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S.I. : APPLICATIONS OF OR IN DISASTER RELIEF OPERATIONS, PART II

Humanitarian aid delivery decisions during the early recovery phase of disaster using a discrete choice multi-attribute value method

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Abstract
The humanitarian aid delivery problem associated with the early recovery phase of a disaster often incorporates multiple attributes. In this paper, the relative importance of various humanitarian aid attributes was measured using a discrete choice multi-attribute value method. This approach identifies all possible non-dominated pairs explicitly ranked by experts and provides an overall complete ranking of attributes. The performance score of each aid delivery plan was then calculated using the attributes' ranking by solving a corresponding linear programming model. As an application study, the issues pertaining to the early recovery phase of 2017 flood in Assam, India, were analyzed. It was concluded that the 'delivery amount' is the most preferred attribute selected by humanitarian experts.

Keywords Humanitarian logistics · Aid delivery · Early recovery phase · Pairwise comparison · Discrete choice method

1 Introduction

During the last few decades, the world has witnessed several anthropogenic and natural disasters that have resulted in casualties and infrastructure destruction (Gad-el-Hak 2008). Such disasters have gradually increased mainly due to the higher frequency of floods and storms (Centre for Research on the Epidemiology of Disasters 2016). Responding immediately to such irregular and unpredictable events so that the impacts can be minimized is a primary global concern, especially to the researchers and practitioners of humanitarian logistics (Özdamar et al. 2004; Kovács and Spens 2012).

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Humanitarian logistics (HL) is concerned with providing survival aids to people during and after disasters. The primary objective is to minimize human sufferings (De la Torre et al. 2012; Dubey and Gunasekaran 2016; Huang and Song 2016; Wang et al. 2016). However, it is not easy to achieve this goal during operation. Various trade-offs exist, which increase the complexity of the decision-making process. Some typical examples include whether to deliver more cargo at a reduced speed or less cargo at a higher speed; load more food, shelter-related materials, or medical kits, etc.

Formulating mathematical models that address these issues and quantitatively express the goals could be an extremely difficult task at times. Nonetheless, researchers have attempted to solve these problems by proposing a range of multiobjective decision aid models for relief delivery (Tzeng et al. 2007), warehouse location-routing during emergency (Rath and Gutjahr 2014), humanitarian aid delivery and trade-offs assessment (Gralla et al. 2014), etc. Furthermore, a two objective model for the emergency resource allocation uncertainties faced during the aid delivery processes (Hu et al. 2016) and another model for coordinating humanitarian relief supplies (Dubey and Altay 2018) have also been devised. Besides, relief distribution performance metrics have also been devised (Huang et al. 2012).

The multiobjective models are known for assessing the trade-offs among several conflicting objectives. In the above studies, the authors have successfully captured such trade-offs in the humanitarian aid delivery that are mostly related to the preparedness and response phases. Nevertheless, there is yet another distinct and important phase, namely the early recovery phase. Evaluating the trade-offs in the objectives and understanding their contribution towards minimizing the suffering encountered during this phase are equally challenging. However, these problems have not been exhaustively addressed in the literature. This lacuna has motivated us to explore the objectives and their trade-offs that are associated with this phase of the disaster.

The present study endeavors to fill this research gap. Six relevant attributes of humanitarian aid delivery pertaining to the early recovery phase were identified, including demand fulfilment, delivery speed; priority by vulnerability; health service; water, sanitation, and hygiene (WASH); and cost. The relative importance of these attributes is then determined using the discrete choice method known as Potentially All Pairwise RanKings of all possible Alternatives (PAPRIKA) (Hansen and Ombler 2008). This method computes all the potential pairwise rankings for the considered attributes and identifies all the non-dominated pairs. Subsequently, point values are obtained corresponding to all the ranked pairs using a linear programming technique. The data required for this study is collected by means of a survey through the online platform of www.1000minds.com. The participants are government officials, logistics heads of NGOs, academic experts, and operational level volunteers who have worked during disasters.

This study contributes to the HL literature in the following ways: We have identified the major response planning attributes related to humanitarian aid delivery for the early recovery phase and measured their relative utilities. This process brings new perspectives to the transition between the response and early recovery phases. The utility factors associated with the planning attributes can be used for improving the resource allocation and hence the outcome of the humanitarian aid delivery programs. The proposed approach may be employed as a decision support framework by the policymakers to arrive at decisions related to humanitarian aid delivery in the early response phase. We have also compared our results with the extant literature and observed that the priority settings vary for each phase.

