

Integrated Framework of Key Facilitators, Motivators and Relief Aids for Flood Resilient Humanitarian Supply Chain

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Abstract

This paper aims to identify, analyze, and prioritize the key supply chain facilitators, their associated motivators, and the relief aids that enable an agile, responsive and resilient Humanitarian Supply Chain (HSC) for flood relief, using Bihar (India) as a case study. A novel three-level decision hierarchy is proposed, consisting of supply chain facilitators as criteria, their associated motivators as sub-criteria, and relief aids as alternatives. A mixed-method approach is employed involving a comprehensive literature review, expert evaluations, and multi-criteria decision-making techniques of Best-Worst Method (BWM) and Technique for Order Performance by Similarity to Ideal Solution (TOPSIS). *Healthcare aids*, followed by *water and sanitation aids*, and *food aids* are found as most critical humanitarian relief items during floods and should be prioritized, in that order, in emergency response operations. At the system level, *quick response time* and *reduction of deprivation cost* emerge as the most critical facilitators of HSC agility. These can be operationalized through motivators, namely, ensuring the *availability of high-quality relief items*, utilizing *optimized transshipment and distribution routes*, implementing effective *reverse logistics*, and *reducing overall lead time*. The study offers actionable insights for policymakers and practitioners to design and operate agile, resilient, and effective flood relief HSC; thereby mitigating the adverse impacts of flood disasters. This is the first study that conducts systematic research on HSC for flood relief in India, and first-ever study that identifies the key facilitators, motivators and relief aids for flood relief HSC. Another novel contribution is the study of flood relief in Bihar, which has been rarely done despite the state's chronic vulnerability.

Keywords- Facilitators of humanitarian supply chain, Bihar's flood relief supply chain, Relief aids, Best-Worst Method (BWM), Technique for order performance by similarity to ideal solution (TOPSIS).

1. Introduction

Floods are among the most frequent and devastating natural disasters, triggered by extreme rainfall, river overflow, rapid snowmelt, storm surges, and coastal hazards such as cyclones and tsunamis. Their impacts are often sudden, widespread, and destructive, leading to large-scale loss of life, displacement of populations, and severe damage to infrastructure and livelihoods. India has experienced several high-impact flood events over the past decades, including 2004 Indian Ocean tsunami, Mumbai deluge (2005), Surat floods (2006), Bihar floods (2008, 2024), Assam floods (2012), Uttarakhand cloudburst (2013, 2025), Jammu and Kashmir floods (2014), Gujarat floods (2017), Kerala floods (2018), and Punjab floods (2025). These events highlight the recurring and geographically diverse nature of flood risks in the country (Srivastava, 2025). The inherent uncertainty in the timing, location, and magnitude of such disasters makes

preparedness and response planning highly complex.

Humanitarian Supply Chains (HSCs) play a pivotal role in mitigating the impacts of flood disasters by ensuring the timely delivery of essential relief supplies, including food, drinking water, medical assistance, and shelter materials. The primary objective of an HSC is to minimize human suffering and mortality through rapid, coordinated, and equitable distribution of relief resources (Baffoe & Luo, 2020; Minguito & Banluta, 2023). However, humanitarian logistics operates in highly uncertain and resource-constrained environments where damaged infrastructure, disrupted transportation networks, communication failures, fragmented coordination among stakeholders, and fluctuating demand often hinder relief operations (Attia et al., 2023; Bardhan & Dangi, 2016; Holguín-Veras et al., 2013). These disruptions increase response time, delay last-mile delivery, and ultimately elevate deprivation costs experienced by affected communities. Such challenges are particularly acute in developing countries such as India, where geographical diversity, institutional limitations, and socioeconomic disparities further complicate disaster response. Consequently, there is a growing need for agile, resilient, and well-coordinated HSCs capable of operating effectively under dynamic flood conditions.

Bihar is one of the most flood-vulnerable regions in India and also is the authors' place of residence; therefore, it was selected as a case study for our research in flood relief HSC. Over the past two decades, Bihar has experienced several extreme floods, notably in 2007, 2008, 2012, 2013, 2016–2020, and 2024, which were declared national emergencies by the Government of India. Bihar faces significant challenges in coordinating flood-relief activities, allocating limited resources, and ensuring timely assistance to remote and severely affected communities (Navalkar et al., 2025; Sharma et al., 2025). The state urgently needs an integrated decision-support framework to improve the agility and resilience of its flood relief HSCs.

Humanitarian Supply Chain (HSC) comprises a network of humanitarian organizations, government agencies, suppliers, donors, logistics providers, and community organizations that coordinate the flow of information, funds, and relief materials pre and post disasters (Baharmand et al., 2021). Within this network, supply chain facilitators represent the organizational, operational, and technological capabilities that enhance supply chain performance (Fu et al., 2013), while motivators are the specific mechanisms that strengthen these capabilities and accelerate effective relief operations (Thaler et al., 2019). Together, facilitators and motivators determine how efficiently humanitarian organizations respond during the critical initial hours following a disaster, when rapid intervention has the greatest potential to reduce human suffering.

Existing research on HSC has identified several facilitators and motivators such as coordination, information sharing, technological integration, leadership, collaboration, and flexibility as critical to disaster response effectiveness (Dubey et al., 2022; Wang et al., 2024; Xu et al., 2021). Recent studies have also highlighted the growing role of emerging technologies – including artificial intelligence, blockchain, and big data analytics – in enhancing forecasting accuracy, coordination, transparency, and performance in humanitarian logistics (Attia et al., 2023; Karuppiah et al., 2025; Talwar et al., 2021; Wang et al., 2024). Other studies have highlighted the importance of donor trust, accountability, and organizational transparency in improving HSC resilience (Gunessee et al., 2018; Xu et al., 2021). Despite these advances, existing research has largely focused on generalized humanitarian settings, with relatively limited attention to unique operational challenges posed by recurrent flood disasters in highly vulnerable regions of India.

In the area of flood-resilient HSC, three significant gaps remain. First, most existing studies examine facilitators and motivators at a general or global level, with limited focus on region-specific disaster contexts. Second, there is a notable lack of empirical and systematic research addressing the facilitators and

motivators of an agile humanitarian relief supply chain specifically for flood disasters in Bihar, despite the state's chronic vulnerability. Third, the incorporation of decision-support tools such as Multi-Criteria Decision-Making (MCDM) methods to build an integrated framework of facilitators, motivators, and relief aids in the Bihar flood context remains largely unexplored.

To address these gaps, this study aims at identifying and prioritizing the key facilitators, motivators, and humanitarian relief aids for Bihar's flood relief supply chain. For this purpose, a structured MCDM framework is proposed that integrates the Best–Worst Method (BWM) and the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS). BWM determines the relative importance of decision criteria through much reduced number of pairwise comparisons than the Analytic Hierarchy Process (AHP) (Rezaei, 2015). This lowers experts' cognitive burden and improves judgment consistency, making BWM particularly suitable for humanitarian decision-making where expert availability and reliable data are often limited. TOPSIS complements BWM by ranking alternatives according to their proximity to the ideal solution and distance from the negative-ideal solution, thereby providing a transparent and computationally efficient mechanism for prioritizing competing relief options. The integrated BWM–TOPSIS framework therefore combines reliable criteria weighting with robust ranking method, making it particularly suitable for flood-prone regions where decisions must be made rapidly under uncertainty. The study provides a context-specific decision-support framework that can assist policymakers and humanitarian organizations in improving preparedness, resource allocation, response efficiency, and equitable aid distribution. The specific study objectives are to determine and prioritize the following: (i) the key supply chain facilitators that enable an agile and resilient HSC during floods; (ii) the motivators associated with each facilitator; and (iii) humanitarian relief aids that support timely, effective, and equitable flood response.

The remaining paper is structured as follows: Section 2 presents the literature review focused on relevant HSC research involving supply chain facilitators and motivators. Section 3 describes the proposed methodology for the study, Section 4 presents the results, and Section 5 presents discussions and implications of the findings of this study. Finally, the conclusions are presented as Section 6.

2. Literature Review

HSC has attracted significant research attention over the past two decades due to the increasing frequency and intensity of disasters worldwide. This section reviews prior studies on HSC, supply chain facilitators and motivators, and humanitarian aid prioritization. It also highlights relevant theoretical foundations for structuring decision criteria and justifies the selection of the proposed MCDM methodology.

2.1 Introduction to Humanitarian Supply Chain, Facilitators and Motivators

HSCs are responsible for the efficient planning, coordination, and execution of the flow of relief goods, information, and services from donors to affected (Holguín-Veras et al., 2013). They play a crucial role in disaster response by ensuring the timely delivery of essential items such as food, water, medical supplies, and shelter. Overstreet et al. (2011) define HSC as the process of managing the efficient and cost-effective movement and storage of goods to alleviate human suffering. Despite extensive research on HSC operations, significant challenges persist, particularly in flood-prone regions such as Bihar. These include infrastructure disruptions, coordination inefficiencies, demand uncertainty, and resource constraints (Bardhan & Dangi, 2016; Minguito & Banluta, 2023). Notably, logistics activities account for a substantial proportion of humanitarian expenditure, and inefficiencies can lead to considerable resource wastage (Baffoe & Luo, 2020).

While prior studies have explored operational challenges and performance metrics, limited attention has been given to systematically identifying and structuring supply chain facilitators and their underlying motivators, particularly in flood disaster contexts. The identification of relevant facilitators, motivators, and humanitarian aid categories is essential for improving decision-making in disaster relief operations. From a theoretical perspective, facilitators can be viewed as enabling factors of the supply chain performance, which primarily constitute the organizational, operational, and technological capabilities that are essential for an agile and resilient HSC (Fu et al., 2013; Lin et al., 2013). Motivators, on the other hand, act as underlying drivers or mechanisms that activate and strengthen these facilitators (Lin et al., 2013; Singh et al., 2018; Thaler et al., 2019).

2.2 Theoretical Foundation for Selection of Supply Chain Facilitators and Motivators

Flood relief HSCs operate in highly uncertain environments where organizational performance depends on operational responsiveness, equitable resource allocation, and institutional capabilities. Their performance extends beyond logistical efficiency and is influenced by operational, humanitarian, and organizational capabilities. Accordingly, this study adopts a multi-theoretical perspective to guide the selection of facilitators and motivators of effective flood resilient HSCs. The selection is further supported by the insights gained from an extensive literature review of papers between 1990–2026 sourced from major academic databases. Their theoretical underpinnings are presented from hereon.

Humanitarian Logistics Theory argues that disaster response should prioritize the rapid delivery of essential supplies while minimizing human suffering rather than transportation cost alone (Holguín-Veras et al., 2013; Tatham & Pettit, 2010). This theoretical perspective provides the rationale for selecting response time and deprivation cost as two principal decision criteria. Furthermore, Supply Chain Resilience Theory suggests that resilient HSCs require agility, flexibility, collaboration, and adaptive capabilities to maintain service continuity under uncertain and disrupted environments (Dubey et al., 2022; Singh et al., 2018; Xu et al., 2021). Consequently, operational motivators such as optimized transportation, inventory visibility, digital information sharing, and reverse logistics are incorporated into the proposed framework.

