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Towards a resilient community: A decision support framework for prioritizing stakeholders' interaction areas

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ABSTRACT

Interactions among community stakeholders act as a buffer against disasters and present a way to build community resilience. Several decision support frameworks have been proposed in the literature to improve community resilience, but none focus on interactions among stakeholders. This paper presents a decision support framework to guide decision-makers in prioritizing areas of interaction based on their mutual impact. The framework is built on three components. The first involved conducting a literature review to identify areas of interaction among community stakeholders; resulting in identifying 27 factors that reflect the various interaction areas. The second was to implement a Delphi study to capture the dependency among the different areas. The third was to prioritize the identified areas of interaction through network analysis techniques to understand the propagating impacts of a change in one area on the others. The framework was applied to Spain, utilizing data provided by Spanish resilience experts. Our findings indicate a high degree of interdependence among all areas of interaction. Decentralization of the decision-making process and effective leading capabilities of emergency organizations have been identified as top priority areas. By utilizing this framework, decision-makers can systematically enhance interactions among diverse stakeholders, creating a roadmap to improve community resilience.

1. Introduction

Economic disaster losses increased by 82% between 1980-1999 and 2000-2019 [1]. The notion of community resilience is gaining popularity [2,3] due to its potential to provide tools for risk preparation, as well as deal with and recover from the consequences of disasters. Various disciplines, including ecology, economics, engineering, and social sciences, have addressed the concept of resilience, with each adapting its definition to fit its respective perspective [4,5]. Due to the shift from infrastructure-based resilience-building approaches to a softer approach that considers the collective role of community members in building resilience [6], this paper focuses on community resilience. 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 unique capacities to manage and adaptively respond to the extraordinary demands on resources and the losses associated with disasters" [7].

A wide range of stakeholders, such as the government, citizens, academia, the private sector, media, civil organizations, and funding entities [8] take part in crisis management. Their involvement, engagement, and collaboration are crucial for improving risk management and enhancing a community's resilience [9] since each entity in society has a unique set of resources and skills [10]. These interactions among the various stakeholders could act as a safety net against disasters [11,12]. Despite the wide range of stakeholder profiles, citizens and civil society organizations, emergency organizations and authorities are key contributors to disaster risk management [9]. As a result, this paper concentrates on three stakeholders: citizens or community members, non-governmental organizations (NGOs), and emergency organizations, including responders and authorities.

Interactions between these stakeholders span a wide range of areas including volunteering, place attachment, and training capacities; they also serve a variety of purposes such as enhancing population preparedness and improving risk awareness [13]. Moreover, these kinds of interactions create complexities because of the underlying conflicts between the stakeholders [14]. To capitalize on the benefits of these

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interactions, while considering their interdependencies and reducing complexities, it is essential to identify the interaction areas that require priority attention. Decision Support Systems (DSS) offer a set of tools that enable effective decision-making while taking into account the different preferences and trade-offs among community groups [15]. DSS also help in the operationalization of resilience, as it offers an in-depth understanding of what we mean by resilience and the entire resilience process [16]; indeed, building resilience depends on effective decision-making [17].

Several published studies have proposed decision support systems and frameworks for community resilience [18–20], yet none of them address areas of community interaction. The present research contributes to the literature on community resilience by developing a priority-setting decision support framework that ranks areas of stakeholder interaction based on their mutual impact.

By building this framework we:

- Identify areas of stakeholder interaction,
- Investigate how the identified areas of interaction impact each other,
- Rank the areas based on their importance by applying different prioritization measures.

The framework presented in this paper could be used by decision-makers in emergency organizations and authorities to (1) determine potential areas for improvement in their communities to enhance interactions among community stakeholders, and (2) make plans and policies to improve these areas, thereby bolstering community resilience as a whole.

Our analysis followed three main steps. First, a systematic literature review was conducted to identify the interaction areas. Second, a Delphi study was performed to identify and assess the relationships between the identified areas. The outcome of the Delphi study is a cross-impact matrix [21] that shows the experts' consensus on how an improvement in one of the areas affects another [22]. Third, to study the synergies between the different factors, we used network analysis techniques applying the framework to the Spanish case.

The rest of this paper is organized as follows: Section 2 reviews previous literature on the importance of stakeholder interactions and decision support systems for community resilience. Section 3 provides a detailed description of the methodology used to collect and analyze the data. Section 4 presents the results of the Delphi study and the network analysis focused on the dependencies of the areas of improvement. Our findings are discussed in Section 5 and our conclusions are presented in Section 6.

2. Literature review

In order to improve community resilience, it is crucial to involve a range of stakeholders, including emergency organizations, authorities, civil society, and the private sector [23], especially since building resilience is a shared responsibility among various stakeholders [14]. Researchers highlight the role of community stakeholder involvement and interaction in enhancing resilience [11] since these interactions and relationships can alleviate the shock caused by disasters, particularly at the local level [11]. Moreover, engagement and collaboration among community stakeholders play a key role in enhancing risk governance and resilience [9]. However, despite the relevant benefits of these interactions, they are difficult to improve since stakeholders have conflicting points of view and different priorities [14]. These conflicts usually revolve around how to improve resilience, how to manage the financial resources needed to implement these improvements, and how to evaluate their efficacy [24]. These conflicts add to the complexity of the interactions between different stakeholders and make disaster-related decisions prone to ineffectiveness and inefficiency [14].

DSS have the potential to deal with these conflicts by developing analytical models that map the various operations and include all stakeholders [16]. For instance, a search for scientific articles related to decision support systems or frameworks for community resilience, revealed two categories of publications. The first includes assessment tools such as [25–29], and the second includes decision support systems that use different modeling techniques such as optimization [30,31], multi-criteria decision analysis [32,33], and combined modeling using fuzzy cognitive mapping with network centrality measures [34]. While resilience assessment tools have become a focal point of research, the extensive lists of metrics can prove to be challenging for decision-making [35]. Hence, this paper focuses on decision support frameworks, given their modeling capabilities that provide an environment for building and testing different resilience-building scenarios [34]. We found that the mentioned papers cover community resilience but not the interaction areas. For example, [34] proposes a methodology for identifying and prioritizing flood resilience intervention actions by utilizing a combination of fuzzy cognitive mapping and centrality measures. The methodology is based on the flood resilience measurement framework and involves the stakeholders in Lowestoft, UK, through a participatory modeling approach. The study uses fuzzy cognitive maps to capture the causal relationships between different types of interventions and ranks them based on their interdependence using centrality measures. In [31] the authors apply a sequential discrete optimization technique to determine near-optimal actions for restoring an electrical power network after an earthquake. The proposed method takes into account the cascading effects among different system components involved in the recovery process.

Although some of the publications mentioned consider stakeholder opinions in their models, whether through participatory modeling [33,34] or as parameters for the mathematical model [30], they do not focus specifically on stakeholder interactions. The papers that cover stakeholder interactions and engagement in building community resilience follow a qualitative approach. Although some efforts have been made in this direction, there is still a lack of best practices for implementing the process of multi-stakeholder engagement in resilience building [6], despite its recognized importance. The authors of [36] described a serious game designed to improve collaboration and communication among the parties involved in drought preparedness activities. Yeo and Lee suggested a "whole community co-production" framework to investigate how all community stakeholders contributed to South Korea's response to the covid-19 pandemic crisis [37]. They utilized a case study approach to identify the key activities carried out by each stakeholder to face the crisis, highlighting the importance of certain resilience practices, such as widely sharing information about the situation and expanding healthcare services. In a city in the USA, interviews and tabletop exercises were conducted to identify the main factors influencing cooperation between community-based organizations, the government, and healthcare to handle crises on a local level [38]. The study emphasized the need to incorporate socially marginalized groups into the conversation to enhance the resilience-building process. It also stressed issues resulting from language barriers, weak relationships across organizations from different sectors, and poor communication. Furthermore, the study capitalized on the idea of building upon already established relationships across the different sectors even when they are not related to disasters.

The previously mentioned studies highlight stakeholder initiatives or important community resilience practices that help to engage multi-stakeholders in resilience-building activities. However, they do not study the interdependencies among these practices and lack any form of prioritization as to what should be done first. In order to take successful actions toward improving relationships among community stakeholders and operationalizing multi-stakeholder involvement in resilience development, we must first decide which steps take priority.

