Stratified delivery aid plans for humanitarian aid distribution centre selection

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ABSTRACT

Humanitarian aid distribution centres (HADCs) are essential for bridging the gap between stranded beneficiaries and relief aid during a disaster. We incorporate three delivery aid plans (DAPs), namely prioritization by relief items, speed of delivery, and disaster location, into the decision to select HADCs. While anticipating decentralized relief aid supplies, humanitarian practitioners face uncertainties in HADC selection. Grounded in Contingency Theory, DAPs assist in anticipating the uncertain relief aid supplies contingent on the external environment. Hence, HADC selection must incorporate DAPs in pursuit of three performance criteria, namely efficiency, effectiveness, and equity. We propose a stratified multi-criterion decision-making (MCDM) approach for HADC selection in the post-disaster planning phase to counter the uncertainty of decentralized relief aid supplies. We perform numerical studies of the proposed dynamic model using the data on Cyclone Fani. The results show that HADC selection incorporating DAPs is more robust and impactful. We also conduct sensitivity analysis to examine the trade-offs between the performance criteria.

1. Introduction

In recent years, the occurrence of natural disasters has become more prevalent and frequent. In 2020, around 416 natural disasters occurred, causing an economic loss of nearly 268 billion USD and more than 8,100 deaths globally (besides the Covid-19 pandemic) (AON, 2020). Moreover, according to the United Nations report *Economic Losses, Poverty and Disasters 1998–2017* (CRED, 2017), climate and geophysical related disasters killed nearly 1.3 million people and left 4.4 billion homeless in need of emergency assistance. The worldwide economic losses over the same period amounted to 2908 billion USD (CRED, 2017). The *World Economic Forum Global Report on Risks 2020* (World Economic Forum, 2020) considered natural disasters (e.g., Hurricane Katrina in 2005, Sidr cyclone in 2007, and the Haiti earthquake in 2010) as the top global risk in terms of likelihood (World Economic Forum, 2020). Such disasters cause large-scale disruptions leading to significant economic and social losses (Padhi & Mukherjee, 2021). To mitigate the impacts of such disasters, humanitarian aid distribution centres (HADCs), called points of distribution (PODs)[1], play a major role as they bridge the gap between the beneficiaries and the relief items (Loree & Aros-Vera, 2018). In the preparedness phase, the PODs are pre-selected facility locations in a region. In the aftermath of a disaster, it becomes essential to select some of these locations as HADCs (or PODs) from where the relief items like food, water, medical supplies, and other essential items are shipped to the affected regions and beneficiaries.

Researchers have highlighted the importance of logistics in disaster relief, which accounts for 80% of all the logistics activities (e.g., Van Wassenhove, 2006). It is estimated that 73% of humanitarian response spending is related to supply chain and logistics activities. In humanitarian logistics, HADC selection in the response phase is considered a crucial and challenging decision (Anaya-Arenas, Renaud, & Ruiz, 2014). Some studies on the humanitarian supply chain recognize the importance of HADC locations, while designing networks in the preparedness, response, and recovery phases (Banomyong, Varadejsatitwong, & Oloruntoba, 2019; Fosso Wamba, 2020). The relevance of HADCs in the humanitarian context has grown because of the impacts of unprecedented events on the decisions made. In addition, the HADC location decision is considered strategic taken in the pre- or post-disaster phase. Meanwhile, for effective and efficient disaster management planning, HADC location selection is of utmost importance (Boonmee, Arimura, &

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[1] In this study, PODs are considered the same as HADCs.

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Asada, 2017). Below we discuss some examples of HADC selection related issues.

In the 2010 Haiti earthquake, the United Nations established 16 highly capacitated HADCs to provide food to 20,000 victims per day (Loree & Aros-Vera, 2018). However, it took 20 days to establish the HADCs, leading to long waiting times for thousands of victims. Also, the number of HADCs was found to be insufficient to meet the beneficiaries' food requirements (Cave & Thompson, 2010). As a result of the delay and inadequacy in the HADC selection process, hunger and chaos escalated in Port-au-Prince. Therefore, improper selection of HADCs induces aggravated human suffering in Haiti. Furthermore, since 2017, hurricanes like Irma, Maria, and Dorian have caused massive devastations in the US (Chinchar, 2021). Specifically, Dorian was one of the strongest hurricanes observed in the Atlantic basin. Here, the unavailability of an HADC in the proximity of the affected region delayed the movement of relief aid and other essential supplies, leading to grave human suffering (Chinchar, 2021).

In view of this, Amazon and Red Cross recently set up the disaster relief hub in Georgia to respond quickly to disasters (Chinchar, 2021). Dönmez, Kara, Karsu, and Saldanha-da-Gama (2021) emphasized that HADC selection depends on the nature of the disaster and the sources of uncertainty that may arise from the supply side, demand side, and network connectivity. The supply-side uncertainty arises from the nature of the facility and the type of relief items. We focus on the supply-side uncertainty arising from decentralized relief aid supplies given the exogenous environment in the disaster response phase (Özdamar, Ekinci, & Küçükyazici, 2004; Seraji, Tavakkoli-Moghaddam, Asian, & Kaur, 2021). In the post-disaster phase, researchers have modelled the HADC selection problem from different perspectives, including the maximal covering location model, location-allocation model, intermediate distribution facility model, and location-transportation model (Habib, Lee, & Memon, 2016). In terms of methodology, robust optimization, stochastic programming, chance-constrained programming, and heuristics have been applied to find the optimal HADC location under uncertainty (Dönmez et al., 2021).

Furthermore, humanitarian actors and stakeholders often develop delivery aid plans (DAPs) for transport planning in the response phase (Gralla, Goentzel, & Fine, 2014). Different DAPs are characterized by prioritization by relief items type, speed of delivery, or disaster-affected location. There are multiple combinations (or states) of DAPs, which we call strata. The nature of HADCs differs based on the associated DAPs. For example, some HADCs may give preference to disaster-affected regions to deliver relief aid. In such circumstances, there is no relief items and delivery speed prioritization, while all the prepositioned and incoming relief aid will be distributed equally to the disaster-affected regions. Incidentally, the operationalization of the DAP state in an HADC depends on the unanticipated external environment causing decentralized relief aid supplies. Why is the HADC selection decision based on DAPs important? After selecting the candidate locations in the preparedness phase, the task of the humanitarian organization (HO) and government body is to choose the final operating HADCs to deliver the relief aid. After the occurrence of a disaster, the roads are destroyed and the streets flooded (in the case of Cyclone Fani), making relief aid delivery from the HADCs difficult. In such circumstances, the final phase of the HADC selection decision must consider whether the incoming relief aid can be prioritized for the beneficiaries, whether the nearby disaster affected regions can be served, and, importantly, whether the HADC can responsively meet the needs of the stranded beneficiaries.

A few studies have considered post-disaster planning during the response phase under the uncertainties stemming from decentralized relief aid supplies and the external environment (e.g., Ahmadi, Seifi, & Tootooni, 2015; Munyaka & Yadavalli, 2021; Roh, Pettit, Harris, & Beresford, 2015; Yılmaz & Kabak, 2020). The literature has not considered the presence of multiple combinations (or states) of the DAPs in anticipating the uncertainties stemming from the external environment. The literature also lacks a theoretical perspective to entwine the contextual characteristics, rendering the HO unable to take effective measures to adapt to the external environment. The existing literature has not adopted an integrated approach that considers prioritization by relief items type, speed of delivery, and disaster-affected location. Although there is an abundance of research on deterministic modelling concerning uncertainties, the dynamic modelling approach to capture uncertainties is scanty. At the same time, uncertainties are in themselves dynamic in nature. Consequently, a holistic approach through integrating distinct DAPs in a dynamic model is essential for HADC selection, which has not been considered in the literature.

Therefore, from the contingency theoretical perspective, we attempt to ascertain the impacts of such unanticipated distinct strata of the DAPs on the HADC selection decision in the response phase. We seek to answer the research question: *Among the pre-selected candidate HADCs in the preparedness phase, how should an HO or government body make the final HADC selection in the response phase anticipating the decentralized relief aid supplies to alleviate the stranded beneficiaries' suffering?* To address the question, we propose a stratified multi-criterion decision-making (SMCDM) model considering multi-strata DAPs for the HADC selection decision in the disaster response phase, given a set of pre-selected relief distribution centres, based on the three performance criteria of efficiency, effectiveness, and equity. Also, we answer the call for research by Asadabadi (2018) on using the concept of stratification in other prominent MCDM methods (TOPSIS in our case). We operationalize multi-strata DAPs in anticipating the uncertainties induced by decentralized relief supplies and the external environment while seeking to optimize the HADC selection decision. Specifically, we propose a holistic approach integrating distinct DAPs in a dynamic decision-making model for HADC selection. We also conduct sensitivity analysis to evaluate the impacts of the criteria weights on the optimal outcomes and perform numerical studies to generate managerial insights from the analytical findings. For the case of Cyclone Fani under consideration (with three pre-selected HADCs, namely "A", "B", and "C"), the results reveal that incorporating multiple combinations of DAPs in HADC selection using the SMCDM approach results in selecting HADC "A" as the best HADC. In contrast, without considering DAPs in HADC selection results in HADC "B" as the best HADC. This shows that the incorporation of multi-strata DAPs changes the HADC selection outcome. The sensitivity analysis exhibits that HADC "A" is the best HADC in four out of the eight scenarios. The HO preferring equitable distribution must open HADC "A". However, the HO pursuing the effectiveness measure should open HADC "B". If cost-efficiency is the priority, then HADC "C" should be opened. Lastly, the sensitivity analysis reveals the importance of the second-best decision in HADC selection.