The competing values framework (Cameron & Quinn, 1999; Oloruntoba & Kovács, 2015) emphasizes that organizational culture strongly influences coordination, employee commitment, learning, and decision quality. Accordingly, organizational culture is included as a strategic facilitator supported by motivators such as employee empowerment, agile decision-making, and effective information management.

2.2.1 Supply Chain Facilitators

Guided by the above theoretical foundations and the reviewed literature, the selected HSC facilitators and motivators and the codes used for representing them are summarized in **Table 1**. This study conceptualizes three key facilitators—response time, deprivation cost, and organizational culture—as critical dimensions influencing HSC performance. Collectively, these facilitators integrate operational efficiency, humanitarian impact, and organizational capability, providing a structured foundation for evaluating and improving flood relief HSC performance.

Response Time (RT): Rapid response is a key determinant of HSC performance, as delays directly increase human suffering and disaster severity (Fahimnia et al., 2017). It reflects supply chain agility and responsiveness, influenced by factors such as pre-positioned inventory, transportation efficiency, and real-time coordination (Anjomshoae et al., 2017; Dubey et al., 2022). Grounded in agility and time-based competition theory, response time contributes by enabling timely access to critical resources and improving overall operational effectiveness. For maximum utilization of donations effectively and efficiently for meeting beneficiaries' needs, humanitarian organizations place a greater emphasis on response time and

operational productivity (Anjomshoae et al., 2017).

Table 1. Summary of the identified facilitators and motivators of HSC.

Supply chain facilitators	Description	Associated motivators	Description	References
Response Time (RT)	Response to disasters at right place in right time	Quality and availability of relief items (RT1)	Relief items should be prepositioned to a certain percentage based on prior data with high quality in the warehouse in order to respond promptly.	Agarwal et al. (2022), Bardhan & Dangi (2016), Kumar et al. (2024), Mahdiraji et al. (2022), Raj et al. (2022)
		Adoption of digital business ecosystem (RT2)	Technical or shared platform should be connected via digital technology in order to promote prompt response.	Baffoe & Luo (2020), Gupta et al. (2022), Khan & Manzoor (2021), Mahdiraji et al. (2022)
		Fund management (RT3)	Funds should be quickly and appropriately disbursed to optimize effective relief efforts during the eight-hour flood impact.	Abbas et al. (2022), Anjomshoae et al. (2017), Damoah (2022), Gupta et al. (2022), Tatham & Pettit (2010)
		Follow optimized route (RT4)	Vehicle routing and transport assessment tools can provide information of road conditions, traffic flow, and structure of the transportation network that can be used to reach relief aid for everyone as soon as possible.	Balaji et al. (2019), Reza et al. (2017)
		Government Support (RT5)	Government supports assist in prepositioning relief aids via financial and policy measures for preparedness and emergency response.	Agarwal et al. (2022), Dohale et al. (2024), Sarker et al. (2021), Yadav & Kumar (2023)
Deprivation Cost (DC)	Economic worth of the pain that people experience when they are unable to obtain a good or service.	Availability of online stock reports (DC1)	Online stock reports enables quick access to the information of availability of relief items in warehouses, which helps in inventory control and can lower the deprivation cost.	Anjomshoae et al. (2021), Dohale et al. (2024)
		Cost structure (DC2)	A sound cost structure of the planning, sourcing, stocking, and shipping costs can improve efficiency of resource utilization causing less waste and cheaper disposal.	Gupta et al. (2022), Kivlehan et al. (2022), Orfanidou et al. (2024), Sahebi et al. (2017)
		Reverse logistics (DC3)	Reverse movement of goods from the end user back to producer or other sites for reuse, refurbishment, recycling, or responsible disposal.	De Brito & Dekker (2004), Dowlatshahi (2000), Hesami (2025), Nayal et al. (2022), Rubio et al. (2008)
		Lead time of relief chain (DC4)	Short lead time enables quick deliveries of relief items within eight hours of flooding, which directly increases customer satisfaction.	Karuppiiah et al. (2021)
Organizational Culture (OC)	Employees will be more receptive to innovation and risk-taking if their workplace culture fosters employee involvement, mutual trust and respect.	Ensuring decision agility (OC1)	An organization's agility in decision-making enables prompt, well-informed, and flexible decisions in changing circumstances.	Agarwal et al. (2022), Attia et al. (2023), Dubey et al. (2022), Xu et al. (2021), Wang et al. (2024), Yadav & Kumar (2023)
		Green public procurement (OC2)	Green Public Procurement's aims to lessen the environmental impact through sustainable purchasing practices.	Orfanidou et al. (2024), Yadav & Kumar (2023)
		Documentation accuracy (OC3)	Records of different deliveries at impacted areas shared with all stakeholders can help in inventory management and relief aid supplies.	Anjomshoae et al. (2019), Kumar et al. (2024)
		Employee empowerment and motivation (OC4)	Culture where employees are motivated by inspiration through training, resources, and acknowledgment of sustainability to encourage engagement in decision-making.	Orfanidou et al. (2024), Sarker et al. (2021)

Deprivation Cost (DC): Deprivation cost in flood relief HSC context can be conceptually defined as the aggregate human, social, and economic burden arising from delayed or inadequate access to essential relief items in flood-affected areas. It reflects the extent of suffering experienced by affected populations when critical needs—such as safe drinking water, food, and medical aid—are not met in a timely manner (Holguín-Veras et al., 2013; Wang et al., 2024). An operational definition of deprivation cost in this context can be framed as a time- and shortage-dependent penalty/ cost associated with delayed fulfillment of essential relief demand at affected locations. A mathematical formulation and discussion of deprivation cost is beyond the scope of this paper. Unlike traditional cost metrics, it emphasizes welfare maximization and prioritization of life-saving aid. Rooted in humanitarian logistics and welfare economics, this facilitator supports efficient resource allocation under scarcity and enhances the equity and impact of relief operations.

Organizational Culture (OC): Organizational culture influences coordination, adaptability, and decision-making in humanitarian operations (Cameron & Quinn, 1999). A collaborative and agile culture improves information sharing, stakeholder alignment, and responsiveness (Dubey et al., 2022). Drawing on organizational behavior theory (Cameron & Quinn, 1999; Oloruntoba & Kovács, 2015), it contributes by strengthening coordination and enabling effective implementation of relief strategies.

2.2.2 Motivators of Response Time

Response time is influenced by several key operational motivators, as discussed below:

Availability and quality of relief items: Humanitarian actors must ensure the ample availability of good quality relief supplies to enable a rapid and effective response during flood events. High-quality readily available items significantly enhance efficiency of HSC operations (Kumar et al., 2024; Raj et al., 2022).

Adoption of Digital Business Ecosystems (DBE) for coordination and information sharing: DBEs function as collaborative networks that connect humanitarian actors through shared or complementary digital platforms, enabling efficient information exchange and coordination (Baffoe & Luo, 2020). Such systems facilitate real-time decision-making and improve response speed. Examples include platforms such as Amazon, eBay, Flipkart, Facebook, and Alibaba.

Effective fund management and transparency: Adequate pre-disaster funding and efficient financial management can substantially reduce response costs and delays (Anjomshoae et al., 2017). Transparency in fund utilization enhances donor trust and enables smoother planning and allocation of resources.

Optimization of vehicle routing and transportation networks: Efficient routing and transportation planning ensure that relief materials are delivered through the shortest or fastest possible routes, thereby reducing delivery time and logistics costs. The vehicle routing problem is a critical component of HSC, supporting the efficient distribution of goods to affected populations (Balaji et al., 2019). Advanced optimization algorithms can identify optimal routes and intermediate pick-up and drop-off points (Reza et al., 2017), while traffic flow models further enhance transportation efficiency.

Government support and policy interventions: Government involvement plays a crucial role in strengthening HSC performance during disasters. Policy support, regulatory interventions, and financial assistance facilitate efficient relief distribution (Sarker et al., 2021). Conversely, inadequate government support can impose significant financial and operational constraints on HSC (Dohale et al., 2024; Dubey et al., 2022).

Collectively, these motivators enhance the agility and responsiveness of HSC operations, enabling more timely and effective disaster relief.

2.2.3 Motivators of Deprivation Cost

Deprivation cost can be minimized through several key operational mechanisms as enlisted below:

Real-time inventory visibility and online stock reporting: Real-time inventory systems enhance supply chain visibility, enabling more responsive and adaptive demand–supply management. Such systems allow every stakeholder to track inventory levels dynamically and ensure adequate pre-positioning of relief supplies (Anjomshoae et al., 2021). This covers more affected population and lowers the deprivation cost.

Efficient cost structure and resource utilization: A well-designed cost structure, encompassing planning, sourcing, storage, and distribution, improves resource utilization and reduces waste. Practices such as energy efficiency, waste minimization, and optimized allocation of resources contribute to cost-effective and sustainable relief operations (Orfanidou et al., 2024).

Implementation of reverse logistics: Reverse logistics refers to the process of moving goods and services from the point of consumption back to earlier stages in the supply chain—such as collection centers, warehouses, or manufacturers—for the purpose of reuse, recycling, repair, redistribution, or proper disposal. In the context of flood relief HSC, reverse logistics will enable agencies, after a relief operation, to collect excess medical supplies or non-perishable food items, inspect them, and redistribute them to other affected areas instead of discarding them. In flood-hit regions such as Bihar, the excess supplies from less-affected areas or relief camps can be redeployed to underserved locations. Reverse logistics acts as a key motivator in flood relief HSC by enabling the recovery, redistribution, and reuse of surplus or unused relief materials, thereby minimizing resource wastage, reclaiming valuable resources and reducing deprivation cost (Agrawal et al., 2015; Dowlatshahi, 2000; Hesami, 2025). Reverse logistics allows for the return of leftover commodities to suppliers, saving them from being wasted. Additionally, the money saved by this method can be used to purchase in-demand items to be distributed to more flood victims, thus reducing human suffering. This strategy will successfully deal with the problem of relief aid shortages. Thus, reverse logistics helps reduce deprivation cost and guarantees the best possible use of finances.

Reduction of lead time across the relief chain: Shorter lead times significantly reduce deprivation costs by ensuring faster delivery of essential goods. Rapid response—often within the critical initial hours following a disaster—enhances service effectiveness and reduces human suffering (Karuppiah et al., 2021).

These motivators are grounded in the principles of operational efficiency, sustainability, and circular supply chain, and collectively contribute to minimizing the human and economic impacts of delayed relief.