Different methods can be used to analyze the interdependencies among indicators. For example, Cai et. al [39] used Bayesian Network to

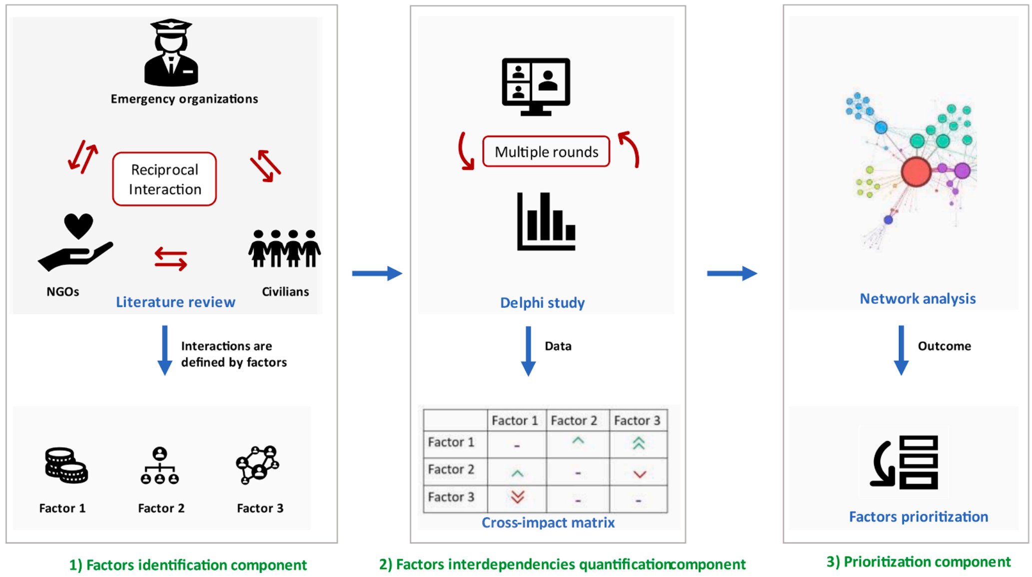

Fig. 1. Summary of research methodology.

analyze the interlinking between resilience indicators and resilience level. Although Bayesian networks capture the interrelationships among indicators and build on factual data, the method's complexity poses a greater challenge for real-world implementation [40]. Moreover, correlation analysis was used in multiple studies [27,41] to study the interlinking between the different resilience indicators. However, correlation analysis gives a sense of how the variables correlate together but does not indicate the magnitude of one factor's impact on another.

Network science includes computational models that could be used to study the interdependencies between the factors. This discipline offers a powerful set of tools to quantitatively approach highly interdependent systems and problems. Network analysis was used to analyze the interaction between different types of risks and their propagation in [40,42]. Network analysis was also used to study the interactions between sustainable development goals and how the goals influence each other [43]. Lu used social network analysis to investigate the role of civil society in the different phases of the disaster management cycle [44]. Social network analysis was applied to identify the important factors that impact green building development in China [45,46]. Also in China, Cui and Li proposed a Social Network Analysis community resilience assessment framework that builds on the community stakeholders' social capital [47]. Furthermore, network science techniques were used to investigate the cascading failures of power systems [48] and railway-power networks [49], and to assess the robustness of infrastructure networks in an urban context [3].

Considering the importance of stakeholder interactions, conflicting points of view, and the need for methods that guide the operationalization of stakeholder engagement in community resilience building, the present article proposes a decision support framework. This framework combines quantitative techniques using centrality measures with qualitative techniques employing the Delphi study to incorporate expert knowledge. The framework helps to identify the factors which reflect the areas of interaction between the community stakeholders and show the interdependencies among the different factors. Finally, it enables prioritization of these factors, allowing decision-makers to know where to start to enhance community resilience by improving stakeholder interactions while detangling some of the associated complexities.

3. Research methodology

This section describes the main components of our framework and the research methodology followed (Fig. 1). To improve community resilience by enhancing the interactions between different groups of stakeholders, a literature review was first conducted to identify factors or areas that reflect these interactions (factor identification component in Fig. 1). A Delphi study was then conducted, asking the experts to define the relationship between the factors identified in the first step. The result of the Delphi panel is a cross-impact matrix capturing the effect of the different factors on each other (factor interdependence component in Fig. 1). The Delphi panel is preferable to surveys [50] because it involves multiple rounds, which enables the sharing of aggregated results with experts after each round, leading to a better understanding of the topic. Moreover, this process of structured communication results in more precise outcomes since it can help to identify areas of consensus and divergence among the panelists [51,52]. Lastly, we applied graph theory and social network analysis techniques to conduct a network analysis, which provided valuable insights into setting priorities to enhance the interactions between different entities in society (prioritization component in Fig. 1). Network analysis is a suitable tool for capturing and analyzing complex interdependencies among system components [40]. Furthermore, network analysis enables the capture of systemic aspects (properties) of interactions [43].

3.1. Literature review for factor identification

A systematic literature review was conducted to identify the indicators that could be used to measure the interaction between different community stakeholders. Details on how the systematic review was carried out can be found in [13]. The interactions encompass a range of actions, from simple information exchange to more complex activities such as monetary and nonmonetary resource allocations. The literature review in [13] was extended by adding more references [53–57], which gave us a comprehensive list of indicators. The final list included 128 indicators.

Had our aim been to study the interdependencies between these 128 indicators, a factor analysis could have been conducted, but data availability is a major problem, especially since the indicators are measured in different ways: some are absolute values or percentages, and others follow a Likert or a binary scale. Moreover, considering the impact of one indicator on another would result in more than 16,000 pairs of relationships, making it impossible to collect data on all their interrelationships. To avoid such complexities, connections between the indicators were identified, which allows for grouping (clustering), which is done based on two dimensions. First, if the indicators refer to

Table 1
Factor definitions.

Interacting entities	#	Factor	Definition
NGOs-Comm	1	Collaboration between NGOs and emergent volunteers	The extent of collaboration between NGO team members and emergent volunteers is based on frequency of interaction and level of intimacy.
Comm-Comm	2	Community interest in accessing information	The frequency in which community members use different media outlets to access disaster information.
EO-Comm	3	Creative capital	Investment in disaster-related research.
EO-EO	4	Decision-making process	The extent to which the decision-making process is decentralized and includes multiple parties to make a decision.
Comm-Comm	5	Digital literacy	Individuals can use information and communication technologies to find, evaluate, create, and communicate information, requiring both cognitive and technical skills[1].
EO-Comm	6	Disaster information availability and accessibility	The availability of disaster awareness programs and materials, and the ability of community members to access this information through different media outlets (tv, internet, broadcasts, books, etc.).
EO-Comm	7	Disaster planning	The extent of existing hazard detection, mitigation, and response plans. This also includes sheltering capacities and the familiarity of citizens with these plans.
Comm-Comm	8	Emergency supplies	A collection of basic items that every household should have on hand in case of an emergency. These things include tools (e.g., a first-aid kit or a fire extinguisher), supplies (e.g., food, water, and medications), a copy of important documents, a mobile phone, and so on.
EO-EO	9	Emergency team readiness	The existence of an emergency team and the extent to which it is prepared to face a disaster through training and having the capacity to produce plans.
EO-Comm	10	Empowering citizens in the decision-making process	The extent to which various groups of the community participate in the decision-making and planning process through elections, the delegation of authority, etc.
EO-Comm	11	Financial aid availability	The availability of governmental financial resources to handle risks, assist victims, and support affected households through loans and cash aids.
EO-Comm	12	Functioning capabilities	The extent to which responsible personnel can work and operate effectively in normal times and emergencies.
EO-NGOs	13	Governmental support for NGOs	The extent to which the government provides funding and incentives to NGOs, and the degree to which legislation facilitates NGO activities.
EO-Comm	14	Government-sponsored insurance programs	The availability of government-sponsored catastrophe insurance policies that protect homes and residents, and cover the costs incurred from natural disasters such as floods and earthquakes, and from man-made disasters such as terrorist attacks.
Comm-Comm	15	Language competency	The extent to which members of the community can speak the official language of the country/area where they live.
EO-Comm	16	Leading capability	The degree to which community officials are accepted by community residents and are capable of efficiently leading and managing their community's requirements in both normal and emergency situations.
EO-EO	17	Multi-level and cross-organizational cooperation	The level of trust, cooperation, and collaboration between various levels of government (vertical) and between different governmental entities, officials, and non-governmental organizations (horizontal).
EO-Comm	18	Open spaces to support social ties	The availability of community service areas (parks, museums, libraries...).
EO-Comm	19	People engage in disaster response activities	Community members participate in the disaster response phase by evacuating voluntarily when something happens, following authorities' recommendations, sharing information about the crisis, and helping in relief work.
Comm-Comm	20	Place attachment	The emotional tie that exists between individuals and their place. This tie is highly impacted by personal experience and individuals' sense of belonging.
EO-Comm	21	Relationship with local community leaders	The strength of the relationship between the representative of emergency responders and authorities with local community leaders.
Comm-Comm	22	Social ties and trust	Connections between different members of a community within which they interact, share information, trust, and support each other and show solidarity.
NGOs-Comm	23	Support from NGOs	The extent to which NGOs support local communities. This could be reflected by the number of volunteer organizations and the extent to which these organizations are engaged in society.
EO-Comm	24	Training capacities (provided by emergency organizations)	The extent to which community members acquire the needed emergency skills through school courses and participation in disaster workshops and drills.
NGOs-Comm	25	Training capacities (provided by NGOs)	The extent to which community members acquire the needed emergency skills through school courses and participation in disaster workshops and drills.
EO-Comm	26	Trust in authorities	The extent to which community members trust in authorities' abilities to make decisions and their transparency.
NGOs-Comm	27	Volunteering	The extent to which civilians willingly donate their time and efforts for the common good. This could be reflected in the number of volunteers and volunteering organizations in a society.