The paper is organized as follows: We present the review of existing literature in Sect. 2, a short description of the aid humanitarian delivery problems related to the early recovery phase of disasters in Sect. 3, the methodology in Sect. 4, a brief note on the 2017 Assam flood in Sect. 5, results and discussions in Sect. 6, and conclusions in Sect. 7.

2 Literature review

This work has two major research streams: humanitarian aid attributes and -value trade-off methods.

The aftermath of any disaster creates the necessity for short and long-term aids. The short-term aid delivery is a part of the response phase in which it is essential to supply relief materials to the victims at the earliest possible time. On the other hand, long-term aid delivery is a part of the recovery phase and assists in developmental activities (Urrea et al. 2016). The early recovery phase is the transition between the response and recovery phases, and it is necessary to have a smooth transition between these two phases. According to Mosel and Levine, (2014), such a transition is possible by linking relief, rehabilitation, and development in a linear single-way transition model from response to the recovery phase. Earlier, Christoplos (2006) pointed out that a superior development will increase the resilience, a better relief may contribute to an enhanced development, and improved rehabilitation will facilitate the smooth transition between relief and development. However, the model was criticized as the link is more analytical at the theoretical level and less empirical at the practical level.

2.1 Humanitarian aid attributes

The HL is a field that connects preparedness with response (Thomas and Mizushima 2005). The discipline possesses many unique features that are different from commercial logistics. During the emergency, HL plays a crucial role in providing essential supplies and services to the disaster-affected people. This characteristic has attracted researchers and practitioners to bring improvements in the aid delivery process. As a result, the HL literature reports various models for supporting and refining the aid delivery process (Wang et al. 2016). Huang et al. (2012) studied the problem of humanitarian aid at the initial days of response and identified that inadequacy in planning is a major hurdle to aid delivery. The researchers argued that a good preparedness planning and practice can mitigate the problems of aid delivery and make the process more effective. Ortuño et al. (2013) proposed a decision aid model to help the decision makers in making rational choices in emergency situations. Holguin-Veras et al. (2014) proposed a humanitarian aid model to minimize the sum of deprivation and logistic costs. These models incorporate different humanitarian aid attributes and their priorities.

Selecting the correct attributes and exploring the trade-off among them are crucial for the effective planning of humanitarian aid delivery. Fiedrich et al. (2000) selected lifesaving effectiveness and equality in accessing emergency medical services as the attributes. Tzeng et al. (2007) considered fairness and efficiency of aid delivery as the two attributes. The first attribute aims to maximize the satisfaction level and the second one aims to minimize the travel time and the total cost. Mete and Zabinsky (2010) and Huang et al. (2012) identified efficacy and equity as the attributes related to aid delivery. In this model, efficacy was linked with speed and sufficiency in the distribution of aid, and equity was linked with the degree of variation in the service received. In allocating emergency resources, Jacobson et al. (2012) examined the trade-off among service times, rescue rewards, and demand urgency.

Gralla et al. (2014) determined the part-worth utility of different attributes applied in the first 7 days of response. The researchers surveyed the preference statements of field experts from the United Nations Joint Logistics Centre and adopted the disease adjusted life year approach for preference elicitation. They considered the amount of cargo delivered, total delivered item type, distribution based on the locations' priority, delivery speed, and cost as the five attributes. Huang et al. (2015) proposed a model for resource allocation during the emergency comprising three attributes: life-saving utility, delay cost, and fairness. This model integrates the distribution of relief items with resource allocation. Gutjahr and Nolz (2016) reviewed the multi-criteria optimization models employed in humanitarian aid delivery and decomposed the attributes into three categories: efficiency, effectiveness, and equity. The investigators described the sub-criteria corresponding to these objectives as response, distance to be travelled, security and reliability, fixed costs for the procurement, supply-side traveling costs, facility-related costs, and costs incurred from human resources utilization.

Our literature review indicates that most of the decision aid models addressed the preparedness and response phases and identified the corresponding attributes. The humanitarian aid attributes for the early recovery phase have not been given enough importance. In the forthcoming section, the value trade-off methods are reviewed.

