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Prioritizing stakeholder interactions in disaster management: A TOPSIS-based decision support tool for enhancing community resilience

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A R T I C L E I N F O

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A B S T R A C T

The escalating impact of disasters underscores the urgency of building resilient communities. Interactions among community stakeholders play a pivotal role in fostering resilience but improving such interactions is often hindered by competing priorities and resource limitations. To address this challenge, this paper proposes a decision support tool aimed at prioritizing context-specific interventions that enhance stakeholder interactions in disaster management. The tool includes two phases: (1) impact-based prioritization, identifying the most significant factors influencing interactions by evaluating the relative importance of each factor based on their direct and indirect influence; and (2) feasibility-based prioritization, assessing the practicality of interventions designed to improve the significant factors identified in phase 1. We surveyed Spanish emergency experts to gather data on the interaction factors and their evaluations against the decision-making criteria. We applied the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to analyze data. The results indicate that initiatives focusing on enhancing the leadership skills of emergency managers emerge as the most feasible and impactful interventions in our case study, followed by initiatives for facilitating community participation in the decision-making process and disaster response activities. On the other hand, initiatives for improving emergency response functionality, and disaster risk management plans are less feasible to implement. Additionally, we evaluated the usability and practicality of the tool together with emergency experts from different sectors. The tool received an overall positive evaluation from the experts, highlighting the significance of human factors such as status quo bias and structuring human judgment in decision-support tools while acknowledging potential resistance from users in utilizing such tools due to lack of education and training. The tool empowers policymakers and practitioners to effectively build resilient communities by offering them a systematic approach to prioritize context-specific interventions that enhance community resilience.

1. Introduction

The severity of disasters has been on the rise globally, with a higher number of casualties and affected individuals in the past five years compared to the preceding five years [1]. Furthermore, the economic toll of disasters has seen a significant increase of 82% between the periods of 1980–1999 and 2000–2019 [2]. Resilience has emerged as one of the crucial concepts that is facilitating effective disaster risk management across various communities [3]. Studies on resilience have introduced innovative perspectives and valuable tools that not only improve emergency response and coping with the aftermath of a disaster but also underscore the importance of anticipatory planning for preparedness and risk reduction activities [4–6]. Additionally, within the realm of disaster risk management, resilience encourages actions aimed at mitigating the impacts of unforeseen events that pose challenges in prediction and management.

Resilience has been studied across multiple fields, such as economics, engineering, ecology, and social sciences, leading each discipline to tailor its definition to align with its specific standpoint [6,7]. Recently, the focus has shifted from infrastructure-centric resilience-building approaches to a softer approach that emphasizes the collaborative role of community members in fostering resilience [8]. Community resilience is defined as “the capability of a community to face a threat, survive and bounce back or, perhaps more accurately, bounce forward into normality newly defined by the disaster-related losses and changes. Community resilience is, in effect, a reflection of people's shared and

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unique capacities to manage and adaptively respond to the extraordinary demands on resources and the losses associated with disasters" [9].

Besides reflecting people's shared capacities [9], community resilience is an inherent characteristic of a community that is influenced by its pre-existing conditions [10]. These pre-existing conditions are not only related to the physical or natural systems in a community but also to the social system including a strong network among different groups of stakeholders, their actions, and their '*interactions'* with one another and with the system [11]. These interactions span a wide range of areas [11] and act as a protective shield against disasters [12,13] especially, since each entity in society has a distinct set of knowledge, skills, and resources [14].

While these interactions are beneficial for resilience, '*enhancing interaction*' among stakeholders is rather complex. This is mainly because interaction is often linked to different and sometimes conflicting preferences and priorities of stakeholders [15]. In addition, it is often hard to decide where to intervene, what interventions to take to enhance interaction, and how to assess the effectiveness of such interventions [15,16]. In the face of such challenges, decision support systems (DSSs) can be used to prioritize the intervention actions related to enhancing stakeholders' interactions. DSS provides a range of tools that facilitate efficient decision-making while considering the diverse preferences and trade-offs among community groups [17]. Additionally, DSS can reduce the subjectivity and normativity of human analysis during a decision-making process, leading to more objective and evidence-based decision-making [18]. Multi-criteria decision analysis (MCDA) is among the techniques used for decision support. MCDA techniques encompass a range of methodologies that enable incorporating multiple stakeholders' viewpoints, alternatives, conflicting objectives, and criteria [19]. Due to these capabilities, MCDA techniques are widely used in resilience-related studies [19–21].

This paper presents an MCDA tool for prioritizing the factors and interventions that improve stakeholders' interactions in the preparation phase of disaster risk management. We refer to intervention as the action of improving factors that impact stakeholders' interaction.[1] The focus on *'preparedness'* is particularly motivated by the fact that "for every dollar invested, disaster preparedness is estimated to yield savings of up to seven dollars" [22]. Currently, the funds directed towards preparedness are relatively small compared to those allocated for emergency response [23]. The MCDA approach [24] proposed in this study evaluates and prioritizes interventions based on the decision-making criteria that impact the implementation of interventions as well as the interdependencies among these interventions. The factors impacting interaction were identified through a literature review [11,25], as well as the decision-making criteria [26,27], while the preferences of the decision-maker were captured through a survey with emergency managers and resilience-building experts in Spain. The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [24] was then used to analyze the results of the survey. Moreover, the proposed tool was evaluated through interviews with emergency and resilience experts.

The tool is primarily intended for use by managers, decision-makers, and policymakers who are responsible for enhancing community resilience, as part of the organizational decision-making process. The tool's application is particularly relevant to the preparedness phase of the disaster life cycle, as it facilitates the identification and prioritization of interventions that can strengthen interactions within the communities before disasters occur. Interaction among different groups of stakeholders is crucial for supporting the response and recovery phases once disasters occur.

The rest of this paper is organized as follows: Section 2 provides an overview of the recent literature related to resilience decision support systems and the importance of improving stakeholders' interactions for building resilience. Section 3 explains the methodology used to develop the proposed tool, encompassing details on survey design, data collection, and analysis. In Section 4 we explore the practical application of the tool in Spain and present the obtained results. Section 5 covers the evaluation of the proposed tool through interviews. Finally, the conclusions drawn from the study are mentioned in Section 6.

2. Literature review

Resilience has emerged as a cornerstone of policymaking as it is recognized as a crucial component in mitigating the devastating impacts of disasters [28,29]. This growing recognition necessitates a comprehensive operationalization and assessment of resilience to foster effective disaster risk reduction strategies [30,31]. Various research endeavors proposed and examined community resilience assessment tools, paving the way for a more holistic understanding of resilience and its potential to safeguard communities from the escalating threats posed by disasters. BRIC [32], PEOPLES [33], and CDRI [34] are just a few examples of these tools. The authors of [5] explored the application of such tools in enhancing climate resilience. Their findings revealed that the majority of the tool mainly focuses on awareness building and knowledge sharing. The paper recommends the refinement of tools to not only assess outcomes but also actively support the processes involved in implementing resilience actions.

Resilience-related decisions not only require the engagement of various stakeholders, such as authorities, civil society, and citizens but also have a significant impact on these stakeholders [35]. These diverse groups often hold distinct and conflicting perspectives and preferences regarding how resilience should be addressed [15]. To ensure effective and inclusive decision-making, it is crucial to consider these heterogeneous perspectives when establishing priorities for actions and investments. While several studies, including [8,36–38] have highlighted specific initiatives and practices that facilitate stakeholder engagement in resilience-building efforts, there still remains a gap in well-established best practices to effectively implement these processes [8]. Furthermore, these studies did not offer any method for prioritizing the needed interventions to enhance these interactions, especially given the conflicting viewpoints among stakeholders. To successfully progress in enhancing relationships among community stakeholders and operationalizing the involvement of multiple stakeholders in resilience development, it is essential to establish a structured approach for determining where to start taking steps and prioritizing actions and investments.

DSSs can offer ways to tackle these prioritization challenges by providing analytical models that incorporate all relevant stakeholders and map the different operations [39]. Searching for community resilience decision support systems and frameworks in the Web of Science, we came across several publications that delve into prioritizing actions for enhancing community resilience [35,40–42], but the majority of these publications lack a significant focus on 'interaction' areas, if not entirely omitting such aspects. For instance, [35,41] capture stakeholders' opinions through participatory modeling, and as parameters within a mathematical model respectively. Nevertheless, both methods lack a distinct emphasis on the specific interactions among stakeholders.