(EO refers to emergency organizations, Comm is community members, and NGOs are non-governmental organizations).

[1] American Library Association (ALA) https://literacy.ala.org/digital-literacy/

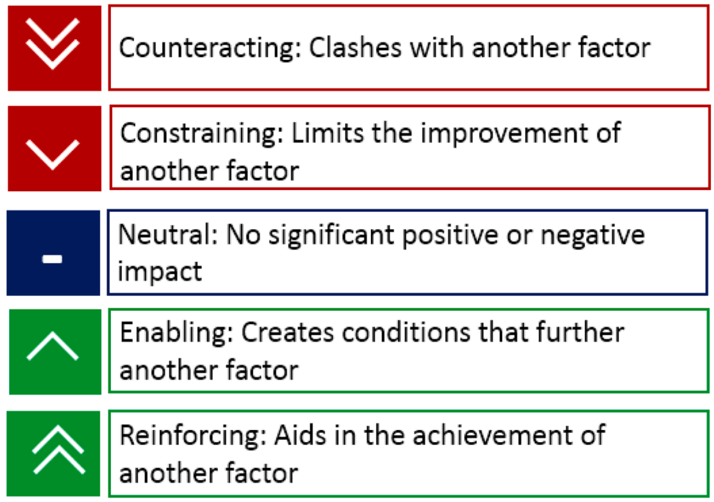

Fig. 2. Scale of Impact.

the same concept or serve the same function, such as “having a first aid kit”, “having fresh water and food for 72 hours” and so on, they could be grouped into “emergency supplies”.

The second group would include indicators that reflect an interaction between any of the stakeholders considered in this study. We have three main entities: NGOs, community members, and emergency organizations. The interaction could be between any two pairs, allowing for interaction within the same entity. Hence, we have 6 pairs of interacting entities: (NGOs – emergency organizations), (NGOs – community), (NGOs – NGOs), (emergency organizations – emergency organizations), (emergency organizations – community), and (community – community). The order of the pair does not matter, since the relationship is reciprocal.

For instance, indicators such as “the existence of disaster detention facilities plans” and “the existence of hazard mitigation plans” [27] are merged into “Disaster planning”. This disaster planning is an interaction between emergency organizations and community members, as the emergency organization is allocating resources to citizens through emergency plans.

In this paper, a factor is a result of grouping several indicators with the same aim while taking into account the stakeholders involved with this factor; a factor presents an area of improvement for the interaction between pairs of community stakeholders. The grouping of the indicators into factors was validated by academic experts in the field. This grouping resulted in the 27 factors shown in Table 1.

3.2. Delphi study

The framework was applied to Spain, a country that experiences a diverse range of hazards, based on data from EM-DAT[1]. Over the past five decades, natural disasters accounted for 59% of the total disasters that impacted Spain. Among these natural disasters, floods were the most common, accounting for one-third of all occurrences, followed by storms and wildfires. As for man-made disasters, transportation accidents are the most frequent type of incident. Both natural and man-made disasters can have significant consequences for the country and its population, highlighting the importance of building a resilient community effort. Moreover, the Spanish government’s structure of high decentralization is an interesting aspect in terms of community resilience. Spain is governed by a parliamentary monarchy system, with public administration divided into three levels: state or national level, autonomous community level, and local level [58]. The Ministry of the Interior oversees national emergencies. If the situation is not a national emergency, the responsibility for the initial response, coordination of rescue efforts, and situation evaluation falls on the highly decentralized autonomous communities [59]. Due to the different levels of the government, emergency planning in Spain is highly decentralized, allowing for consideration of the unique characteristics of each autonomous community. The high level of coordination between the various autonomous communities is one reason for the success of emergency planning in Spain. In addition, the government is in charge of training emergency responders, which is another contributing factor to effective coordination [59].

3.2.1. Process description

The Delphi method is a widely used technique for data collection from domain experts [60,61]. It is based on the idea that *"two heads are better than one, or …n heads are better than one"* [62]. It consists of a series of rounds to reach a consensus on a specific phenomenon. The rounds are done anonymously to eliminate peer pressure or the dominance of a specific group of experts [62]. Some of the main limitations of the Delphi technique are that it is time-consuming and the high drop-out rate between different rounds [60].

The aim of this process was to determine the exact values of the impacts of the factors on each other, which is necessary for conducting network analysis. Using the Delphi technique, consensus can be reached through multiple rounds.

We designed the questionnaire to capture the effect of one factor (defined in Table 1) on another to create the cross-impact matrix. The main question in the survey was, “if progress is made on factor x, how does this influence progress on factor y?”, which we adapted from [43]. The participants were asked to choose the value of such an impact on a five-point scale. The scale is shown in Fig. 2. The scale ranges from -2 to +2 [22]:

[1] 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 March 2023.

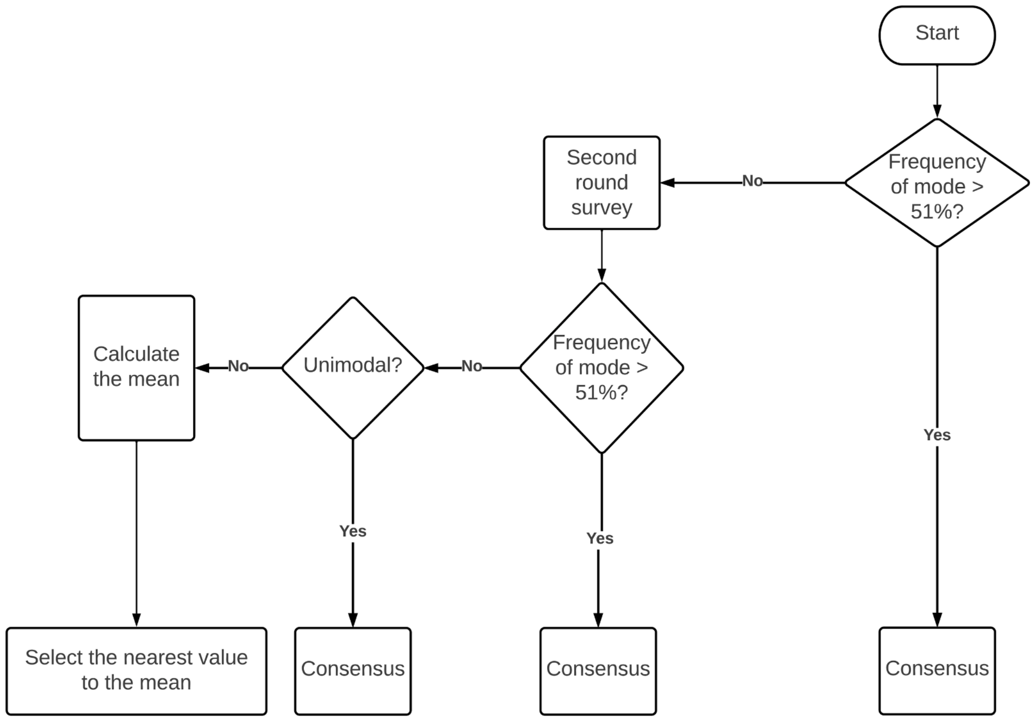

Fig. 3. Delphi process flowchart.

- Counteracting (-2): Clashes with another factor. e.g.: Paying for your child's private education will hinder your ability to organize trips every holiday.
- Constraining (-1): Limits the improvement of another factor, e.g., working from home limits your ability to make friends from work.
- Neutral (0): No significant positive or negative effect. e.g., the food you have for breakfast does not impact the means of transportation you will use to go to work.
- Enabling (+1): Creates conditions that further another factor, e.g., good quality education, increases your children's chance of getting good job opportunities.
- Reinforcing (+2): Aids in the achievement of another factor, e.g., physical exercise keeps you fit.

The scale has been adapted from [22]. This scale enables us to determine whether the impact is the same in both directions. For instance, increasing the level of "Place attachment" of the population does not necessarily impact the "Support from NGOs"; however, increasing the "Support from NGOs" could directly enhance people's "Place attachment". We eliminated the two extreme cases of (-3 canceling and +3 indivisible) since the nature of the factors identified in this study would not allow for such an extreme impact. With 27 groups of factors, the questionnaire includes a total number of 702 relationship pairs (27*27 – 27).

The questionnaire was designed in English because all the factors come from papers written in English. We then translated the questionnaire into Spanish to make it easier for the participants, who are from Spain (the focus of our study). After collecting the results, we translated the questionnaire back into English to work on the data.

The Delphi study was done in two rounds. First, we invited the experts to participate in the study via email and provided a link to the first-round questionnaire for those willing to do so. In the first part, they consent to participate in the study and complete the rest of the questionnaire. The second round was to obtain consensus. We created a new online questionnaire covering the questions lacking consensus. We sent the participants an email with a link to the new questionnaire and a file showing their previous replies to each question and the distribution of other participants' responses associated with each question.