2.2 Value trade-off methods

In humanitarian aid delivery, decision makers often encounter situations that require trade-off between areas competing with each other for resources from the same pool, such as the delivery time and the amount of cargos. Practitioners in the field of health sector face situations of medical triage where resource allocation determines who will receive treatment and who will not. The academicians and field experts accept three methods for measuring the relative values, namely, contingent valuation (CV), direct utility (DU) measurement, and multi-attribute analysis (MA) (Baron 1997). These approaches are known as the stated preference methods in which the valuator defines the social, economic, and environmental parameters and enquires the respondents regarding their preference for one outcome over another. The conceptual theory behind these methods is that the value of goods and services is a manifestation of the end user preferences and needs. Determining the relative preferences of beneficiaries and experts can define the comparative value of goods and services. Economists suggested that the ultimate way to trade-off non-marketable goods and services is on the basis of utility and not money. Although money also has utility, the context is different; the same amount of money differs in utility. Weinstein et al. (2009) defined utility as "… preference weights, where preference can be equated with value or desirability". Hence, the utility of goods and services that eliminate human suffering should be measured as preference weights (Whitehead and Ali 2010).

In CV methods, respondents are asked to record their willingness to pay for available alternatives (Sudman et al. 1991). The economic theory of consumers provides justification for the CV theory. This concept is based on the idea of maximising the utility function for various goods rendered to people (Mitchell and Carson 2013). The DU methods are mostly applied in holistic ratings as well as person and time trade-offs. These methods do not apply money as a standard of comparison; instead they make use of the difference between unhealthy and hypothesised ideal healthy lives (Baron 1997). In MA, respondents record the trade-offs for more than two attributes (Green and Srinivasan 1978; Keeney and Raiffa 1993). PAPRIKA is a method of MA having advantageous features over its counterparts as it can identify all "pairwise rankings of undominated pairs" (Hansen and Ombler 2008). The method has been exploited successfully in the healthcare domain for prioritizing cardiac surgery patients; however, it has not been used in the HL field. In this study, we exploit the method for arriving at humanitarian aid delivery decisions in the early recovery phase of a disaster.

3 Humanitarian aid delivery problems related to the early recovery phase of disasters

Anthropogenic and natural disasters are increasing worldwide over the years. In such situations, life supporting systems such as private supply chain, communication, and health centre are either destroyed or damaged. This scenario makes people unable to access their basic needs, such as water, shelter, protection from hazard, etc. without the help of external aid (Holguin-Veras et al. 2014). Unfortunately, the transportation and distribution of essential aids are quite challenging due to the extreme social disruption and the severe impact on support systems and technical activities.

In the HL, various activities pertaining to emergency management are performed in four phases, namely, mitigation, preparedness, response, and recovery. The activities of the first two phases are performed before the disaster, while those of the last two phases are conducted after the disaster (Tomasini and van Wassenhove 2009). Proper utilization of resources during the post-disaster activities is a pertinent issue. It is always a demanding task to optimize the utilization of resources by maximizing the positive outcome and minimizing the cascading effects of a disaster. Unfortunately, some cascading effects are beyond the control of human beings. For example, the Great Eastern Japan earthquake leading to tsunami and the tsunami in turn resulting in a nuclear crisis in Fukushima were entirely unanticipated (Holguin-Veras et al. 2014).

The needs of the affected people change once the crisis moments are over. The inhabitants start seeking mid to long-term assistance for rebuilding the essential facilities, securing health services, future planning, etc. This demand puts forth the challenge of fulfilling every group's requirement with the objective of eliminating their sufferings in a sustainable manner. For achieving these goals, logistics managers need to trade-off among diverse aid activities competing with each other for the same resource pool (Gralla et al. 2014). For example, the decision of whether to focus on health services or on water, sanitation, and hygiene can be quite confusing. Which one of these two factors will have a more positive effect on minimizing human sufferings in different phases of the disaster? Should aid planners focus on vulnerability differences caused by socio-economic status (poverty, cast, and religion) and physiological characteristics (age, gender, and disability) while distributing the aid or only on functional criteria of HL such as the delivery speed and operational cost? Evaluating these multiple goals and understanding their relative importance in aid delivery programs will play a crucial role.

The early recovery phase of disasters is crucial as it is a transitional post-disaster phase which bridges the gap between the response and recovery phases. Health related hazards can cause adverse impacts, especially in the case of flood. It has been evidenced in many countries that despite the efforts undertaken by the governments for resilience building, health programmes, and sanitation initiatives, sudden disasters disrupted these programmes. Both the affected people and humanitarian aid agencies who facilitate essential supplies and services are severely impacted (Etkin 2016).

A better co-ordination mechanism is required to allocate resources in a more effective way, so that the different humanitarian actors can coordinate with each other in collating their complementary resources and achieving optimization. This co-ordination will help in the smooth transition from providing humanitarian aids to offering developmental assistance. The primary focus of this study is to address the need priorities of the beneficiaries during the early recovery phase of the disaster and suggest appropriate changes in the coordination practices of the inter-agency groups involved in humanitarian aid operations.

