The algorithm of FF-AHP involves the steps for the evaluation and ranking of the alternatives. However, we only utilized the FF-AHP algorithm for attribute weighting in this study, and the alternative evaluation steps were not utilized.

Step 1. Constructing a decision hierarchy

The modeling approach of the AHP is based on constructing a hierarchy of the decision problem. At Level 0, the goal is exposed, followed by the main attributes at Level 1. The hierarchy continues with the sub-attributes and sub-sub-attributes related to the main attributes or other sub-attributes at Levels 2, 3, and so on, with the alternatives at the bottom level. Attributes are represented as a_i, where i denotes the index number of the attribute. If a main attribute has sub-attributes, the index is adjusted accordingly. Assume a_i (i = 1,…,n) shows the main attributes and has sub-attributes represented by index k. These sub-attributes are represented by a_{ik}. The alternatives, where j is their index, are listed at the bottom level: s_j (j = 1,..,m).

Step 2. Completing individual pairwise comparison matrices with the expert judgments

The dataset used in the AHP involves comparison judgments gathered from experts about the relative importance of elements at each level. Experts refer to a scale that is tailored to the AHP's specific decision-making approach. Saaty (1980) created a 9-point scale, where a value of 1 represents equal importance between the compared elements, and a value of 9 indicates that one element has a significantly greater importance than the other. Camci et al. (2022) applied a similar fuzzification process with Kutlu Gündoğdu and Kahraman (2020) in converting the classical 9-point scale of the AHP into an FFS environment. Table 4 shows the evaluation scale developed to collect expert judgments required in FF-AHP pairwise comparison matrices.

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Table 4
Evaluation scale for FF-AHP

SI	Linguistic term	FFN	SI	FFN
9	Absolutely more importance (AMI)	(.970, .233)	8	(.929, .121)
7	Very high importance (VHI)	(.900, .307)	6	(.844, .107)
5	High importance (HI)	(.794, .083)	4	(.737, .068)
3	Slightly high importance (SHI)	(.670, .091)	2	(.585, .059)
1	Equal importance (EI)	(.465, .082)	1/2	(.369, .062)
1/3	Slightly low importance (SLI)	(.322, .038)	1/4	(.293, .054)
1/5	Low importance (LI)	(.272, .050)	1/6	(.256, .048)
1/7	Very low importance (VLI)	(.243, .040)	1/8	(.233, .053)
1/9	Absolutely low importance (ALI)	(.224, .050)		

An expert chooses the proper linguistic term that is the closest to his/her opinion. All pairwise comparisons are recorded and shown in a pairwise comparison matrix, which is a square because each element of the level is compared with all the other elements in the same level. For example, the pairwise comparison matrix built for the main criteria can be shown as $D_e = [x_{i\varepsilon}]_e$ (i,ε = 1,…,n). When ε=i, $x_{i\varepsilon} =$ EI because the comparison judgment of one element with itself reveals an equal importance for the decision problem. These EI terms are placed on the diagonal of the matrix. The corresponding FFN is$[x_{i\varepsilon}]_e = (T_{i\varepsilon}^e, F_{i\varepsilon}^e)$, which is read on the scale for each comparison.

The same pairwise comparison matrix structuring system is applied to all sub-attributes under a main attribute and all alternatives at the lowest level of the hierarchy: *(i)* main attributes are compared with respect to the goal; *(ii)* sub-attributes under a main attribute are compared in an attribute-wise manner; and *(iii)* alternatives are compared with respect to the main attributes if they do not have sub-attributes or sub-attributes if a main attribute has.

Step 3. Structuring group comparison matrices

The individual pairwise comparison matrices are aggregated in a group comparison matrix to reveal the final weights of attributes. The Fermatean fuzzy weighted geometric mean (FFGW) operator (Senapati & Yager, 2019b) is performed as given in Equation 10 where e is the index of the expert who provides the individual comparison matrix (e=1,…,E). Experts can have different levels of expertise and knowledge so that their importance and significance for the problem can be taken into account as an expert weight: ω_e.

$$FFWG(D_e) = \left(\prod_e (T_{i\varepsilon}^e)^{\omega_e}, \prod_e (F_{i\varepsilon}^e)^{\omega_e}\right) \qquad (10)$$

Step 4. Checking the potential inconsistency in the group judgment

The AHP’s effectiveness hinges on its ability to assess the consistency of expert judgments. With a consistency ratio, the AHP identifies potential inconsistencies within the decision-making process. While perfect consistency may be unrealistic, the AHP establishes a 10% threshold for tolerable inconsistency, as proposed by Saaty (1980). Lower ratios indicate greater consistency. If a matrix has an inconsistency greater than this threshold, experts are prompted to reevaluate their judgments. To facilitate consistency analysis within the framework of FF-AHP, the current approach defuzzifies matrices using Equation 8 and then applies traditional AHP consistency checks. However, developing a tailored consistency analysis for FF-AHP presents a promising avenue for future research, as it could enhance the accuracy and reliability of decisions made using this methodology.