We organize the rest of the paper as follows: In Section 2, we provide the theoretical background of the study, review the relevant literature on facility location models in the humanitarian setting and on the concept of stratification. We focus on MCDM-based facility location models in the humanitarian context. Section 3 elaborates on our proposed research methodology, followed by a case study on Cyclone Fani, a discussion on data collection activity and optimal HADC selection by integrating stratified DAPs. Section 4 discusses the sensitivity analysis results and numerical studies to generate managerial insights. In Section 5, we discussed the theoretical and managerial contributions of the study. Finally, in Section 6, we conclude the paper and suggest topics for future research.

2. Relevant studies

In this section, we have reported the theoretical underpinning for HADC selection decision, studies on facility location that captures uncertainty in the humanitarian setting, especially the HADCs, and discuss the concept of stratification.

2.1. Theoretical underpinning

Contingency Theory (CT) is a widely adopted lens to view organizations. The tenet of CT is that organizations adapt to environmental changes to maintain the fit between the environment and organizational structure to achieve higher organizational performance (Donaldson, 2001). Contingency studies mainly include three types of variables, namely contextual, response, and performance variables (Sousa & Voss, 2008). The contextual or contingency variables are the situational characteristics that the organization does not control. At the same time, response variables are the actions taken by the organization to counter the contingencies. Lastly, performance variables measure the fit between the contextual and response variables. In the humanitarian supply chain (HSC) literature, the humanitarian context brings enormous uncertainties in different phases of the disaster and is considered a contextual variable (Prakash, Besiou, Charan, & Gupta, 2020). Another prominent contextual variable could be the disaster type. In addition, HOs take measures to anticipate the external uncertainties based on the contingencies, as observed in the example of the relief hub established by Amazon and the Red Cross. Another example could be demand forecasting in the preparedness phase to anticipate the relief aid uncertainties in the disaster response phase. Moreover, for an HSC to be effective and efficient, the performance measure plays a vital role as it highlights the goals of the HO (Abidi, De Leeuw, & Klumpp, 2014). Applying the CT lens, we focus on the contingency in the disaster response phase and on the actions taken by the HO for optimal HADC selection.

In different phases of the disaster, the effectiveness of humanitarian operations gets strangled by the lack of coordination amongst the stakeholders and the decentralized HSC (Balcik, Beamon, Krejci, Muramatsu, & Ramirez, 2010; Seraji et al., 2021). Particularly in the disaster response phase, the supplies of relief aid items to HADCs remain uncertain because of decentralized HOs, government bodies, local communities, and other HSC actors. Accordingly, it becomes highly uncertain for the decision-maker to predict the DAP state in which the HADC will be operating in the response phase. For example, because relief supplies are unpredictable in terms of quantity and timing, the HO is uncertain whether or not the DAPs, such as prioritization by relief items, disaster-affected regions, and timely delivery to impacted regions, can be executed. Van Wassenhove (2006) highlighted the uncertainty components that the HO faces regarding demand, supply, beneficiary needs, and complex situations. The uncertainty arises because of relief aid supplies, while the disaster response phase environment is exogenous to the HO. Such contingencies or contingency factors must be accounted for while considering the HADC selection decision. Indeed, the humanitarian context brings several exogenous contingencies that the HO does not control. In this study, the contextual uncertainty stemming from decentralized relief aid supplies from HSC actors in the disaster response phase is the contingency factor that needs considering.

In addition, the DAP states incorporated by the HO to anticipate the uncertain environment arising from the decentralized relief aid supplies is a response variable as suggested by Sousa and Voss (2008). The decision-maker considers the DAP states in making the HADC selection decision to anticipate the uncertain relief aid supplies. Furthermore, the performance variable plays a crucial role in evaluating the fit between the contingency factor and the action taken by the HO. The performance measure must consider the stranded beneficiaries' suffering while evaluating the fit between the uncertain relief aid supplies and the DAP states. The efficiency-effectiveness-equity (3E) framework has been adopted in several fields like health care (Davis et al., 2013), spatial sciences (Tulloch & Epstein, 2002), humanities (Hinrichs-Krapels & Grant, 2016), sustainability (Young & Tilley, 2006), and management science (Golany & Tamir, 1995; Savas, 1978). In the extant literature on humanitarian logistics, researchers have adopted different humanitarian relief models considering the three most essential criteria, namely efficiency, effectiveness, and equity (Abidi et al., 2014; Anaya-Arenas et al., 2014; Dönmez et al., 2021; Gralla et al., 2014; Huang, Smilowitz, & Balcik, 2012). We observe that the 3E framework is well established and recognized in the humanitarian context. Accordingly, we propose using the 3E criteria as the performance variables to assess the fit between the uncertain relief aid supplies and the DAP states. The efficiency criterion focuses on the operational cost of the DAP states. On the other hand, the effectiveness criterion emphasizes responsiveness in the relief aid distribution, and the equity criterion adheres to the equitable distribution for all disaster-affected regions. Lastly, the 3E criteria assist in evaluating the impact of all DAP states on the HADC selection decision.

In sum, we adopt the contingency theoretical perspective to understand the environmental contingencies arising from the decentralized relief aid supplies in the disaster response phase. To counter the contingency, the HO adapts by incorporating the DAPs for the HADC selection decision considering the 3E criteria as the performance measures. We depict a structural outline of the CT variables in Fig. 1.

2.2. HADC selection

To classify the related literature for a concise review, we apply the theory-context-characteristics-method (TCCM) framework (Paul & Rosado-Serrano, 2019). The TCCM framework briefly classifies and sums up the literature by four dimensions: theory, context, characteristic, and research method. The literature reviewed in this study lacks the theory dimension. So we classify each study by its research objective or objective function. In the TCCM framework, the context dimension specifies the study setting and characteristics that reveal the attributes or scope of the study, while the method dimension covers the research methods used in the study. Thus, the TCCM framework provides a holistic overview of the literature, as shown in Table 1.

Furthermore, the context dimension plays a significant role in the humanitarian relief network. So we split context into two subdimensions, namely disaster phase (preparedness, response, recovery, rehabilitation, and reconstruction) and facility type. Similarly, the sources of uncertainty, judgments to make, and criteria are all included in the characteristics dimension. In addition, we classify the sources of uncertainty as supply side, demand side, and network connectivity related (Dönmez et al., 2021).

Considering the location selection decision only, Lu (2013) proposed a robust weighted vertex *p*-centre model to minimize the worst-case deviation in the maximum demand-weighted travel time between urgent relief distribution centres and relief nodes. He focused on the disaster response phase and considered responsiveness and cost as the criteria with demand uncertainty. Song, Zhou, and Song (2019) adopted the qualitative flexible (QUALIFLEX) MCDM method to select the best shelter site location in the pre-disaster phase. The criteria include location and logistics efficiency, costs, environmental conservation, and social aspects. Yılmaz and Kabak (2020) adopted the Fuzzy-AHP and Fuzzy TOPSIS techniques to propose a multi-criterion support system to prioritize the distribution centres for efficient relief operations in the disaster preparedness and response phases. The criteria comprise transport and logistics, costs, infrastructure, and security. Liu, Cui, and Zhang (2019) proposed selecting temporary medical services facilities to provide medical assistance to beneficiaries. They developed a bi-objective model to maximize the number of expected survivals (effectiveness) and minimize operational costs (efficiency).

For the location-allocation decision, Álvarez-miranda, Fernández, and Ljubic (2015) sought to minimize the first stage costs and the second stage recovery costs using a robust optimization method in the response phase. They explored four distinct uncertainties, namely provider-side uncertainty, receiver-side uncertainty, in-between uncertainty, and uncertainty related to the cost parameters, considering an uncapacitated facility with the cost criterion. Jia, Ordo, and Dessouky (2007) proposed a maximal covering facility location model for allocating medical supplies to large-scale emergencies in the disaster response phase. They studied demand-side uncertainty for the medical supply facilities and

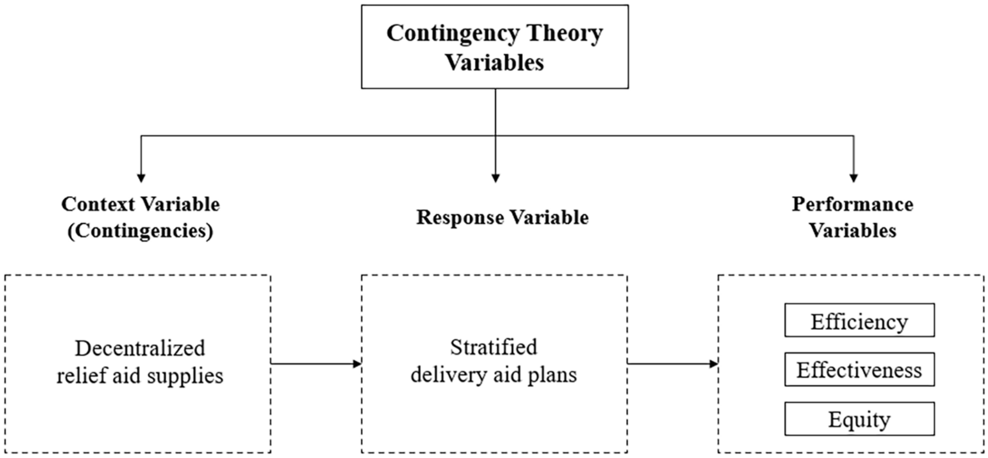

Fig. 1. Structural outline of contingency theory variables.

developed the model incorporating only the equity criterion. Considering the preparedness phase, Lu, Ran, and Shen (2015) included the cost and reliability criteria to minimize the expected cost using a robust optimization method considering supply uncertainty. In addition to the cost and reliability criteria, Yahyaei and Bozorgi-amiri (2019) considered the equity criterion and proposed a robust and reliable relief network comprising distinct facilities like shelters and unreliable and supportive distribution centres using the robust optimization method considering demand uncertainty. Shu, Lv, and Na (2021) proposed a relief network design comprising emergency facility locations and prepositioning of relief aid in the preparedness phase. They formulated the problem as a non-linear mixed-integer program (MIP) based on the Ψ-expander to capture the uncertain demand in the disaster-affected areas.