Table 1 Attributes and levels

Attributes	Levels
Delivery rate at a nearby warehouse	Between 3 and 4 days, 90% of cargo
	Between 2 and 3 days, 60% of cargo
	Within one-day, 20% of cargo
Demand fulfilment	40% of the demanded supplies for the second week
	60% of the demanded supplies for the second week
	80% of the demanded supplies for the second week
Health service	Mobile health clinic + prevention campaign
	Mobile health clinic + prevention campaign + health camp
	Mobile health clinic + prevention campaign + health camp + special services for women and children
Water, sanitation, and hygiene (WASH)	Bleaching powder and chlorine tablet (BP & CT)
	BP & CT + targeted hygiene promotion + hygiene kit
	Targeted hygiene promotion + hygiene kit + temporary toilet
Priority by vulnerability	Serve the highly vulnerable with 90% of the resources
	Serve the highly vulnerable with 70% of the resources and allocate 30% for the others
	Serve the highly vulnerable with 50% of the resources and allocate the remaining for others
Cost	80% of the available fund for this attribute
	60% of the available fund for this attribute
	40% of the available fund for this attribute

4 Methodology

To identify the non-dominated pairs of all the considered attributes, we use the potentially all pairwise rankings of all possible alternatives (PAPRIKA) approach developed by Hansen and Ombler (2008). Here, we briefly mention about the approach and the selection of attributes and levels.

4.1 PAPRIKA approach

To rank the different alternatives, additive multi-attribute value models with performance classes are widely adopted for locating the trade-off features based on multiple criteria (Hansen and Ombler 2008). PAPRIKA specifically addresses multi-attribute value models with mutually exclusive and unambiguously labelled criteria (See Table 1). At each level, score values indicate the relative importance and utility. The total score for each attribute is obtained by adding the values across levels. Ranking of attributes is done based on these scores. PAPRIKA incorporates the pairwise ranking of all the possible non-dominated pairs for all the attributes and ranks them in a pairwise manner. The method also identifies all the potential pairwise rankings for all the possible combinations suggested by the value model.

Assume a value model having a attributes and b levels. Let $c(= 2, 3, \ldots, a)$ be the degree of none-dominated pairs. Then, the total number of none-dominated pairs, $N(a, b, c)$, of degree c, including all possible combinations can be written as follows (Hansen and Ombler 2008):

$$N(a, b, c) = \binom{a}{c}(2^{c-1} - 1)\left\{\binom{b}{2}\right\}^{c} b^{a-c}, \tag{1}$$

where, $\binom{a}{c}$ is the binomial coefficient. The number of unique pairs of degree c, denoted by $U(a, b, c)$, can be written as follows:

$$U(a, b, c) = \binom{a}{c}(2^{c-1} - 1)\left\{\binom{b}{2}\right\}^{c} \tag{2}$$

A consistent pairwise ranking approach can determine the overall ranking of the attributes. From strict preferences (inequalities) and indifferences (equalities) with respect to the ranked pairs, point scores can be calculated. Further details about point score calculations can be obtained from Hansen and Ombler (2008).

4.2 Selection of attributes and levels

In the beginning of the preference survey, we identified the attributes to be considered. A large number of attributes creates a mental burden for the respondents as the pairwise comparisons increase exponentially (Hansen and Ombler 2008). We included many possible attributes, such as food and nutrient distribution, gender sensitivity, and protection of young girls and children. However, to keep the survey simple, we limited our attributes to six. We focussed on the attributes that mattered most to the humanitarian aid provider in the second week of the post-disaster phase. Several previous models suggested that capacity (amount of supplies) and time (arrival time of supplies at the warehouse) are important criteria for effective responses (Gutjahr and Nolz 2016). Hence, we considered these as our first two attributes. We also included cost as the third attribute as it is a measure of efficiency (Haghani and Oh 1996).

The Humanitarian Policy Report (Humanitarian and Group 2003) has explicitly mentioned the core needs as security, subsistence, safety of life, and health. We analyzed the SPHERE Project (Charter and Response 2011) and the District Disaster Management Plan and Joint Need Assessment Report (2017) and discussed with two experts possessing a minimum of 10-year experience in this field before selecting our attributes. The documents and expert suggestions provided us sufficient evidence to include WASH and health service as the fourth and fifth attributes of the humanitarian aid delivery for the second week. The sixth attribute pertains to the selection of recipients for the aid based on their proximity to an acute risk factor for the disaster's cascading effect, such as malnutrition, contagious disease outbreak, and insect-borne diseases among others. The recipients are not individuals but rather a group of people with a common socio-economic status. The final list of six attributes and their levels are presented in Table 1.