3.2.2. *Expert selection*

Experts were selected based on various criteria, such as their geographical location, years of experience, and job title. We were interested in including experts who work and live in Spain, have 10 or more years of experience, and work in one of the following categories: academia, non-governmental organizations (NGOs), and emergency management organizations. We sent a participation request to more than 20 experts but only nine agreed to participate in the study, distributed as follows: five from academia (one with nine years of experience), two from NGOs, and two are emergency organization managers. Given that we are targeting a heterogeneous population (experts from different backgrounds), nine experts is a reasonable number of participants for our Delphi panel [63].

3.2.3. *Reaching a consensus*

The first round included the original 702 relationship pairs. After the end of the first round, the data was analyzed, revealing that a consensus was not reached in 248 relationship pairs. The consensus was defined as $> 51\%$ of participants agreeing on a specific value from the scale (counteracting, constraining, neutral, enabling, reinforcing). Many Delphi studies use a level of agreement as a consensus method [64,65]; the 51% in our study was based on [66,67]. If a higher percentage were chosen for the consensus, it would tremendously increase the number of questions, jeopardizing the response rate in the second round due to participants' complaints about the length of the survey. We excluded the responses from the percentage calculation when the participant left the question empty [68].

In the second round, the same consensus criterion was used as in the first round to obtain the value for the cross-impact matrix. This resulted in 93 relationships with no consensus, requiring a third round of the study. Thus, the condition of $> 51\%$ was relaxed and the mode of the data was used. The motive behind using the mode (the value with the highest frequency) is that a discrete value from the scale was needed to include in the cross-impact matrix, avoiding all fractions. Of these 93 relationships without consensus, 33 of the relationship pairs were

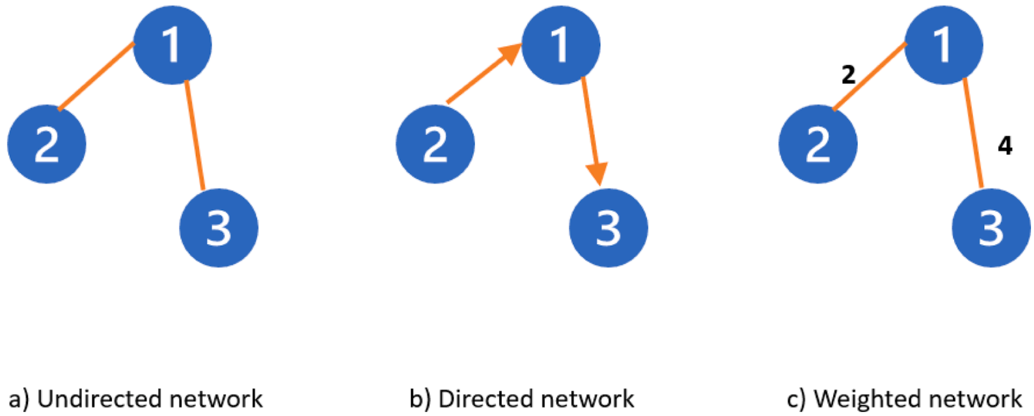

Fig. 4. Different types of networks.

bimodal. In this case, the mean of the responses was calculated, and the value nearest to the mean was chosen. For example, having two modes $+1$ and $+2$, calculating the mean of the responses results in 1.3. Then $+1$ is selected as the final value to include in the cross-impact matrix. Fig. 3 summarizes the process of reaching consensus in the Delphi study.

3.3. Network analysis

A network (graph) is a representation of pairwise relations among a set of elements. These elements are called nodes or vertices, and the links between the nodes are called edges, links, ties, or arcs. A network could be directed or undirected [69]. In a directed network, the order of the connected nodes is important (asymmetric relationships), e.g., in the case of a road network, there is a one-way road from location x to location y, but not the other way around. While, in an undirected network the order of the pair does not count (symmetric relationships), e.g., a relationship between two friends. The graph structure considered in this study is a directed graph $G = (N, E)$, which consists of a set of nodes N and a set of edges E whose elements are ordered pairs of different nodes. A network can also be weighted or unweighted; in a weighted network, not all the relationships are equal. Fig. 4 shows different types of networks; each network consists of three nodes, $N = \{1, 2, 3\}$ and two edges, $E = \{(1, 2),\ (1, 3)\}$ in the case of networks a and c, while for network b, $E = \{(2, 1), (1, 3)\}$. A network can have many other properties [69,70] that are beyond the scope of this study. In general, network science has a set of powerful techniques that allow us to tackle complex systems and problems. In this study, the factors in *Table 1* are considered nodes, so N includes 27 nodes; the edges are the relationships between the factors – there can be up to 702 edges – and the value of the impact of each factor on the other acts as the weight on the edges.

A set of centrality measures will be utilized to conduct our analysis. Centrality measures identify the most important nodes in the network [70]. There are many centrality measures, but the focus here is exclusively on the ones used in this study: degree centrality, closeness centrality, and betweenness centrality.

3.3.1. Degree centrality

Degree centrality considers that the most important node is the one with the highest number of neighbors (connections). In the case of an undirected network, the degree of a node is simply the number of edges it has. In a directed network, each node also has an in-degree and an out-degree, presenting the number of incoming links into a node and the outgoing links, respectively. Another variation of the degree centrality is the weighted degree centrality, which is the same but considering the weights of the incoming or outgoing edges of the node. Equations (1) and (2) show how to calculate weighted out-degree and weighted in-degree respectively. w_{ij} is the weight on the edge between nodes i and j.

$$w_i^{out} = \sum_{j=1}^{N} w_{ij} \tag{1}$$

$$w_i^{in} = \sum_{j=1}^{N} w_{ji} \tag{2}$$

3.3.2. Closeness centrality

The main assumption behind closeness centrality is that important nodes are closer to each other. A node being central in this way means that it is the most efficient in sharing information; it would take the shortest time possible to reach the entire network (cascading effect). Closeness centrality is the reciprocal of farness (sum of distances from a specific node to all other nodes). Equation (3) explains the calculations of closeness centrality, where $d(i, j)$ is the distance between nodes i and j.

$$closeness(i) = \frac{1}{\sum_{j=1,\ i\neq j}^{N} d(i, j)} \tag{3}$$

Table 2
Number of factors per each pair of interacting entities.

	Community members	NGOs	Emergency organizations
Community members	6		
NGOs	4	0	
Emergency organizations	13	1	3

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	Sum
1		1	0	1	0	1	1	1	1	2	0	1	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	20
2	1		1	1	2	2	1	0	1	2	0	2	0	1	1	0	1	1	1	1	1	1	1	1	1	1	1	26
3	0	1		1	1	1	2	1	1	1	2	2	0	1	0	2	1	0	1	0	0	0	0	1	0	1	0	20
4	0	1	0		1	1	2	0	1	1	0	2	1	0	0	2	2	1	2	1	2	2	1	2	1	2	1	29
5	1	1	0	1		2	1	0	1	1	0	2	0	1	1	1	1	1	1	0	1	1	0	2	1	0	1	22
6	1	1	1	2	2		2	1	2	1	0	1	0	0	1	2	2	1	1	1	0	1	1	2	1	2	1	30
7	1	0	1	2	1	2		2	2	1	1	2	0	1	0	2	2	1	1	0	1	1	1	1	1	1	0	28
8	0	0	0	1	0	0	1		1	0	1	2	0	0	0	2	1	0	1	0	0	0	0	0	0	1	0	11
9	0	0	1	1	0	1	2	1		0	0	2	1	0	0	2	1	0	1	0	0	0	1	2	0	1	0	17
10	2	2	0	2	1	1	1	0	0		0	1	0	1	0	1	2	1	2	1	1	2	1	1	1	2	1	27
11	0	0	2	0	1	1	2	2	2	1		2	2	2	0	1	1	0	1	0	0	1	1	2	1	1	0	26
12	1	1	1	1	0	2	2	1	1	1	1		1	0	0	1	1	1	2	0	1	1	1	2	1	2	0	26
13	1	1	1	1	1	1	1	1	1	0	2	2		0	0	1	1	1	1	0	1	1	1	1	1	1	1	24
14	0	0	1	0	0	0	1	1	0	0	1	1	1		0	2	1	0	0	1	1	0	0	1	0	2	0	14
15	1	1	0	1	1	1	0	0	0	1	0	1	0	0		0	0	1	1	1	1	1	0	0	1	1	0	14
16	1	1	1	1	1	2	1	1	1	1	2	2	1	1	0		2	1	1	0	2	1	1	1	0	2	0	28
17	1	1	1	1	1	2	1	1	1	1	1	2	1	1	0	1		1	1	0	1	0	1	1	1	1	1	25
18	1	1	0	1	1	1	1	0	0	1	0	1	0	0	0	0	1		2	2	1	2	1	1	1	1	1	21
19	1	2	1	1	1	1	0	1	1	2	0	2	1	1	0	1	1	2		1	1	2	1	1	1	1	1	28
20	1	1	0	1	0	0	0	0	0	1	0	1	0	0	1	0	2	1	2		1	1	1	1	0	0	1	16
21	0	1	0	1	0	1	1	0	1	1	1	2	0	1	0	2	1	1	1	1		1	1	1	0	1	1	21
22	1	1	0	1	0	1	1	0	1	2	0	1	0	0	0	1	1	1	2	1	1		1	1	1	1	2	22
23	1	0	0	1	1	1	1	1	0	1	0	1	1	0	1	0	1	1	1	1	1	1		2	1	1	2	22
24	1	2	1	1	2	1	1	0	1	2	0	2	0	0	0	2	1	1	2	0	1	1	1		0	2	1	26
25	2	1	1	1	2	1	1	1	1	1	0	1	1	0	0	2	1	0	2	0	1	1	2	1		1	2	27
26	1	1	1	1	0	1	1	0	0	1	0	1	0	1	0	2	1	1	2	1	2	1	1	1	0		1	22
27	1	1	0	1	0	1	1	0	0	1	0	1	0	0	0	1	1	1	1	1	1	1	2	1	1	0		18
Sum	21	23	15	27	20	29	29	16	21	27	12	40	11	12	5	31	31	21	34	15	24	25	23	31	17	30	20	

Influencing factors

Influenced factors

Fig. 5. Results of the Delphi study represented as a cross-impact matrix. Lighter cell colors present less impact, while darker colors present a higher impact.