2.2.4 Motivators of Organizational Culture

Organizational culture is strengthened through the following key motivators:

Decision agility and adaptive capabilities: Agility is a critical capability required in the humanitarian organizations in the HSCs. Agility and adaptability can enable organizations to take quick informed decisions, enabling rapid and flexible responses in uncertain and dynamic environments (Oloruntoba & Kovács, 2015). Effective information sharing and visibility foster trust and collaboration among stakeholders, thereby enhancing coordination and responsiveness (Dubey et al., 2022; Xu et al., 2021).

Green public procurement practices: Green public procurement practices by humanitarian organizations promote environmentally responsible purchasing decisions and support broader sustainability goals within HSC. The adoption of sustainable procurement practices enhances long-term resilience and reduces the environmental footprint of humanitarian operations (Orfanidou et al., 2024).

Accurate documentation and information management: Accurate and reliable documentation improves decision-making, operational efficiency, and accountability of a humanitarian organization. Effective information management systems ensure data integrity and facilitate better coordination among stakeholders (Anjomshoae et al., 2019; Kumar et al., 2024).

Employee empowerment and motivation: Empowering employees to participate in decision-making processes enhances organizational commitment, innovation, and performance. A supportive work environment encourages proactive problem-solving and the adoption of sustainable practices, thereby strengthening overall organizational effectiveness (Muduli et al., 2013; Orfanidou et al., 2024).

Collectively, these motivators enhance coordination, adaptability, and innovation within humanitarian organizations. The enhanced work culture eventually aids in more resilient and effective HSC operations.

2.3 Humanitarian Aid Prioritization

Effective prioritization of humanitarian aid is critical for maximizing the impact of limited resources. Based on prior studies (Holguín-Veras et al., 2013; Sarma et al., 2018), this study categorizes relief items into five groups: water, food, healthcare, shelter, and non-food items. Among these, water, food, and healthcare are considered primary needs due to their direct impact on survival, while shelter and non-food items are typically addressed in later stages. Flood disasters significantly exacerbate vulnerabilities such as food insecurity, water contamination, and health risks, particularly in regions like Bihar (Kumar et al., 2016). Therefore, prioritizing essential relief aid categories is crucial for reducing deprivation and improving HSC effectiveness.

2.4 Multi-Criteria Decision-Making in Humanitarian Supply Chains

MCDM methods have been widely applied in HSC research to address complex decision problems involving multiple, often conflicting criteria. Techniques such as the AHP, BWM, TOPSIS, and hybrid approaches have been used for supplier selection, performance evaluation, and resource allocation (Anjomshoae et al., 2017; Reza et al., 2017; Zulqarnain et al., 2020). These methods enable decision-makers to systematically evaluate alternatives based on both qualitative and quantitative criteria.

Recent studies have increasingly adopted hybrid MCDM frameworks to enhance decision accuracy and robustness. For example, integrated BWM-TOPSIS and fuzzy-based approaches have been used to analyze supply chain resilience, sustainability, and risk management (Bafail & Abdulaal, 2022; Xiaomei et al., 2019; Wang et al., 2024). These methods work especially well in humanitarian settings when ambiguity, uncertainty, and inadequate information are prevalent.

Although inspired by the previous studies based on BWM-TOPSIS method, this paper presents the first-ever study that has applied this integrated BWM-TOPSIS method for flood-relief HSC, particularly using a real-life case study of Bihar floods. Moreover, this paper presents a novel decision framework that uses supply chain facilitators as decision criteria, motivators as decision sub-criteria and relief items as alternatives. Given the hierarchical structure of the decision problem in this study—comprising facilitators, motivators, and aid alternatives—a hybrid MCDM approach is well justified. It allows for systematic prioritization, incorporation of expert judgment, and handling of complex interrelationships among criteria.

The detailed methodology for this study is presented from hereon.

3. Research Methodology

This section describes the methodology followed for this research study. A hybrid MCDM method that uses BWM and TOPSIS is proposed to develop an integrated framework of key facilitators, motivators, and relief aids for HSC in the Bihar flood context.

3.1 Case Study of Bihar Floods

Bihar, a flood-prone state located in eastern India, has long suffered from recurrent and devastating flood disasters that significantly affect human lives, livelihoods, and infrastructure. Based on Census 2011, it ranks first in terms of population density, with 1,106 people per square kilometer. Geographically, the state lies downstream of the Himalayan foothills and is bordered to the north by Nepal, encompassing large stretches of the fertile Indo-Gangetic alluvial plains. Nearly 80–90% of Bihar's annual rainfall is received during the southwest monsoon season between June and September, making the region highly vulnerable to seasonal flooding. Flooding in Bihar is not an occasional phenomenon but a recurring crisis with severe socio-economic consequences. Approximately 6.868 million hectares out of the state's total geographical area of 9.416 million hectares are classified as flood-prone, accounting for nearly 17.2% of India's total flood-prone land (National Remote Sensing Centre, 2020). Almost every year, floods affect 28 out of 38 districts in Bihar, with 15 districts experiencing chronic and severe impacts (Patrika, 2025). The state's vulnerability is largely driven by hydrological factors, including the concentration of rainfall within the short two-months' monsoon period and presence of several major Himalayan rivers, (Kosi, Gandak, and Bagmati), which transport high sediment loads, leading to riverbed aggradation, unstable flow paths, and frequent embankment breaches (Kumar et al., 2025; Matheswaran et al., 2019; National Remote Sensing Centre, 2020). These hydrological characteristics create rapid-onset and spatially unpredictable floods that severely disrupt transportation networks, isolate communities, and complicate relief distribution. The devastating 2008 Kosi floods, amongst the worst flood disasters in India's history, which affected more than 3.3 million people and displaced nearly one million residents, illustrate how such hydrological disruptions can overwhelm existing disaster response systems (Bharti et al., 2025; Prakash, 2013). Various government agencies, humanitarian organizations, and voluntary institutions are presently involved in flood relief activities in Bihar; however, they face significant challenges in coordinating relief operations, distributing limited resources, and providing quick support to remote and severely affected communities (Navalkar et al., 2025; Sharma et al., 2025). These operational complexities demand a scientifically grounded decision-support framework for improving the agility and effectiveness of flood relief HSCs, that can be directly applied and tested in a state like Bihar. Due to the above reasons, Bihar floods were selected as a case study for our research. This choice was also driven by the fact that Bihar is the authors' place of residence, thereby making it easier to collect data and contact experts from this region.

3.2 Proposed Integrated Framework

After selecting Bihar as a case study, the research methodology, outlined in **Figure 1**, comprised of five stages as described below.

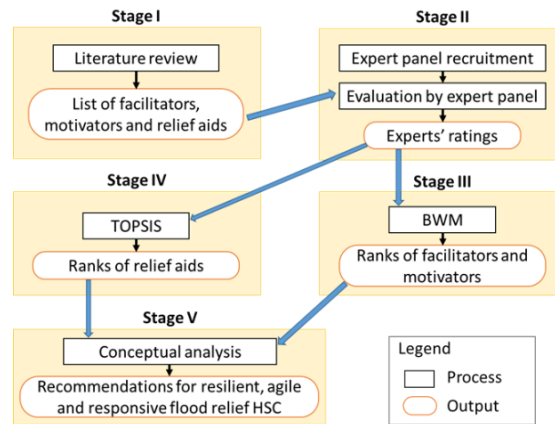


Figure 1. Proposed research methodology.

Stage I: In this stage, a comprehensive literature review was done to identify the HSC facilitators, their associated motivators and the relief aids. The literature was extensively searched using Google Scholar, Web of Science, and Scopus databases. The keywords used for the searches were “humanitarian supply chain”/ “relief supply chain”, “facilitators”, “motivators”, “Bihar floods”, and “flood relief”. All possible combinations of these keywords were searched. Relevant papers, published within the years 1990–2026, were studied and the list of supply chain facilitators, their motivators and humanitarian relief aids were identified and compiled.

Stage II: Following this, many experts were identified based on their long-term experience in the fields of government, private humanitarian relief centers, NGOs, academics, transport companies, FMISC (Flood Management Improvement Support Center), Bihar, and BSDMA (Bihar State Disaster Management Authority). A novel integrated framework is proposed and used where, HSC facilitators were presented as criteria, HSC motivators were presented as sub-criteria and humanitarian relief aids were presented as alternatives to them. The conceptual view and rationale for this framework is described later in Section 4. The instructions for evaluation and the link for online evaluation forms were shared with the identified experts by email communication. In the first evaluation form, experts were presented with the facilitators in pairs, and they had to rate these facilitators’ relative importance using pairwise comparisons on the evaluation scale given in **Table 2**. In the second evaluation form, the experts were asked to evaluate the motivators using pairwise comparisons in the same format as followed for rating the facilitators. In the third evaluation form, experts were asked to rate the importance of relief aids against each motivator, whose detailed method is given in Section 3.4. Six experts completed the evaluation tasks, whose profile is shown in **Table 3**.

Table 2. Evaluation scale used by the experts.

Number	Significance
01	Equal importance
02	Somewhat between equal and moderate
03	Moderately more important than
04	Somewhat between moderate and strong
05	Strongly more important than
06	Somewhat between strong and very strong
07	Very Strong important than
08	Somewhat between very strong and absolute
09	Absolutely more important than

Table 3. Profile of the expert panel.

Experts (E)	Designation	Experience (Years)	Affiliation
E1	Chief Medical Officer cum Civil Surgeon	40+	Member of Disaster Management Department, Bihar
E2	Chief engineer in Water Resource Department (WRD)	25	Member of Flood Management Improvement Support Centre (FMISC)
E3	Flood Management Specialist cum Project Advisor	20	Member of Flood Management Improvement Support Centre (FMISC)
E4	Executive Engineer	10	Public Health Engineering Department (PHED), Bihar
E5	Section Officer	12	Bihar State Disaster Management Authority (BSDMA)
E6	District Magistrate (DM)	15	Member of Disaster Management Department, Bihar & president of the District Branch of the Indian Red Cross Society in Bihar

Stage III: The facilitators and their corresponding motivators were ranked based on their weights, which were calculated using the BWM tool. BWM is one of the most modern MCDM techniques (Rezaei, 2015), which offers clear advantages over traditional approaches such as the AHP and the Analytic Network Process (ANP), particularly in data-scarce and time-sensitive humanitarian settings. Firstly, AHP requires $\frac{n(n-1)}{2}$ pairwise comparisons for n criteria (comparisons are made on all possible pairs of criteria), whereas BWM reduces this burden to only $(2n - 3)$ comparisons by focusing only on comparisons of each criterion with the single best and worst criterion (Rezaei, 2015). This substantial reduction in comparisons minimizes cognitive load on experts and decreases the likelihood of inconsistent or contradictory judgments. In contrast, ANP introduces additional complexity by accounting for interdependencies among criteria, which significantly increases the number of comparisons and computational effort (Bafail & Abdulaal, 2022; Xiaomei et al., 2019). Second, the AHP uses the 1/9-9 scale, but the BWM's structured comparing procedure only uses integers on the 1-9 scale. In this way, comparisons become further less complicated. By simplifying the elicitation process while maintaining a structured comparison framework, BWM improves the consistency ratio of judgments and enhances the stability of derived weights. Consequently, these features lead to greater reliability and accuracy in decision outcomes by BWM. Thus, BWM is particularly suitable for evaluating supply chain facilitators and motivators under the uncertainty and urgency characteristic of flood relief operations. Since facilitators and motivators do not contribute equally to the development of an agile humanitarian relief supply chain in Bihar's flood-affected areas, the global weights of the supply chain motivators were computed. The BWM was implemented using BWM Excel solver, and its mathematical formulations are given in Section 3.3.