Assume the group pairwise comparison matrix is $D = [x_{i\varepsilon}]$ where $x_{i\varepsilon} = (T_{i\varepsilon}, F_{i\varepsilon})$ and the defuzzified pairwise comparison matrix is $\overline{D} = [\bar{x}_{i\varepsilon}]$ where $\bar{x}_{i\varepsilon} = T_{i\varepsilon}^3 - F_{i\varepsilon}^3$.

The classical consistency analysis is performed as follows (Saaty, 1987):

Step 4.1. The column vector presenting the crisp attribute weights is obtained. First, Equation 10 is applied in each row of $[\bar{x}_{i\varepsilon}]$, and the geometric mean values of rows are determined in this manner. Then, these geometric means are normalized by dividing each element by the sum of all geometric means. The crisp weight of matrix element i is shown by $\overline{w}_i$.

Step 4.2. The pairwise comparison matrix and the weight column vector are multiplied: $A = [\bar{x}_{i\varepsilon}] * [\overline{w}_i]$. This multiplication produces a column vector: $A = [\delta_i]$.

Step 4.3. Each δ_i element is divided by the corresponding weight value: $E = [\delta_i / \overline{w}_i] = [\epsilon_i]$.

Step 4.4. The eigenvalue (λ) is calculated as the arithmetic mean of the values ϵ_i.

Step 4.5. The Consistency Index (CI) is calculated: $CI = (\lambda - n)/(n - 1)$ where n is the number of the elements in the pairwise comparison matrix.

Step 4.6. The Consistency Ratio (CR), representing the inconsistency level in the judgments, is computed: $CR = CI/RI$ where RI is the random index that is read from a table in terms of n value. If $CR \leq 0.10$ is satisfied, the matrix is accepted as consistent.

Step 5. Obtaining local FFN weights

In this step, the local weights for the primary attributes, sub-attributes associated with each primary attribute, and alternatives related to each attribute or sub-attribute (if there are any) are determined. For each pairwise comparison matrix, FFGW operator (Equation 10) is applied to each row of the matrix with the aim of obtaining the row element's local FFN weight. It is assumed $\omega = 1/n$ where n is the number of the element in the matrix.

Step 6. Calculating global FFN weights

In MADM, the final valuable information is the prioritization of the attributes and/or alternatives. The AHP ranks these elements by considering the global scores. To calculate them, local weights of the elements in the decision hierarchy are combined following the hierarchical order. The local FFN weights, determined at each level, are combined starting from the top level (main criteria) and progressing down to the bottom level (alternatives). The global weight of each child's element is calculated by distributing the weight of its parent element among its child elements. This distribution is done by multiplying the corresponding local weights.

Step 7. Prioritizing the attributes or alternatives

The AHP ranks the alternatives and/or attributes in descending order based on their defuzzified global weights using. Equation 8. The attribute, sub-attribute, or alternative with the highest final global priority is considered the most important or

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the most suitable. The weights can be determined by normalizing the defuzzified priorities. These crisp weights will be used in the ranking of alternatives in the next phase.

3.3. Borda function-based alternative ranking

Decision-making in a group environment is made up of multiple experts who have the knowledge and background about the managerial decision problem the decision analyst works on. This field is called Group Decision Making (GDM). It is separated into two methodological perspectives: *(i)* process-oriented approaches which aim to produce new opinions and courses of action to structure the problem and reveal its details; *(ii)* content-oriented approaches which deal with the content of the decision problem and try to obtain a solution. Content-oriented approaches include three different types of evaluation: implicit evaluation or Social Choice Theory focuses on the ranking of the alternatives or the votes of the decision experts; explicit evaluation or MADM analyses the decision problem with all details, i.e., attributes, sub-attributes, attribute weights, alternatives, experts, expert judgments; the game theoretic approach is a study of confliction, competitiveness, and collaboration between experts (Kabak & Ervural, 2017).

In this work, we utilized the implicit multiple-attribute evaluation to facilitate the data-gathering process and provide a practical methodology for our experts. It is clear that MADM or explicit evaluation needs a greater number of judgments from the decision experts, and it is generally found as time-consuming and hard to understand by the experts who have no or little knowledge about MADM. Instead, this study prefers a social choice-based perspective, which only needs the ranking of the alternatives with respect to each attribute. An expert is asked to order the alternatives for each attribute according to his/her expertise, knowledge, and background in the field. These rankings should be aggregated at the end because the decision problem receives different evaluations from different experts, and the evaluations are obtained with respect to multiple attributes having different levels of importance.

Hwang and Lin (1987) set forth a very detailed piece about GDM. The classical social choice theory deals with a question about how votes cast in a community will be counted and accepted as an aggregated selection of the society. These vote aggregation (counting) approaches are called social choice functions. All these methods do not consider what the decision-makers (voters) consider while casting their votes. Hwang and Lin (1987) proposed an aggregation process for GDM environments that are formed of multiple experts and multiple attributes. Kabak and Ervural (2017) generalized this concept and tried to build a more systematic perspective.

The algorithm of the Borda function-based alternative ranking method is as follows:

Step 1. Each expert e ranks the alternatives s_j (j = 1,..,m) with respect to each attribute a_i (i = 1,…,n). So, the ranking judgment of the expert is represented by r_{ij}^{e}, meaning the expert e's rank for alternative i with respect to attribute j. The expert e's evaluations are collected in the matrix $R^e = [r_{ji}^{e}]$.