Moreover, it is noteworthy to highlight that while many of the identified studies consider resources required for decision-making, only a limited number of publications incorporate a cost-benefit analysis into the development of the proposed DSSs. For example, [43] introduces a two-stage strategic framework for effective risk mitigation. The first stage employs deep learning to enhance the predictability of financial losses triggered by natural disasters, while the second one concentrates on project-level risk mitigation through cost–benefit analysis. They argue that the second stage is particularly significant since cost-benefit analysis stands as the primary decision-making tool in investment within the public sector [43]. Additionally, it is important for DSSs to

[1] For example, "community participation in decision-making" is one factor that impact interaction. Intervention discussed here refer to the actions that could be taken for "improving community participation in decision-making".

take into account aspects such as political will and change of laws as these aspects often play a crucial role in public sector decision-making processes [26,44].

Many of the identified publications employ Multi-Criteria Decision Analysis (MCDA) as their primary modeling approach, such as [19–21], mainly because of their easiness of application by non-technical decision-makers and their capacity to incorporate both quantitative and qualitative data, and that they enable group decision-making and the integration of stakeholders' preferences. TOPSIS is utilized to prioritize various flood risk management alternatives across two catchment areas in the UK and Germany [19]. The ranking is done based on five objectives such as the magnitude of the flooding, damage to the infrastructure, and feasibility of alternative implementation. Publicly available data is used to assess the alternatives against the first objective, while experts' opinions were used for the second and third objectives. Moreover, several studies have demonstrated the utility of TOPSIS in assessing and prioritizing urban resilience efforts. For instance, [45] employed TOPSIS to rank Tehran's districts based on flood resilience, providing valuable insights for decision-makers for building resilience-oriented strategies. Similarly, [46] utilized TOPSIS to analyze community disaster resilience in a Chinese city across seven dimensions, concluding that "community capital" plays a pivotal role. Furthermore, [47] applied the method in China to evaluate urban resilience across four key indicators: economic development, municipal facilities, social development, and ecological environment. These applications highlight the versatility and effectiveness of TOPSIS in guiding resilience-oriented planning.

[21] employs the Analytical Hierarchy Process (AHP) to assess decisions related to coastal adaptation in a coastal community in Canada. The decisions are ranked against four main pillars: cultural, social, economic, and environmental. Various groups of community stakeholders participated in the decision-making process and expressed their preferences through the AHP scores. Meanwhile, [20] suggests an emergency shelter allocation decision support framework, building upon both TOPSIS and AHP. These studies highlight the adaptability and efficacy of MCDA methodologies in prioritizing interventions and initiatives that foster resilience and enhance disaster management strategies. However, to the best of our knowledge, none of them covers the prioritization of the interactions among community stakeholders.

Considering the significance of stakeholder interactions in building community resilience and recognizing the need to navigate trade-offs arising from conflicting perspectives, the current study presents a decision-support tool for prioritizing the factors and interventions that influence stakeholders' interactions in a community.

3. Methodology: tool development

3.1. Background

This study is part of the ENGAGE European project aiming at increasing the ability of communities to adapt before, during, and after disasters. This part of the project, focusing on enhancing interactions among stakeholders involved in disaster risk management, has two phases:

1. To identify important factors that impact interactions among stakeholders, and
2. To assess and prioritize interventions for enhancing the interaction factors based on feasibility analysis.

The first phase of the project is completed in early 2023 and the outcome is explained in [25]. In this phase, we conducted a literature review that led to the identification of 27 factors influencing various interaction areas. We then utilized a Delphi study to identify the interdependencies among these 27 areas via the knowledge and perceptions of stakeholders. Then to prioritize the identified factors, we used network analysis techniques, namely centrality measure, to understand the accumulated impacts of a change in one factor on the others and to prioritize the factors based on their direct and indirect cascading impact.[2]

This paper presents the second phase of this project, focusing on the feasibility of actions/interventions required to improve factors identified in phase 1. This is motivated by the fact that decision-makers often take various aspects into account when making decisions. It is not solely dependent on the importance of an intervention or part of the system that should be improved but also the feasibility of implementation. In the second phase, we maintain the idea of combining both experts' opinions and quantitative methods. To carry out this extension, first, we selected the top 30% of factors identified in phase 1. Then, to evaluate the feasibility of interventions to improve such factors, we developed a set of criteria impacting decision-making through a literature review. Taking into account these criteria, we applied a multi-criteria analysis technique, TOPSIS, to rank the different interventions. The information required for the ranking was collected through an online survey of emergency experts conducted from August until the end of October 2023.

Fig. 1 summarizes the research steps in phases 1 and 2. Out of the initial pool of 27 factors identified in phase 1, only nine were incorporated in phase 2 (presented in Table 1). The selection was based on the outcomes of the network analysis in the first phase, specifically focusing on the top 30% of factors. This nuanced ranking approach enhances precision and offers a finer granularity that proves more manageable for experts working on the study. Working with 27 factors could be challenging for experts while using a subset of the factors provides a more detailed and practical perspective for their assessment.

Table 1 shows the prioritized factors and their definition identified in phase 1 of this project [25]. Additionally, the table shows examples of the interventions that could enhance the factors.

3.2. Decision-making criteria

The criteria impacting decision-making were identified through a literature review [26,27,44,48–50] and sense-checked with emergency and resilience experts involved in the European project. The literature reviewed discussed various criteria related to organizational decision-making for emergencies, constraints faced by governments in decision-making for disaster preparedness, and factors typically taken into account in governmental decision-making processes. We particularly extracted those criteria that appeared in multiple publications. Extracted criteria were then homogenized and categorized. For example, the availability of technology was merged into the category of non-human resources alongside equipment and materials. Once the criteria were identified and categorized, they underwent validation and verification by consulting with experts in the field.

The criteria are:

[2] The Delphi study was conducted in two rounds including nine resilience experts from academia, non-governmental organizations, and authorities and emergency organizations. Each round included a survey asking the experts to identify how one factor could impact another through a five-point scale. The Delphi study resulted in a "cross-impact matrix" showing the interconnectedness of these factors. Then, the cross-impact matrix was transformed into a network structure, where the nodes present the factors, and edges present the impact of the factors on each other. Using the network structure, centrality measures (namely degree centrality, closeness and betweenness measures) were applied to rank the factors. Results highlight high interdependency among factors, with "collaborative decision-making" and "leaders' credibility and capability" ranking first based on outdegree and closeness centrality and betweenness centrality, respectively. The methodology and the results are explained in detail in [25].

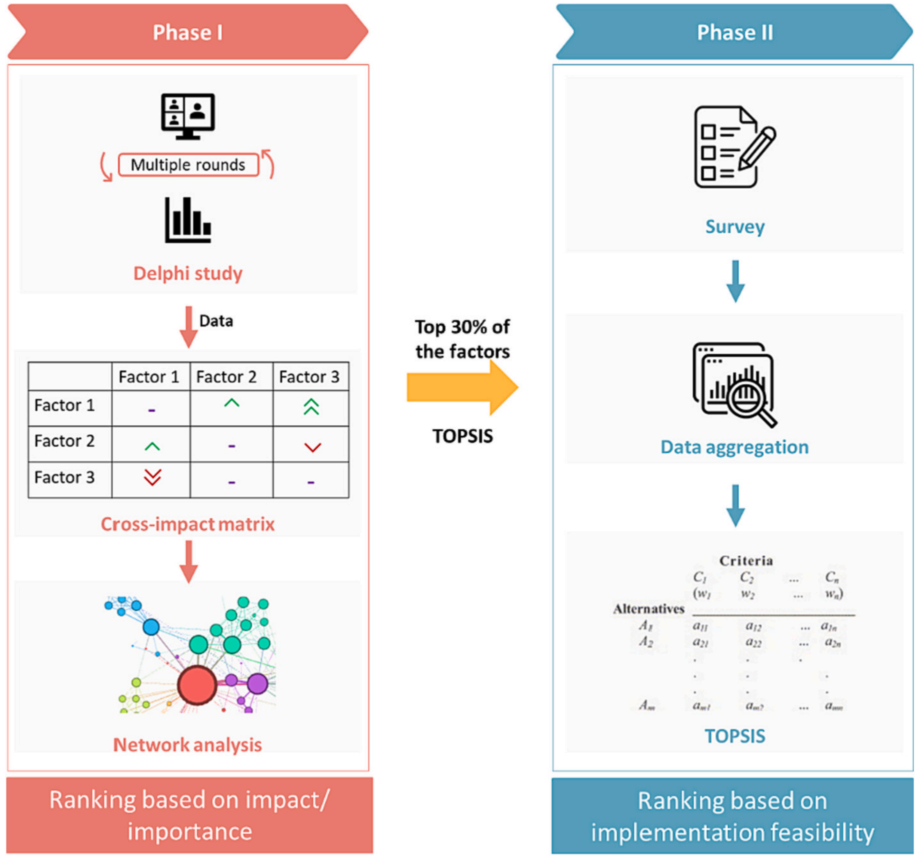

Fig. 1. Summary of the research methodology.