Stage IV: The humanitarian relief aids with respect to the identified motivators were ranked using the TOPSIS MCDM tool. Based on this, the most valuable humanitarian relief aid was identified. TOPSIS was used as it offers advantages such as a simple, intuitive logic, handling of both quantitative and qualitative data, clear ranking based on relative closeness to ideal, and ease of programming. Its core strength lies in balancing trade-offs by considering both ideal (best) and anti-ideal (worst) scenarios simultaneously, unlike some methods that focus solely on one extreme. The TOPSIS was implemented using Microsoft Excel solver using the mathematical formulations as illustrated in Section 3.4.

Stage V: Finally, with the identified key facilitators as criteria, key motivators as sub-criteria and most valuable relief aid as alternative, recommendations were proposed for attaining more resilient, agile and responsive HSC for flood relief. This would assist decision-makers in delivering the right aid, at the right location, at the right time, and in the right quantity.

3.3 Best-Worst Method (BWM)

As illustrated above, BWM was an important part of our research methodology, whose detailed procedure is described in this sub-section. Rezaei (2015) created BWM, a robust and innovative MCDM method that compares the worst and best criteria pairwise (Rezaei, 2015). The steps of the BWM applied to determine the weights of the significant supply chain facilitators and their motivators are described below.

First, the list of facilitators obtained from literature review were represented as a set of n criterion $\{C_1, C_2, C_3, \dots, C_n\}$ that can influence the agility of HSC in the context of Bihar floods. Experts evaluated the relative importance of each criterion using pairwise comparisons on the evaluation scale of 1 (equally important) to 9 (absolutely more important than). The meanings of each number on this scale are presented in **Table 2**. The global preference rating of i^{th} criteria (p_i) was evaluated as a sum of expert ratings across all comparisons as follows:

$$p_i = \sum_{k=1}^m \sum_{j=1}^n p_{ij}^k \quad (1)$$

where, m, n represent the number of experts and number of criteria respectively. p_{ij}^k represents the evaluation number given to criteria i when compared with criteria j by the expert k .

The best (most important) criterion, C_B and worst (least important) criterion C_W were identified as those having the highest and lowest global preferential weights respectively. Consequently, the “Best to Others” vector, P_B , was obtained by assessing the preference of the best criterion C_B over each criterion $\{C_1, C_2, C_3, \dots, C_n\}$ as follows:

$$P_B = (p_{B1}, p_{B2}, p_{B3}, \dots, p_{Bn}) \quad (2)$$

where, p_{Bj} indicates the preference number of the best criterion C_B over criterion j (refer to **Table 2** for these numbers). Hence, it is obvious that $p_{BB} = 1$.

Similarly, “Other to Worst” vector, P_W was obtained by assessing the preference of each criterion $\{C_1, C_2, C_3, \dots, C_n\}$ over the worst criterion C_W as follows:

$$P_W = (p_{1W}, p_{2W}, p_{3W}, \dots, p_{nW}) \quad (3)$$

where, p_{jW} indicates the preference number of criterion j over the worst criterion C_W . Hence, $p_{WW} = 1$.

Let $w = (w_1, w_2, \dots, w_n)$ be the vector of unknown weights associated with the criteria, where $w_1 \geq 0$ and $\sum_{j=1}^n w_j = 1$. The optimal weights $(w_1^*, w_2^*, w_3^*, \dots, w_n^*)$ of each criterion were calculated. The optimal weight for a criterion j is the one where, for each pair of $\frac{w_B}{w_j}$ and $\frac{w_j}{w_W}$, we have $\frac{w_B}{w_j} = a_{Bj}$, and $\frac{w_j}{w_W} = a_{jW}$.

To satisfy these conditions for all j , optimization was done such that the maximum absolute differences $\left| \frac{w_B}{w_j} - a_{Bj} \right|$ and $\left| \frac{w_j}{w_W} - a_{jW} \right|$ for all j was minimized. This was formulated as the min-max optimization model as follows:

$$\minmax = \left\{ \left| \frac{w_B}{w_j} - a_{Bj} \right|, \left| \frac{w_j}{w_W} - a_{jW} \right| \right\} \quad (4)$$

The constraints were as follows and were applied to all $j = 1, 2, \dots, n$.

$$\sum_j w_j = 1 \quad (5)$$

$$w_j \geq 0 \quad (6)$$

$$\left| \frac{w_B}{w_j} - a_{Bj} \right| \leq \xi \quad (7)$$

$$\left| \frac{w_j}{w_w} - a_{jw} \right| \leq \xi \quad (8)$$

The ξ represented the arbitrarily chosen error factors in optimization problems. Solving the above equations, the optimal weights ($w_1^*, w_2^*, w_3^*, \dots, w_n^*$) and as well as the optimal value of ξ^* (lowest value of ξ in optimization problem) were obtained. ξ^* can be seen as a direct indicator of the comparison system's consistency. The closer the value of ξ^* is to zero, the higher the consistency, and, consequently, the more reliable the comparisons become.

Rezaei (2015) have provided a table of consistency index (CI) depending on the type of comparisons made and have proposed consistency ratio (CR) as a measure of the degree of consistency for the obtained preference relation. They suggest that when the CR is less than the specific value obtained from the consistency index table, the preference relation has acceptable consistency; otherwise, the collected preference relation is not consistent and will be again returned to experts for pair-wise comparison. CR is defined as follows:

$$CR = \frac{\xi^*}{CI} \quad (9)$$

Preferably, CR should be close to zero and always be less than 1. The same process was followed for the motivators to the supply chain facilitators. Here, the list of motivators obtained from literature review were represented as a set of m sub-criterion $\{C_1', C_2', C_3', \dots, C_m'\}$ that can influence the agility of HSC in the context of Bihar floods.

3.4 Technique for Order Performance by Similarity to Ideal Solution (TOPSIS)

As illustrated in Section 3, TOPSIS was another important part of our research methodology, whose detailed procedure is described in this sub-section. Hwang and Yoon developed the TOPSIS method in 1981. The TOPSIS is based on the concept that the chosen alternative should have the shortest geometric distance from the positive ideal solution (PIS) and the longest geometric distance from the negative ideal solution (NIS) (Ma et al., 2019). TOPSIS views an MCDM problem with m -alternatives as a geometric system with m points in the n -dimensional space (Zulqarnain et al., 2020). TOPSIS was used for collaborative decision-making by the experts in order to choose appropriate humanitarian aid, when information is ambiguous. By reducing an alternative's distance from a PIS and increasing its distance from a NIS, this method ranks alternatives according to their distance being farthest from the NIS, while being closest to the PIS. The PIS aims to maximize the beneficial criteria, whereas the NIS aims to maximize the conflicting criteria while lowering the beneficial criteria (Ganguly et al., 2025). Below is a description of how TOPSIS was implemented for ranking and prioritizing humanitarian relief aid with respect to the HSC motivators.

First, the experts were asked to rate the performance of the relief aids using the Likert scale shown in **Table 4**. Let there be l alternatives $\{A_1, A_2, A_3, \dots, A_l\}$ evaluated against m sub-criteria $\{C_1', C_2', C_3', \dots, C_m'\}$. Let the performance of i^{th} alternative, A_i with respect to j^{th} sub-criterion C_j' be denoted by X_{ij} . The decision matrix $X = [x_{ij}]_{m \times n}$ with l alternatives and m sub-criteria, was calculated as follows:

$$(X_{ij})_{l \times m} = \begin{bmatrix} A_1 [X_{11} & X_{12} & \dots & X_{1m}] \\ A_2 [X_{21} & X_{22} & \dots & X_{2m}] \\ \vdots & \vdots & \ddots & \vdots \\ A_l [X_{l1} & X_{l2} & \dots & X_{lm}] \end{bmatrix} \quad (10)$$

Table 4. Likert scale for rating importance in the TOPSIS.

Rating	Description	Meaning
1	Equal importance	The humanitarian aid is of equal importance and has a minimal impact on logistics and agility of HSC
2	Moderate importance	The humanitarian aid is of moderate importance and has limited impact on logistics and agility of HSC
3	Strongly importance	The humanitarian aid is of strong importance and has a strong impact on logistics and agility of HSC
4	Very strongly importance	The humanitarian aid is of very strong importance and has significant impact on logistics and agility of HSC
5	Extreme importance	The humanitarian aid is of extreme importance and has a critical impact on logistics and agility of HSC

To eliminate the effect of different units of measurement, the decision matrix was normalized using vector normalization, and Normalized Decision Matrix, $R = [r_{ij}]_{l \times m}$, was obtained as follows:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}} \quad (11)$$

where, r_{ij} is the normalized performance value, with $i = 1, 2, \dots, l$, and $j = 1, 2, \dots, m$.

Then, the weighted normalized decision matrix ($V = [v_{ij}]_{l \times m}$) was calculated by multiplying the normalized decision matrix by the weights of the criteria as shown below.

$$v_{ij} = w_j r_{ij} \quad (12)$$

where, w_j is the weight of the j -th criterion.

The PIS was calculated as the maximum value of beneficial criteria or minimum value of non-beneficial criteria as denoted by $(V_i^+ = \{v_1^+, v_2^+, v_3^+, \dots, v_n^+\})$. Accordingly, the NIS was calculated as the minimum value of beneficial criteria or maximum value of non-beneficial criteria as denoted by $(V_i^- = \{v_1^-, v_2^-, v_3^-, \dots, v_n^-\})$. The PIS and NIS can be mathematically formulated as the following optimization problems.

$$V_i^+ = \{[\min(v_{ij} | i = 1, 2, \dots, l) | j \in J^-], [\max(v_{ij} | i = 1, 2, \dots, l) | j \in J^+]\} \quad (13)$$

$$V_i^- = \{[\max(v_{ij} | i = 1, 2, \dots, l) | j \in J^-], [\min(v_{ij} | i = 1, 2, \dots, l) | j \in J^+]\} \quad (14)$$

where, J^+ and J^- represent the beneficial criteria set and non-beneficial criteria set.

Now, the distance of each alternative was obtained from the PIS and the NIS given by the following Euclidean distance equations.

$$D_i^+ = \sqrt{\sum_{j=1}^m (v_{ij} - V_j^+)^2} ; j = 1, 2, \dots, m \quad (15)$$

$$D_i^- = \sqrt{\sum_{j=1}^m (v_{ij} - V_j^-)^2} ; j = 1, 2, \dots, m \quad (16)$$

The relative closeness coefficient CC_i of each i^{th} alternative to the ideal solution was calculated as follows.

$$CC_i = \frac{D_i^-}{D_i^+ + D_i^-} ; 0 \leq CC_i \leq 1; i = 1, 2, \dots, l \quad (17)$$

The alternative with the maximum value of CC_i had the highest-ranking score, which was selected as the optimal alternative.