In addition, researchers have also considered the prepositioning decision while deciding on HADC selection. Akgun, Gumusbuga, and Tansel (2015) sought to minimize the maximum risk exposure for a demand point in the preparedness phase. In their study, the facility type is a relief supply facility that should be used to preposition relief aid materials. They modelled the problem as a non-linear MIP with the equity and reliability criteria considering supply uncertainty. Mohamadi, Yaghoubi, and Pishvaee (2019) evaluated the demand and network connectivity as the uncertainty sources to minimize the expected value of the total demand-weighted travel distance, maximize the expected value of demand coverage, and minimize the expected value of the probability of the evacuee's failure in arriving at a shelter location. They applied the multi-objective stochastic mathematical method to solve the problem of locating the shelters and relief distribution centres in the preparedness phase, considering the equity and responsiveness criteria.

Roh et al. (2015) proposed a model to select warehouse locations in the preparedness phase based on subjectivity (individual's opinions), uncertainty (likelihood of disaster occurrence), and ambiguity (conflicting messages) using the AHP-Fuzzy TOPSIS MCDM method. The criteria comprise macro criteria (location, national stability, cost, cooperation, logistics) and micro criteria (distance, security, office facilities, warehouse facilities, convenience). Timperio, Panchal, Samvedi, Goh, and De Souza (2017) adopted Fuzzy AHP to identify the most appropriate locations to set up the emergency response facilities in Indonesia for the preparedness phase. They comprised several criteria, including coverage, accessibility, risk access to infrastructure, congestion, costs, and national development plans. Considering the response phase, Munyaka and Yadavalli (2021) developed a decision-making model for emergency response facilities optimizing the prepositioned relief supplies and allocating them to demand points using the AHP MCDM and linear programming methods. The criteria comprise accessibility, security, population coverage, cost, and transportation capacity.

Addressing the location-routing decision, Ahmadi et al. (2015) proposed a location-routing model to minimize the total distribution time, penalty cost of unsatisfied demand, and fixed costs of opening local depots. They focused on the disaster response phase and considered network connectivity as the uncertainty source. They used two-stage stochastic programming to formulate the location-routing model considering the cost and equity criteria. Kim, Lee, and Moon (2019) proposed a set-covering location model using chance-constrained programming to find the optimal drone facilities by minimizing the drone-related costs. They only considered the cost criterion, comprising the cost of opening the drone facilities and the operations and maintenance costs of the drones and drone facilities. They applied the proposed model in the disaster response phase capturing the drone's characteristics like battery capacity, payload, and flight distance as the sources of uncertainty.

The literature review summarized in Table 1 concludes that no study has included all 3E criteria in the HADC selection model. In addition, no study has considered the nature of the facilities, especially the DAPs. Also, no study has considered the dynamic characteristics of the facilities. To plug the research gap, we study the impacts of dynamic DAPs in the disaster response phase on the HADC selection decision. Specifically, we position our study on HADC selection in the disaster response phase, considering supply-side uncertainty arising from the decentralized relief aid supplies. We operationalize and measure stratified DAPs using the 3E criteria to anticipate the uncertainty. Thus, we contribute to the HADC selection literature by proposing an integrated dynamic HADC selection model using the stratified MCDM method.

2.3. Concept of stratification (CST)

Zadeh (2016) introduced the concept of stratification, whereby a stratum of data is being considered, and the system transitions from a set of transitioning states to the desired state, called the target state. Basically, there may exist nested or stacked strata (multiple levels) through which the system initiates with input and transitions through all the multiple levels or strata to reach the target or desired level. Such a system is called a stratified system. Moreover, Zadeh (2016) highlighted the potential applications of CST in fields like robotics, optimal control, planning, multi-objective optimization, search, and exploitation. Also, like the dynamic programming approach, CST is considered to be much easier and more straightforward for implementation. Further discussing CST's benefits and various applicable areas, Asadabadi, Saberi, and Chang (2018) highlighted some preliminary practical applications for CST in fields such as artificial intelligence, natural language processing,

Table 1
Classification of related literature based on the TCCM framework.

Reference	Research Objective/ Objective Function	Context		Characteristic			Research method
		Disaster phase	Facility type	Source of uncertainty	Decision to make	Criterion	
Ahmadi et al. (2015)	To propose a location-routing model by minimizing the total distribution time, penalty cost of unsatisfied demand, and fixed costs of opening local depots.	Response phase	Local depots	Network connectivity	Location-Routing	Cost, equity	Two-stage stochastic programming
Akgun et al. (2015)	Minimize the maximum risk a demand point may be exposed to.	Preparedness	Supply facility	Supply	Prepositioning	Equity, reliability	Non-linear mixed-integer programming model
Álvarez-miranda et al. (2015)	Minimize the first-stage costs plus the second-stage recovery costs.	Response phase	Uncapacitated facility	Supply and demand	Location-Allocation	Cost	Robust optimization with Mixed integer programming model
Jia et al. (2007)	To propose a mathematical model for locating-allocating medical supplies to large-scale emergencies.	Response phase	Medical supply facilities	Demand	Location-Allocation	Equity	Maximal covering facility location model
Kim et al. (2019)	The objective is to find optimal facility locations and transport capacity by minimizing all the drone-related costs.	Response phase	Drone facilities	Drone's characteristics	Location-Transportation	Cost	Set-covering location model incorporating chance constraints
Liu et al. (2019)	Bi-objective model to maximize the number of expected survivals and minimize the operational costs.	Response phase	Temporal medical service facilities	NS	Location	Cost, effectiveness	∊-constraint method
Lu (2013)	The objective is to propose a robust weighted vertex *p*-centre model to minimize the worst-case deviation in the maximum demand-weighted travel time between the urgent relief distribution centres and relief nodes from the optimal solution.	Response phase	Urgent relief distribution centres	Demand	Location	Responsiveness, cost	Robust weighted *p*-centre model
Lu et al. (2015)	Minimize the expected cost.	Preparedness	Distribution centre	Supply	Location-Allocation	Cost, reliability	Robust Optimization
Mohamadi et al. (2019)	Minimize the expected value of the total demand-weighted travel distance/ Maximize the expected value of the coverage of the entire demand/Minimize the expected value of the total probability of evacuee's failure to arrive at the shelter location.	Preparedness phase	Shelter and relief distribution centres	Demand and network connectivity	Prepositioning	Equity, responsiveness	Multi-objective stochastic mathematical model
Munyaka and Yadavalli (2021)	1. Explore the SADC supply relief operations. 2. Develop a decision-making model for emergency response facilities. 3. Optimize the prepositioned relief supplies and allocate them to the demand points using linear programming.	Response phase	Emergency response facility	NS[1]	Prepositioning and allocation	Access to affected areas, security, population coverage, cost, capacity of relief to be transported	AHP MCDM
Roh et al. (2015)	Select warehouse location based on subjectivity (individual's opinions), uncertainty (likelihood of occurrence), and ambiguity (conflicting messages)	Preparedness (pre-disaster)	Warehouse	NS	Prepositioning	Macro criteria (location, national stability, cost, cooperation, logistics) and micro criteria (distance, security, office facilities, warehouse facilities, convenience)	AHP-Fuzzy-TOPSIS MCDM
Shu et al. (2021)	Minimize the facility costs and relief supply prepositioning costs.	Preparedness (pre-disaster)	Emergency facility location	Demand	Location-Allocation	Costs	Non-linear MIP
			Shelter site	NS	Location		

(*continued on next page*)

Table 1 (*continued*)

Reference	Research Objective/ Objective Function	Context		Characteristic			Research method
		Disaster phase	Facility type	Source of uncertainty	Decision to make	Criterion	
Song et al. (2019)	Select the best shelter site location in the pre-disaster phase.	Preparedness (pre-disaster)				Location & logistic efficiency, costs, environmental conservation, Social aspects	Qualitative Flexible (QUALIFLEX) MCDM
Timperio et al. (2017)	The objective is to identify the most appropriate locations to set up emergency response facilities in Indonesia.	Preparedness (pre-disaster)	Emergency response facility	NS	Prepositioning	Coverage, access to affected zones, risk, access to infrastructure, access to the corridor, congestion, costs, national development plan	Fuzzy AHP
Yahyaei and Bozorgi-amiri (2019)	The objective is to propose a robust and reliable relief network comprising distinct facilities like shelters, unreliable distribution centres, and supportive distribution centres.	Pre-disaster phase	Supply facility/ distribution centre	Demand	Location-Allocation	Cost, equity, reliability	Robust optimization with Mixed integer programming model
Yılmaz and Kabak (2020)	The objective is to propose a multi-criteria support system to prioritize the distribution centres for efficient relief operations.	Preparedness and response phases	Distribution centre	NS	Location	Transport/logistics, cost, infrastructure, security	Fuzzy AHP, Fuzzy TOPSIS
This study	Applying the CT lens, the objective is to propose an HADC selection model with integrated stratified DAPs.	Response phase	Humanitarian aid distribution centre (HADC)	Supply-side (decentralized relief aid supplies)	Location selection	Efficiency, effectiveness, equity, priority by items, disaster location, and speed of delivery	Stratified MCDM using TOPSIS

[1] Not specified.

big data, and robotics.