- Human resources [26,27,44]: The personnel, staff time, skills, and expertise required.
- Non-human resources [27,44,48]: The physical, technological, and material assets or resources required.
- Implementation time [27,48]: The time it takes to implement or complete the set of actions.
- Political will [26,44,49,50]: The determination, commitment, and support demonstrated by government or decision-making authorities towards implementing specific policies, initiatives, or actions.
- Change of regulations [48,49]: The creation of new or modification/ revision of existing rules, laws, or guidelines to accommodate new policies, practices, or requirements.
- Co-benefits [26,50]: The additional positive outcomes or advantages that arise because of implementing a particular action or intervention, beyond the primary intended goal.

3.3. Survey design

The survey designed to evaluate decision-making criteria for each intervention included two main questions besides the demographic ones. The first question was a scaling question, where the participants were asked to scale the different interventions (in Table 1) against the set of criteria mentioned above. For example, participants were asked to rank the human resources, non-human resources, implementation time, political will, etc. required for facilitating community participation in decision-making. For all the criteria, we used a five-point scale; the scale ranges from very low to very high for the following criteria: "human resources", "non-human resources", "change of regulations", and the "co-benefits". While for the "political will" criterion the scale ranges from very weak to very strong, and for the "implementation time," the scales are very short (few months), short (1 to 2 years), medium (3 to 5 years), long (6 to 10 years), and very long (> 10 years). All the scales included a "Not related" option. Using a five-point scale is recommended by [51] and it allows for differentiation in opinions while being straightforward and less prone to respondent confusion. The second question was related to assigning weights to each criterion, reflecting the degree of importance attributed to each criterion by the decision-makers. All the weights should have summed to 100. In this case, the weights of the criteria are determined through fixed point scoring technique since it provides a clear and direct approach for collecting decision-maker preferences and encourages explicit consideration of trade-offs during the decision-making process [52]. The survey questions can be seen in the supplementary.

3.4. Data collection

The survey was designed and hosted using the Qualtrics tool. It was available both in English and Spanish and open for responses for 90 days. We opted for the Snowball sampling method to distribute the survey and collect the required data, given the unique characteristics of the intended survey participants. Our objective was to survey decision-makers who have a direct relation with disaster management and resilience-building activities and work in Spain. We included participants who work in the government or entities such as civil protection and the Ministry of Interior.

The participants signed a consent form -as part of the survey- to participate in the study and they had the right to opt-out at any time. The survey questions were evaluated and approved by the ethical committee at the London School of Economics (approval no. 244821).

3.5. Analysis

3.5.1. Data aggregation

To aggregate the expert responses, we used the mean value of their

Table 1
Factors influencing interaction among stakeholders in disaster management and their definition. These are the most important factors identified in Phase 1.

#	Factor	Definition	Interventions examples
1	Collaborative decision making	The extent to which the decision-making process is decentralized and includes multiple departments and organizations to make a decision.	-Create/ improve the operational process that allows for decentralization. -Enhance the involved parties' communication and teamwork skill. -Create/change the policies & regulations required for decentralization
2	Community participation in decision-making	The extent to which various community groups (such as civil organizations, faith-based groups, etc.) participate in the decision-making and planning process.	-Changing some laws to allow for people's participation. -Building partnerships with local community representatives [citizen corps, church community schools, etc.] to be represented in the decision-making process. -Incorporating emergency planning discussions into community meetings.
3	Disaster information availability and accessibility	The availability of hazard prediction models, risk maps, awareness campaigns, and the ability of community members to access this information through different media outlets or educational resources.	-Developing hazard prediction models and risk maps. -Making the hazard information available via websites, printed leaflets and media -Designing the awareness campaign programs and materials. -Making the campaigns accessible for all populations.
4	Disaster response fund	The availability of governmental financial resources to handle risks, assist victims, and support affected households through loans and cash aids.	-Allocating funds from the general budget. -Designing programs to check the eligibility of affected people to get the funds. -Building insurance programs for different disasters. -Allocating national or local government funds for disaster response materials, etc.
5	Disaster risk management plans	The availability and communication of disaster-specific plans that include roles and responsibilities as well as response and protection measures that should be taken by different stakeholders, e.g., when to evacuate and the location of evacuation shelters.	-Designing hazard mitigation and response plans. -Conducting awareness campaigns to familiarize the population with the plans and sheltering capacities. -Communicating plans with public via websites, printed leaflets, media, school.
6	Emergency management training for citizens	The extent to which various community members acquire emergency response skills through school courses and disaster response workshops and drills.	-Design and conduct targeted training programs. -Integrating disaster training into the school curriculum. -Tailor training programs for different communities including social/ economic/geographical minorities.
7	Emergency response functionality	The extent to which responsible personnel can work and operate in a timely and efficient manner before, during, and after emergencies.	-Hold capacity building activities and exercises. -Continuous evaluation of emergency personnel performance.
8	Leaders' credibility and capability	The degree to which community officials are trusted by community members and are capable of leading and managing the community before, during, and after a disaster event.	-Provide leadership training and classes. -Build relationships with team-members and subordinates. -Initiatives to work with the community members and hear them out. -Being transparent and sharing credible updated information with the community to increase their trust.
9	People's participation in disaster response activities	Community members participate in the disaster response phase by evacuating voluntarily when an emergency occurs, following authorities' recommendations, sharing information about the crisis, and helping in rescue and relief work.	-Improving communication of risks and protection measures with citizens, raising awareness on both potential risks and actions before and immediately after an event. -Engaging voluntary sector enhances the emotional trust between responders and the public, as they work alongside responders and build personal relationships. -Offering some training and exercises for citizens to acquire the needed skills to participate in response activities. -Developing all-inclusive response measures considering all minorities when developing response plans.

responses. For the first question, we first transformed the textual scale into a numerical scale where the lowest point in the scale equals 1 and the highest point equals 5, for example, scales from very low to very high: very low = 1, low = 2, medium = 3, high = 4, and very high = 5. Then we averaged the responses across each intervention in association with each criterion. The averaging of the values excluded the values corresponding to the "Not related" option of the scale. [53] Regarding the second question, we followed a two-step approach to analyze the expert responses. First, we calculated the average score for each criterion based on all individual responses. This step aggregates the opinions of the entire group and provides a value for each evaluation element. Next, all the averages were normalized to be between 0 and 1 [53].

3.5.2. *Technique for order of preference by similarity to ideal solution (TOPSIS)*

Numerous Multi-Criteria Decision Analysis (MCDA) techniques exist to facilitate the ranking of alternatives in decision-making processes [19,53]. Among these are the analytic hierarchy process (AHP), simple additive weighting, COMET, and TOPSIS. The choice and utilization of a specific MCDA method depends on the study's objective and data availability [19,54]. TOPSIS is preferred in our case since it is straightforward, simple, easy to implement, not time-consuming (compared to AHP and COMET for example since it does not require pairwise comparison) [20], and easily comprehendible by decision-makers [54]. This is important especially since our target users, decision-makers in emergency organizations do not have the technical knowledge to understand more complicated methods. This type of comprehensibility and transparency that TOPSIS offers are crucial for decision-makers (especially in a field such as disaster management) because they provide clarity and insight into the decision-making process. Understanding how a model arrives at its conclusions allows decision-makers to trust and interpret the results more effectively [55]. Moreover, we used the questions proposed in [56] and the guidelines in [57] to guide our choice of the appropriate MCDA/MCDM technique for our problem.