Step 2. Borda function scores are calculated for each alternative for each attribute. Borda function assigns scores to the alternatives: $b_{ji}^{e} = n - r_{ji}^{e}$ where n is the total number of alternatives. Thus, the first-ranked alternative received a score of n-1; the

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second-ranked alternative received a score of *n*-2; and it continues in the same manner. At the end, the last-ranked alternative will get a score of 0 (=*n*-*n*). To obtain an alternative's Borda score, $b_{ji} = \sum_{e=1}^{E} b_{ji}^{e}$ are calculated for each attribute. The aggregated Borda score matrix is represented by $B = [b_{ji}]$.

Step 3. The alternatives are ranked according to b_{ji} values for each attribute j. The collective ordered matrix is represented by $R = [r_{ji}]$ where r_{ji} is the collective rank of alternative *j* with respect to attribute *i*. When a tie (equality of Borda scores) occurs, the median rank value is considered.

Step 4. The Borda rankings determined for each attribute are aggregated by taking the attribute weights into consideration. The attribute weights (w_i) are generated by FF-AHP in this study. For this aggregation, a square *m*x*m* sized matrix ($\pi = [\pi_{ji}]$) is built. The alternatives are written on the row and the ranks are depicted on columns. The entries π_{jil} represent the number of ranks where the alternative *j* is placed in the l^{th} rank position for a given attribute *i*. Given the attribute weights, the assignment optimization model is utilized to assign the alternatives to the most appropriate rank.

Let's assume $\pi_{jil} = 1$ if the alternative j is placed in the i^{th} position; otherwise, $\pi_{jil} = 0$. The objective here is the maximization of the corresponding assigned weight value, where the collective weighted matrix is $G = [g_{jl}]$ where $g_{jl} = \sum_{i=1}^{n} \pi_{jil} * w_j$. So, the mathematical model needed for this assignment task is as follows:

$$Max\ \sum_{j=1}^{m} \sum_{l=1}^{m} g_{jl} x_{jl}$$

subject to

$$\sum_{j=1}^{m} x_{jl} = 1 \quad , \quad l = 1, \dots, m$$
$$\sum_{l=1}^{m} x_{jl} = 1 \quad , \quad j = 1, \dots, m$$
$$x_{jl} \in \{0,1\}$$

where $x_{jl} = 1$ if alternative *j* is assigned to position *l* and $x_{jl} = 0$ otherwise.

Therefore, the proposed method is performed in this sequence of steps: (*i*) FF-AHP determines the weights of attributes; (*ii*) Borda function ranks the alternatives with respect to each attribute; (*iii*) assignment optimization model aggregates the Borda scores by considering the attribute weights and reveals the final ranking of alternatives.

4. Application

This study evaluated the barriers to big data adoption in disaster management. Accordingly, it proposed solutions to overcome these barriers. For this purpose, three methods were hybridized: the FF-AHP method was used to reveal the priorities of the barriers, which are considered as attributes; the Borda function was utilized to rank the strategies as alternatives with respect to attributes; the assignment method was performed to aggregate the Borda scores and determine the final order of strategies.

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4.1. FF-AHP to prioritize the barriers

A total of 24 barriers (attributes) to big data adoption within the HSC were identified as a result of an extensive literature review and discussion with the experts. Figure 2 presents the main attributes and their sub-attributes in a hierarchical structure. These 24 sub-attributes are grouped within five main attributes: technological factors, human-related factors, financial factors, managerial factors, and infrastructural factors. The definitions were given in section 2.

In order to obtain the importance (priorities) of the barriers, the FF-AHP method was performed with the judgments of 12 experts. The backgrounds of the experts are explained in Table 5. Their organizations and individual information are not mentioned because of the regulative secrecy requirements (HO stands for "Humanitarian Organization").

A special survey, which was specifically designed for this study, was conducted with the experts. The survey asked the experts to complete pairwise comparisons between attributes and then sub-attributes under each attribute. We only show how the algorithm worked for the main attributes, but the algorithm was performed similarly for each sub-attribute.