4. Results

This section presents the findings of our study. It begins with the description of the integrated framework of facilitators, motivators and relief aids, and how they position in an MCDM tool for flood relief HSC. This is presented in sub-section 4.1. The most significant flood relief HSC facilitators and their motivators, prioritized using BWM, are listed in sub-section 4.2 as key facilitators and motivators. Section 4.3 presents the key humanitarian aids, i.e. the most critical relief aids found using TOPSIS, and Section 4.4 displays the sensitivity analysis of the applied methodology.

4.1 Integrated Framework of Facilitators, Motivators and Relief Aids of Flood Relief HSC

The facilitators and their motivators as found from the comprehensive literature review are already stated in **Table 1**. Similarly, the identified Humanitarian aids in flood relief context were: (i) water and sanitation, (ii) food (gram, puffed rice, gram flour, rice, wheat flour, etc.), (iii) non-food (clothing, blankets, mosquito nets, hygiene kits, and cooking equipment), (iv) healthcare (medicines, first aid, and essential healthcare services such as medical diagnosis, treatment, ambulance and rehabilitations), and (v) shelter (distributed material to rebuild house or camp) and protection. The objective of an HSC is to ensure the timely, efficient, and equitable delivery of relief aid to affected populations under conditions of uncertainty, resource scarcity, and infrastructural disruption. Achieving this objective requires not only the selection of appropriate relief aid options but also a systematic evaluation of the organizational and operational factors that enable effective supply chain performance. Accordingly, the present study adopts a three-level decision hierarchy comprising supply chain facilitators as criteria, their motivators as sub-criteria, and relief aid options as alternatives. **Figure 2** presents this integrated framework adopted for application of BWM and TOPSIS.

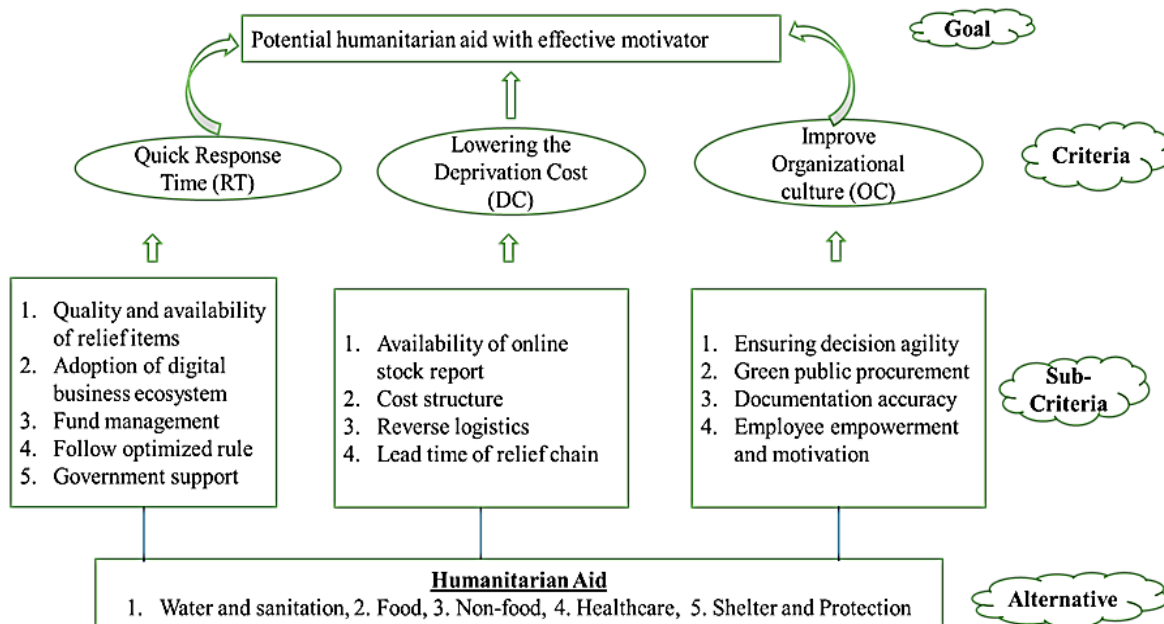


Figure 2. Integrated framework of facilitators, motivators and relief aids for flood relief HSC.

Supply chain facilitators represent the principal enabling dimensions that determine the performance of humanitarian operations. These facilitators capture system-level capabilities, namely, Quick Response Time, Lowering the Deprivation Cost, Improving the Organizational Culture, which directly influence the feasibility and effectiveness of relief efforts. Treating these facilitators as criteria allows for a structured evaluation of the foundational elements required for successful humanitarian response.

The effectiveness of each facilitator is driven by a set of underlying motivators, which explain the conditions under which facilitators become operationally effective. Modelling these motivators as sub-criteria enables a granular assessment of each facilitator, improves measurability, and enhances the transparency of expert judgments. This hierarchical decomposition is consistent with the requirements of the BWM, which relies on structured pairwise comparisons to derive reliable and consistent weights for criteria and sub-criteria.

Relief aid options are modelled as alternatives, as they constitute the actionable outcomes of HSC decisions. Different relief aid types impose varying demands on logistics capacity, coordination, and resources; therefore, their performance must be evaluated relative to the identified facilitators and motivators. The TOPSIS method is employed to rank the relief aid alternatives, thereby identifying the aid option that best aligns with the weighted facilitator–motivator structure.

4.2 Key Facilitators and Motivators for Flood Relief HSC

Table 5 shows the Best to Others supply chain facilitators and **Table 6** shows the Best to Others supply chain motivators to the facilitators. Four experts out of six, rated Response Time (RT) as the most important supply chain facilitator. Quality and availability of relief items (RT1) (motivator of response time), Lead time of relief chain (DC4) (motivator of deprivation cost), and Employee empowerment and motivation (OC4) (motivator of organizational culture) were rated as the most important motivators.

Table 5. Best to others supply chain facilitators.

Expert	Best facilitators	Ranks		
		RT	DC	OC
E1	RT	1	3	8
E2	RT	1	8	3
E3	RT	1	6	3
E4	DC	2	1	9
E5	RT	1	2	6
E6	DC	3	1	8

Table 6. Best to others supply chain motivators.

Expert	Motivators of response time facilitator						Motivators of deprivation cost facilitator				Motivators of organizational culture facilitator					
	Best	RT1	RT2	RT3	RT4	RT5	Best	DC1	DC2	DC3	DC4	Best	OC1	OC2	OC3	OC4
E1	RT1	1	2	3	4	9	DC4	3	9	2	1	OC4	3	2	9	1
E2	RT4	2	4	3	1	9	DC3	3	9	1	2	OC4	8	3	2	1
E3	RT3	2	8	1	3	9	DC4	2	5	9	1	OC4	3	9	2	1
E4	RT1	1	9	2	4	7	DC3	3	9	1	2	OC3	3	9	1	2
E5	RT3	2	9	1	3	6	DC4	3	8	2	1	OC4	3	9	2	1
E6	RT3	2	4	1	3	9	DC4	8	5	2	1	OC3	9	4	1	2

Table 7 shows the Others to Worst supply chain facilitators and **Table 8** shows the Others to Worst supply chain motivators to the selected facilitators. Organizational Culture (OC) out of three facilitators, is rated

as the least important. The least important motivators are Government support (RT5) for Response time (RT) facilitator, Cost structure (DC2) for Deprivation cost (DC) facilitator, and Green public procurement (OC2) for Organizational Culture (OC) facilitator.

Table 7. Others to worst supply chain facilitators.

Expert	Worst facilitators	Ranks		
		RT	DC	OC
E1	OC	8	2	1
E2	DC	9	1	3
E3	DC	8	1	2
E4	OC	4	6	1
E5	OC	5	3	1
E6	OC	3	7	1

The optimal weights (w_1^* , w_2^* , w_3^* , ..., w_n^*) of each of the supply chain facilitators and their motivators are presented in **Tables 9** and **10** respectively. It also shows the final weights of the supply chain facilitators and motivators by calculating the arithmetic mean of the weights of each expert. ξ^* value of the facilitators for the individual experts, as well the mean ξ^* remained within 0.1 and were considered acceptable as per the standards of the previous research (Liang et al., 2020). Similarly, ξ^* value of the motivators for the individual experts, as well the arithmetic mean ξ^* remained within 0.2 and were considered acceptable. This validated the consistency of the presented approach. It was found that Response Time (RT) has the highest weight and is the most important facilitator. Moreover, the Quality and availability of relief items (RT1), Lead time of relief chain (DC4), and Employee Empowerment and motivation (OC4) have the highest weightage and are crucial motivators of their respective facilitators.

Table 8. Others to worst supply chain motivators.

Expert	Motivators of response time facilitator						Motivators of deprivation cost facilitator				Motivators of organizational culture facilitator					
	Worst	RT1	RT2	RT3	RT4	RT5	Worst	DC1	DC2	DC3	DC4	Worst	OC1	OC2	OC3	OC4
E1	RT5	9	8	3	2	1	DC2	5	1	6	9	OC3	6	7	1	9
E2	RT5	8	6	7	9	1	DC2	4	1	9	7	OC1	1	5	7	9
E3	RT5	7	2	9	6	1	DC3	6	5	1	7	OC2	5	1	7	9
E4	RT2	9	1	8	6	3	DC2	5	1	9	7	OC2	5	1	9	7
E5	RT2	7	1	9	5	2	DC2	4	1	6	8	OC2	7	1	8	9
E6	RT5	6	2	9	5	1	DC1	1	3	7	8	OC1	1	5	9	7

Table 9. Weights of supply chain facilitators.

	RT	DC	OC	ξ^*
E1	0.703	0.216	0.081	0.036
E2	0.699	0.082	0.219	0.082
E3	0.7	0.1	0.2	0.067
E4	0.579	0.316	0.105	0.033
E5	0.239	0.672	0.09	0.018
E6	0.261	0.652	0.087	0.042
Mean weight	0.530167	0.3396667	0.1303333	0.046333

Table 10. Weights of motivators of supply chain facilitators. (AM = Arithmetic Mean).