TOPSIS, first introduced by Hwang and Yoon in [24], is primarily used to identify the best option among a group of alternatives that are evaluated based on multiple criteria. It measures the relative Euclidian distances of each alternative to both the positive ideal solution (representing the best criterion values) and the negative ideal solution (representing the worst criterion values). The alternative that has the shortest distance to the positive ideal solution and the farthest distance from the negative ideal solution is considered the most advantageous choice. This systematic and effective approach to decision-making allows stakeholders to make well-informed selections, especially in complex decision scenarios. The algorithm and all the calculations are explained in Appendix 10.1 and Appendix 10.2 respectively. The algorithm was implemented using Python programming language. While applying the algorithm, we considered the following:

1. Using fixed point scoring technique to determine the weights assigned to the different criteria.
2. Using vector normalization to construct the normalized decision matrix.
3. All the data points are aggregates (averages) of the experts' responses in the survey.

3.6. The structure of the tool

The tool follows the basic structure of a DSS [48,58] while integrating experts' knowledge with quantitative modeling techniques. It comprises three fundamental components: 1) data, which captures the knowledge provided by experts and acts as input for the next stage; 2) processing, where quantitative models are applied; and 3) output, where the final results, including the ranking of various factors, are obtained. A summary of the structure of the tool including both development phases is shown in Fig. 2.

The data component of the tool encompasses both the factors and the experts' opinions derived from both the Delphi study and the survey. The data from each round of Delphi is stored as well as the data resulting from the survey. Storage of data occurs for each Delphi round and survey responses. The processing component integrates a statistical analysis module for questionnaire data and a prioritization module. This module incorporates both network analysis and TOPSIS, which can be used independently or sequentially. Users have the option to visualize various graphs generated by network analysis[3] and a table illustrating the final TOPSIS ranking alongside intermediate calculations, if needed. The tool is supposed to be used for making strategic decisions.

The input of the system depends on experts' opinions, for which we conducted a Delphi study in the first phase, and an expert survey in the second phase. While the Delphi panel was well-suited for the first phase, it was not needed in the second phase due to the different nature of the data required. The Delphi method enabled the sharing of aggregated results with the experts after each round, contributing to an enriched collective comprehension of the subject matter [59,60]. Additionally, we aimed to establish a consensus on how the factors interrelate. In the second phase, however, our focus is not on reaching a consensus but rather on obtaining values associated with each intervention in relation to each criterion. In fact, we intentionally wanted to mitigate any potential interaction among various experts to prevent bias towards a particular factor.

The models in the processing component are applied to the data provided by the experts. In the first phase, to investigate the interrelations among the factors and rank them based on their importance, we applied centrality measures. Centrality measures offer a way to identify and quantify the importance of nodes in a network [61]. In the second phase, our focus was on ranking the interventions for enhancing the factors against multiple criteria, so we employed a multi-criteria decision analysis technique, namely TOPSIS.

The output of the first phase is the values of the centrality measures. The output of the second phase is the ranking of the interventions based on their implementation feasibility.

4. The application of the tool in Spain

The tool was applied in Spain, which is susceptible to a variety of natural and man-made hazards. Based on EM-DAT[4] data, natural disasters have accounted for 59% of all disasters in Spain over the past five decades. Floods, which make up one-third of all occurrences, are the most prevalent natural catastrophe [62]. Transportation accidents are the most frequent type of man-made disaster [62]. Both natural and man-made catastrophes can have a significant impact on the country and its population, emphasizing the importance of developing a resilient community effort. The Spanish government's highly decentralized structure is also an interesting aspect in terms of community resilience. Spain has a parliamentary monarchy system of governance, with public administration divided into three levels: state or national, autonomous community, and local [63]. The Ministry of the Interior oversees handling national emergencies. When a situation is not declared a national emergency, the highly decentralized autonomous communities are in charge of the first response, coordinating rescue operations, and assessing the situation [64]. Because of the numerous levels of government, Spain's emergency planning is highly decentralized, allowing for each autonomous community's unique characteristics to be considered. One factor contributing to the effectiveness of Spain's emergency planning is the high level of cooperation between the various autonomous communities. Another significant factor is the government's role in training emergency responders [64].

4.1. Results of the second phase

11 experts participated in the survey. 64% of the respondents work in the government and 36% work in emergency organizations. All the experts were males.

Table 2 shows the aggregated scores of the scaling question in the survey. Each expert assigned a score to each intervention in association with the different criteria, and then we calculated the average of the assigned scores, presented in Table 2. Looking at the “human resources” criterion, it becomes evident that most of the interventions require a medium to high level of human resources. Similarly, within the “nonhuman resources” category, the majority follow the same trend, except for the “Leaders' credibility and capability” factor, which tends to need a low level of resources. In terms of the implementation time, most

[3] Since this part of the tool was implemented using Gephi software, all the capabilities of the software could be used to show different visualizations and analysis.

[4] EM-DAT is a database containing data about natural and technological disasters from all over the world. It is maintained by CRED center at Université Catholique de Louvain, Belgium. https://www.emdat.be/ The data was accessed on 22nd of November 2023.

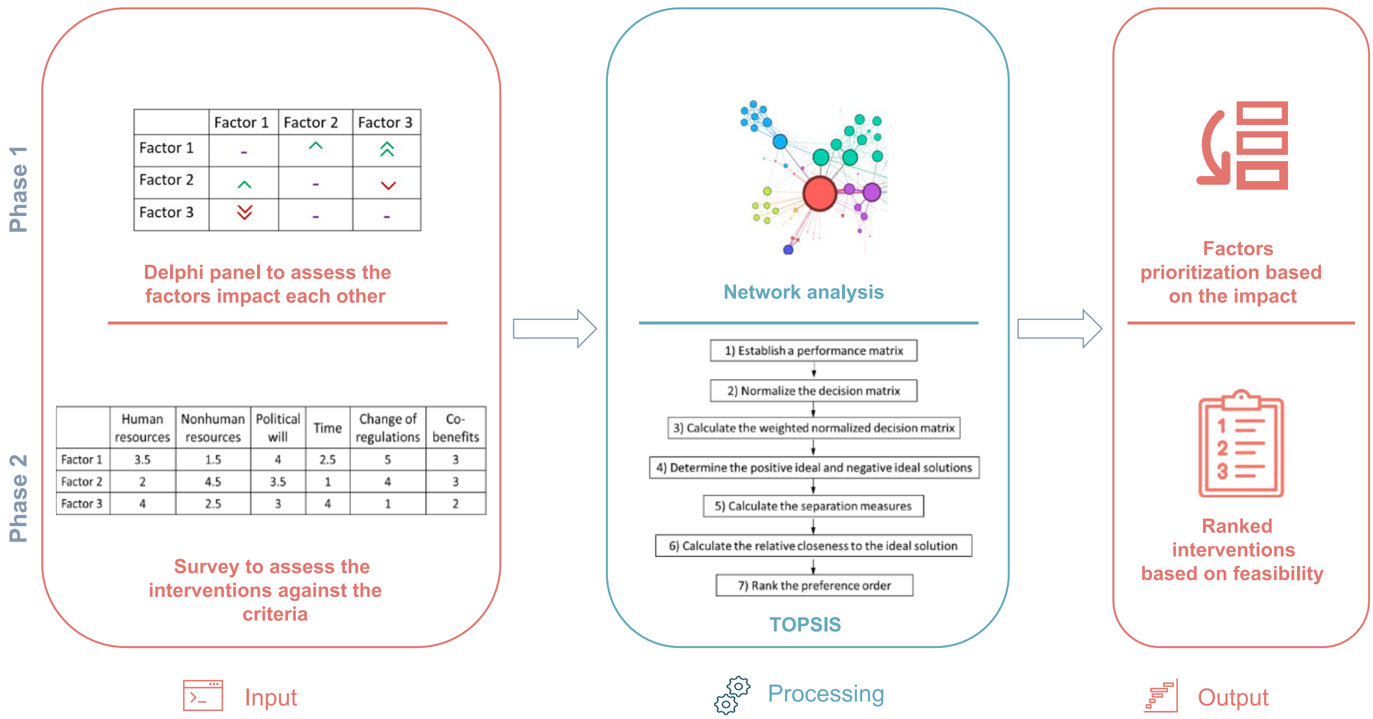

Fig. 2. Proposed priority setting decision support tool.