Because of its newness, few research in the management sector has incorporated CST. Using examples of information dominance and requirements elicitation, Asadabadi, Saberi, and Chang (2017) proposed the practical use of CST in logistics informatics. They gave five examples to demonstrate the usefulness of CST in improving and simplifying logistics informatics. Recently, Asadabadi (2018) developed a new MCDM method called stratified multi-criteria decision making (SMCDM), which aims to consider future events that are likely to occur and thus influence decision-making. He highlighted the impacts of the changing weights of the criteria on selecting the alternatives based on future events, constituting a dynamic system to address such fluctuations in the criteria weights.

More recently, Asadabadi and Zwikael (2021) incorporated CST into addressing risk and uncertainty for project planning and estimating project time and costs. They considered the stratified time and cost parameters for anticipated future events during project execution. The stratified method aids in the incorporation of future events that may have an impact on the project's execution. It strengthens the project planning phase and aids the completion times and cost projections for project activities. We contribute to the CST literature by utilizing the SMCDM using TOPSIS (S-TOPSIS) method to integrate multiple strata of DAPs, i.e., stratified DAPs, in the process of HADC selection in the disaster response phase.

3. Research methodology

The research methodology comprises a systematic approach for HADC selection decision-making. Initially, the decision-maker has to identify the key criteria and number of HADCs to be considered for HADC selection. Then, the weights of the criteria and the HADCs must be accounted for in terms of the expert's opinion. The expert's opinion includes the weights given to the HADCs based on the criteria under consideration. The next step is to introduce the distinct possible scenarios of DAPs inducing uncertainty in HADC selection. Now, the decision-maker has to re-evaluate the weights of the criteria as the expert's opinion for all the considered DAP states. Also, the transition probabilities from the base state to another state must be captured. Moreover, after obtaining the data for all the input parameters (criteria, HADCs, and transitioning probabilities), we perform stratified MCDM to find the best HADC location. Fig. 2 depicts the entire flow of the research methodology adopted in this study.

Furthermore, we have organized the subsections as follows: The next section discusses the case of Cyclone Fani, highlighting the importance of the HADC selection decision. We first discuss the data collection method. Then we numerically illustrate application of the methodology for the case of Cyclone Fani.

3.1. A case of Cyclone Fani

Odisha is an Indian state in the eastern region vulnerable to cyclonic disturbances due to its proximity to the Bay of Bengal. Every alternate year, high windstorms with heavy rain linked to cyclones cause damage to Odisha's coastal region. Cyclones in Odisha typically form in the sea (Bay of Bengal) and dissipate on land. Compared with other Indian states, Odisha has a nearly two-year re-visit time for cyclones. From 1891 to 2000, Odisha reported the country's largest number of cyclones (98 cyclones). In view of this, we present a case study of Cyclone Fani, which struck Odisha, India, on 3 May 2019. We obtained secondary data on Cyclone Fani from the official website of Odisha's Special Relief Commissioner, Revenue & Disaster Management Department (https://srcodisha.nic.in/cyclone.php) and related news reports. The data consist of a memorandum and daily reports published by government officials between 1 May and 4 June 2019, highlighting the preparedness measures, extent of damage, response actions, and government relief packages. The reports contain minute details about the human casualties, livestock losses, and other damages caused by Cyclone Fani and the departmental actions.

Cyclone Fani crossed the Odisha coast between 8:00 a.m. and 10:00 a.m. (IST) on 3 May 2019, with a maximum wind speed of approximately 175 kmph. According to Odisha government officials, the cyclone severely impacted nearly 16.55 million people, 18,388 villages,

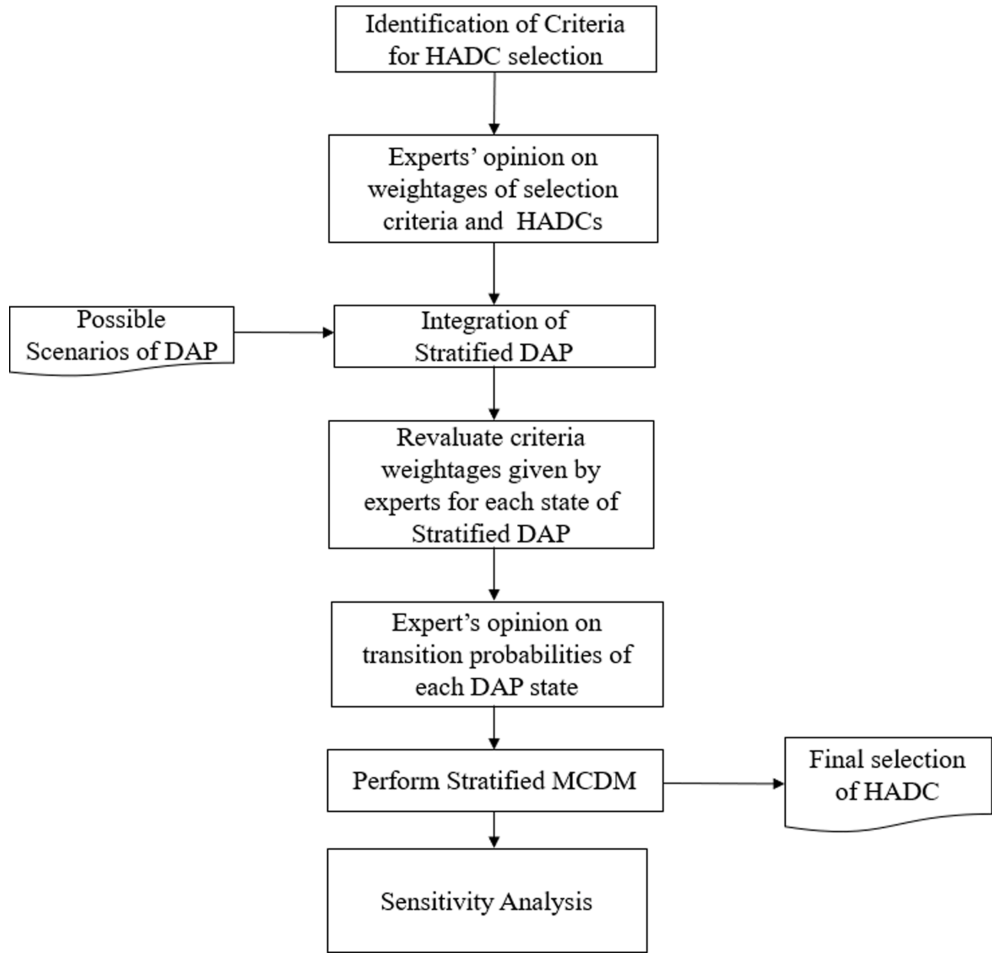

Fig. 2. Ranking of HADCs based on DAPs.

159 blocks, 51 urban local bodies, and 8.80 million livestock. Cyclone Fani severely affected 14 districts of the state, causing 64 human casualties and 41.68 lacs livestock casualties (see Fig. 3 depicting the affected districts). The district of Puri had the highest number of human casualties (39). Furthermore, during the preparedness phase, the Odisha government opened some pre-selected free kitchens, medical relief centres, and shelter locations to evacuate vulnerable people living near the coast or in low-lying areas. During the response phase, the government expanded the number of pre-selected free kitchens and medical relief centres located near the affected districts. Also, the government

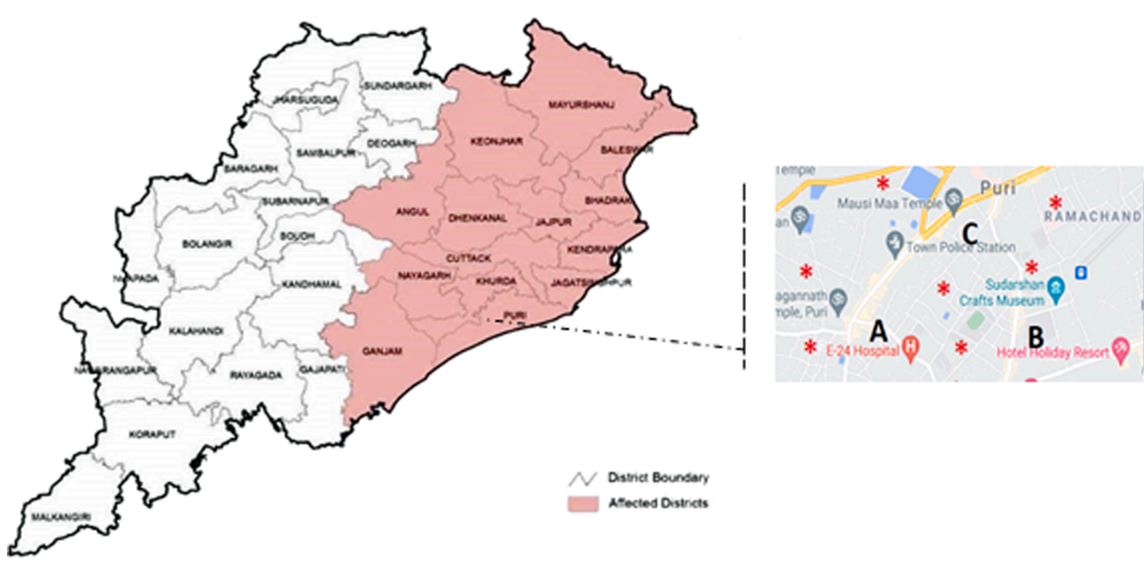

Fig. 3. Districts severely impacted by Cyclone Fani. *Note.* Extracted from the official website of the Government of Odisha's Special Relief Commissioner, Revenue & Disaster Management Department.

operationalized the relief distribution centres at the *block* and *panchayat* levels. Furthermore, government organizations such as the National Disaster Response Force (NDRF), the Odisha Disaster Rapid Action Force (ODRAF), the Indian Coast Guard, and the Odisha Forest Development Corporation (OFDC) collaborated with HOs such as Child Care Institutions, Swadhar, and Ujjwala Homes to carry out response phase activities as shown in Fig. 4.