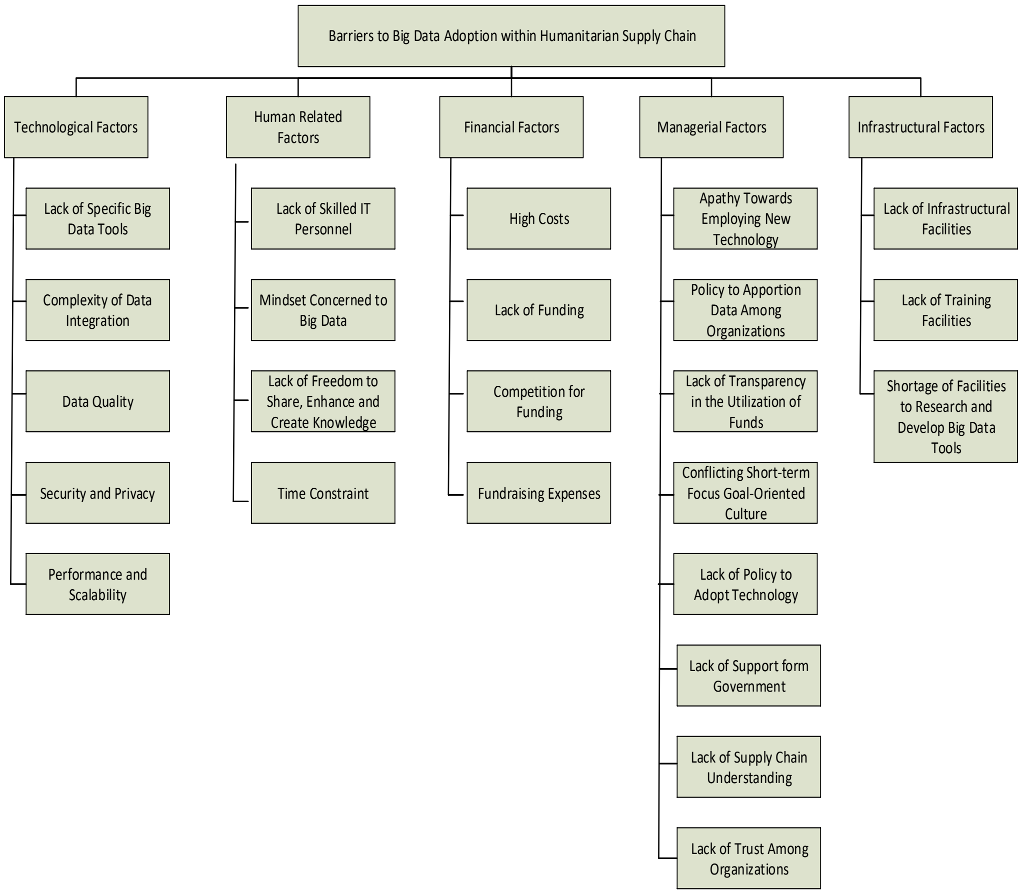

Figure 2 Hierarchy of the barriers to big data adoption in the HSC

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Table 5
Backgrounds of experts

Expert no	Organization	Engagement department	Designation	Experience
1	HO 1	Disaster Preparedness	Disaster Response Coordinator	12 years
2	HO 1	Crisis Management	Chairman	24 years
3	HO 1	Disaster Coordination	Supply Chain Manager	10 years
4	HO 1	Risk Reduction	Specialists of Risk Reduction	6 years
5	HO 2	Training	Disaster Training Manager	22 years
6	HO 2	Infrastructure	Software Specialist	8 years
7	HO 2	Relations with Volunteers and Civil Society	Public Information Officer	2 years
8	HO 2	Logistics	Logistics Manager	15 years
9	HO 3	Crisis Management	Disaster Recovery Analyst	16 years
10	HO 3	IT	Software Specialist	7 years
11	HO 3	Procurement Management	Purchasing Manager	14 years
12	HO 3	Disaster Coordination	Supply Chain Manager	18 years

Step 1. Constructing a decision hierarchy

The AHP assumes that there are no relationships among the attributes and sub-attributes. Thus, a hierarchy demonstrates the main structure of a decision problem in the AHP. The study's hierarchy is shown in Figure 2. a_i (i = 1,…,5) shows the main barriers and their sub-attributes are represented by a_{ik} where k is changing from one attribute to another.

Step 2. Completing individual pairwise comparison matrices with the expert judgments

$D_e = [x_{i\varepsilon}]_e = [(T^e_{i\varepsilon}, F^e_{i\varepsilon})]$ where e = 1,…,12 are constructed by each expert referring to the pairwise comparison scale designed for FF-AHP (Table 4). The first expert's D_1 comparison matrix is given in Table 6. The empty cells are filled with the symmetric values of the linguistic terms selected by the expert because of the technical requirement of FF-AHP. Table 7 shows the complete table we need in calculations.

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Table 6
First expert's main barriers pairwise comparison matrix

D_1	a_1	a_2	a_3	a_4	a_5
a_1	EI	AMI			
a_2		EI			
a_3	Between SHI and HI	Between HI and VHI	EI	VHI	
a_4	HI	VHI		EI	
a_5	HI	Between VHI and AMI	Between SHI and HI	Between HI and VHI	EI

Table 7
FFNs corresponding to linguistic terms

D_1	a_1		a_2		a_3		a_4		a_5	
a_1	0.465	0.082	0.970	0.233	0.293	0.054	0.272	0.050	0.272	0.050
a_2	0.224	0.050	0.465	0.082	0.256	0.048	0.243	0.040	0.233	0.053
a_3	0.737	0.068	0.844	0.107	0.465	0.082	0.900	0.307	0.293	0.054
a_4	0.794	0.083	0.900	0.307	0.243	0.040	0.465	0.082	0.256	0.048
a_5	0.794	0.083	0.929	0.121	0.737	0.068	0.844	0.107	0.465	0.082

Step 3. Structuring group comparison matrices
Twelve pairwise comparison matrices are aggregated via the FFWG operator (given in Equation 10). $\omega_e = 1/12$ is assumed as the expert weights. The group comparison matrix of the main barriers is depicted in Table 8.