3.3.3. *Betweenness centrality*

Betweenness centrality reflects the extent to which a node lies on the shortest paths (acts as a bridge) between other nodes. The benefit of a node with high betweenness centrality is that it can control the flow of information; its removal disrupts the network. In equation (4), we explain the calculation of the betweenness of a node *i*. $\sigma_{s,t}$ is the number of shortest paths between nodes *s* and *t*, and $\sigma_{s,t}\ (i)$ is the number of shortest paths between nodes *s* and *t* that pass-through node *i*.

$$betweenness(i) = \sum_{\substack{s,t=1 \\ s\neq t}}^{N} \frac{\sigma_{s,t}(i)}{\sigma_{s,t}} \tag{4}$$

4. Results

4.1. *The identified factors*

Table 1 presents the factors (groups of indicators) included in this study with their definitions and the entities between which the interaction happens. We defined 27 factors; one of the factors (training capacities) is repeated twice because it could be between the NGOs and community members or between emergency organizations and community members. Table 2 shows the number of factors per pair of stakeholders. We can see from the table that most of the factors are concentrated between emergency organizations and community members.

4.2. *Cross-impact matrix*

We compiled the experts' inputs from the Delphi study and created the cross-impact matrix shown in Fig. 5. The matrix captures the experts' opinions by showing how improving the factor in the row affects the improvement of the factor in the column. By examining the matrix, we note that none of the relationships is negative, 29% are neutral, 56% are enabling, and 15% are reinforcing. This means that the experts believe that most of the interactions have a strengthening influence.

In the matrix, the row-sum represents the net influence of the factor in the row on all other factors. The higher the row-sum, the greater the influence of the factors on other factors. On the other hand, the column-sum shows the extent to which the factor in the column is influenced by all other factors. A higher column-sum indicates that the factor is greatly influenced by other factors.

By looking at the row-sums we see that factor number 6, "Disaster information availability and accessibility", is the one with the highest impact on all other factors, followed by factor no. 4, "Decision-making process", and factor nos. 7, 16, and 19, respectively, "Disaster planning", "Leading capability", and "People engage in disaster response activities". We can also see that the majority of these interactions are between emergency organizations and community members, except for factor no. 4, which reflects interactions between emergency organizations themselves. On the other hand, the factor with the least influence is factor no.

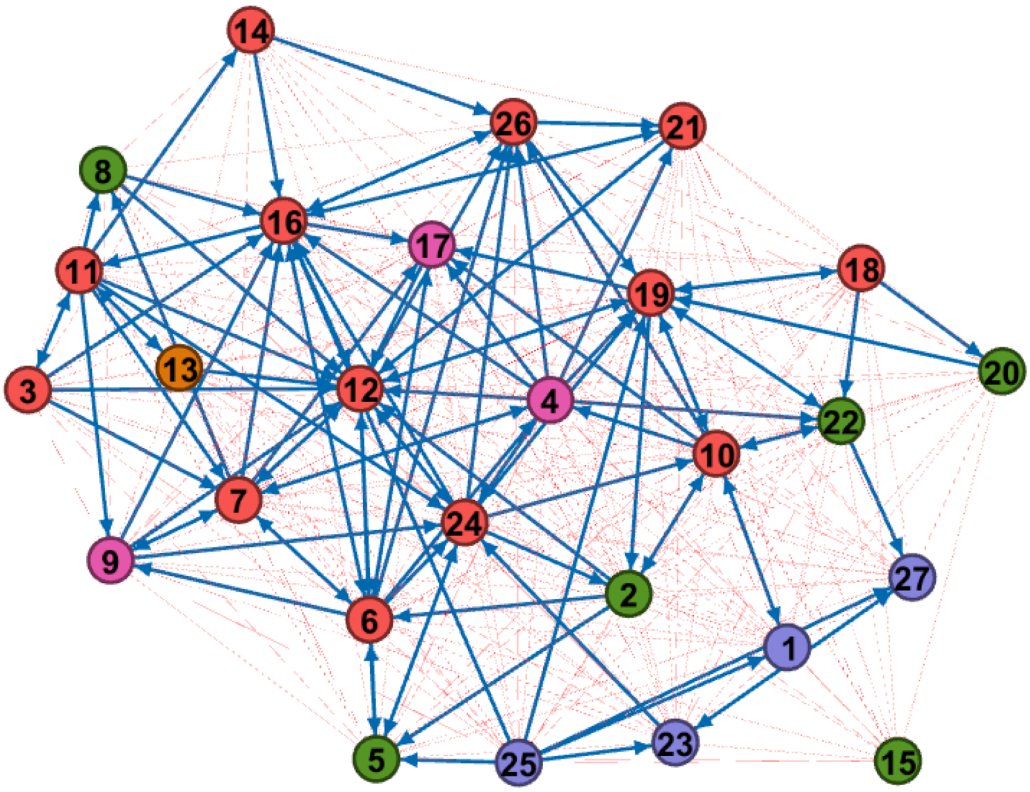

Fig. 6. The cross-impact matrix presented as a network.

8, "Emergency supplies".

Considering the column-sum, we find that factor no. 12, "Functioning capabilities", is the factor that is mostly influenced by others; none of the factors have a neutral effect on this factor, which means that any positive change in another area would affect this factor (area) positively. Factor no. 19, "People engage in disaster response activities", is second place. Factor no. 15, "Language competency", is the least influenced factor. It is worth noting here that the factor "People engage in disaster response activities" appears in both the most highly influenced and influencing factors. This indicates that this factor is susceptible to network changes, which could result in significant network volatility. This is true when there is a negative impact, but in our case, we only have positive impacts. Additionally, factor no. 20, "Place attachment", and factor no. 8, "Emergency supplies", are neither highly influenced nor highly influential.

Although using row-sum and column-sum provides overall information about which factors have the highest impact on the progress of other factors, or which ones are highly influenced by others, it is insufficient for prioritizing where to focus the improvement actions. To reach this goal, it is essential to conduct a meticulous analysis of the data and how the interactions between the factors cascade across other factors. Network analysis techniques will be used to achieve this.

4.3. Network analysis and factors prioritization

First, it is necessary to create and visualize our network. Fig. 6 presents the cross-impact matrix as a network, where the nodes are the factors, and the edges are the impact of one factor on another. The solid line edges present a reinforcing relationship (+2) and the dashed lines present an enabling relationship (+1). The nodes are color-coded based on the interacting entities: the red nodes are where the interaction happens between emergency organizations and the community; the green nodes, between community members; the violet nodes, between NGOs and community; fuchsia, within and between different emergency organizations; and the orange nodes, between emergency organizations and NGOs. It is important to visualize the data and not only depend on the numbers and statistical analysis [71]. Although Fig. 6 does not provide much information, it does depict the complex structure of the interdependence of the factors.

Second, to see how the factors affect each other we calculated the centrality measures (explained in section 3.3) for all the nodes (Table 4 in the Appendix). We used Gephi[2] software [72] to conduct the network analysis and calculate all the centrality measures. A close look at Table 4 shows that there is an overlap between the different centrality measures, especially with the highest and lowest-ranked nodes. For instance, when examining the closeness centrality, it is apparent that two nodes share the highest value: factor no. 17, "Multi-level and cross-organizational cooperation", and factor no. 19, "People engage in disaster response activities", which are the same nodes that rank in the first two positions, respectively, in betweenness centrality. Factor no. 19 also ranks second for weighted in-degree and third for weighted outdegree. A similar pattern appears in the nodes with the least importance. For example, factor no. 8, "Emergency supplies", is of the least importance considering closeness centrality and weighted out-degree, and second-lowest when considering betweenness centrality. The same thing happens with factor no. 15, "Language competency": it ranks last considering betweenness and weighted in-degree centrality and second-lowest in weighted out-degree centrality. There could be different reasons for these overlaps between the nodes including: their importance in the network, or because some of the centrality measures used (betweenness and closeness) do not consider the weight on the edge between the nodes in their calculations. As it is not possible to confirm the importance of the nodes in these settings, the focus of the study will be the subset of the network that has strongly positive relationships (reinforcing relationships) for a better understanding of the different roles the nodes play.