In the case of Cyclone Fani, HADCs were free kitchens, medical relief centres or relief distribution centres at the *block* level from where relief aid was distributed in the last mile. For brevity, we only consider free kitchens and relief distribution centres at the *block* level as HADCs for storing and carrying out the last mile distribution of the relief aid. Moreover, several news agencies highlighted that the response phase of Cyclone Fani faced several challenges and food shortages. Despite having centralized GO-NGO mobilization, less focus was given to the response and recovery phases of Cyclone Fani, especially relief aid distribution (Choudhury & Thakur, 2019). Even after informing the government officials, no relief aid supplies were distributed to the beneficiaries stranded in their self-created shelters/homes (Barik, 2019b). Another reason for the decentralized relief aid supplies was that the government created shelters were given the primary focus (Choudhury & Thakur, 2019). The beneficiaries stranded in their own created tarpaulin shelters were left out. Moreover, because of the absence of electricity, coordination among GO-NGO mobilization was complex, leading to disperse relief aid distribution (Mridula Chari, 2019). Several disaster-affected regions were inaccessible, and accurate information on some regions was unavailable, posing significant challenges to the actors for relief distribution (Dash, 2019). In addition, a village called Siara in the Puri district reported food unavailability because of uncertain relief aid supplies from GO-NGO mobilization (Satapathy, 2019). Consequently, the unavailability of food supplies created uncertainty amongst the beneficiaries, resulting in protests, roadblocks, and looting of relief supplies (Barik, 2019a; Dash, 2019; Koshy & Barik, 2019; Chari, 2019; Mohanty, 2019).

Despite getting applause from the global community for the evacuation phase (Mohan, 2019), the Odisha government faced challenges in relief aid distribution, as highlighted above. Moreover, Dash (2021) highlighted the lack of discussion of the quantity and quality of the relief aid to be distributed to the stranded beneficiaries in government and self-created tarpaulin shelters. Also, no prioritization of the relief items was found. Some instances reveal that beneficiaries at first received raw food (rice and pulses) but did not receive fuel (kerosene) for cooking (Dash, 2021). Grounded in CT (Fig. 1), several contingencies like the absence of electricity, lack assessment of the disaster-affected regions, lack of accessibility, lack of relief aid prioritization, and complex coordination environment for GO-NGO mobilization aggravated the disaster-affected beneficiaries suffering. Some of the contingencies like electricity absence, devastated roads, and lack of accessibility were found not to be under the control of the GO-NGO operating in the response phase and caused delays in relief aid supplies distribution. Specifically, operationalized in the preparedness and the response phase, the free kitchen centres and *block/panchayat* level relief distribution centres could not fully meet the beneficiaries need. The free kitchen centres operating under the government shelters were unable to meet the food demand of the beneficiaries in those shelters (Koshy & Barik, 2019). Such free kitchen centres could not assist the stranded beneficiaries in their tarpaulin shelters in nearby locations. Similarly, the relief supplies were uncertain for the relief distribution centres at the block level, and their reachability to nearby disaster-affected regions or the beneficiaries was restricted.

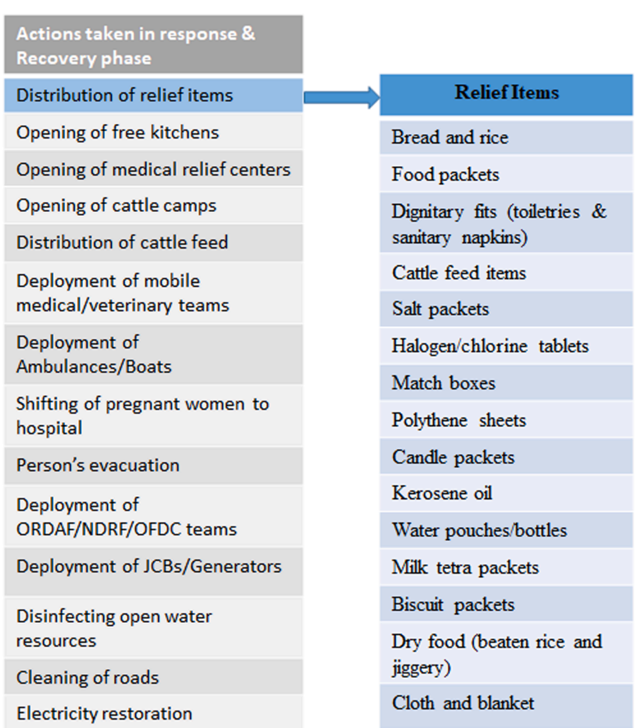

Fig. 4. Response and recovery phase activities during Cyclone Fani.

Since the response and recovery phases of Cyclone Fani lasted more than 20 days, the prioritization of relief items, of cyclone-affected districts, and of high-demand places within the districts, and the speed of GO-NGO mobilization emerged as critical attributes when deciding whether or not to open free kitchen centres or *block*-level relief distribution centres within an affected area. Therefore, we attempt to overcome the aforementioned contingencies by incorporating stratified DAPs in the HADC selection decision. We propose the selection of free kitchen or *block*-level relief distribution centres in the response phase to anticipate the exogenous contingencies beyond the HO's control. In fact, the stakeholders and experts involved in the planning and response phases of Cyclone Fani confirmed that the DAP attributes were not taken into account in selecting the free kitchen centres. However, prioritizing the DAP attributes for HADC selection in the response phase was indeed necessary. We close the gap by developing an integrated HADC (or free kitchen centre) selection model incorporating stratified DAPs.

During the preparedness phase, the Odisha government maintained 879 multi-purpose cyclone shelters throughout 14 districts, ready to evacuate the beneficiaries and deliver medical and food support (see Fig. 4 for different relief items distributed). Furthermore, 259 medical relief centres were established during the response phase in the Puri district. In comparison, 152 free kitchen centres were set up in the Khordha district, which provided aid to the victims. Free kitchens were opened in pre-selected shelters, covering nearby shelters and affected areas. As a result, in consultation with the expert panel involved in the Cyclone Fani response phase, we selected three pre-selected free kitchen centres as the HADCs, namely centres "A", "B", and "C" near the most severely impacted Puri district of Odisha, for illustration purposes in the subsequent sections (shown in Fig. 5). Note that we use free kitchen centres, *block*-level relief distribution centres, and HADCs interchangeably.

3.2. Data collection

We collected the data for this study by conducting in-depth interviews with the humanitarian experts and stakeholders involved during the preparedness and response phases of Cyclone Fani. Following the multi-dimensional approach of (Holguín-veras et al., 2007), we discussed the incorporation of DAPs into HADC selection with the humanitarian experts. We asked them to weigh the 3E criteria and all the states of the DAPs. As discussed in the previous section, no DAPs were incorporated into the HADC selection decision. We interviewed ten humanitarian experts comprising officials from GO/NGOs, volunteers,

Fig. 5. Pre-selected free kitchen centres "A", "B", and "C" during Cyclone Fani for illustration purposes. *Note.* Extracted from Google Maps. The red asterisks denote the cyclone-affected regions.

local community actors, academicians, and military personnel involved in the response phase. The experts interviewed were affiliated with organizations like the National Disaster Response Force (NDRF), the Odisha Disaster Rapid Action Force (ODRAF), the Odisha Forest Development Corporation (OFDC), Child Care Institutions, and Ujjwala Homes. Also, to maintain unbiased responses and heterogeneity, we contacted two humanitarian experts from Goonj and Smile Foundation, both NGOs working in the disaster relief who were not involved in the Cyclone Fani response phase.

We conducted telephone and face-to-face interviews between May and September 2021. All the responders were actively involved in disaster relief and response activities, having an average experience of eight years or more with their associated organizations. Of the 12 respondents, seven were based in Odisha, and five were based in Delhi. For reasons of confidentiality, we kept each respondent anonymous. As a result, we present the findings without revealing the respondent's identity, designation, work description, or other information that could jeopardize the interviewee's confidentiality.

3.3. HADC selection with stratified DAPs

We wish to select the best HADC for the response phase of a disaster with respect to the 3E criteria. For the case under consideration, we picked three HADCs, namely "A", "B", and "C", in consultation with the expert panel involved in Cyclone Fani. The decision-maker must select the best HADC incorporating the stratified DAPs with respect to the 3E performance criteria. Whilst incorporating the stratified DAPs into HADC selection, the weights of the performance criteria will change for each state of the DAP. Since the humanitarian practitioners are concerned with the initial criteria weights, they will change the weights for each combination (or state) of the multi-level DAPs. Therefore, we need to undertake stratified MCDM to resolve the practitioners' concerns and address the uncertainties induced by decentralized relief aid supplies by incorporating distinct combinations of DAPs while making the HADC selection decision.