Table 8
Group comparison matrix of main barriers

$FFWG(D_e)$	a_1		a_2		a_3		a_4		a_5	
a_1	0.465	0.082	0.467	0.092	0.601	0.119	0.376	0.070	0.375	0.080
a_2	0.466	0.103	0.465	0.082	0.338	0.061	0.374	0.073	0.384	0.087
a_3	0.361	0.064	0.643	0.146	0.465	0.082	0.453	0.088	0.389	0.079
a_4	0.577	0.112	0.579	0.128	0.480	0.096	0.465	0.082	0.471	0.107
a_5	0.577	0.109	0.565	0.111	0.558	0.104	0.462	0.087	0.465	0.082

Step 4. Checking the potential inconsistencies in the group judgments
One of the most distinctive features of the AHP is its tool for measuring the inconsistency level in judgments. For this purpose, Steps 4.1 to 4.6 were applied as explained in section 3. The CR values are as follows: 6.5% for main barriers, 9.9% for technological barriers, 7.7% for human-related barriers, 8.2% for financial barriers, 10% for managerial barriers, and 7.4 % for infrastructural barriers. All are lower than or equal to 10%, so we assumed all group pairwise comparison matrices included tolerable inconsistencies. They were appropriate for weight calculation.

Step 5. Obtaining local weights
For each group pairwise comparison matrix, FFGW operator (Equation 10) was applied. Then, the score function (Equation 8) was used to defuzzify the local FFN

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weight, and these crisp values are normalized. Table 9 demonstrates the details of the main barriers.

Table 9
Local weight calculation of main attribute

	Local FFN weight		**sc**	**Local w_i**
a_1	0.450	0.087	0.090	0.173
a_2	0.402	0.080	0.065	0.124
a_3	0.453	0.088	0.092	0.176
a_4	0.512	0.104	0.133	0.255
a_5	0.523	0.098	0.142	0.272

Let's calculate the geometric means of the first row of Table 7. $FFWG(a_1) = (\prod(T_{i\varepsilon}^{1/5}), \prod(F_{i\varepsilon}^{1/5}))$ where

$$T_{i\varepsilon}^{1/5} = 0.465^{\frac{1}{5}} * 0.467^{\frac{1}{5}} * 0.601^{\frac{1}{5}} * 0.376^{\frac{1}{5}} * 0.375^{\frac{1}{5}} = 0.450$$
$$F_{i\varepsilon}^{1/5} = 0.082^{\frac{1}{5}} * 0.092^{\frac{1}{5}} * 0.119^{\frac{1}{5}} * 0.070^{\frac{1}{5}} * 0.080^{\frac{1}{5}} = 0.087$$

In this manner, the geometric means of other rows were calculated. $sc(Z) = T^3 - F^3$ was applied for defuzzying these FFNs.

$$sc(a_1) = 0.450^3 - 0.087^3 = 0.090$$

The local crisp weights were computed in a normalization process. For this purpose, first, the crisp defuzzified values are summed, and then each was divided by this sum.

$$w_1 = \frac{0.090}{0.090 + 0.065 + 0.092 + 0.133 + 0.142} = 0.173$$

These local weights are shown in the last column of Table 7.

Step 6. Calculating global FFN weights

Applying the same procedure for sub-attributes, all local weights were calculated. The product of a specific barrier's local weight and the associated main attribute gave the barrier's global weight. Table 10 presents the local and global weights of all barriers within five main groups.

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Table 10
Local and global weights of barriers

Main attributes	Sub-attributes	Local weights		Global weights	Ranking
a_1	a_{11}	0.173	0.149	0.026	14
	a_{12}		0.041	0.007	24
	a_{13}		0.451	0.078	4
	a_{14}		0.094	0.016	21
	a_{15}		0.265	0.046	8
a_2	a_{21}	0.124	0.237	0.029	13
	a_{22}		0.153	0.019	19
	a_{23}		0.467	0.058	6
	a_{24}		0.143	0.018	20
a_3	a_{31}	0.176	0.579	***0.102***	***2***
	a_{32}		0.237	0.042	9
	a_{33}		0.055	0.010	23
	a_{34}		0.129	0.023	16
a_4	a_{41}	0.255	0.075	0.019	18
	a_{42}		0.095	0.024	15
	a_{43}		0.055	0.014	22
	a_{44}		0.078	0.020	17
	a_{45}		0.136	0.035	11
	a_{46}		0.281	0.072	5
	a_{47}		0.162	0.041	10
	a_{48}		0.117	0.030	12
a_5	a_{51}	0.272	0.207	0.056	7
	a_{52}		0.327	***0.089***	***3***
	a_{53}		0.466	***0.127***	***1***

Step 7. Prioritizing the attributes or alternatives

The ordering of barriers was obtained by considering the ordering of their weights. The main barriers are ordered as $a_5 \gg a_4 \gg a_3 \gg a_1 \gg a_2$. The most influential barrier is infrastructural, followed by managerial factors. The human-related factors play the least impactful role in this problem.