Table 2
Aggregated scores associating the different improvement interventions to the criteria.

Interventions for	Criterion: Human resources	Nonhuman resources	Implementation time	Political will	Change of regulation	Co-benefit
Improving collaborative decision making	4.18	3.64	2.36	3.55	3.45	4.36
Facilitating community participation in decision-making	3.73	3.00	2.82	3.55	3.27	4.00
Improving disaster information availability and accessibility	3.45	4.00	2.00	3.82	3.00	3.64
Increasing disaster response fund	3.50	3.73	2.60	3.91	3.73	4.09
Developing/improving disaster risk management plans	4.09	4.00	3.18	3.82	3.91	4.18
Providing emergency management training for citizens	4.00	3.45	2.73	3.64	3.27	4.09
Improving emergency response functionality	4.36	4.45	2.18	3.55	3.09	4.09
Enhancing leaders' credibility and capability	3.91	2.40	2.22	3.27	2.44	3.91
Facilitating people's participation in disaster response activities	3.91	3.20	2.78	3.45	3.36	4.09

of the identified interventions require a duration ranging from short (1 to 2 years) to medium-term (3 to 5 years) to be executed. When examining the level of political will required, it falls within the spectrum of moderate to strong. Regarding changes in regulations, most interventions within this criterion demand medium to high adjustments, except for the ones related to the “Leaders' credibility and capability” factor, which requires a low level of change. As for co-benefits, they typically range from medium to high in this context.

The interventions for “Improving emergency response functionality” score high in most of the criteria except for the “implementation time” and “change of regulations”. Interventions for “Developing/improving disaster risk management plans” are also assigned a high score in almost all criteria. On the other hand, the interventions related to “Enhancing leaders' credibility and capability” score low on the “nonhuman resources”, “implementation time”, and “change of regulation” criteria and high on the other ones.

Similarly, Table 3 presents the aggregated weights assigned to each criterion (question two in the survey). The experts consider that the most important criteria for decision-making in this case are human resources (31%), nonhuman resources (22%), and political will (19%) respectively. The co-benefits criterion comes least in terms of importance.

Based on the collected data, we applied the TOPSIS methodology resulting in the rankings presented in Table 4. We considered all criteria as a “cost” criterion except for “political will” and “co-benefits” criteria. In TOPSIS a criterion is a “benefit” one, where the more the better, for example, high co-benefits is desirable, on the other hand, a “cost” criteria” is where the more the worse, for example, if an alternative is associated to a high level of human resources, it means that it is harder to enhance this alternative. All the criteria are considered as monotonic criteria. And we used vector normalization as the normalization method to obtain the final ranking of the interventions (Eq. (1) in Appendix 10.1).

“Enhancing leaders' credibility and capability” ranks first after applying TOPSIS, while “Improving emergency response functionality” and “Developing/improving disaster risk management plans” rank last.

4.2. *The ranking of the interventions*

The results presented in Table 4 show the ranking of the

Table 3
Aggregated normalized weights associated with each criteria.

Criteria	Human resources	Nonhuman resources	Implementation time	Political will	Change of regulations	Co-benefits
Weight	0.31	0.22	0.12	0.19	0.11	0.06

Table 4
Ranking of the interventions using TOPSIS.

Rank	Interventions for	Relative closeness
1	Enhancing leaders' credibility and capability	0.74
2	Facilitating community participation in decision-making	0.62
3	Facilitating people's participation in disaster response activities	0.52
4	Improving disaster information availability and accessibility	0.50
5	Increasing disaster response fund	0.49
6	Providing emergency management training for citizens	0.46
7	Improving collaborative decision making	0.397
8	Improving emergency response functionality	0.28
9	Developing/improving disaster risk management plans	0.26

interventions based on their implementation feasibility not based on their impact on interaction. “Enhancing leaders' credibility and capability” ranks first. According to the survey participants, enhancing leadership abilities requires a low level of non-human resources (machines, row materials…etc.), a short time to see a change, and a low change of regulation. In general, leadership roles are vital not just in routine operations but also in times of emergencies. Emergency managers play a critical role in keeping communities safe before and during times of crisis. Effective emergency managers must have strong leadership skills to be successful in their roles. Some researchers even claim that a lack of leadership skills -among other things- during a crisis could lead to institutional failure [65]. Scholars identify some key leadership skills and competencies that are likely to positively influence outcomes in disaster scenarios. These include adaptability to the environment, cooperation with other stakeholders, flexibility in decision-making and operations, and effective communication with other stakeholders and the public [66–68]. It is important to train leaders in emergency organizations to build these skills. For example, the World Health Organization offers classes for building competencies for effective leadership [69]. The classes are divided into two modules; the first one focuses on developing different leadership skills, and the second is more related to incident management and working in a team. Additionally, a firefighting organization in Australia instead of solely depending on an exam to promote its middle management staff, it developed a three-month professional development program, to ensure that the new managers have the necessary leadership and managerial skills [70].

On the other hand, interventions such as “Improving emergency response functionality” and “Developing/improving disaster risk management plans” respectively rank last in the feasibility of implementation. Implementing initiatives to enhance these factors faces inherent challenges rooted in the complexity and dynamic nature of emergency scenarios.

Improving emergency response functionality involves complex coordination among various agencies, each with its own set of responsibilities and protocols [71]. This complexity is compounded by the unpredictability and diversity of emergencies, ranging from natural disasters to human-made crises. Crafting a response mechanism that caters to this variability requires substantial planning, investment in resources, and ongoing training programs [72,73]. Additionally, the dynamic and evolving nature of threats necessitates a high degree of adaptability, making it challenging to design a one-size-fits-all approach [74,75]. Moreover, factors such as communication infrastructure, resource availability, and the rapid mobilization of personnel contribute to the intricacy of implementing robust emergency response functionality. Despite its undeniable importance, the complex and dynamic nature of emergency scenarios makes the effective implementation of this factor a continuous challenge for emergency management systems.

The need for complex coordination among various stakeholders, and the challenge of a one-size-fits-all approach also apply to “Developing/improving disaster risk management plans”. Additionally, predicting the exact nature, magnitude, and occurrence of disasters poses a significant challenge, making it difficult to formulate comprehensive plans that cover all possible scenarios. Moreover, due to the dynamic nature of risks, plans need to be adaptable and regularly updated [76], adding a layer of complexity to their long-term effectiveness.

However, it is important to note that all the factors/interventions in this study are important for effective disaster preparedness and resilience building, and even those with lower implementation feasibility should be pursued whenever possible.

4.3. Co-benefits and the relationship with the closeness centrality

We also calculated the closeness centrality of factors, a metric gauging the significance of a node within a network based on its cascading impact. Essentially, closeness centrality serves as a proxy for measuring the co-benefits associated with a particular factor. We compared the values derived from the closeness centrality calculations [25] with the scores provided by experts, reflecting the perceived co-benefits of enhancing a specific factor. The results of this comparison are detailed in Table 5. The objective of this comparison was to investigate the extent to which expert opinions align with the outcomes generated by the model. Please note that the closeness centrality presented in the table encompasses 26 factors (included in [25]), extending beyond the nine specifically addressed in this study. Our rationale for examining the entire network of factors is that it provides a more comprehensive representation of a factor's actual impact, considering its interplay with all other factors. This approach reveals the relative importance of the factor within the larger network. In contrast, the perspectives of experts may not inherently account for this relational context.