In addition, the three DAPs under CST, i.e., prioritization by relief items type, speed of delivery, and disaster location, may affect the criteria weights in the response phase. We use the following vector notation, as illustrated by Asadabadi (2018), to model the inputs, outputs, and the tabular form of CST. Let the input vector $i_t = (l, m, n)$ consist of three arrays of DAPs in the state s_t, which is associated with the output vector $o_t = (p, q, r)$. The input vector i_t consists of the following DAPs, namely priority by relief items l, by disaster-affected regions m, and speed of delivery n, as follows:

$$l = \left\{ \begin{array}{ll} -1, & \textit{storing and delivery of low priority items} \\ 0, & \textit{no effect of items priority on storing and delivery} \\ 1, & \textit{storing and delivery of high priority items} \end{array} \right\}$$

$$m = \left\{ \begin{array}{ll} -1, & \textit{highest priority disaster affected regions first} \\ 0, & \textit{even mix of disaster affected regions} \\ 1, & \textit{more high}-\textit{priority disaster affected regions} \end{array} \right\}$$

$$n = \left\{ \begin{array}{ll} -1 & \textit{complete } 80\% \textit{ of deliveries between } 72 \textit{ hours} - 168 \textit{ hours; only few } (20\%) \textit{ are delievered within } 72 \textit{ hours.} \\ 0 & \textit{even delieveries through } 0 - 168 \textit{ hours.} \\ 1 & \textit{complete } 80\% \textit{ of deliveries within } 48 \textit{ hours; rest } 20\% \textit{ are delivered between } 48 \textit{ hours } - 144 \textit{ hours.} \end{array} \right\}$$

Table 2
Tabular CST for DAPs.

States (s_t)	i_t	s_{t+1}	o_t
s_0	(0, 0,0)	s_0	(0.3, 0.5, 0.2)
	(0, 0, 1)	s_1	(0.25, 0.25, 0.5)
	(0, 0, −1)	s_2	(0.1, 0.72, 0.18)
	(0, 1, 0)	s_3	(0.15, 0.6, 0.25)
	(0, −1, 0)	s_4	(0.3, 0.5, 0.2)
	(1, 0, 0)	s_5	(0.2, 0.55, 0.25)
	(−1, 0, 0)	s_6	(0.34, 0.52, 0.14)
s_1	(0, 1, 1)	s_7	(0.21, 0.32, 0.47)
s_1, s_6	(−1, 0, 1)	s_8	(0.45, 0.23, 0.32)
s_2	(0, 1, −1)	s_9	(0.21, 0.23, 0.56)
s_2, s_5	(1, 0, −1)	s_{10}	(0.41, 0.25, 0.34)
s_3, s_5	(1, 1, 0)	s_{11}	(0.05, 0.45, 0.5)
s_4, s_5	(1, −1, 0)	s_{12}	(0.31, 0.64, 0.05)
s_7	(1, 1, 1)	s_{13}	(0.04, 0.19, 0.77)
s_9	(1, 1, −1)	s_{14}	(0.13, 0.36, 0.51)
	(−1, 1, −1)	s_{15}	(0.21, 0.3, 0.49)

Moreover, the output vector consists of the modified criteria weights, i.e., the efficiency weight p, the effectiveness weight q, and the equity weight r, in each state. Since there are three input arrays with three levels each, the total number of states is $3^3 = 27$ states. At the stratified levels, all the states are discrete, so the transition can occur from the base state s_0 to the other 26 states. The base state with the input vector is $s_0 = (0, 0, 0)$, which means there is no effect of items priority on storing and delivery, the disaster-affected regions selected for deliveries are evenly mixed, and 100% of the deliveries are made evenly throughout the week. The expert panel of humanitarian practitioners and other key stakeholders decided the appropriate criteria weights in each situation. For example, the state $s_2 = (0, 0, -1)$ implies that 80% of the relief aid is delivered between 72 and 168 h, and only 20% is delivered within 72 h. In such a situation, the importance of effectiveness increases substantially, and the following vector will be used as the criteria weights (efficiency, effectiveness, equity) = (0.1, 0.72, 0.18).

According to the expert panel, the likelihood of state transitions of DAPs in the response phase plays a crucial role. In the humanitarian context, measuring the state transition probability is challenging, so we asked the expert panel members to intuitively estimate the likelihood of a state occurrence (Asadabadi & Zwikael, 2021). As cyclones typically come around every two years in Odisha, the experts were well aware of the likelihood of cyclone occurrence. As a result, estimating the state transition probabilities for them was not difficult. Moreover, we observe that some states have a small likelihood of occurrence. For example, the state with the input vector (−1, −1, −1) may not occur in considering HADC selection. In view of this observation, with the help of the expert panel, we reduced the number of states to 16, as shown in Table 2, and removed the states that were unlikely to occur. We show the transition probability of each state in Fig. 6. For example, P_{07} expresses the probability that high-priority disaster-affected regions need to be served earlier than lower priority ones, i.e., 80% of the deliveries should be completed within 48 h. This is also in line with the opinion of the experts. Also, P_{00} denotes the likelihood that the current situation persists. In addition, we compare the alternative HADC locations based on each performance criterion and report the results in Table 3.

Given the criteria weights for each state (as shown in the last column of Table 2), we compute the weightings of alternative HADCs with respect to the criteria for each state. To this end, we perform Technique for Order Preferences by Similarity to an Ideal Solution (TOPSIS) MCDM to rank the HADCs with respect to the criteria (Roh et al., 2015; Yılmaz & Kabak, 2020). Consider n HADCs with m criteria (in our case $n = m = 3$ as shown in Table 3) and X_{ij} is an $n \times m$ matrix, $\forall\, i = 1, 2\ldots, n$ and $j = 1, 2\ldots, m$. We calculate the normalized decision matrix $r_{ij} = \frac{X_{ij}}{\sqrt{\sum_{j=1}^{n} X_{ij}^2}}$, $\forall\, i = 1, 2\ldots, n$ and $j = 1, 2\ldots, m$. We then multiply each column of the normalized decision matrix r_{ij} by the weights of each criterion w_j (given in Table 2) to obtain a weighted normalized decision matrix $W_{ij} = r_{ij} \times w_j$, $\forall\, i = 1, 2\ldots, n$ and $j = 1, 2\ldots, m$. We calculate V_j^{+} and V_j^{-}, $\forall\, i = 1, 2\ldots, n$ and $j = 1, 2\ldots, m$, representing the ideal best and ideal worst values, respectively. Then we calculate the Euclidean distance from ideal best value $S_i^{+} = \sqrt{\sum_{j=1}^{m} (V_{ij} - V_j^{+})^2}$, $\forall\, i = 1, 2\ldots, n$, and ideal worst value $S_i^{-} = \sqrt{\sum_{j=1}^{m} (V_{ij} - V_j^{-})^2}$, $\forall\, i = 1, 2\ldots, n$. Finally, we obtain the performance score for each alternative HADC for each DAP state as follows: $P_i =$

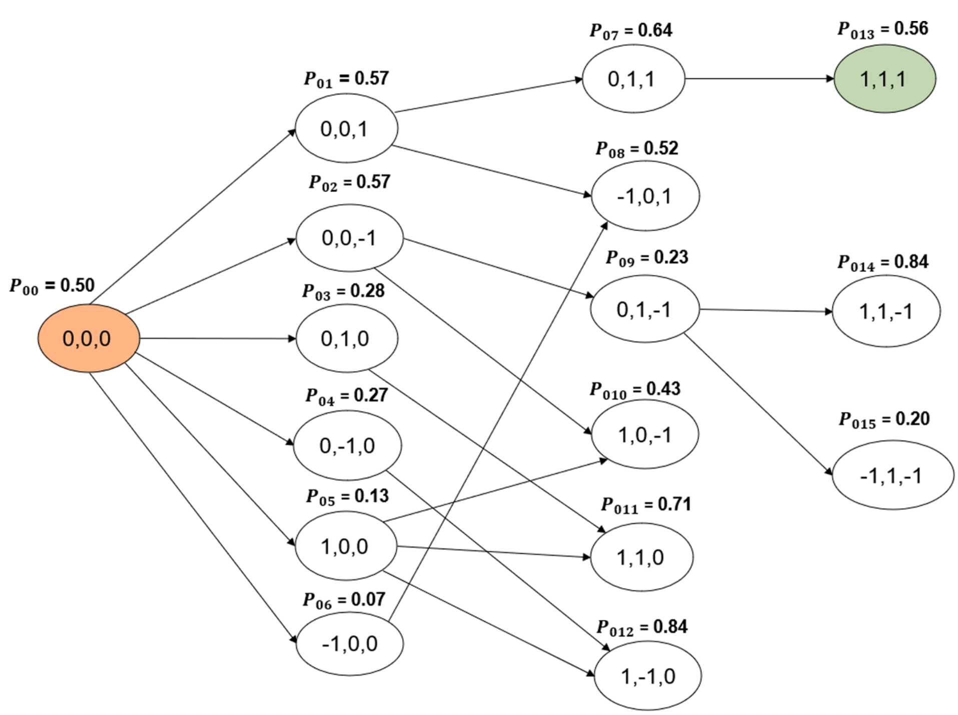

Fig. 6. State transition probabilities.

Table 3
Comparing HADCs with respect to the 3E criteria.

Alternative	Criterion		
	Efficiency	Effectiveness	Equity
Location "A"	0.26	0.27	0.49
Location "B"	0.22	0.48	0.23
Location "C"	0.52	0.25	0.28

Table 4
Performance scores of alternative HADCs.