[2] https://gephi.org/

Table 3
Centrality measures associated with each factor considering the reinforcing relationships.

Factor no.	Factor	Indegree	Outdegree	Closeness centrality	Betweenness centrality
1	Collaboration between NGOs and emergent volunteers	2	1	0.32	0.75
2	Community interest in accessing information	3	4	0.41	12.88
3	Creative capital	1	4	0.41	0.37
4	Decision-making process	3	**9**	**0.53**	38.67
5	Digital literacy	4	3	0.38	3.98
6	Disaster information availability and accessibility	6	***8***	***0.48***	69.43
7	Disaster planning	6	7	0.44	35.87
8	Emergency supplies	2	2	0.37	0.37
9	Emergency team readiness	3	4	0.42	1.21
10	Empowering citizens in decision-making process	5	7	0.46	84.85
11	Financial aid availability	3	***8***	0.47	91.63
12	Functioning capabilities	**14**	5	0.44	107.80
13	Governmental support for NGOS	1	2	0.38	0.00
14	Government-sponsored insurance programs	1	2	0.36	0.80
16	Leading capability	***11***	6	0.44	**131.04**
17	Multi-level and cross organizational cooperation	6	2	0.35	15.63
18	Open spaces to support social ties	1	3	0.32	24.00
19	People engage in disaster response activities	9	5	0.41	***126.70***
20	Place attachment	1	2	0.33	2.08
21	Relationship with local community leaders	3	2	0.36	0.73
22	Social ties and trust	4	3	0.36	48.19
23	Support from NGOs	2	2	0.36	23.83
24	Training capacities (Provided by emergency organizations)	7	7	***0.48***	93.52
25	Training capacities (Provided by the NGOs)	0	6	***0.48***	0.00
26	Trust in authorities	7	3	0.41	34.35
27	Volunteering	3	1	0.27	23.33

The cells in **bold** present the nodes with the highest centrality measure, the ones in **bold and italic** present the nodes that have the 2nd highest rank, and the ones shaded in grey present the nodes with the lowest centrality rank

The cells in **bold** present the nodes with the highest centrality measure, the ones in **bold and italic** present the nodes that have the 2nd highest rank, and the ones shaded in grey present the nodes with the lowest centrality rank.

In Table 3 we show the centrality measures considering only the reinforcing relationships. Factor no. 15, "Language competency", was dropped from the network as it is not associated with any strongly positive relationship. The majority of the most influential nodes considering all centrality measures have changed from Table 4 (in the appendix) to Table 3. Closeness centrality goes hand in hand with the outdegree centrality, the most important node being factor no. 4, "Decision-making process", and the least important factor being "Volunteering" (factor no. 27). In outdegree centrality, "Collaboration between NGOs and emergent volunteers" (factor no. 1) is also considered the least important. Considering the indegree centrality, it becomes evident that factor no. 12, "Functioning capabilities", is of the highest importance, while factor no. 25, "Training capacities provided by the NGOs", ranks the least. As for betweenness centrality, there is a huge gap in the values between the most important nodes and the least important ones; for instance, the most important node is factor no. 16, "Leading capability", with a betweenness value of 131.04, while the least important are factors no. 13 and 25, "Governmental support for NGOs" and "Training capacities provided by the NGOs", respectively, with a betweenness measure of zero.

Fig. 7 shows a representation of Table 3 as a network. The graph presents an easier way than the table to compare all the centrality measures, since all the nodes are in the same location in the network and the size of the node is proportional to the centrality measure of the node, whereas the bigger nodes had a higher centrality measure than the smaller ones.

4.4. Decision support framework

The main contribution of this research is the decision support framework shown in Fig. 8. The framework builds upon the general structure of a decision support system [73], including three main components (1) input representing the data, (2) processing representing the model(s), and (3) an output component representing the processed data or the results of the model(s). The input component covers both the interaction areas (factors), which are identified through a literature review, and the experts' knowledge about how these areas impact each other, which was captured through a Delphi panel. This component includes the preparation of the data from the Delphi panel. The processing component relies on network analysis techniques, namely centrality measures, as the modeling techniques. Finally, the output component relies on the result of the network analysis to provide a

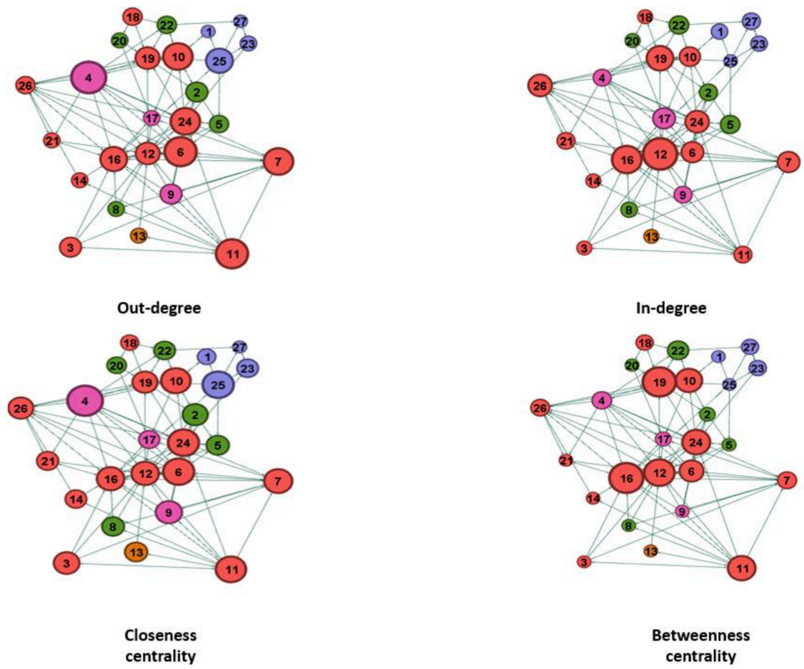

Fig. 7. Network visualization of the centrality measures considering only the reinforcing relationships. The node size is proportional to the node centrality measure. The color of the node represents the interacting entities: red nodes are where the interaction happens between emergency organizations and the community; green nodes, between community members; violet, between NGOs and community; fuchsia, within and between different emergency organizations; and orange, between emergency organizations and NGOs.

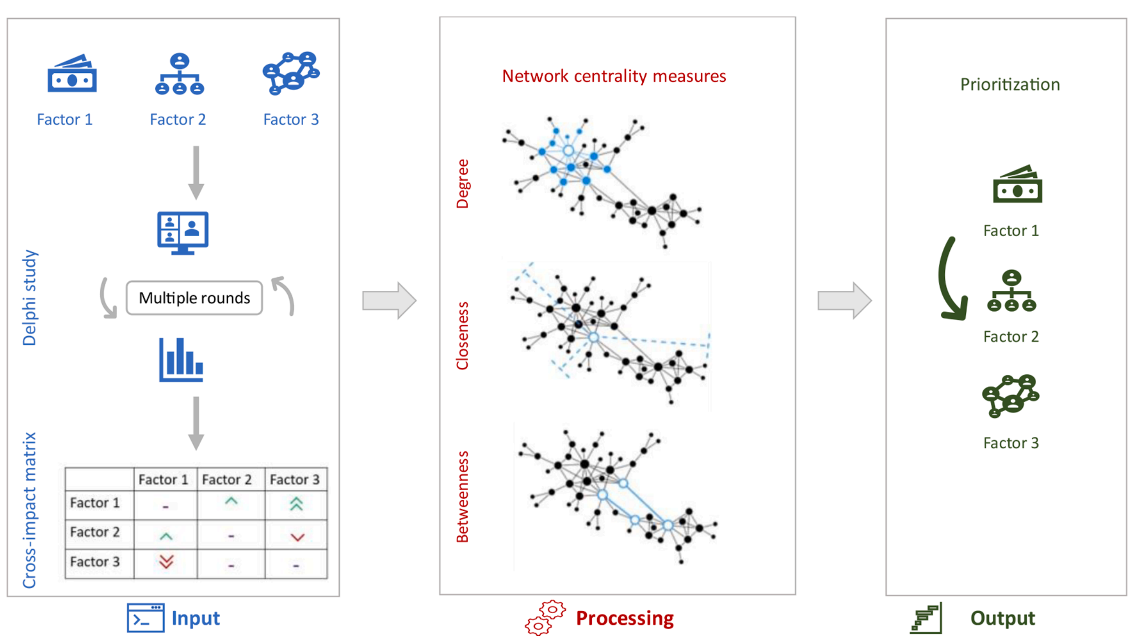

Fig. 8. Decision support framework for prioritizing the interaction areas among community stakeholders.

recommendation on which factors should be tackled first.