The second step is designing the preference involved in shaping the proper levels of 'performance' for each attribute. For example, demand fulfilment was drawn in three tiers: 40% of the demanded supplies for the second week (lowest ranked), 60% of the demanded supplies for the second week (second lowest ranked), and 80% of the demanded supplies for the second week (highest ranked). Table 1 presents all the six attributes and their respective levels.

While defining the attributes and levels, we were very careful about the language. We used only simple language understandable to the professionals and cheap talk to minimize the cognitive biases associated with such surveys. We avoided values such as 100 and 0 because they might lead to framing biases. For example, we used 80% of the demanded supply instead of 100% because 100% is the best possible amount, and it would hence influence a responder's preference. The *1000mind* software provides a function for setting impossible paired comparisons; hence, we have fixed a few such comparisons. For instance, short arrival time requires fast delivery that is achievable only by spending more money. This implies that low cost could not be a possible pair for high delivery speed since both could not be achieved simultaneously.

4.3 Process of data collection

We used *1000minds* software for collecting the data ("www.1000minds.com") (Hansen and Ombler 2008). Five steps were involved in this process. The first step was to enter the six selected attributes (criteria) and their priority levels. The second one was to feed the alternatives, if any. After saving the inputs of these steps, the survey link was emailed to the participants. In the third step, a series of simple questions were generated using the PAPRIKA method, and the respondent had to choose one of the two available options having a trade-off. The answer determined the weight or importance of the attribute and was calculated in the fourth step. Depending upon the preference values, the alternatives were ranked in the fifth step. Interested readers may use the given link[1] for fetching additional details.

To validate this study, we adopted the consistency checker feature available in the software. We fixed the number of repeated questions to one as an increase in the number of such questions could prolong the survey time. We also enabled the filter to exclude those participants who failed to give consistent answers to the repeated questions. If the median time spent per question was less than 5 s, we excluded such responses too from the study.

5 A case example based on the 2017 Assam flood in India

Today's world is vulnerable to disasters which cause destructions and leave the citizens with a scarcity of goods and services. In such situations, the humanitarian actors rely on logistics to serve the victims. According to World Risk Report (United Nations University 2016), India stands 77th among the 171 countries. National Disaster Management Authority (NDMA) has documented that forty million hectares of land in the country are under a high risk of flooding.

The case example discussed here is based on the flood that occurred in the Assam State of India in July 2017 during which 1.7 million people across 26 districts 2450 villages, and 81 revenue circles were affected. The disastrous event claimed 83 lives (Inter-Agency Group Assam 2017). The crops that mainly sustained the livelihood of the state's rural area were destroyed. The State Disaster Management Authority set up 123 relief camps and 259 relief distribution centres. 56% of the affected population had food security for less than a week, and only 9% had sufficient food. Moreover, only 62% of the relief camps were accessible to the socially deprived people.

In addition to these factors, WASH concerns were crucial as only 31% of the villages had access to uncontaminated potable water. Almost two-thirds of the affected villagers

[1] https://www.1000minds.com/about/how-it-works/decision-making-prioritization.

defecated in the open field, which triggered cholera/diarrhoea outbreaks. 78% of the villagers were vulnerable to water contamination at source. The health service was facing an alarming situation because most of the health centres were inaccessible due to the damage caused by siltation or the ruined infrastructure resulting from the extreme hydrological force.

The government notified the public that the post-disaster situation might probably worsen. Water clogs in the pits with debris caused communicable diseases and other health difficulties for all. Among the most vulnerable were the pregnant women, lactating mothers, elderly, and the differently abled persons of the villages. No safe and private facilities were available for the women and girls. The government administrations were concerned about eliminating the possibility of cascading effects after the flood. Hence, special instructions were given to the Inter Agency Group (IAG) of Assam to coordinate with all the humanitarian actors. IAG organized state and district level meetings to effectively handle the relief activity. Furthermore, they were contemplating on the transition phase from immediate response to mid and long-term relief. They wanted to prioritize the different objectives of humanitarian aid so that a proper coordination among the actors could be established.