State	Location "A"	Location "B"	Location "C"	Best Location
*s_0	0.29	0.53	0.42	B
s_1	0.61	0.28	0.39	A
s_2	0.24	0.75	0.15	B
s_3	0.33	0.64	0.24	B
s_4	0.29	0.53	0.42	B
s_5	0.34	0.59	0.30	B
s_6	0.22	0.53	0.45	B
s_7	0.59	0.35	0.35	A
s_8	0.41	0.25	0.61	C
s_9	0.67	0.25	0.34	A
s_{10}	0.43	0.28	0.57	C
s_{11}	0.58	0.44	0.16	A
s_{12}	0.12	0.62	0.38	B
s_{13}	0.83	0.18	0.19	A
s_{14}	0.62	0.38	0.25	A
s_{15}	0.61	0.33	0.35	A

* s_0 reports the outcome of TOPSIS analysis.

$\frac{S_i^-}{(S_i^+ + S_i^-)}$, $\forall\ i = 1, 2\ldots, n$. Table 4 lists the performance scores of the alternative HADCs for each DAP state.

In line with the above discussion, we provide an algorithm (pseudocode) for HADC selection using the stratified MCDM approach in the following. As per the current situation for the case of Cyclone Fani (see Table 4), without incorporating stratified DAPs (state s_0), HADC "B" outperforms the other two locations. However, as we move down to Table 4, the other states have different combinations of DAPs, resulting in other HADCs as the best ones. For example, the ideal state s_{13} has HADC "A" as the best one. It demonstrates that for HOs to deliver 80% of relief aid in 48 h to highly prioritized disaster-affected areas, HADC "A" should be opened, taking efficiency, effectiveness, and equity into account. In addition, to determine the final weightings of the HADCs, the performance score of each of the HADC in each state needs to be multiplied with the occurrence probability of each state. So the weights obtained in Table 4 for each HADC need to be multiplied by the transition probabilities given in Fig. 6. These final weightings enable the proper ranking of the alternatives incorporating all the states and their likelihood of occurrence. Table 5 lists the final weights and rankings of the HADCs considering all the states and the weighting criteria. We find that without considering the DAPs (base state s_0), HADC "B" emerges as the best location. However, when the DAPs are integrated, and SMCDM applied, HADC "A" becomes the best location to provide relief assistance to the stranded beneficiaries in the response phase (see Fig. 5).

Algorithm (pseudocode) for HADC selection using the stratified MCDM approach

Inputs

1. The weightings of the 3E criteria for all the states t:
$o_t = (p, q, r)$,
where p : weight of the efficiency criterion
q : weight of the effectiveness criterion
r : weight of the equity criterion
2. Transitioning probabilities from the current state to the other 15 states:
$P_i = \begin{array}{cccc} s_0 & s_1 & \cdots & s_{15} \\ [P_0 & P_1 & & P_{15}] \end{array}$, where s_i is the ith state.

(continued on next column)

(continued)

3. Normalized decision matrix, $r_{ij} = \frac{X_{ij}}{\sqrt{\sum_{j=1}^{n} X_{ij}^2}}$.
4. Define the number of DAP states, $s \rightarrow 16$
5. Define the number of criteria, $c \rightarrow 3$
6. Define the number of HADCs, $n \rightarrow 3$

Output

1. Rankings of the HADCs, H_r

Pseudocode

1. Compute the normalized decision matrix (alternative weights w.r.t. the 3E criteria):

```
for i in range(s): #states loop
  for j in range(n):
    for k in range(c):
      ndm_jk = O_ik r_jk
    end for
  end for
```

2. Compute the ideal best and ideal worst values from the normalized decision matrix:

```
for k in range(c):
  V_k^+ = max(ndm_jk), ∀j
  V_k^- = min(ndm_jk), ∀j
end for
```

3. Compute the Euclidean distance from the ideal best and worst values:

```
for j in range(n):
  dummy_S_j^+ = 0
  dummy_S_j^- = 0
  for k in range(c):
    var1 = (ndm_jk − V_k^+)^2
    var2 = (ndm_jk − V_k^-)^2
    dummy_S_j^+ + = var1
    dummy_S_j^- + = var2
  end for
  S_j^+ = √dummy_S_j^+
  S_j^- = √dummy_S_j^-
end for
```

4. Compute the performance scores of each HADC using the obtained Euclidean distance.

```
for j in range(n):
  perf_ij = S_j^- / (S_j^+ + S_j^-)
end for
end for #states loop
```

5. Compute the final weightings of the HADCs (multiplying the transition probabilities by the performance scores):

```
for i in range(n):
  for j in range(s):
  Fwts_ji = perf_ji P_j
```

6. Compute the ranks of the HADCs based on the final weights:

```
for i in range(n):
  var = 0
  for j in range(s):
    var = Fwts_ji
    fwts_i + = var
  end for
end for
for j in range(n):
  H_r = sorted(fwts_j)
end for

return H_r
```

4. Sensitivity analysis

In the humanitarian setting, the trade-offs between the 3E criteria differ across HOs. Some HOs may weigh equity more than efficiency and effectiveness. Some may emphasize efficiency while operationalizing the DAPs in the disaster response phase. To examine such trade-offs and understand how variations in the criteria weights as judged by the experts impact the performance scores of the HADCs, we perform a sensitivity analysis by changing the criteria weights for each DAP state

Table 5
Final weights and ranks of the HADC locations.

State	Location "A"	Location "B"	Location "C"
s_0	0.15	0.27	0.21
s_1	0.35	0.16	0.23
s_2	0.14	0.43	0.09
s_3	0.09	0.18	0.07
s_4	0.08	0.14	0.11
s_5	0.05	0.08	0.04
s_6	0.02	0.04	0.03
s_7	0.38	0.22	0.22
s_8	0.21	0.13	0.31
s_9	0.16	0.06	0.08
s_{10}	0.19	0.12	0.24
s_{11}	0.41	0.32	0.12
s_{12}	0.10	0.52	0.32
s_{13}	0.47	0.10	0.11
s_{14}	0.52	0.32	0.21
s_{15}	0.12	0.07	0.07
Final Weight	3.42	3.14	2.46
Ranking	1	2	3

under the assumption that the transition probabilities remain unchanged. Specifically, we randomly sampled the experts' responses for each criterion in each DAP state. This is essential because, for each DAP state, the criteria weights differ based on the DAP strata. Therefore, the random criteria weights data must adhere to the nuances brought in by the DAP states comprising prioritization by relief items type, speed of delivery, and disaster location. The steps involved in the sensitivity analysis are as follows:

Step 1: Generate 5,000 random numbers for each criterion in each DAP state from experts' responses using the sample from the columns method in Minitab.
Step 2: Categorize the three 3E criteria into two levels, i.e., Low (L) and High (H), where $L \in [0,0.49]$ and $H \in [0.49,1]$. Hence, a total of $2^3 = 8$ scenarios are generated for the simulations. These scenarios depict the interactions amongst the three criteria.
Step 3: For each scenario, randomly select the sample data from the 5,000 observations in each DAP state of each criterion. Then, normalize the criteria weights in each state so that they sum to 1.
Step 4: Input all the 16 states' criteria weights in the algorithm for HADC selection (proposed above) and obtain the best HADC location.
Step 5: Perform Steps 3–4 for all the eight scenarios to obtain the best HADC location. Fig. 7 exhibits the performance scores of the three HADCs for each scenario of the criteria weights.

The random values generated for each scenario of Low and High levels of the criteria depict variations in the criteria weights and the consequent best HADC location decision. Out of eight scenarios, HADC "A" results as the best HADC for four scenarios, namely *LLL*, *HHH*, *LLH*, and *LHH*. Specifically, for the scenario *LLH*, HADC "A"'s performance score is much higher than the other two locations. This can be interpreted as when the HO focuses on equitable distribution of the relief items and emphasizes equity based on each DAP state, HADC "A" is the optimal location. Moreover, when all three criteria weights are low, i.e., scenario *LLL*, HADC "A" is the best location, followed by HADC "C". Comparatively, both locations are very close in terms of their performance scores. The HO or decision-maker can eventually opt for either location by considering other operational constraints like network connectivity, security, and accessibility to disaster-affected regions. In addition, when all three criteria are considered essential, i.e., scenario *HHH*, HADC "A" results as the best location, followed by HADC "B". In the sensitivity analysis, we cannot rule out the importance of the second-best HADC for any scenario, as shown in Fig. 7. Considering the response phase of the disaster, because of external eventualities like destructed road network, it may happen that the HO cannot opt for the theoretical optimal location. Then, it should opt for the second-best location in such cases. Moreover, HADC "A" results as the optimal location when effectiveness and equity are emphasized. The findings of the SMCDM model corroborate with the sensitivity analysis outcomes as HADC "A" results as the optimal location in four scenarios of the analysis.