The ranking of sub-attributes is presented in the last column of Table 10. Three of the most important barriers are listed as Shortage of Facilities to Research and Develop Big Data Tools, High Costs, and Lack of Training Facilities. For each main group, the most influential barrier is obtained as follows:

- Technological factors: Data Quality.
- Human-related factors: Lack of Freedom to Share, Enhance, and Create Knowledge.
- Financial factors: High Costs
- Managerial factors: Lack of Support from Government
- Infrastructural factors: Shortage of Facilities to Research and Develop Big Data Tools

All these findings will be detailed and discussed in section 5.

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4.2. Borda function-based approach to rank the strategies

Based on the literature review and expert opinions, eight strategies (s_j; j = 1,..,8) were determined to deal with the barriers studied in the previous section. The details of these strategies are given in section 2. To understand how much each strategy is beneficial for overcoming the barriers, we asked the experts for their rankings of the strategies with respect to each barrier.

Step 1. Ten experts were consulted for their rankings of alternatives s_j concerning attributes a_i. r_{ji}^e values are collected in $R^e = [r_{ji}^e]$.

Step 2. r_{ji}^e values were transformed into b_{ji}^e values as Borda function scores. Then, $b_{ji} = \sum_{e=1}^{E} b_{ji}^e$ are calculated for each attribute and are collected in the matrix $B = [b_{ji}]$ (Table 11).

Table 11
Borda function scores

	a_{11}	a_{12}	a_{13}	a_{14}	a_{15}	a_{21}	a_{22}	a_{23}	a_{24}	a_{31}	a_{32}	a_{33}	a_{34}
s_1	24	50	30	35	48	54	47	42	38	25	21	41	27
s_2	40	44	48	43	36	26	27	28	36	34	27	30	34
s_3	27	47	41	36	42	29	34	40	49	29	34	29	39
s_4	49	16	28	20	30	32	40	40	24	47	38	44	32
s_5	40	24	30	32	27	36	34	29	27	56	47	33	41
s_6	36	40	33	37	42	55	36	33	29	25	37	25	27
s_7	35	24	37	52	30	21	30	37	38	29	37	35	36
s_8	29	35	44	25	25	27	32	31	39	35	39	42	43

	a_{41}	a_{42}	a_{43}	a_{44}	a_{45}	a_{46}	a_{47}	a_{48}	a_{51}	a_{52}	a_{53}
s_1	37	34	23	38	26	18	39	34	28	37	18
s_2	26	23	17	21	29	25	39	27	35	36	44
s_3	39	49	37	39	39	34	45	50	39	34	39
s_4	47	35	31	27	28	39	36	31	47	36	35
s_5	29	29	52	50	38	52	36	27	44	42	42
s_6	37	23	23	40	23	29	27	22	21	31	25
s_7	31	43	48	33	54	53	25	51	33	39	41
s_8	31	44	49	32	43	30	33	38	33	25	36

Step 3. The collective ordered matrix $R = [r_{ji}]$ (Table 12) was built where r_{ji} is the collective rank of alternative j with respect to attribute i. In the determination of r_{ji}, b_{ji} values were considered for each attribute. In case there is an equality of Borda scores, the median ranks were taken into account.

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Table 12
Collective ordered matrix

	a_{11}	a_{12}	a_{13}	a_{14}	a_{15}	a_{21}	a_{22}	a_{23}	a_{24}	a_{31}	a_{32}	a_{33}	a_{34}
s_1	8	1	6.5	5	1	2	1	1	3.5	7.5	8	3	7.5
s_2	2.5	3	1	2	4	7	8	8	5	4	7	6	5
s_3	7	2	3	4	2.5	5	4.5	2.5	1	5.5	6	7	3
s_4	1	8	8	8	5.5	4	2	2.5	8	2	3	1	6
s_5	2.5	6.5	6.5	6	7	3	4.5	7	7	1	1	5	2
s_6	4	4	5	3	2.5	1	3	5	6	7.5	4.5	8	7.5
s_7	5	6,5	4	1	5.5	8	7	4	3.5	5.5	4.5	4	4
s_8	6	5	2	7	8	6	6	6	2	3	2	2	1

	a_{41}	a_{42}	a_{43}	a_{44}	a_{45}	a_{46}	a_{47}	a_{48}	a_{51}	a_{52}	a_{53}
s_1	3.5	5	6.5	4	7	8	2.5	4	7	3	8
s_2	8	7.5	8	8	5	7	2.5	6.5	4	4.5	1
s_3	2	1	4	3	3	4	1	2	3	6	4
s_4	1	4	5	7	6	3	4.5	5	1	4.5	6
s_5	7	6	1	1	4	2	4.5	6.5	2	1	2
s_6	3.5	7.5	6.5	2	8	6	7	8	8	7	7
s_7	5.5	3	3	5	1	1	8	1	5.5	2	3
s_8	5.5	2	2	6	2	5	6	3	5.5	8	5

Step 4. The r_{ji} rankings were aggregated by considering the attribute weights (w_i) obtained by FF-AHP (Table 8). The square *mxm* sized matrix $\pi = \left[\pi_{ji}\right]$ was built for this aggregation (Table 13). For example, π_{11} value showed the sum of the attribute weights in which the alternative is ranked as the first one. s_1 was ranked first by attributes a_{12}, a_{15}, a_{22}, a_{23}. Therefore, their sum is calculated, i.e., $\pi_{11} = w_{12} + w_{15} + w_{22} + w_{23} = 0.007 + 0.046 + 0.019 + 0.058 = 0.130$. For the ranks including decimals, the weight was distributed partially. For example, $\pi_{22} = \frac{w_{11}}{2} + w_{14} + \frac{w_{47}}{2} = \frac{0.026}{2} + 0.016 + \frac{0.041}{2} = 0.050$.