To help the IAG, we determined six attributes that played a pivotal role in the planning of aid delivery during the early recovery phase. We performed literature review of various decision aid models and research articles on LRRD. Besides, we interviewed academicians, IAG members, logistics heads of NGOs, and the volunteers who worked during the flood. We emailed the survey to 50 such executives having prior experience in the planning and execution of humanitarian responses. A short description of the situation was provided in the email. The survey mail was followed by four reminders. The time given to the respondents was 10 days. The survey was performed with the help of the web-based discrete choice experiment software *1000minds* ("www.1000minds.com") (Hansen and Ombler 2008).

6 Results and discussions

The performance scores or utilities for the attributes were calculated by employing the PAPRIKA method. This utility amount was contributed by the respective attributes to the total utility of the humanitarian aid decisions. The sum of the part-worth utility of each attribute constitutes the total utility. Figure 1 presents the mean part-worth with specific utilities for each respondent.

In Fig. 1, the thick lines denote the mean part-worth with specific utilities for each respondent (thin lines). In this study, the part-worth utilities were evaluated for three distinct levels of the individual attributes and the radar graphs contain streaks connecting the attributes of aid delivery. In Table 2, the average and median part-worth utilities are presented.

The attribute levels are considered in a cardinal scale with non-zero data. As a result, these levels can be compared based on the part-worth utilities within an attribute. For example, fulfilling 90% aid delivery is superior to fulfilling 70% and much more superior to fulfilling 30%, and so on. However, the comparison is infeasible across attributes. For example, fulfilling 70% may not always be a superior plan when it costs 50% of the available fund.

The comparison is possible across attributes by considering how much an attribute contributes to the total utility. The difference in utilities between two levels of the same attribute measures what amount of utility can be increased through an additional higher level. Therefore, more important attributes are the ones that cover a larger utility range. The higher importance of one attribute may also be due to the range it covers. For example, we can observe a higher amount of utility over a domain of 40–80% than over 60–70% of the demand

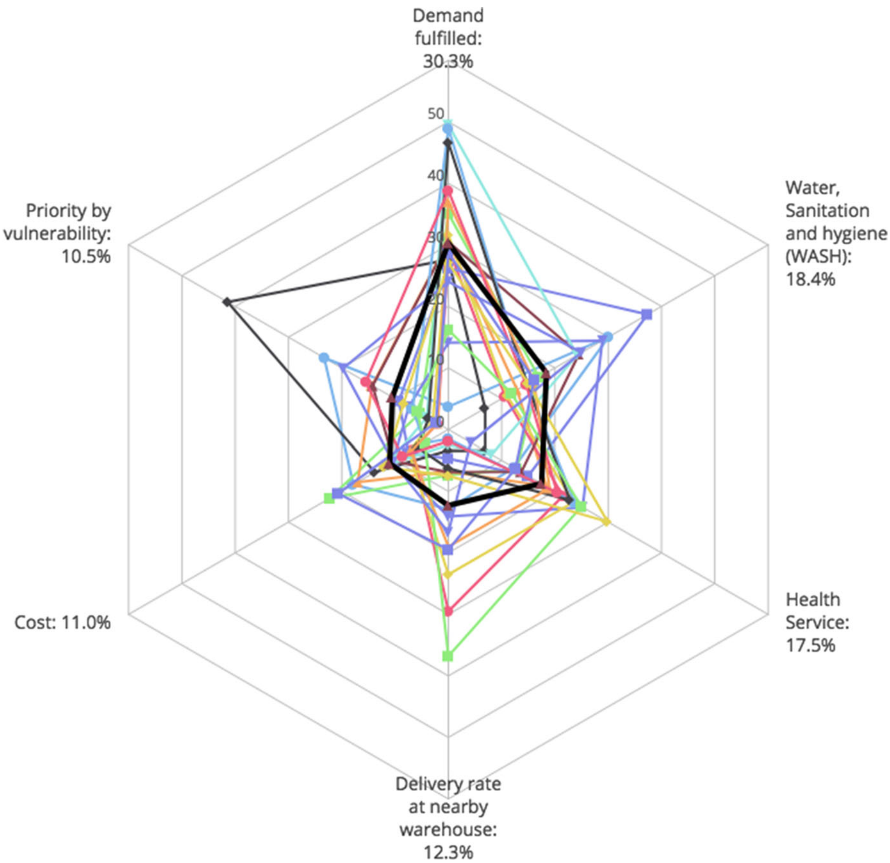

Fig. 1 Mean part-worth utilities for the respondent

fulfilment. Hence, a pairwise comparison among attributes is allowed for a particular level chosen in the study.