	Motivators of response time facilitator						Motivators of deprivation cost facilitator					Motivators of organization culture facilitator				
Expert	RT1	RT2	RT3	RT4	RT5	(ξ)	DC1	DC2	DC3	DC4	(ξ)	OC1	OC2	OC3	OC4	(ξ)
E1	0.426	0.269	0.129	0.097	0.043	0.097	0.192	0.051	0.242	0.515	0.083	0.198	0.245	0.047	0.509	0.125
E2	0.3	0.082	0.118	0.464	0.036	0.208	0.184	0.048	0.493	0.275	0.069	0.051	0.186	0.28	0.483	0.125
E3	0.269	0.048	0.461	0.179	0.043	0.125	0.318	0.127	0.052	0.502	0.222	0.184	0.048	0.276	0.492	0.083
E4	0.585	0.046	0.207	0.103	0.059	0.208	0.184	0.048	0.492	0.276	0.083	0.184	0.048	0.492	0.276	0.083
E5	0.283	0.043	0.478	0.13	0.065	0.083	0.182	0.055	0.273	0.491	0.071	0.204	0.044	0.248	0.504	0.167
E6	0.274	0.095	0.463	0.126	0.042	0.083	0.055	0.121	0.302	0.522	0.125	0.05	0.157	0.537	0.256	0.153
AM	0.356	0.097	0.309	0.183	0.048	0.132	0.185	0.075	0.309	0.430	0.107	0.145	0.121	0.313	0.42	0.122

Table 11 shows the global weights of motivators and their facilitators, which are calculated as the arithmetic mean values of the weights by the individual experts. In this table, the global weight of a motivator is calculated as the multiplication of its facilitator's weight and that motivator's weight. These calculations also confirm that Response Time (RT) is the most important facilitator for flood relief HSC. Additionally, the Quality and availability of relief items (RT1), Fund management (RT3), Lead time of relief chain (DC4), Follow optimized route (RT4), Reverse logistics (DC3), and Employee Empowerment and motivation (OC4) are the most influential motivators for flood relief HSC.

Table 11. Global weights of the supply chain facilitators and their motivators.

	Weight	Sub-criteria	Weight	Global weight	Category rank	Overall rank
Criteria C1	0.530166667	RT1	0.356166667	0.188827694	1	1
		RT2	0.097166667	0.051514528	4	8
		RT3	0.309333333	0.163998222	2	2
		RT4	0.183166667	0.097108861	3	5
		RT5	0.048	0.025448	5	11
Total			0.993833 ≈ 1			
C2	0.339667	DC1	0.185833333	0.063121389	3	6
		DC2	0.075	0.025475	4	10
		DC3	0.309	0.104957	2	4
		DC4	0.430166667	0.146113278	1	3
Total			1			
C3	0.130333333	OC1	0.145166667	0.018920056	3	12
		OC2	0.121333333	0.015813778	4	13
		OC3	0.313333333	0.040837778	2	9
		OC4	0.42	0.05474	1	7
Total	1		1	1		

4.3 Key Humanitarian Aids for Flood Relief HSC

The rank of the humanitarian aids for relief work was determined with respect to lowering the deprivation cost with quick response by humanitarian actors in a healthy organizational culture. The comprehensive review and expert's interviews gave the five life-saving humanitarian aids as – water and sanitation (A1), food (A2), non-food (A3), healthcare (A4), and shelter protection (A5), and they were compared against the thirteen motivators as the evaluation criteria. For applying the TOPSIS technique, the motivators were categorized as beneficial criteria and non-beneficial criteria, as listed below.

Beneficial criteria (J^+): Quality and availability of relief items, adoption of digital business ecosystem, fund management, follow optimized routes, government support, availability of online stock report, reverse logistics, ensuring digital agility, green public procurement, documentation accuracy, employee empowerment and motivation were identified as beneficial criteria.

Non-beneficial criteria (J^-): Cost structure and Lead time of relief chain were considered non-beneficial criteria.

After TOPSIS application, the calculated relative closeness coefficient (CC_i) to the ideal solution is shown in **Table 12**. Humanitarian aids were ranked in the descending order of the arithmetic mean value of CC_i from all experts. The ranked humanitarian aids are shown in **Table 13**. Hence, the preference order of the humanitarian aids for the decision maker should be healthcare aid, water and sanitation aid, food aid, shelter protection, and lastly non-food aid.

Table 12. Relative closeness coefficient (CC_i) to the ideal solution.

	Expert1 (CC_i)	Expert 2 (CC_i)	Expert 3 (CC_i)	Expert 4 (CC_i)	Expert 5 (CC_i)	Expert 6 (CC_i)	Arithmetic mean (CC_i)
A1	0.438	0.474	0.480	0.601	0.433	0.487	0.486
A2	0.530	0.419	0.627	0.476	0.463	0.394	0.485
A3	0.466	0.328	0.509	0.501	0.451	0.297	0.425
A4	0.642	0.482	0.657	0.602	0.603	0.613	0.600
A5	0.416	0.517	0.355	0.426	0.447	0.427	0.431

Table 13. Ranking of the most important humanitarian aids in flood relief HSC.

Rank	Humanitarian aid	Arithmetic mean (CC_i)
1	Healthcare (A4)	0.600
2	Water and sanitation (A1)	0.486
3	Food (A2)	0.485
4	Shelter protection (A5)	0.431
5	Non-food (A3)	0.425

In order to find the priorities of the motivators with respect to humanitarian aid in flooded areas, the average of all experts' ratings obtained on a five-point Likert scale (refer to **Table 4**) were calculated. Its results are shown in **Table 14**, where the highest score motivator is the most valuable for that humanitarian aid. **Figure 3** represents these results using a radar plot to show the effect of the identified supply chain motivators on the identified humanitarian aids. The top priority "healthcare" aid (A4) and the second priority "water and sanitation" aid (A1) are both individually most influenced by the same set of motivators, namely, "Quality and availability of relief items" (RT1), "Follow optimized route" (RT4), and "Lead time of relief chain" (DC4). For the third priority "food" aid (A2), the motivators namely, "Follow optimized route" (RT4) and "Reverse logistics" (DC3) are most influential. Overall, the motivators within the criteria of Organizational Culture do not significantly influence the flood relief HSC of any of the identified humanitarian aids. This supports the results from BWM where Organizational Culture is found as the least important supply chain facilitator (refer to **Tables 5, 7 and 9**).

Table 14. Priority of motivators for each humanitarian aid. The most important scores are highlighted in bold.

	RT1	RT2	RT3	RT4	RT5	DC1	DC2	DC3	DC4	OC1	OC2	OC3	OC4
A1	4.5	3.833	4.167	5	3.333	3.833	2.667	3.667	5	3.5	4.167	3.5	4.333
A2	4.167	4	3.5	4.333	2.833	3.833	2.667	4.5	4.167	3.333	4	3.667	4.167
A3	3.5	3.667	3.5	3.667	2.833	4.167	3	5	3.833	3	4	3.286	3.667
A4	5	4	4.167	5	3.333	4.167	2.5	4.333	5	4	4	3.667	4.667
A5	3.167	3.167	3.667	4	3	3	3.167	4	2.833	3.167	3.833	3.833	3

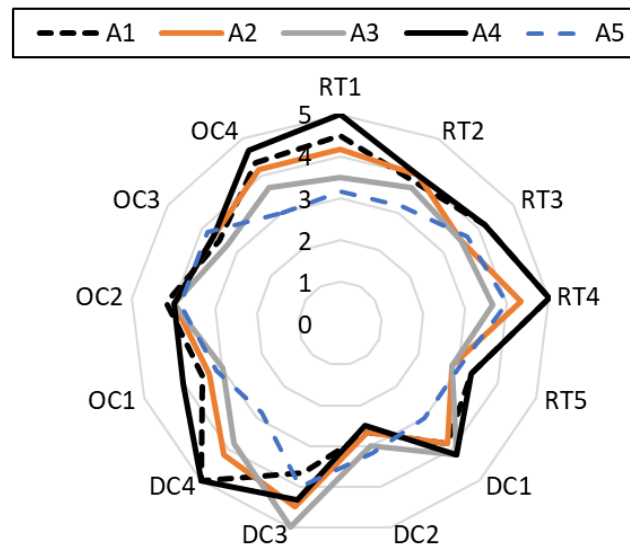


Figure 3. Effect of motivators on the humanitarian aids.

4.4 Sensitivity Analysis

The results of this study are influenced by subjective evaluations of facilitators, motivators, and humanitarian relief alternatives. Consequently, the final rankings may be sensitive to variations in expert judgement, which in turn will vary the assigned weights, making it essential to assess the robustness of the outcomes. To this end, a sensitivity analysis was conducted to examine the stability of the humanitarian aid rankings under different weighting scenarios.

Four additional cases with alternative weighting strategies of motivators were considered. In Case 1, all motivators were assigned equal weights. In Case 2, beneficial and non-beneficial motivators were each assigned 50% of the total weight. In Cases 3 and 4, the weight distributions between beneficial and non-beneficial motivators were set at 80%:20% and 90%:10%, respectively. These modified weights were used to compute the relative closeness coefficients (CC_i), for each alternative, based on the TOPSIS method (sample calculations are provided in Appendix 1). The corresponding end results of weights of aids and their rankings are illustrated in **Table 15** and **Figure 4**. The results indicate that the top three humanitarian aid alternatives remain unchanged across all cases, demonstrating strong stability in priority rankings. The lower-ranked alternatives exhibit minor variations, with the last two positions interchanging only in the most extreme weighting scenario (Case 4). Overall, the rankings show minimal sensitivity to weight adjustments.

Table 15. Result of sensitivity analysis.

	Case 1	Rank	Case 2	Rank	Case 3	Rank	Case 4	Rank	Initial weight	Rank
Water and sanitation(A1)	0.488	2	0.552	2	0.485	2	0.53	2	0.486	2
Food(A2)	0.487	3	0.509	3	0.490	2	0.495	3	0.485	3
Non-food(A3)	0.431	4	0.455	4	0.461	4	0.454	4	0.425	5
Healthcare(A4)	0.639	1	0.649	1	0.586	1	0.657	1	0.6	1
Shelter and protection(A5)	0.375	5	0.344	5	0.416	5	0.347	5	0.431	4

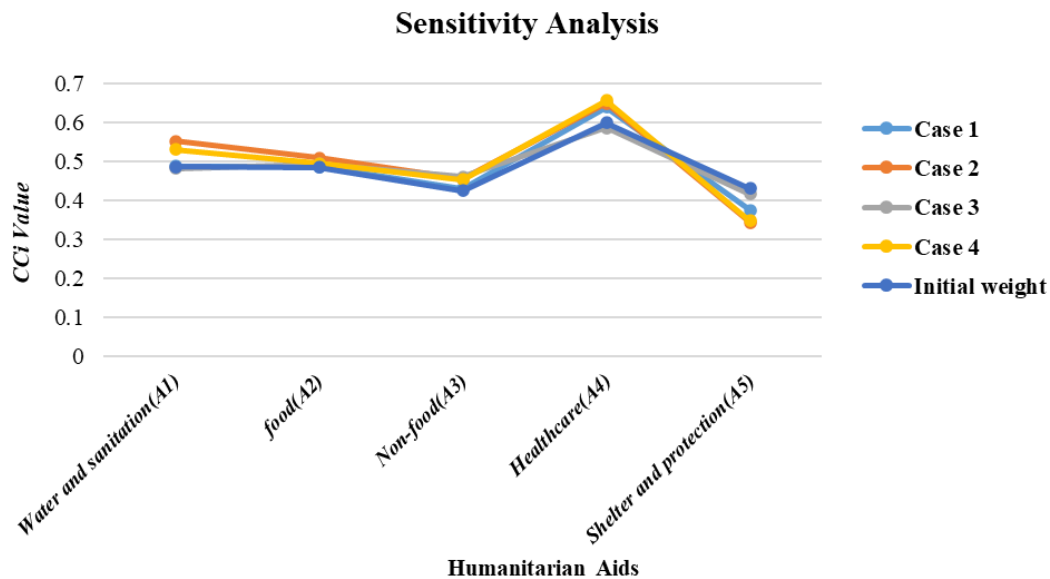


Figure 4. Resultant weights of humanitarian aids after the sensitivity analysis.