On the other hand, when effectiveness is preferred to the other two criteria, i.e., scenario *LHL*, HADC "B" becomes the optimal location. Contrary to effectiveness, when efficiency is emphasized, i.e., scenario *HLL*, HADC "C" becomes the best location. An interesting insight about HADC "C" is that it is the optimal location considering cost-efficiency operationalization of the distribution centres (for scenarios *HLL*, *HHL*, and *HLH*). In contrast, HADC "A" is the optimal location for equitable distribution. In addition, if the HO's only goal is to provide relief aid to stranded beneficiaries as soon as possible, then HADC "B" will definitely be the optimal location for storing and delivering the relief items. Such insightful results can facilitate the HO to attain its goal by examining the trade-offs among the 3E criteria based on its mission and vision. Lastly, the sensitivity analysis accounts for the changing criteria weights for all the DAP states when their transition probabilities are assumed to be

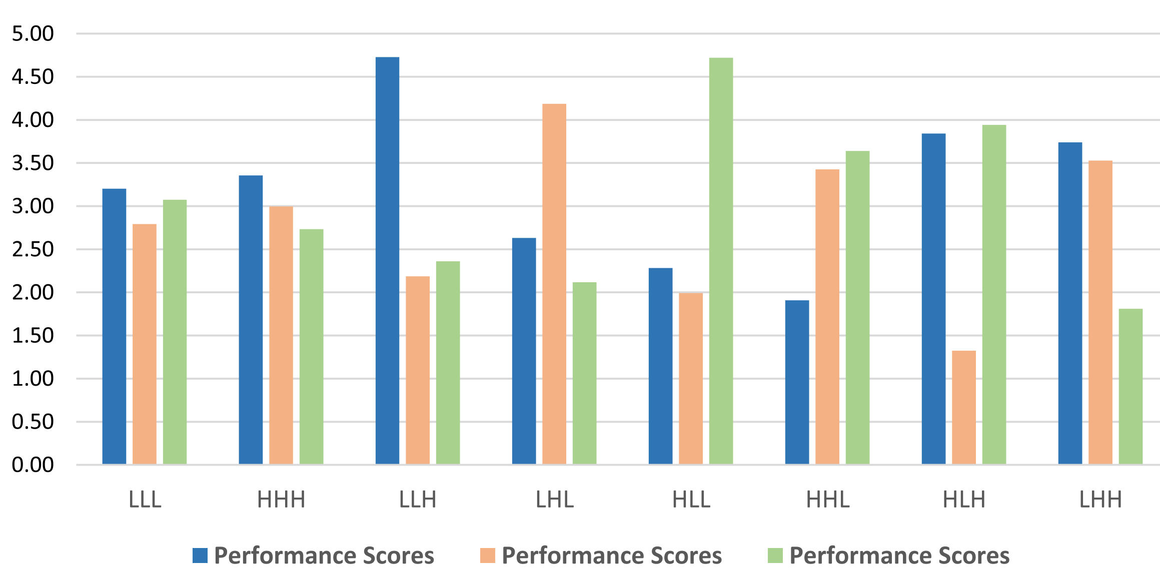

Fig. 7. Sensitivity analysis results.

fixed. We do not show the DAP state-wise optimal locations for all the scenarios to keep the analysis concise. The final HADC selection decision comprising all the DAP states is essential as the decision-maker is uncertain about the likelihood of the DAP states in the response phase of the disaster.

5. Discussions

The HADC selection problem in the humanitarian supply chain is generally treated by OR modelling techniques with a single- or multi-objective function. The objective function attempts to minimize the facility cost or maximize the covering in terms of distance or rapidity in relief aid items delivery (Dönmez et al., 2021). In contrast, grounded in CT, we address the uncertainty issue arising from the exogenous contingencies in the form of decentralized relief aid supplies in the disaster response phase. To anticipate the contingencies, the HO must operationalize the stratified DAPs while making the HADC selection decision in pursuit of the 3E criteria. In HADC selection decision-making, the CT perspective enhances understanding of the relationship between contingency factors, response variables, and performance variables. In addition, even with centralized GO-NGO mobilization in the case of Cyclone Fani, the stranded beneficiaries faced several food shortages due to decentralized relief aid supplies because of exogenous eventualities. The case highlights the importance of incorporating the stratified DAPs into HADC selection decision-making to mitigate the beneficiaries' suffering.

5.1. Academic contributions

This study makes three significant theoretical contributions to the HADC selection literature. First, we fill a gap in the literature by addressing the uncertain eventualities that arise from decentralized relief aid supplies while making the HADC selection decision in post-disaster planning during the response phase. Second, we propose using stratified DAPs, namely prioritization by relief items type, speed of delivery, and disaster-affected location, to address the challenges of decentralized relief aid supplies in HADC selection decision-making. Third, taking the CT perspective enables us to gain a good understanding of the relationships among the contingency factor (decentralized relief aid supplies), the response variable (stratified DAPs), and the performance variables (the 3E criteria). The CT view provides a coherent structure for HADC selection decision-making, which has not been used in the literature. In addition, we pioneer the use of the stratified MCDM technique to address the HADC selection problem. Considering the probabilistic nature of the DAP states, the stratified MCDM method facilitates incorporating multiple criteria and distinct state probabilities into anticipation of uncertain eventualities.

5.2. Managerial contributions

In addition, we also make three substantial managerial contributions for humanitarian practitioners and HOs. First, the humanitarian practitioner carrying out the relief delivery process in the response phase must account for the DAPs while making the HADC selection decision. Multiple combinations of DAPs include the possible transitioning states, which further aid in anticipating the exogenous contingencies arising from the decentralized relief supplies. For example, the ideal state s_{13} resulted in HADC "A" being the best one (see Table 4). Similarly, for each DAP state, the resultant HADC will differ based on the importance of the 3E criteria weights given by the experts. Thus, our findings assist practitioners in making informed HADC selection decisions for each DAP state. Second, incorporating the 3E criteria as performance variables to measure the fit between the decentralized relief aid supplies and stratified DAPs is helpful for practitioners as it accounts for the cost (efficiency), responsiveness (effectiveness), and equitable distribution (equity) in making the HADC selection decision. Given the trade-offs among the 3E criteria in the sensitivity analysis, the practitioner weighing the equity criterion high will go for opening HADC "A". On the other hand, the decision-maker weighing the responsiveness of relief delivery high will prefer opening HADC "B". Such comparative analysis amongst the performance variables will guide practitioners to make an informed HADC selection decision based on the context.

Lastly, we provide a helpful tool, i.e., the proposed SMCDM model and the corresponding algorithm (pseudocode), to the decision-maker to select HADCs in the disaster response phase. The tool is generic as the decision-maker has the flexibility to adjust the input weights as per the external eventualities depending on the disaster type. Also, the provided algorithm assists in identifying the second-best HADC selection decision. Anchored in the unprecedented contingencies during the disaster response phase, the operationalization of the first best HADC may be problematic sometimes. In such circumstances, it becomes of utmost importance for the practitioner to look for the second-best option without greatly compromising the performance variables. However, we also demonstrate via numerical studies the good performance of the tool by applying it to the case of Cyclone Fani.

6. Conclusions and limitations

We conduct this study to understand the HADC selection decision in the disaster response phase from the contingency theoretical (CT) perspective. The CT lens assist in discerning the importance of the contextual variables (decentralized relief aid supplies), response variables (stratified DAPs), and performance variables (3E criteria) in making the HADC selection decision. The DAPs help anticipate the contingencies arising from the decentralized nature of supply chains. However, to assess the fit between the contingencies and the response variables, we perform stratified MCDM using TOPSIS for HADC selection, providing the likelihoods of the multiple DAP strata.

Our findings reveal that the HADC selection decision made without considering the possibilities of DAPs is different from the selection decision considering multiple DAP strata. Moreover, each DAP state results in a distinct HADC selection decision, highlighting the importance of the context in which decisions are being made. The change in the final selection of the HADCs by incorporating the multiple DAP strata corroborates with other studies on SMCDM (e.g., Asadabadi (2018); Asadabadi and Zwikael (2021)). The findings of the sensitivity analysis highlight the trade-offs amongst the 3E criteria and the changes in the HADC selection decision. The numerical studies unveil the importance of criterion weights, which subsequently highlights the decision-maker's priority or the actions they want to take while operationalizing the DAP strata, whether to weigh equity, effectiveness, or efficiency high. For example, decision-maker preferring effectiveness so as to reach the beneficiaries fast will go for opening HADC "B". However, if the decision-maker's ultimate goal is to provide equitable distribution to the affected regions will opt for opening HADC "A". However, if the decision-maker considers all the 3E criteria weights high, then HADC "A" will again be the optimal HADC to pick.

This study has a few limitations, which can be addressed in future research. First, we use three DAPs with three strata and 16 states. However, more DAPs can be incorporated with distinct levels to capture a more uncertain environment, e.g., the total aid delivered to the disaster affected regions. Second, there are two primary concerns about SMCDM. The first concern is that it is computationally demanding when the numbers of states and levels increase. Advanced software tools can deal with this concern by dealing with more states and levels. The second concern is related to the state transition probabilities. Based on past experience, practitioners can intuitively estimate the likelihoods of the states of the DAPs in the humanitarian setting. Third, we consider the DAPs in a single period for HADC selection. Future studies should consider multiple periods in the response phase to address the more practical HADC selection problem. Lastly, the inherent issue in the MCDM approach concerns decision reversals (Aires & Ferreira, 2019;

Mufazzal & Muzakkir, 2018), which also exist in the SMCDM approach. Also, collecting data for the input parameters for a large-sized problem is an issue as the data may have a high chance of missing values for some parameters. The unavailability of data may lead to a decision reversal situation for some instances. Therefore, applying the SMCDM approach to deal with large-sized problems may face the issues of evaluating the criteria, DAP states, and alternative HADCs. Future studies should focus on avoiding decision reversals in performing stratified MCDM.

CRediT authorship contribution statement

Mohammed Nawazish: Conceptualization, Methodology, Data curation, Software, Formal analysis, Writing – original draft. **Sidhartha S. Padhi:** Conceptualization, Methodology, Validation, Writing – review & editing. **T.C. Edwin Cheng:** Formal analysis, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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