We initially centred our analysis on the usefulness of an attribute at different levels. As predicted, participants on an average preferred cargo with more supplies. Therefore, “Level-3″ priority plan was preferred over Level-2 and Level-1. It is counter intuitive to expect an equal allocation of resources among the low and high vulnerability groups. However, in telephonic conversations, respondents rationalised that they preferred to allocate equal resources because of political reasons as well as a lack of information regarding socio-economic and physiological status. In the case of WASH and health services, our result conformed to our expectations, mostly because the second week of response aimed at eliminating the risk of cascading effects. In Fig. 2, an overall score of each attribute is depicted graphically.

It could be inferred from Fig. 2 that the most preferred attribute is the total demand fulfilment. The second least preferred is cost; however, the utility of cost Level-3 is significantly higher than that of the other levels. This trend was consistently observed in all the respondents who commented that during the second week, humanitarian aid undergoes a transition from the response to the recovery phase, where cost plays an important role. Owing to this rationale, the low-cost level has a higher utility than the high cost level.

Table 2 Performance scores

	Attribute weight (sum to 1)	Median (%)	Mean (%)
Delivery rate at nearby warehouse	0.123		
Between 3 and 4 days, 90% of the cargo		0	0
Between 2 and 3 days, 60% of the cargo		4.1	5.8
Within 1-day, 20% of the cargo		7.5	11.5
Demand fulfilment	0.303		
40% of the demanded supplies for the second week		0	0
60% of the demanded supplies for the second week		18.4	18.2
80% of the demanded supplies for the second week		30.4	34.0
Health service	0.175		
Mobile health clinic + prevention campaign		0	0
Mobile health clinic + prevention campaign + health camp		7.4	6.8
Mobile health clinic + prevention campaign + health camp + special service for women and children		18.8	18.0
Water, sanitation and hygiene (WASH)	0.184		
Bleaching powder and chlorine tablet (BP & CT)		0	0
BP & CT + targeted hygiene promotion + hygiene kit		8.2	8.3
Targeted hygiene promotion + hygiene kit + temporary toilet		15.7	17.6
Priority by vulnerability	0.105		
Serve the highly vulnerable with 90% resources		0	0
Serve the highly vulnerable with 70% resources and allocate 30% for the rest		4.6	5.9
Serve the highly vulnerable with 50% resources and allocate the other 50% for the rest		6.9	8.3
Cost	0.115		
80% of the available fund for this attribute		0	0
60% of the available fund for this attribute		5.2	4.7
40% of the available fund for this attribute		10.3	9.7

The trade-offs among equity, efficiency, and effectiveness are evidenced from the obtained results. The highest utility attribute 'demand fulfilment' implies that effectiveness is the most significant factor. The delivery rate, which is a measure of effectiveness, is significantly less important. It can be attributed to the transition phase in which humanitarian logistics shift from a responsive to an efficient mode. Priority by vulnerability, which is one of the representative measures of equity, is the least important attribute. This fact leads to the conclusion that equity is a secondary objective. The cost of the aid programme, which is a measure of efficiency, has lesser utility than demand fulfilment, but more utility than prioritisation by vulnerability.

In the early response phase, humanitarian actors are more concerned about catering to the needs that arise from ground zero. Like the response phase, the second and third most important concerns are WASH and health. Contrarily, time plays a crucial role in the response phase. This finding suggests that the humanitarian actors are more focused on eliminating the cascading effects, such as health service disruption, contaminated water, open defecation, etc.