In line with established criteria in prior studies (Govindan et al., 2013, 2014), such limited variation under different weighting schemes confirms the robustness and reliability of the proposed methodology. These findings strengthen confidence in the model's applicability for decision-making under uncertain and subjective conditions.

5. Discussions

In this section, the findings of the study are discussed and interpreted in the context of the existing literature and the recommendations for the policy makers are highlighted. The section ends with the description of the scholarly contribution of the research, and its managerial and policy implications.

Figure 5 shows the conceptual view of the finalized recommendations that can be used as actionable insights directly by the policy makers and supply chain managers to ensure the timely, efficient, and equitable delivery of relief aid to affected populations. The present study proposes a three-level decision hierarchy for the flood relief HSC, comprising supply chain facilitators as decision criteria, their corresponding motivators as sub-criteria, and relief aid options as alternatives. Based on the findings, it is recommended that healthcare aids, water and sanitation aids, and food aids be prioritized during emergency flood response within 24 hours from event, with the HSC explicitly oriented toward the rapid and effective delivery of these critical items. Once the immediate requirements for these essential aids are adequately addressed, secondary relief items such as shelter protection materials and non-food items may be supplied in subsequent phases. To enhance the agility, responsiveness and resilience of the flood relief HSC, decision-makers should focus on achieving key system-level capabilities, namely *quick response time* and *reduction of deprivation cost*. To implement these capabilities operational key enablers are identified. The most influential operational motivators of *quick response time* include ensuring the *availability of high-quality relief items* and *identifying and utilizing optimized transshipment and distribution routes*. Furthermore, *reducing the overall lead time* of the flood relief HSC is critical to lowering deprivation costs and improving service levels. In parallel, *minimizing deprivation cost* can be operationally supported through the implementation of effective *reverse logistics* mechanisms, which reduce the wastage of unused

relief items and enable their timely redeployment to other affected or underserved areas.

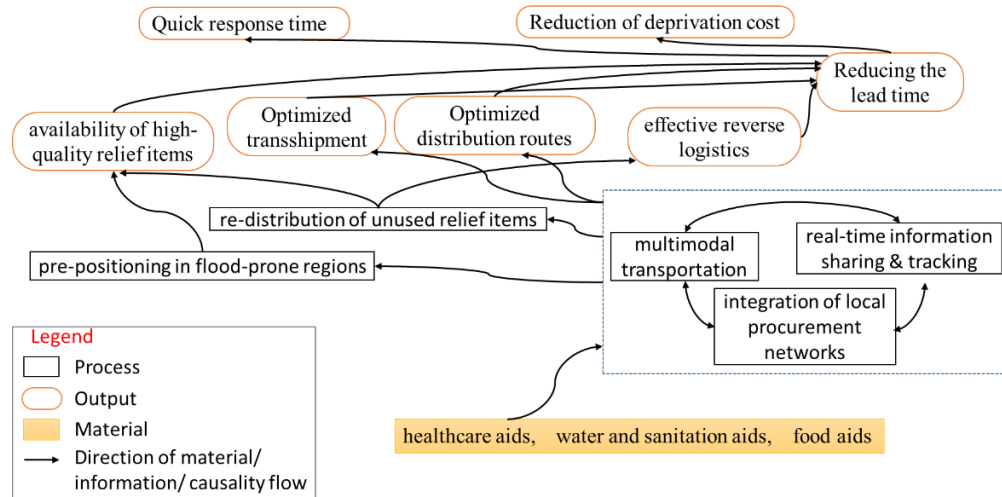


Figure 5. Conceptual view of actionable insights for agile, responsive and resilient HSC for flood relief.

To achieve these objectives, the study recommends several strategic interventions, including the *pre-positioning of essential relief goods in flood-prone regions*, the *integration of local procurement networks* to enhance flexibility, the use of *real-time information and tracking systems* to improve visibility and coordination, and the adoption of *multimodal transport strategies* to overcome infrastructure disruptions.

The developed framework inherently incorporates equity considerations in aid distribution by integrating deprivation cost and time sensitivity into the evaluation process. By assigning higher weights to critical relief items and prioritizing alternatives that minimize unmet demand and delivery delays, the model ensures that underserved and highly affected locations receive greater attention. This approach moves beyond efficiency-driven allocation by explicitly accounting for disparities in access caused by disrupted infrastructure and geographic isolation. As a result, the model promotes a more balanced and just distribution of relief supplies, ensuring that vulnerable populations—particularly those in remote or severely impacted areas—are not overlooked during emergency response operations.

5.1 Interpretations of the Findings and Comparison with Existing Literature

The findings provide important insights into HSC decision-making for flood disasters by integrating operational, humanitarian, and organizational dimensions within a single decision-making framework. Unlike previous studies that have primarily examined these dimensions independently, the proposed framework demonstrates that effective flood relief depends on simultaneously improving response efficiency, minimizing human suffering, and strengthening organizational capabilities. This integrated perspective is consistent with recent calls for more comprehensive and resilient HSC frameworks for addressing increasingly complex disaster situations (Damoah, 2022; Kumar et al., 2024; Wang et al., 2024).

The identification of response time as the most influential facilitator reinforces its role as the primary determinant of HSC performance. This finding agrees with previous studies highlighting rapid response as essential for reducing disaster losses and improving relief effectiveness (Dubey et al., 2022; Fahimnia et

al., 2017; Xu et al., 2021). However, the present study extends this understanding by showing that response time depends not only on transportation efficiency but also on the combined influence of quality relief inventories, optimized routing, transparent fund management, digital information sharing, and government support. These findings support the organizational information processing perspective of Dubey et al. (2022) and recent evidence that digital technologies and coordinated decision-making significantly improve humanitarian responsiveness (Baffoe & Luo, 2020; Wang et al., 2024). They also suggest that technological interventions should complement traditional preparedness strategies such as inventory pre-positioning and route optimization.

The ranking of deprivation cost as the second most important facilitator highlights the growing shift from cost-oriented logistics toward human-centered HSC. While Holguín-Veras et al. (2013) first argued that humanitarian logistics should prioritize reducing human suffering over minimizing transportation costs, recent work by Wang et al. (2024) further formalized deprivation cost as a measure of the societal consequences of delayed relief. By incorporating deprivation cost directly into the decision framework, the present study prioritizes humanitarian aid according to its potential to reduce unmet demand and delivery delays, thereby promoting equitable relief allocation. This finding is consistent with recent studies emphasizing social sustainability, resilience, and equity in humanitarian logistics (Karuppiah et al., 2021; Raj et al., 2022; Sarker et al., 2021).

Although organizational culture received a lower weight, it remains an important enabling capability. The results indicate that employee empowerment, agile decision-making, accurate documentation, and environmentally responsible procurement improve coordination and adaptability across humanitarian organizations. These findings agree with Attia et al. (2023), Cameron & Quinn (1999), and Damoah (2022), who identified organizational capabilities and stakeholder collaboration as essential for resilient humanitarian operations. Rather than directly influencing relief outcomes, organizational culture strengthens the institutional capacity required to implement effective humanitarian logistics.

The prioritization of individual motivators further indicates that preparedness-oriented interventions contribute most significantly to improving HSC performance. High-quality relief inventories, optimized transportation routes, reduced lead times, reverse logistics, and real-time information sharing collectively enhance responsiveness while reducing deprivation costs. These findings support existing studies that emphasize preparedness, flexibility, and adaptive capacity as key characteristics of resilient HSCs (Singh et al., 2018; Xu et al., 2021). They also complement recent studies advocating the adoption of digital business ecosystems, artificial intelligence, blockchain, and data analytics to improve visibility, coordination, and resource allocation during disaster response (Baharmand et al., 2021; Karuppiah et al., 2025; Talwar et al., 2021; Wang et al., 2024).

The prioritization of healthcare aid, followed by water and sanitation and food aid, reflects the immediate survival requirements of flood-affected populations. These priorities are consistent with previous humanitarian logistics studies that identify medical assistance, safe drinking water, sanitation facilities, and food security as the most urgent needs during the first 24-48 hours after flooding (Bardhan & Dangi, 2016; Damoah, 2022; Navalkar et al., 2025; Sharma et al., 2025). Unlike previous research that primarily discusses relief priorities qualitatively, the proposed framework quantitatively ranks humanitarian relief aid alternatives. Consequently, it provides a transparent evidence-based mechanism for prioritizing scarce relief resources while simultaneously considering operational efficiency and humanitarian equity.

Overall, the findings largely corroborate previous humanitarian logistics research while extending it in several important respects. Earlier studies have independently identified agility, resilience, coordination,

and digital technologies as key drivers of HSC performance (Dubey et al., 2022; Wang et al., 2024; Xu et al., 2021). The present study advances this body of knowledge by integrating facilitators, operational motivators, and humanitarian relief alternatives into a single hierarchical framework that explicitly incorporates both efficiency and equity considerations. This integrated approach provides a more comprehensive, practical and evidence-based tool for HSC decision-making for recurrent flood disasters.

5.2 Theoretical Contributions

This study makes four important contributions to HSC literature. First, it proposes an integrated conceptual framework linking response time, deprivation cost, and organizational culture with their operational motivators and humanitarian relief alternatives. This extends previous studies that typically examine these dimensions independently. Second, the study operationalizes deprivation cost within flood relief decision-making by explicitly incorporating equity and human welfare into the prioritization process. This advances recent developments in humanitarian logistics that advocate balancing operational efficiency with social impact (Holguín-Veras et al., 2013; Wang et al., 2024). Third, the research demonstrates the applicability of the hybrid BWM–TOPSIS methodology for complex humanitarian decision problems characterized by uncertainty, limited data availability, and multiple stakeholders. Compared with conventional AHP- and ANP-based approaches, the framework offers greater consistency, lower cognitive burden, and improved robustness. Finally, the study provides context-specific empirical evidence from one of India's most flood-prone regions; thereby extending the relatively limited body of research on flood-specific HSC decision-making in developing countries.