The table shows that the ranking was the same for almost half of the factors (four out of nine). Specifically, factors such as “Collaborative decision making”, and “Disaster response fund” demonstrated similarity between the closeness centrality values and the expert scores, suggesting a shared recognition of their importance and co-benefits. However, notable discrepancies emerged for other factors (such as “Disaster risk management plans” and “Disaster information availability and accessibility”), pointing to divergent viewpoints between the model-driven assessments and expert opinions. This contrast underscores the nuanced nature of evaluating factors within a complex network, where relational dynamics may influence perceived importance. Such insights shed light on the complex interplay of factors, indicating the necessity of using modeling techniques for holistic considerations in resilience planning.

4.4. Sensitivity analysis

To test the reliability and robustness of our results we conducted a sensitivity analysis This analysis reveals how potential changes in the decision-making process might influence the preference for each alternative [77–79]. Our analysis employed three distinct approaches. Two focused on varying the weights assigned to each criterion. By adjusting these weights, we aimed to understand how shifts in their relative

Table 5
Co-benefits vs closeness centrality.

Factor	Co-benefit	Rank of co-benefit	Closeness centrality	Rank of closeness
Collaborative decision making	4.36	1	0.53	1
Disaster risk management plans	4.18	2	0.44	5
Emergency management training for citizens	4.09	3	0.48	2
Disaster response fund	4.09	3	0.47	3
Emergency response functionality	4.09	3	0.44	5
People's participation in disaster response activities	4.09	3	0.41	6
Community participation in decision-making	4.00	4	0.46	4
Leaders' credibility and capability	3.91	5	0.44	5
Disaster information availability and accessibility	3.64	6	0.48	2

importance impact the ranking of the alternatives. However, as [77] point out, solely examining weight sensitivity might not be sufficient. Therefore, we incorporated a third approach that explored the sensitivity of our results to the formulation of the criteria themselves. This analysis adheres to the principle of Criteria Formulation Independence [77], ensuring that individual preferences remain unaffected by variations in how alternatives are presented, provided these variations offer equivalent information [80]. For instance, choosing between therapies A and B for the same illness. When presented with survival rates (positive framing), most individuals favor therapy A. However, switching to mortality rates (negative framing) leads to a preference for therapy B. Despite the different framing, both convey the same information, as mortality always equals 100% minus the survival rate. This demonstrates that provided the information is equivalent, individual preferences should not be affected by how options are presented.

The first method we used to change the weights of the criteria is to apply the RANCOM method. The RANCOM (RANking COMparison) is a method that is used to assign weights to the different criteria based on experts' knowledge [81]. The RANCOM method is repeatable, easy to apply, and deals with imprecision in expert judgments. We followed the steps mentioned in [81]. We first used the average scores presented in Table 3, to create a rank for the different criteria. Then we created the ranking comparison matrix. Finally, using the matrix we obtained the new weights. The resulting weights are [0.306, 0.25, 0.139, 0.194, 0.083, 0.028] for criteria 1 to 6 respectively. The new weights resulted in the same ranking of alternatives as the one we got using Fixed Point Scoring (Table 6). This finding aligns with the findings of [81] especially for a small number of criteria.

The second method we applied to assess the sensitivity of our results to weight changes, is the method of relative weight variation for a specific criterion [79]. We changed the weights of the first criterion "human resources" since it is the most important criterion (the one assigned the highest weight, see Table 3). We systematically reduced and increased its weight by 5%, 10%, 20%, and 50%, resulting in eight different scenarios. Table 6 presents the detailed results.

Table 6
Sensitivity analysis results.

Scenario	Rank*
Original	8, 2, 9, 3, 4, 6, 1, 7, 5
RANCOM	8, 2, 9, 3, 4, 6, 1, 7, 5
Scenario 1: −5% C1	8, 2, 9, 3, 4, 6, 1, 7, 5
Scenario 2: −10% C1	8, 2, 9, 3, 4, 6, 1, 7, 5
Scenario 3: −20% C1	8, 2, 9, 3, **6, 4,** 1, 7, 5
Scenario 4: −50% C1	8, 2, 9, **6, 3, 1, 4,** 7, 5
Scenario 5: +5% C1	8, 2, 9, 3, 4, 6, 1, 7, 5
Scenario 6: +10% C1	8, 2, 9, 3, 4, 6, 1, 7, 5
Scenario 7: +20% C1	8, 2, **3, 4, 9,** 6, 1, **5, 7**
Scenario 8: +50% C1	8, 2, **4,** 3, **9,** 6, 1, **5, 7**
Reverse scale (political will)	8, 2, **4,** 3, **6, 9,** 1, **5, 7**
Reverse scale (change of regulation)	8, 2, **3, 9, 6, 4,** 1, 7, 5
Reverse scale (both)	8, 2, **3, 4, 6, 9,** 1, **5, 7**

* The changes from the original rank are highlighted in bold

Our analysis reveals a stable ranking for minor weight adjustments (± 5%, 10%). However, larger changes trigger more significant shifts. A decrease of 20% in the weight results in two alternative swaps, while a 50% reduction alters the ranking of four alternatives. Interestingly, the top and bottom two ranks remain consistent in both scenarios. Conversely, substantial weight increases (+20%, 50%) lead to more drastic rank changes, though the top two positions again remain unchanged. These findings suggest that while significant weight adjustments can influence rankings, the overall decision structure exhibits stability, particularly regarding the highest and lowest-ranked options.

The final stage of our sensitivity analysis focused on changing the formulation of specific criteria (Table 6). We implemented three changes. The first change covers the "political will" criterion, shifting the focus from existing political will to required political will (the scale becomes 5 - current value). This reframed the criterion as a "cost" instead of "benefit," leading to the rank of five alternatives changing, though the top-ranked options remained the same.

The second change is related to the "change of regulation" criterion, instead of assessing needed changes, we analyzed existing regulations supportive of the interventions. This transformed the criterion into a "benefit" one, resulting in four rank changes while the top and bottom options maintained their positions.

The third change was simultaneously reversing the scales of both criteria (political will and change of regulations) impacting nearly 70% of the rankings while maintaining the top two alternatives in their position.

These modifications highlight the potential influence of criteria framing on our results. While top-ranked alternatives stayed in the same position, significant shifts occurred when altering how criteria were measured or interpreted. This underscores the importance of carefully considering criteria formulation and its potential impact on decision-making processes.

Overall, the sensitivity analysis demonstrates the robustness of our core findings regarding the top and bottom alternatives, while acknowledging the potential influence of significant weight adjustments and criteria framing on specific rankings (especially the middle ones).

5. Evaluation of the tool

After completing phase 2 of the project, we co-evaluated the feasibility and usefulness of the tool with four emergency experts, using semi-structured interviews. During the interviews, we presented our proposed tool, including the first phase from [25] as well as the second phase presented in this paper. After the presentation, we asked the experts questions regarding their evaluation of the proposed tool, followed by a set of questions concerning the utilization of such decision-support tools in their daily operations. The latter was to understand whether and how decision support tools are employed as integral components in the decision-making processes of emergency organizations. The interviewed experts represented a variety of emergency organizations, including an NGO, a regional government, a fire brigade, and an anti-terrorism organization, in different European countries. The interviews were conducted online in English and took around 30–40 mins on average. Participants had the right to withdraw from the interview at any time. The interview script can be found in Appendix 10.3.