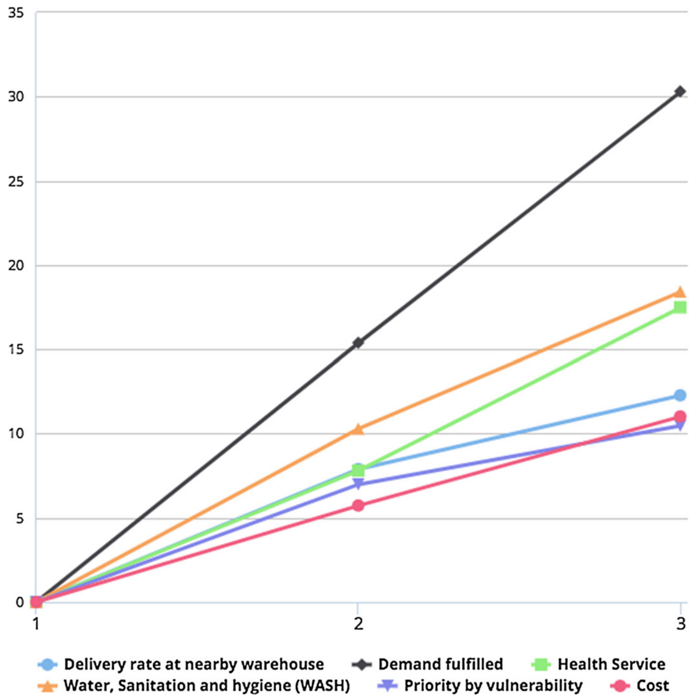

Fig. 2 Performance scores of attributes

The least important attribute is the vulnerability. This finding is contrary to our expectation. One possible explanation is the lack of proper information related to physiological and socio-economic conditions. This unavailability of information made it difficult to define the different vulnerability levels in the Indian setting. This study suggests that the IAG members should adopt the decision making tools developed by the WASH cluster Wash Information Management Toolkit (2014) for the prioritization of people according to their vulnerability level.

The findings of this study were related with the existing literature (Nolz et al. 2010; Lin et al. 2011; Gralla et al. 2014). We agree with Gralla et al. (2014) that comparing different models is difficult as there are differences in the formulation of each one. In terms of the nature of the humanitarian aid delivery problem and the attributes considered, the present study matches closely with that of Gralla et al. (2014). Therefore, the priority structure of the major attributes has been equated with this model. Some similarities and differences could be inferred from this process. Both the present study and the work of Gralla et al. (2014) have identified demand fulfilment as the highest priority attribute. The current research has established WASH as the second priority attribute owing to the cascading effects of the disaster witnessed during this phase, such as insect- and water-borne diseases, wound infection, etc. On the other hand, Gralla et al. (2014) identified prioritization by item type as the second priority attribute.

The attributes considered in this study, as well as the others in literature (Nolz et al. 2010; Lin et al. 2011; Gralla et al. 2014) were finally mapped to effectiveness, efficiency, and equity of humanitarian aid delivery. The effectiveness of aid delivery has been found to be the highest priority objective by Lin et al. (2011) and Gralla et al. (2014). This result agrees with our finding, but contradicts with Nolz et al. (2010) because of selecting a different priority setting. Gralla et al. (2014) discerned equity and efficiency to be the second and third important objectives, respectively. But in our study, efficiency has emerged as the second and equity as the third important objectives. This implies that as the humanitarian operations change from the response to the recovery phase, the priority of the attributes shifts from responsiveness to efficiency. Hence, the priority of the cost attribute is not the least throughout the early recovery phase. In the initial period, it was the least. However, towards the end of the recovery phase (see Fig. 2), it has gained greater importance than the equity. This is a significant finding of our study, and it contradicts the observation of Gralla et al. (2014) that the priority of the cost attribute is always the least. This is one of the advantageous features of the method employed in this study as it can identify all the "pairwise rankings of non-dominated pairs" over its counterparts. Finally, this investigation has established that the overall ranking of objectives during the response phase differs from that of the early recovery phase.

7 Conclusions

The humanitarian aid delivery decisions require an understanding of the diversified needs of the disaster affected people and trade-offs related to the various response planning attributes. This study addressed issues pertaining to the early recovery phase after the flood. Six attributes of humanitarian aid delivery were selected, and their relative importance was measured using a discrete choice multi-attribute value method called PAPRIKA. The method can identify all the possible non-dominated pairs of attributes. The performance scores of aid delivery plans were then measured by using the ranks of attributes through the solutions of an equivalent linear programming problem. These scores eventually helped in quantifying the trade-offs among the humanitarian aid delivery attributes and prioritizing them.

The findings of this study reveal that out of six attributes, aid delivery amount is the most important attribute, followed by WASH and health services. The delivery time appeared as a relatively less preferred attribute. Cost and vulnerability occupied lower slabs, and cost was relatively more important than priority by vulnerability towards the end of the early response phase. It was also noticed that the priority settings of the objectives in the early recovery phase were different from those of the other phases.

This study contributes to the HL field by improving decisions related to relief services and reducing the complexities of resource allocation during floods. The work also bridges the research gaps between the response and recovery phases. The methodology used here can be applied as a decision-making tool for arriving at humanitarian aid delivery decisions by appropriately changing the attributes and their levels as suitable to other instances. Our study is more appropriate for the developing and less developed countries where resources are scarce, and decisions are taken in the light of the bureaucracy. The estimation of part-worth utility may help the executioner in allocating the funds in a proportionate manner to effectively enhance the planning, execution, and outcomes of humanitarian aid delivery.

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