5.3 Managerial and Policy Implications

The findings provide several actionable recommendations for disaster management agencies and humanitarian organizations. Government agencies should prioritize investments that reduce response time, including strategic pre-positioning of emergency inventories, optimized transportation planning, digital information-sharing platforms, and real-time inventory tracking. During the first 24 hours following flooding, healthcare supplies, drinking water, sanitation facilities, and food should receive the highest allocation priority, followed by shelter materials and non-food items during subsequent recovery phases.

Decision-makers should implement reverse logistics systems to recover, inspect, and redistribute unused relief materials, thereby minimizing deprivation costs and reducing resource wastage. Greater integration among government departments, NGOs, healthcare institutions, transport agencies, and community organizations should be supported through inter-operable digital platforms and standardized information-sharing protocols. Finally, investments in artificial intelligence-enabled decision support, GIS-based route optimization, blockchain-supported supply chain transparency, and employee capacity building can substantially improve the agility, resilience, transparency, and equity of HSCs.

6. Conclusions

This study aimed to identify, analyze, and prioritize the key facilitators, motivators and relief aids that enable a resilient and agile HSC for flood relief. A case study of Bihar floods is used. A three-level decision hierarchy is proposed for flood relief HSC, comprising supply chain facilitators as decision criteria, their associated motivators as sub-criteria, and relief aids as alternatives. Methodology includes a comprehensive literature review and theoretical analysis, followed by expert's evaluation and the use of hybrid BWM–TOPSIS for ranking. *Healthcare aids*, *water and sanitation aids*, and *food aids*, in that order, are found as the most critical flood relief humanitarian aids. They should be prioritized during emergency flood response, with the HSC explicitly oriented toward the rapid and effective delivery of these critical items.

To enhance the agility and responsiveness of the flood relief HSC, decision-makers should focus on achieving key supply chain facilitators representing system-level capabilities, namely *quick response time* and *reduction of deprivation cost*. A *quick response time* could be operationally implemented using the enablers namely, ensuring the *availability of high-quality relief items* and *identifying and utilizing optimized transshipment and distribution routes*. In parallel, *minimizing deprivation cost* can be operationally supported through the implementation of effective *reverse logistics* mechanisms and *reducing the overall lead time* of the flood relief HSC. To achieve these objectives, the study recommends several strategic interventions that use data-driven and advanced technologies. This study provides actionable guidance for policymakers and practitioners seeking to design and operate an agile, resilient, and effective flood relief supply chain.

Despite its contributions, this study has some limitations. It relies on expert judgments in the BWM–TOPSIS framework, introducing some subjectivity into the weighting process. Moreover, the framework was developed using Bihar as the case study; hence, the priorities may vary across regions with different disaster characteristics, socio-economic conditions and institutional settings. Further, the model provides strategic prioritization without including some dynamic operational factors (such as real-time demand fluctuations, stochastic travel times, infrastructure recovery, or resource availability) under evolving flood conditions.

Future studies should validate the framework in other disaster-prone regions and integrate GIS, real-time hydrological data, and optimization or simulation models for dynamic decision-making. Incorporating emerging technologies such as artificial intelligence, Internet-of-Things, and blockchain, together with validation using post-disaster operational data, would further enhance the robustness and practical applicability of the proposed framework.

Appendix 1: Sensitivity Analysis

Case 1- (Expert 1), (Benf. = Beneficial motivator, Non-benf. = Non- beneficial motivator)

Normalized matrix													
	Benf.	Benf.	Benf.	Benf.	Benf.	Benf.	Non-benf.	Benf.	Non-benf.	Benf.	Benf.	Benf.	Benf.
	RT1	RT2	RT3	RT4	RT5	DC1	DC2	DC3	DC4	OC1	OC2	OC3	OC4
A1	0.4833 68245	0.3905 66733	0.4417 26104	0.5241 42418	0.5547 00196	0.4417 26104	0.3651 48372	0.3144 85451	0.5241 42418	0.4850 7125	0.5299 9894	0.3464 10162	0.4417 26104
A2	0.4833 68245	0.5207 55644	0.4417 26104	0.4193 13935	0.4160 25147	0.4417 26104	0.3651 48372	0.4193 13935	0.4193 13935	0.3638 03438	0.4239 99152	0.3464 10162	0.4417 26104
A3	0.3866 94596	0.3905 66733	0.4417 26104	0.3144 85451	0.4160 25147	0.4417 26104	0.5477 22558	0.5241 42418	0.4193 13935	0.3638 03438	0.4239 99152	0.4618 80215	0.4417 26104
A4	0.4833 68245	0.5207 55644	0.5521 5763	0.5241 42418	0.4160 25147	0.5521 5763	0.3651 48372	0.5241 42418	0.5241 42418	0.6063 39063	0.4239 99152	0.5773 50269	0.5521 5763
A5	0.3866 94596	0.3905 66733	0.3312 94578	0.4193 13935	0.4160 25147	0.3312 94578	0.5477 22558	0.4193 13935	0.3144 85451	0.3638 03438	0.4239 99152	0.4618 80215	0.3312 94578
Weight	0.0769 23	0.0769 23	0.0769 23	0.0769 23	0.0769 23	0.0769 23	0.0769 23	0.0769 23	0.0769 23	0.0769 23	0.0769 23	0.0769 23	0.0769 23
Weighted normalized matrix													
	RT1	RT2	RT3	RT4	RT5	DC1	DC2	DC3	DC4	OC1	OC2	OC3	OC4
A1	0.0371 82173	0.0300 43595	0.0339 78931	0.0403 18648	0.0426 69246	0.0339 78931	0.0280 88336	0.0241 91189	0.0403 18648	0.0373 13173	0.0407 69149	0.0266 46936	0.0339 78931
A2	0.0371 82173	0.0400 58126	0.0339 78931	0.0322 54918	0.0320 01934	0.0339 78931	0.0280 88336	0.0322 54918	0.0322 54918	0.0279 8488	0.0326 15319	0.0266 46936	0.0339 78931
A3	0.0297 45738	0.0300 43595	0.0339 78931	0.0241 91189	0.0320 01934	0.0339 78931	0.0421 32504	0.0403 18648	0.0322 54918	0.0279 8488	0.0326 15319	0.0355 29247	0.0339 78931

A4	0.0371 82173	0.0400 58126	0.0424 73664	0.0403 18648	0.0320 01934	0.0424 73664	0.0280 88336	0.0403 18648	0.0403 18648	0.0466 41466	0.0326 15319	0.0444 11559	0.0424 73664
A5	0.0297 45738	0.0300 43595	0.0254 84198	0.0322 54918	0.0320 01934	0.0254 84198	0.0421 32504	0.0322 54918	0.0241 91189	0.0279 8488	0.0326 15319	0.0355 29247	0.0254 84198
Ideal best and ideal worst value													
	benf.	benf.	benf.	benf.	benf.	benf.	non- benf	benf.	non- benf.	benf.	benf.	benf.	benf.
V+	0.0371 82173	0.0400 58126	0.0424 73664	0.0403 18648	0.0426 69246	0.0424 73664	0.0280 88336	0.0403 18648	0.0241 91189	0.0466 41466	0.0407 69149	0.0444 11559	0.0424 73664
V-	0.0297 45738	0.0300 43595	0.0254 84198	0.0241 91189	0.0320 01934	0.0254 84198	0.0421 32504	0.0241 91189	0.0403 18648	0.0279 8488	0.0326 15319	0.0266 46936	0.0254 84198
Euclidean distance from the ideal best													
		Di+	Di-										
A1		0.0352 07401	0.0315 65949										
A2		0.0354 32742	0.0276 47472										
A3		0.0387 51392	0.0249 09749										
A4		0.0209 85028	0.0490 16281										
A5		0.0442 27181	0.0216 57282										
Relative closeness coefficient													
	CCi												
	0.4737 33												
	0.4382 81												
	0.3912 87												
	0.7002 19												
	0.3287 16												

We had calculated CCi for all experts in all 4 cases, which is summarized below.

Case 1: Equal weight to motivators ($\frac{1}{13}$)								
	E1	E2	E3	E4	E5	E6	Avg. CCi	Rank
A1	0.473733	0.525544	0.5556	0.504985	0.433142	0.433142	0.488	2
A2	0.438281	0.476969	0.607302	0.39138	0.505318	0.505318	0.487	3
A3	0.391287	0.426229	0.551591	0.459558	0.380117	0.380117	0.431	4
A4	0.700219	0.6191	0.625653	0.608223	0.639061	0.639061	0.639	1
A5	0.328716	0.373876	0.33405	0.42626	0.39236	0.39236	0.375	5
CASE 2: (beneficiary motivators: non-beneficiary motivators = 50% of total weight: 50% of total weight)								
	E1	E2	E3	E4	E5	E6	Avg. CCi	Rank
A1	0.519655	0.605574	0.61594	0.602877	0.446419	0.519655	0.552	2
A2	0.473048	0.497748	0.636694	0.478111	0.494122	0.473048	0.509	3
A3	0.413907	0.424338	0.543577	0.557443	0.377843	0.413907	0.455	4
A4	0.578628	0.678664	0.709742	0.653132	0.698058	0.578628	0.649	1
A5	0.386533	0.311466	0.237238	0.402228	0.34276	0.386533	0.344	5
CASE 3: (beneficiary motivators: non-beneficiary motivators = 80% of total weight: 20% of total weight)								
	E1	E2	E3	E4	E5	E6	CCi	Rank
A1	0.471617	0.484032	0.51168	0.522536	0.430998131	0.479919	0.485	3
A2	0.465722	0.468444	0.58247	0.480876	0.510716928	0.446397	0.490	2
A3	0.384716	0.429686	0.554954	0.549597	0.380602196	0.464302	0.460	4
A4	0.662016	0.603026	0.571109	0.554342	0.602509074	0.522848	0.586	1
A5	0.364402	0.391859	0.392906	0.46621	0.423984362	0.455179	0.416	5
CASE 4: (beneficiary motivators: non-beneficiary motivators = 90% of total weight: 10% of total weight)								

	E1	E2	E3	E4	E5	E6	CCi	Rank
A1	0.473796	0.575983	0.598743	0.587375	0.438847	0.507936	0.530	2
A2	0.412746	0.489879	0.63162	0.478572	0.495467	0.462764	0.495	3
A3	0.397015	0.422118	0.548621	0.556122	0.379713	0.418483	0.454	4
A4	0.741351	0.644148	0.684168	0.632988	0.676144	0.564575	0.657	1
A5	0.290122	0.346342	0.267942	0.413931	0.361159	0.403355	0.347	5

	Case 1 (CCi)	Case 2 (CCi)	Case 3 (CCi)	Case 4 (CCi)
Water and sanitation (A1)	0.488	0.552	0.485	0.53
Food (A2)	0.487	0.509	0.490	0.495
Non-food (A3)	0.431	0.455	0.461	0.454
Healthcare (A4)	0.639	0.649	0.586	0.657
Shelter and protection (A5)	0.375	0.344	0.416	0.347

Conflicts of Interest

The authors declare they have no potential conflict of interest.

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