Table 13
Aggregated weight matrix

	rank 1	**rank 2**	**rank 3**	**rank 4**	**rank 5**	**rank 6**	**rank 7**	**rank 8**
s_1	0.130	0.050	0.138	0.068	0.041	0.046	0.199	0.328
s_2	0.205	0.050	0.041	0.249	0.120	0.025	0.170	0.142
s_3	0.083	0.108	0.264	0.238	0.090	0.182	0.035	0.000
s_4	0.111	0.150	0.142	0.119	0.132	0.207	0.020	0.119
s_5	0.267	0.290	0.042	0.065	0.040	0.098	0.198	0.000
s_6	0.029	0.043	0.068	0.063	0.157	0.096	0.339	0.205
s_7	0.153	0.089	0.174	0.198	0.178	0.115	0.023	0.071
s_8	0.023	0.220	0.132	0.000	0.243	0.231	0.016	0.135

By considering the matrix including aggregated weight values, the assignment model was run. The resulting assignment model is given in Table 14. The ranking of alternatives is $s_2 \gg s_5 \gg s_3 \gg s_7 \gg s_8 \gg s_4 \gg s_6 \gg s_1$. Therefore, it is understood that the first three strategies that are beneficial for overcoming barriers of big data technologies in HSC are, infrastructural improvements, government support, and strategic plan development, respectively. These results are discussed in the next section.

Table 14
Resulting assignment matrix

	rank 1	rank 2	rank 3	rank 4	rank 5	rank 6	rank 7	rank 8
s_1	0	0	0	0	0	0	0	*1*
s_2	*1*	0	0	0	0	0	0	0
s_3	0	0	*1*	0	0	0	0	0
s_4	0	0	0	0	0	*1*	0	0
s_5	0	*1*	0	0	0	0	0	0
s_6	0	0	0	0	0	0	*1*	0
s_7	0	0	0	*1*	0	0	0	0
s_8	0	0	0	0	*1*	0	0	0

5. Discussion

This research aimed to offer a comprehensive understanding of the challenges related to big data adoption in Türkiye. Qualitative insights were acquired through an FF-AHP-based survey completed by 12 participants. It identified and structured 24 barriers, which were arranged into five categories: infrastructural, technological, administrative, financial, and people-related challenges of the HSC. The lack of a big data research laboratory in the HSC is considered one of the most significant barriers. It directly impacts the ability to effectively analyze, process, and apply large datasets that are crucial for advancing predictive models, real-time analytics, and machine learning algorithms. These tools are essential for predicting needs in disaster zones, optimizing supply routes, and forecasting resource demands. HSC organizations struggle to administer large volumes of data effectively without a big data research laboratory. Moreover, HSC stakeholders might not share data or may rely on incompatible systems without a big data research laboratory dedicated to coordinating the use of data such as personal information, health data, and financial records. A big data research laboratory could establish secure, ethical applications around data usage, providing that data privacy and security standards are preserved in disaster processes.

Other crucial barriers involve high costs, lack of training facilities, data quality issues, and government support. Big data applications require a significant investment in technology infrastructure, including hardware, software, and data storage solutions. Many humanitarian organizations operate with limited funding and face unpredictable challenges (e.g., natural disasters, conflicts) and may prioritize immediate needs (e.g., food, medical supplies) over long-term technological advances. The high costs related to implementing, maintaining, and scaling big data solutions create a substantial financial burden, such as uncertainty in return on investment, high costs of expanding storage, processing capabilities, training staff, maintenance and hiring skilled personnel for humanitarian organizations, limiting big data ability to adopt despite their potential benefits.

Big data systems can be overly complex, involving various stages from data collection to analysis and decision-making. Data often comes from a wide range of sources, each with varying levels of quality, formats, and consistency, which requires standardization, but the lack of standardization causes discrepancies in the big data implementations. Low-quality or unstructured data can lead to a mindset concerned about big data and hinder collaboration between relief actors. If relief personnel are not well-trained, this can result in delays, poor decision-making, or inefficiencies, errors, or incomplete analyses, which could negatively impact disaster risk resilience. The overall objective of the training facilities should be to enhance the volunteers and relief workers' management skills and facilitate the application of knowledge and skills gained from training into practice. Moreover, training programs may help ease resistance to adopting innovative technologies and increase awareness of big data implementation about decisions in critical areas such as distribution logistics, resource allocation, or need assessments.