The framework presented in this study has been applied to data from Spain to show its applicability. By adhering to the framework's structure, it can easily be adapted to other case studies. For instance, researchers can conduct a new Delphi study with experts from other countries or communities if they intend to use the framework for enhancing interaction areas in other communities. Alternatively, they can substitute the interaction areas with different variables or events they want to prioritize, such as different types of risks (e.g., climate change, heat waves, droughts), critical infrastructures (e.g., water, energy, transportation networks), or community resilience factors. To account for the interdependencies between these variables, historical data or expert knowledge can be utilized. Overall, the framework's flexibility makes it a valuable tool for decision-making in various contexts.

The framework provides a structured mechanism for collecting data on community resilience interaction factors, evaluating their interconnectedness, and prioritizing factor targeting. It also considers the rippling effects across the system caused by the interdependence of the factors. The framework has the potential to assist policymakers and decision-makers in prioritizing actions aimed at enhancing community resilience by improving stakeholder interactions.

5. Discussion

5.1. Modularity analysis

Looking further into the data, a modularity analysis was conducted using Gephi software (with the default parameters and considering the

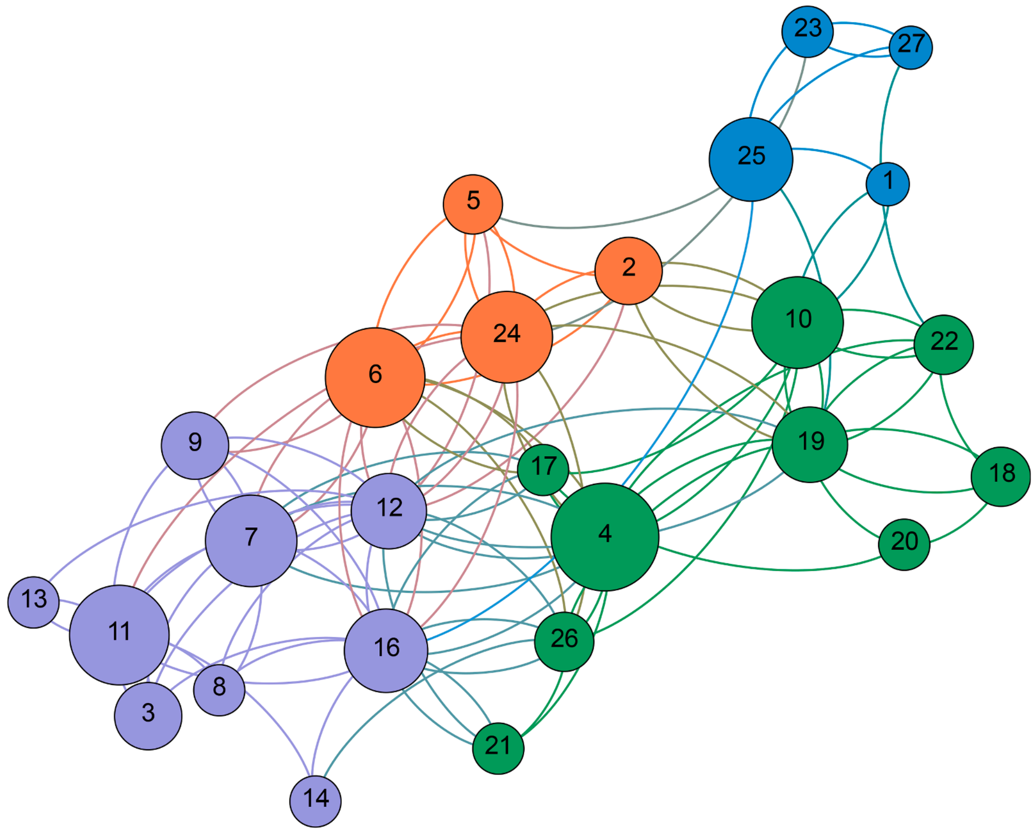

Fig. 9. Nodes clustering using modularity analysis. The network is divided into four clusters: blue is related to NGOs and volunteering, orange to communication and information exchange, green to social ties, collaboration, and trust, and violet to preparedness activities.

+2 sub-network), resulting in Fig. 9. Modularity analysis refers to partitioning the network into different clusters or groups, where more edges in a network fall between nodes of the same type than what would be expected by chance [70]. The figure shows four main clusters: the blue cluster is related to NGOs and volunteering, the orange, to communication and information exchange, the green, to social ties, collaboration, and trust, and the violet cluster to governance and preparedness activities. These four clusters represent the primary domains/areas in which we can improve interactions among community stakeholders.

All of the factors contained in the blue cluster are connected to volunteer activities, and the two interacting entities are always NGOs and community members. The orange cluster includes four factors, two of which reflect the interactions among community members, while the other two reflect the interaction between community members and emergency organizations. These factors are either directly related to communication and exchanging information (factors number 2, 5, and 6) or the exchange of information aimed at building and enhancing the skills and capacities of the population to effectively face disasters (factor no. 24).

The green cluster is more diverse than the previous two clusters; it contains factors that indicate three different types of interactions. Some are related to the interactions among community members, such as factors number 20 and 22 (“Place attachment” and “Social ties and trust”); others are related to the interaction within emergency organizations, such as factors 17 and 4 (“Multi-level and cross-organizational cooperation” and “Decision-making process”); the rest of the factors

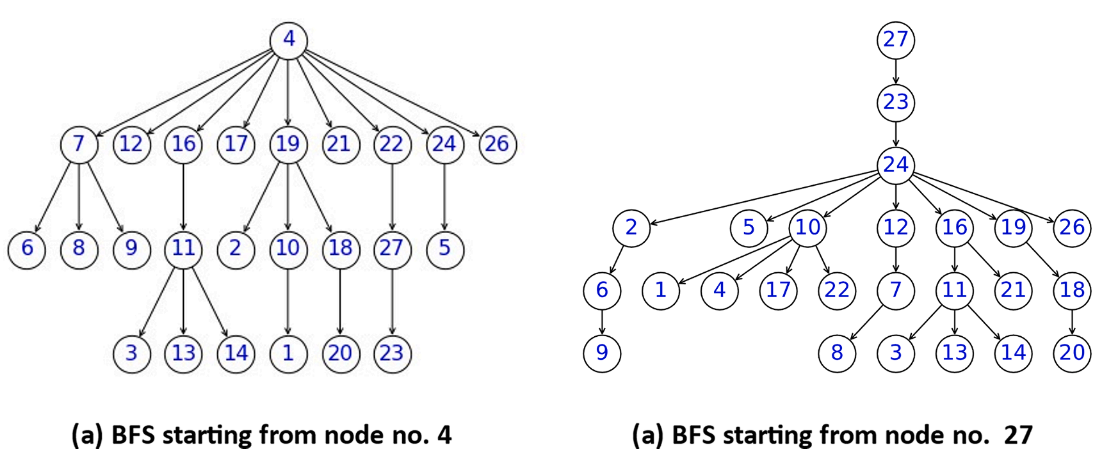

Fig. 10. Breadth-first search tree starting from node number 4, "Decision-making process" (sub-Fig. a,) and starting from node number 27, “Volunteering” (sub-Fig. b).

reflect the interactions between emergency organizations and community members. Although there are many interacting stakeholders here, all the factors reflect the collaboration and ties either between different stakeholders or within the same group of stakeholders.

The last one is the violet cluster, which includes factors that also reflect the interaction between various stakeholders, but all these factors are related to preparedness activities and the disaster management process. Preparedness can be achieved through the efforts of both citizens, by having the necessary emergency supplies at hand, and emergency organizations and government by having disaster plans, insurance, and financial aid programs.

5.2. Important nodes

The results section addressed which nodes are important considering a specific centrality measure. Here, these results are discussed further.

Closeness centrality and outdegree centrality have the same factors in both the most important and the least important positions. The most important position is reserved for factor no. 4, “Decision-making process”, and the least important, is factor no. 27, “Volunteering”. A node with the highest closeness centrality has the highest cascading effect; i.e., any change in this node (factor) will quickly ripple across the entire network. Moreover, a node with the highest outdegree centrality is the most influential in the network as it has the most outgoing connections, impacting many other nodes directly.

In Fig. 10, we show breadth-first search trees starting from both nodes no. 4 (Fig. 10a) and no. 27 (Fig. 10b). These are the nodes with the highest and lowest closeness centrality values. The impact of factor no. 4 could cascade to all other factors in a maximum of three steps. However, in the case of factor no. 27, it takes five steps. Furthermore, the effect of a change in node no. 4 can reach nine other nodes in a single step, whereas in node no. 27, it only reaches one node in a single step. The tree also helps to prioritize which areas to work on first. For example, it may be preferable to begin working on node no. 19, "People engage in disaster response", rather than node no. 17, because no. 19 may affect more nodes – its children – but no. 17, has no descendant nodes.

Factor no. 4, “Decision-making process”, covers the idea of decision decentralization where authority is distributed and includes multiple parties to take decisions. Decentralized decisions are characterized by being time-critical and require local information, which fits the context of a disaster situation. The importance of this factor aligns with [74], where crisis decision-makers emphasized that in times of crisis it is necessary to shift towards a decentralized decision-making approach. This was also underlined in the main disaster risk reduction frameworks, including the Hyogo framework [75] and the Sendai framework [76]. The importance of this factor aligns with the decentralized nature of the Spanish public administration.