5.1. Evaluation of the tool

The interviewees confirmed the usefulness of the tool and its applicability to other fields of disaster management and resilience building beyond enhancing the interactions. One interviewee said "*I think it's an interesting approach when you're trying to redevelop or develop, […] a strategy for disaster resilience management or any [other strategies], even if it's not a disaster. […] especially when you're looking at collaboration across different institutions or across different levels and you need to prioritize resources which are often limited or look for what is the most effective.*" Another expert mentioned, "*I think it is a really important tool from research that would be fantastic to be used in organizations like mine, in that case, we would be much more efficient choosing the next steps in a project or what kind of project we could do.*"

It has also been highlighted that the tool offers a systematic and efficient way to promote the different projects or interventions in an organization since it follows a systematic approach to collect data and then applies the mathematical models to produce the ranking of the interventions (or projects within organizations). Moreover, participants discussed the usefulness of the tool in terms of eliminating or reducing the subjectivity attached to individual decision-making, through integrating collective opinion. It provides a more generalized scheme about the preferences of the stakeholders included. In other words, it eliminates the decision-making based on feelings, for example, one interviewee mentioned *"We have a 4 steps guideline to make decisions about new initiatives. (1) Is this in our mandate to do this? (2) Are there others who are more capable or more competent than us to do this? (3) Do we have the required resources in terms of equipment, money, and personnel? (4) Is this something we prioritize? If there are yes on every item, then we can start, and it's not a really good tool because if you really want to start something you can say that even though someone else are doing the same activity you will always find a way to say that in XX we do it differently and, therefore, we can always make it fit if we really want to do it. So, it gives us a more feeling-based answer than a data-based answer."* Finally, the participatory modeling part has also been found useful, particularly, when it comes to eliminating some factors/projects as we go back and check the participants' opinions to know their point of view. *"I think that's useful to do even once the process is activated, when it's operational, when it's already implemented to, you know, go back when you're doing some sort of an evaluation or an assessment of processes and stuff. It would be useful because some things might change over time, and you want to improve it or implement new things. I think it might be really useful to see the different perspectives of different users and stakeholders to see where you can improve certain things."*

On the other hand, one of the interviewees highlighted that depending solely on ranking factors or projects could be problematic, in the sense that some projects/factors may not have a big impact on the other factors (across the whole network) but are still important. For example, projects related to minority groups, targeting people at high risk, are crucial in any disaster risk management process but they may not get a high rank in terms of their impacts on other factors or implementation criteria. To avoid such a limitation the decision-makers could make a list of the "must-do" interventions and implement them anyway even if they are not highly ranked by the tool. It is, therefore, important to note that this tool should be used in cases where prioritizing interventions is not clear and that investing in all interventions is also not possible.

Another area of improvement discussed by the interviewees was to transfer the tool to an online application, so it could be used easily by the decision-makers across the different sectors.

5.2. The usefulness of DSS

During the interviews, we asked the experts if they use any decision-support tools in their daily operations. The participants mentioned that they use some - not necessarily prioritization - tools even in the most basic forms. For example, the participant from the NGO mentioned that they use a set of yes-no questions to reach a decision. In general, decisions are made based on the national action plan. The national action plan is decided every three years, based on which, the local organizations have the targets that they should work on, and they must prioritize and fit them into their local community needs. The local organizations adopt yes-no questionnaires to determine which action to take. Additionally, the national association does not use any kind of systems or tools to support their decisions other than municipality mapping data, for example, the number of children dropping out of school in a specific area, the number of people who show signs of mental illness …etc. "*So even in the National Association they don't use any kind of tools, they have this idea that now we need to enhance X and we have tools from the government where they are mapping every community in Norway so we can get data regarding [, for example,] how many children drops out of school, how many persons have mental illnesses or symptoms of mental illness, how many is reported feeling lonely, how is the economy in the community and things and analysis like this that is done by the government.[……] And in the case where there should be a choice between two options that serve the same purpose, for example, building retreats for elderly with mental health issues or providing home healthcare services, the politicians are the ones who are going to make the decision.*" It seems that the "tools" outlined by the experts, such as the yes-no protocols, adaptation plans, and population data, constitute the "input" data in the context of DSS terminology. This information needs to undergo a thorough and systematic analysis (processing) before reaching a decision (output). Consequently, there is a gap in conducting a rigorous and systematic analysis of the available data to effectively support decision-making in such organizations.

On the other hand, the government expert overseeing regional heatwave plans in Italy highlighted the use of statistical models to categorize the population into distinct groups, with a focus on identifying those deemed vulnerable. They also mentioned that decision-making is often a collaborative effort involving an expert task force, informed by the outcomes of statistical models and literature reviews. However, while this relates to the decision-making process for the plan's content, the responsibility for implementing tactics lies with individual entities, such as civil protection or medical professionals, each adhering to their respective protocols in specific cases. In this scenario, the employed models serve as valuable tools in the decision-making process by providing the expert task force with comprehensive data analysis. This analysis guides high-level decision-making but does not extend to tactical decisions.

The emergency expert from the Netherlands, holding roles as an incident commander and an innovation manager in one of the regions in the Netherlands, emphasized the importance of employing DSSs during times of actual emergencies, when there is a pressure to make quick decisions. Conversely, when there is no emergency, the use of DSSs is not as critical. During these periods, the decisions are typically made through the advisory board.

Regarding the barriers or challenges that could hinder the adoption of DSSs, one of the experts emphasized that organizations must possess the necessary skills and expertise for constructing such models, interpreting results, and effectively communicating findings to policymakers. The development of models and recommendations must align with a profound understanding of policymakers' needs and the issues they aim to address. Moreover, responses should be practical within the given context and available resources. For instance, suggesting the hiring of 15 nurses to aid vulnerable populations might not be feasible if only five are realistically attainable. Another expert highlighted the importance of creating a culture among the organization members about using these tools and systems.

An additional challenge arises from the reluctance of emergency organization personnel to adopt these tools, stemming from a belief that their own expertise surpasses the capabilities of the systems, *"they know better"* as noted by one interviewee. There is a lack of trust in these systems, necessitating efforts to persuade and educate users about how the various recommendations are generated, the rationale behind them and the different datasets used in the system. One expert emphasized "*The biggest issue is the human, that we have to convince. And how do you convince? You give them a little bit more insights into what you did to reach this decision or in the decision support system you show on the screen for the user explaining the different results*". Moreover, there is always the risk that once the emergency personnel start trusting these systems and using them on a regular basis, they become overly dependent on the systems to the extent that their intuitive decision-making abilities diminish, hindering their capacity to make informed decisions without relying on the system. The interviewee said that the personnel *"could become lazy"* once they highly depend on the systems. These systems should act as a tool in the hands of the emergency personnel not replacing them, they should act as a "*safety net, where there is a hybrid situation about a system and a human working together"*.

6. Conclusions

This paper proposes a decision support tool and a systematic research approach to prioritize interventions aimed at enhancing interaction among community stakeholders in response to escalating natural and man-made disasters. Community resilience, the capacity of a community to withstand and recover from disruptions, hinges on effective interactions among various stakeholders. However, limited resources often constrain the ability of entities like governments and emergency organizations to enhance these interactions. Therefore, prioritizing resilience-related projects and interventions is crucial to optimizing resource utilization. To address this challenge, this paper proposes a tool to support decision-making for enhancing interaction. The tool evaluates the feasibility of implementing interventions related to each factor, considering criteria such as human and non-human resources, and political will. By integrating these criteria, the tool provides a comprehensive assessment of interaction factors, enabling policymakers and decision-makers to focus their efforts on those that have the greatest impact on community resilience while being feasible to implement.

The tool was applied in Spain, using data provided by Spanish emergency experts. We found that prioritizing initiatives and policies to enhance the *leadership skills and capabilities of emergency managers* emerges as the most feasible factor to implement. This factor does not only positively influence the other factors but also it is the most feasible to enhance without requiring significant regulatory changes nor a high level of nonhuman resources. *Facilitating community participation in decision-making* ranks second in the implementation feasibility. Involving community members in disaster-related decision-making fosters a sense of ownership, and brings in local knowledge, ensuring that decisions are contextually relevant and reflective of the community's needs and vulnerabilities. Integrating community members into decision-making processes does not necessitate significant investments in time or nonhuman resources according to the evaluation of participants. Simple yet effective strategies, such as community meetings, participatory workshops, and knowledge-sharing platforms, can effectively engage community members in the disaster management process. On the other hand, despite the importance of factors such as "emergency response functionality" and "disaster risk management plans", improving these factors are relatively less feasible to implement. This is due to the requirement for high levels of human and nonhuman resources to initiate improvements.

To ensure the reliability of our findings, we performed a sensitivity analysis using three distinct methods. The results demonstrate stability when employing an alternative weight setting technique (RANCOM) and when adjusting the weights of specific criteria within a narrow range. However, larger changes in weights exert a more substantial impact on the ranking of the alternatives. Moreover, altering the formulation of criteria leads to shifts in rankings, particularly for alternatives positioned in the middle. This underscores the significance of accounting for diverse criteria framings during data collection and result interpretation.