5.1. Theoretical contributions

The study has some useful theoretical contributions to the big data adoption and disaster risk resilience literature. We examined mixed methods of research design to provide scientific rigor in our study. The conceptual model was developed using the FF-AHP to obtain the weights of barriers and Borda Social Choice Function to analyze potential solutions. Moreover, this research was based on RBV theory. RBV theory focuses on the optimum utilization of available resources (Dubey et al., 2019). RBV theory offers a framework that supports the development of strategic, efficient, and adaptable decision-making in big data adoption for HSC (Bag et al. 2023). In the context of big data adoption, the RBV can clarify how HSC organizations use their technological, human, financial, and infrastructural resources to overcome the barriers to adopting big data and enhancing disaster risk resilience.

5.2. Managerial implementation

Big data analytics can allow public and private sectors to track disaster progress in real time, enabling faster decision-making and adaptive responses. Both sectors can share data, resources, and expertise to ensure that HSCs are more resilient, responsive, and efficient. Big data presents a comprehensive foresight to managers for more precise identification of where supplies are needed, decreasing waste and ensuring that resources are used where they will be most effective in a disaster. Also, relief managers can strengthen operational visibility and responsiveness, especially in high-risk and crisis environments with big data implementations.

Relief actors are key stakeholders in HSC operations. However, they are often unaware of the potential benefits that big data can provide, such as enabling faster and more effective decision-making in response to front-line needs. Disaster managers can learn how to improve their operations, reduce costs, and enhance decision-making by being trained in the best ways to process and analyze large volumes of data. They may be resistant to learning innovative technologies such as big data, which is complex, so it is important to foster a culture that values learning and innovation. Employees need to be educated on the foundational principles of BDA, including its tools, systems, and infrastructures. This includes comprehending data collection, data storage, data processing, and data analysis. Volunteers and staff should also understand data privacy and security to ensure that sensitive data is handled responsibly. Humanitarian organizations should arrange various knowledge-sharing initiatives, such as regional and sub-regional training workshops, seminars, conferences, exhibitions, and expert meetings, which are designed to develop as new tools, techniques, and best practices emerge for disaster management. These programs could include advanced training modules or certifications to keep relief

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actors up to date. However, training programs can be costly and time-consuming; humanitarian organizations must balance this with public and private collaboration.

Government organizations often have the infrastructure and legal authority to coordinate humanitarian relief efforts at the national or regional levels. Freight forwarders contribute with expertise in supply chain and transportation in disaster management. For example, Ekol Logistics, UPS, DHL, Kuehne-Nagel, Panalpine, TNT and FedEx often play a role in managing logistics for disaster response. BDA tools help freight forwarders optimize routes, track deliveries, and predict demand for supplies. Despite its advantages, managers may also face many challenges with big data. Public and private sectors may use dissimilar technologies and platforms for data collection, analysis, and communication in disaster processes. Standardizing or integrating these tools can be challenging; however, it is essential for strengthening disaster risk resilience.

6. Conclusion, limitations, and further research directions

Türkiye has encountered various threats from both natural and human-made disasters in the recent past. The country's economy is growing rapidly, but the increasing frequency of disasters in recent years poses a significant challenge to its overall development. BDA technology plays a crucial role in decreasing the impact of disasters and enhancing disaster risk resilience. Big data adaptation may facilitate the efficient management of humanitarian operations and the analysis of the huge unstructured data collected from the disaster areas, supporting long-term strategic planning. Barriers to big data adoption hinder the efficient management of relief efforts, creating challenges for both managers and strategists in disaster risk resilience. Although big data adoption offers numerous advantages, integrating it into HSC is a complex process. As a result, all stakeholders must engage in long-term planning to develop cohesive systems.

This study offers a more effective, efficient, and systematic method for overcoming the barriers of big data adoption and presenting strategic solutions for strengthening disaster risk resilience in HSCs. By using a literature review allied with expert discussions, the study explored and prioritized a comprehensive set of big data adoption barriers in humanitarian organizations. First, the emphasis on big data adoption shows the importance of further integrating advanced BDA technology to support more efficient resource allocation, enhance demand forecasting, and optimize decision-making processes in disaster management.

By addressing these priorities, relief actors can decide which obstacles to tackle first, second, and last in HSC management. They should coordinate their methods and work in a systematic manner to focus on the most critical big data barriers that have the highest priority and potential to improve disaster risk resilience. The findings highlight the need for strengthening infrastructure, increasing financial support, and preparing a strategic plan on big data applications in HSC. This study suggests that the infrastructure of the big data in HSC management should be the priority. The process of strategic solutions for strengthening disaster risk resilience in Türkiye should be viewed holistically and requires a radical change to replace the current ad-hoc disaster risk resilience efforts.

The prioritization of big data barriers is based entirely on discussions and subjective insights developed from 12 expert consultations. Therefore, even though the study

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provides valuable insights, the findings cannot be generalized. A more diverse sample of relief actors can provide valuable perspectives. Second, disaster experts consulted were all from Türkiye. It may be interesting to compare the results with other disaster experts in Europe and the United States to seek out any potential generalizations that would further develop our skills in big data adoption to guide future recovery policy. It is recommended to investigate all stakeholders such as donors, logistics providers, suppliers, manufacturers, private sector partners, humanitarian organizations, and media channels for barriers to big data adoption in the future study.

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