Indegree centrality helps identify which factor (area of improvement) is most influenced by others. Here, factor no. 12, “Functioning capability”, is the most impacted factor by improvements that could happen in other factors. This means that this factor is highly susceptible to change; in our case, none of the impacts was negative (Fig. 5), which means that in the Spanish context changes in other factors would have a positive impact on the ability of the responsible personnel to work and operate effectively both in times of emergencies and normality.

Combining this finding with that of outdegree centrality (the Decision-making process is the most influential factor), it becomes apparent that both factors are interrelated. For example, decentralization allows for more innovative ideas on how things should work, as new ideas do not have to go all the way up the chain of command to be approved [77]. Furthermore, it enables a high level of responsiveness by allowing for the development of solutions and alternatives to address situations based on existing information from the disaster scene, rather than waiting for orders from a higher authority, thus avoiding delays [74]. Decentralization also allows for resource mobilization [78]. Although decentralization could hinder communication and collaboration between different personnel [79], when emergency personnel overcome this problem, they have better communication and cooperation skills.

Betweenness centrality implies that the node works as a bridge or intermediary between all other nodes. Factor no. 16, “Leading capability”, has the highest betweenness centrality. Improving this factor enhances the overall effectiveness of the interaction network; otherwise, it acts as a bottleneck. Leadership ability is a sensitive matter, especially in times of disaster, as it can either mitigate the consequences and facilitate the road to recovery or exacerbate the situation [80]. In the response phase, leadership traits are also challenged [81], especially with the overwhelming list of expectations and the possibility that family or friends of leaders may be affected by the crisis on a local level [82]. Leaders should be equipped with tools that enhance their leadership skills and go through continuous development and training [83].

5.3. Interacting parties

Considering the most impactful nodes regardless of the centrality measure (except for the indegree centrality), “emergency organizations” emerges as the main player in all of them. The “Decision-making process” mainly refers to how emergency organizations organize among themselves and handle decision-making. While the "Leading capability" factor includes citizens as part of the interaction, considering their satisfaction and trust levels, they are primarily concerned with the role of emergency responders and their abilities. Hence, emergency organizations can be considered the primary player affecting community resilience. On the other hand, considering the least impactful nodes, we can see that NGOs are always a part of the interacting entities. Thus, the factors/areas impacted by NGOs can be considered isolated from other factors; therefore improving them would not have a significant impact on or be influenced by other factors. This also means that NGOs, with the help of the community, can fulfill their role in disaster management without being overly reliant on emergency organizations. This aligns with the modularity analysis shown in Fig. 9 which shows that the factors related to volunteering and NGOs cluster together.

5.4. Language competency

The importance of language competency as an indicator for measuring community resilience has been highlighted in many studies [25,84,85]. Research [86] and fieldwork [87] suggest that poor language proficiency makes certain groups less resilient and more susceptible to the impacts of disasters. However, in this study, the “Language competency” factor was dropped off the strongly positive network, since it is not strongly influenced by nor influencing any of the other factors. This does not mean that language competency is not important for enhancing the interactions between various community stakeholders, but that the factors we included here are not highly impacting/impacted by the language abilities of community members.

6. Conclusion

In this article, we proposed a decision support framework for enhancing community resilience by prioritizing the interaction areas of community stakeholders. The framework captures the interdependencies among the different areas of interactions and prioritizes them based on their impact on each other utilizing centrality measures techniques. These interaction areas were identified through a literature review. Emergency organizations could use the decision support framework to focus their investments on the areas that have the greatest potential impact on enhancing the resilience of their communities.

Moreover, we draw on the collective experience of disaster management and resilience experts in Spain to study the interrelationships among the factors that influence the interaction dimension within community resilience, while also reflecting on the interactions of three

Table 4
Centrality measures associated with each factor considering both positive and strongly positive relationships.

Factor no.	Factor	Weighted indegree	Weighted outdegree	Closeness centrality	Betweenness centrality
1	Collaboration between NGOs and emergent volunteers	21	20	0.79	4.17
2	Community interest in accessing information	23	26	***0.87***	10.97
3	Creative capital	15	20	0.72	3.60
4	Decision-making process	27	***29***	0.81	10.22
5	Digital literacy	20	22	0.79	6.81
6	Disaster information availability and accessibility	29	**30**	***0.87***	13.43
7	Disaster planning	29	28	0.84	12.26
8	Emergency supplies	16	11	0.59	1.51
9	Emergency team readiness	21	17	0.67	3.24
10	Empowering citizens in decision-making process	27	27	0.81	6.42
11	Financial aid availability	12	26	0.76	3.77
12	Functioning capabilities	**40**	26	0.84	15.40
13	Governmental support for NGOS	11	24	***0.87***	4.42
14	Government-sponsored insurance programs	12	14	0.65	3.32
15	Language competency	5	14	0.68	0.59
16	Leading capability	31	28	***0.87***	11.27
17	Multi-level and cross organizational cooperation	31	25	**0.90**	**17.11**
18	Open spaces to support social ties	21	21	0.76	3.02
19	People engage in disaster response activities	***34***	28	**0.90**	***15.87***
20	Place attachment	15	16	0.68	4.67
21	Relationship with local community leaders	24	21	0.79	8.77
22	Social ties and trust	25	22	0.79	4.07
23	Support from NGOs	23	22	0.81	11.86
24	Training capacities (provided by emergency organizations)	31	26	0.79	6.76
25	Training capacities (provided by NGOs)	17	27	0.84	5.83
26	Trust in authorities	30	22	0.79	9.87
27	Volunteering	20	18	0.74	1.76

The cells in **bold** present the nodes with the highest centrality measure, the ones in ***bold and italic*** present the nodes that rank 2nd, and the ones shaded in grey present the nodes with the lowest centrality rank

major community stakeholders: NGOs, community members, and emergency organizations. The results show that according to the experts, most of the factors impact each other. Enhancing one factor would lead to the enhancement of others. This highlights the substantial interdependence of the various factors influencing community resilience, implying the need to prioritize them. To achieve this, network analysis was used in this study to uncover the underlying patterns in their interactions. As a result, the observed pattern can assist decision-makers in devising strategies to enhance community resilience by improving relationships among diverse stakeholders.

We used four distinct network centrality measures to define the importance of the factors: outdegree, indegree, closeness, and betweenness centrality. "Decision-making process" is the most significant factor/area of improvement, whether we consider a factor critical because it is highly influential (highest outdegree) or because it has the greatest cascading impact (closeness centrality). If we evaluate the importance of a factor based on its function as a link or bridge between all other factors (betweenness centrality), then the most important factor is "Leading capability". Depending on how the decision-makers measure the importance of the factor, they should begin by working on and investing in one of the previous factors to improve community resilience.

Moreover, we found that four main clusters define the interaction factors: 1) NGOs and volunteering; 2) communication and information sharing; 3) social ties and collaboration; and 4) preparedness activities. These clusters represent the main areas where efforts can be directed towards improving the interactions among community stakeholders.

Furthermore, we found that emergency organizations are key to enhancing community resilience by improving stakeholder interactions. NGOs, on the other hand, are the most autonomous entity; the factors in which they play the most significant roles are those that have little impact on other areas.

A factor such as “Language competency” is not significantly influenced by any of the other factors, which emphasizes the interdependence of all community resilience factors. Given that the chosen set of factors, which reflect the interactions among community stakeholders, do not highly impact “Language competency”, and since language competency is important for community resilience, it can be inferred that other non-interaction factors might have an impact on “Language competency”.

By leveraging network analysis, a framework has been provided to capture the systemic impact of community resilience interaction factors. The framework builds upon previous research to identify the interaction factors and provides a structured mechanism to collect data about the typology of the relationships between the factors. A network analysis was then performed to investigate the rippling effects across the system based on the interdependence between the factors. The framework could be used to support policymaking and decision-makers.

One potential limitation of our approach is that the relationship between the different factors relies heavily on the consensus among Delphi participants. While nine participants are enough [63,88], a higher number of participants could improve the reliability of the data. Despite contacting more than 20 experts, only nine agreed to participate in the study due to the length of the survey. Nevertheless, the nine experts were able to represent a diverse range of emergency expert profiles, therefore rendering a representative sample. Moreover, text analytics techniques could have been used to cluster the indicators into factors, rather than doing this manually.

Further research is required to develop policies and concrete procedures to improve the top priority areas. One way to prioritize these tasks is to use a three-criterion assessment technique: ease of policy implementation, policy impact (high, medium, or low), and the time it takes to implement the policy. Moreover, a web tool could be built to capture the entire methodology (questionnaire design, data collection, consensus building, and network analysis). Other researchers and decision-makers might use this tool to define the components of their particular system and investigate the underlying patterns of interactions between these components. Furthermore, the extent to which each factor influences community resilience itself can be studied. Applying the same analysis to a country with different characteristics than Spain can reveal how the context impacts the prioritization of factors.

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CRediT authorship contribution statement

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

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

Table 4 shows the values of the centrality measures associated with all the factors considering both positive and strongly positive relationships.

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