Furthermore, we interviewed emergency managers to evaluate the usability and applicability of the proposed tool and explore the general usage of decision-support tools within emergency organizations. The tool received an overall positive evaluation from the experts, highlighting the need to consider the human factor, i.e. Status quo bias, structuring human judgment, and training requirements, when dealing with decision-support tools. They noted potential resistance from users to utilize such tools in their regular decision-making and highlighted the need for clarifying the added value of these tools compared to traditional decision-making without DSS. Also, our findings revealed that emergency organizations employ various types of tools, even if not specifically prioritization tools, indicating a broader usage of support tools in general.

A potential limitation of this study pertains to the relatively small number of survey participants. However, it is crucial to note that the survey is designed for implementation within the board of an emergency department or organization. In such high-level decision-making contexts, the number of participants is inherently limited, reflecting the strategic nature of the survey. Therefore, the study's focus on key decision-makers ensures relevance and applicability within the intended organizational setting.

Moreover, while our analysis addresses economic, technical, and political criteria in decision-making, we acknowledge the importance of considering normative factors. Understanding how societal pressure, ethical considerations, and organizational values influence decision-making processes is crucial for a comprehensive perspective. Therefore, future research should explore the role of these normative factors in shaping decision-making outcomes.

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Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT and Google Bard in order to paraphrase some of the text to improve its readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

CRediT authorship contribution statement

Sahar Elkady: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Sara Mehryar:** Writing – review & editing, Validation, Supervision, Methodology, Investigation, Conceptualization. **Josune Hernantes:** Writing – review & editing, Supervision, Investigation. **Leire Labaka:** Writing – review & editing, Validation, Supervision, Project administration, Investigation, Funding acquisition, Conceptualization.

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.

Data availability

The data that has been used is confidential.

Appendix

A.1. The TOPSIS algorithm

Given a set of alternatives, $A = \{A_k \mid k = 1, \ldots, n\}$ and a set of criteria, $C = \{C_j \mid j = 1, \ldots, m\}$, where $X = \{x_{kj} \mid k = 1, \ldots n; j = 1, \ldots m\}$ denotes the set of performance ratings and $w = \{w_j \mid j = 1, \ldots m\}$ denotes the set of weights associated with each criterion, the TOPSIS algorithm works as follows [53]:

1	Construct a normalized matrix: $r_{kj}(x) = \dfrac{x_{kj}}{\sqrt{\sum_{k=1}^{n} x_{kj}^2}} \forall k \in n, j \in m$	(1)
2	Construct the weighted normalized decision matrix: $v_{kj}(x) = w_j \times r_{kj}(x) \forall k \in n, j \in m$ Where w_j is the weight associated with the criterion j and $\sum_{j=1}^{m} w_j = 1$	(2)
3	Determine positive ideal solution *PIS* and negative ideal solution *NIS*: $PIS = A^* = \left\{v_1^*(x), v_2^*(x), \ldots\ldots, v_j^*(x), \ldots. v_m^*(x)\right\} = \{max_k\ (v_{kj}(x) \mid j \in J_1), min_k(v_{kj}(x) \mid j \in J_2) \mid k = 1, \ldots., n\}$	(3)
	$NIS = A^- = \left\{v_1^-(x), v_2^-(x), \ldots\ldots, v_j^-(x), \ldots. v_m^-(x)\right\} = \{min_k\ (v_{kj}(x) \mid j \in J_1), max_k(v_{kj}(x) \mid j \in J_2) \mid k = 1, \ldots, n\}$ Where J_1 *and* J_2 *are the benefits and cost attributes respectively*	(4)
4	Calculate the separation measures. First, the separation of each alternative from the positive ideal one is calculated by: $D_k^* = \sqrt{\sum_{j=1}^{m} (v_{kj}(x) - v_j^*(x))^2} \forall k \in n$	(5)
	Similarly, the separation from the negative ideal solution is calculated by: $D_k^- = \sqrt{\sum_{j=1}^{m} (v_{kj}(x) - v_j^-(x))^2} \forall k \in n$	(6)
5	Calculate the relative closeness to the ideal solution C_k^* $C_k^* = \dfrac{D_k^-}{D_k^* + D_k^-}\ 0 < D_k^* < 1, \forall k \in n$	(7)
6	Select the option with C_k^* closest to 1.	

A.2. TOPSIS intermediate results

In the following tables we present all the calculations done to obtain the final ranking resulting from applying the TOPSIS method.

Table 7
Normalized decision matrix.

Alternative	Human resources	Nonhuman resources	Implementation time	Political will	Change of regulation	Co-benefit
Collaborative decision making	0.356017	0.338159	0.306580	0.326630	0.348005	0.358472
Community participation in decision making	0.317689	0.278702	0.366337	0.326630	0.329848	0.328873
Disaster information availability and accessibility	0.293841	0.371603	0.259814	0.351473	0.302613	0.299275
Disaster response fund	0.298100	0.346520	0.337758	0.359754	0.376249	0.336273
Disaster risk management plans	0.348351	0.371603	0.413104	0.351473	0.394405	0.343673
Emergency management training for citizens	0.340686	0.320508	0.354646	0.334911	0.329848	0.336273
Emergency response functionality	0.371347	0.413408	0.283197	0.326630	0.311691	0.336273
Leaders' credibility and capability	0.333020	0.222962	0.288393	0.300868	0.246125	0.321474
People participation in disaster response activities	0.333020	0.297282	0.361141	0.317430	0.338926	0.336273

Table 8
Normalized weighted matrix with positive and negative ideal solutions.

Alternative	Human resources	Nonhuman resources	Implementation time	Political will	Change of regulation	Co-benefit
Collaborative decision making	0.110365	0.074395	0.036790	0.062060	0.038281	0.021508
Community participation in decision making	0.098484	0.061314	0.043960	0.062060	0.036283	0.019732
Disaster information availability and accessibility	0.091091	0.081753	0.031178	0.066780	0.033287	0.017956
Disaster response fund	0.092411	0.076234	0.040531	0.068353	0.041387	0.020176
Disaster risk management plans	0.107989	0.081753	0.049572	0.066780	0.043385	0.020620
Emergency management training for citizens	0.105613	0.070512	0.042557	0.063633	0.036283	0.020176
Emergency response functionality	0.115118	0.090950	0.033984	0.062060	0.034286	0.020176

(*continued on next page*)

Table 8 (*continued*)

Alternative	Human resources	Nonhuman resources	Implementation time	Political will	Change of regulation	Co-benefit
Leaders' credibility and capability	0.103236	0.049052	0.034607	0.057165	0.027074	0.019288
People's participation in disaster response activities	0.103236	0.065402	0.043337	0.060312	0.037282	0.020176
Positive ideal solution	*0.091091*	*0.049052*	*0.031178*	*0.068353*	*0.027074*	*0.021508*
Negative ideal solution	*0.115118*	*0.090950*	*0.049572*	*0.057165*	*0.043385*	*0.017956*

Table 9
Calculation of positive separation, negative separation, and relative closeness.

Alternative	Positive separation	Negative separation	Relative closeness
Collaborative decision making	0.034792	0.022862	0.396541
Community participation in decision making	0.022271	0.035552	0.614842
Disaster information availability and accessibility	0.033512	0.034564	0.507724
Disaster response fund	0.032168	0.030789	0.489050
Disaster risk management plans	0.044301	0.015328	0.257058
Emergency management training for citizens	0.030163	0.025583	0.458920
Emergency response functionality	0.049336	0.018833	0.276270
Leaders' credibility and capability	0.017011	0.048871	0.741796
People participation in disaster response activities	0.027080	0.029746	0.523452

A.3. Interview script

After presenting the tool, we asked the participants the following questions:
Usefulness and Limitations (related to the proposed tool)

- What are your thoughts on the proposed tool? Are there any major limitations or areas for improvement?
- Do you think the proposed tool could support your decision-making and prioritizing actions related to resilience building?

Framework or other tools Integration (more general)

- In general, how do you make decisions and prioritize different interventions to reduce disaster risk impacts and build resilient communities?
- Do you have any experience working with decision-making frameworks or decision-support tools?
- To what extent these kinds of tools are useful in supporting the decision-making process for enhancing resilience?
- How these frameworks and tools could be/are fitted into the current decision-making process for resilience? What are the barriers or challenges you see in integrating these tools into the decision-making process?

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.pdisas.2024.100320.

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