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The European emergency number 112: Exploring the potential of crowd-sourced information for emergency management

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ABSTRACT

The rapid evolution of social media has transformed the landscape of emergency management by enhancing information sharing during critical events. However, the pervasive nature of social media also presents challenges related to the accuracy, reliability, and timeliness of the information it provides. In contrast, the European Emergency Number 112, designed to gather precise, standardized data, offers a potential data source to social media information, by managing emergency calls, in crisis situations. This study investigates the hypothesis that crowdsourced information from 112 emergency calls may provide superior situational awareness when compared to the content available on social media. Three primary research questions addressed: (1) What key information from social media supports emergency response, and how is it extracted? (2) What key information from 112 calls is essential for effective response, and how is it extracted? (3) How do 112 calls and social media content compare in terms of information accuracy and reliability? The case study to test such hypothesis was the October 2018 Vaia Storm which hit the Ligurian region in Italy. The results show that 112 emergency calls provided more accurate situational information, while the social media data required higher processing, and it was not always reliable. These findings highlight the potential of the 112 system to enhance emergency response.

List of Acronyms

AML	Advanced Mobile Location	GSM	Global System for Mobile communications
API	Application Programming Interface	ICT	Information and Communication Technologies
CAD	Computer-Aided Dispatch	NER	Name Entity Recognition
ERO	Emergency Response Organization	NLP	Natural Language Processing
GNSS	Global Navigation Satellite System	OTT	Over-The-Top (application)
GPS	Global Positioning System	PSAP	Public Safety Answering Point

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1. Introduction

Constant progress in Information and Communication Technologies (ICT) is accelerating the digitization of data across various sectors. In particular, the widespread adoption of mobile devices equipped with advanced sensors and communication capabilities has furthered the concept of Cyber-Physical Convergence [1]. This refers to the seamless integration of computer systems and physical processes, creating a unified, interconnected environment where information flows continuously between the real and virtual domains [2]. Such integration enhances real-time monitoring, decision-making, and automation, leading to improved efficiency, safety, and sustainability across multiple fields. In this highly technological context, social media has become a key platform for information exchange and communication. In 2023, the number of social media users worldwide reached 5.17 billion, representing 63.7 % of the global population and 94.9 % of all internet users. Additionally, 282 million new users joined that year alone, marking a 5.8 % annual increase [3]. While the most common use of social media is maintaining personal connections (50.3 %), they also serve as a tool for information retrieval (e.g., news, articles, and videos, 30.0 %), particularly during rapidly evolving crises [3]. In disaster scenarios, social media platforms become critical sources of real-time, on-site data, as users post information-rich messages that contribute to situational awareness, effectively functioning as human sensors [4].

However, the role of individuals as real-time data-providers extends beyond social media and is described in formal emergency communication systems. One of the most structured and widely implemented frameworks in Europe is the European Emergency Number 112. Established in 1991 by the European Union, 112 operates as a unified emergency number across all member States, enabling citizens to contact police, medical, or fire services regardless of location [5]. The near-universal adoption of this system across Europe (Fig. 1A) underscores its central role in emergency management, ensuring a standardized and well-coordinated response infrastructure. In Italy, the 112 system is relatively young, having been introduced through Law No. 124 of August 7, 2015, concerning the reorganization of public administrations [6]. At the time this article was written, 14 out of 20 Italian regions had developed and implemented the system (Fig. 1B), with the remaining regions expected to activate the service by the end of 2025. According to the latest report from the European Emergency Number Association [7], which monitors 112 implementation across Europe, Italian emergency response centers processed nearly 11 million emergency calls in 2019, 80 % of which originated from mobile phones. This data highlights the increasing role of mobile technology in emergency response, reinforcing the concept of citizens as active participants in crisis communication. The widespread use of mobile devices for emergency calls, combined with the expanding role of social media in crisis communication, highlights the enormous potential of human sensors in disaster response. Both 112 emergency calls and social media content embodies forms of crowdsourced information, namely the practice of obtaining information from a large number of people, despite their significant differences in the knowledge extraction process. Understanding these differences is key for developing integrated models of emergency information management useful for situational awareness and decision-making. Against this backdrop, our research investigates the usability and effectiveness of 112 emergency call and social media content in crisis scenarios.

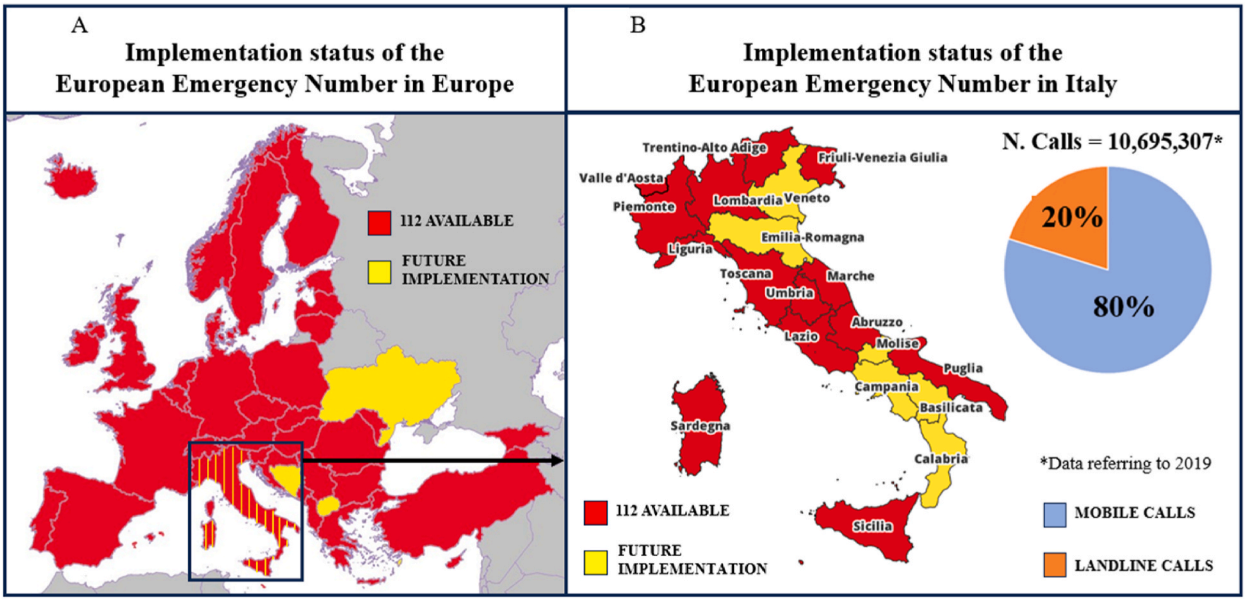

Fig. 1. Overview of the 112 system. (A) Implementation status in Europe. (B) Implementation status in Italy - Percentage of calls from mobile and landline phones in 2019. (GIS elaboration based on data from "Public Safety Answering Points Global Edition", [7]).

2. The crisis communication matrix

The Crisis Communication Matrix [8] summarizes over two decades of research on the use, role, and perception of emergency information flows through social media. The matrix identifies citizens and authorities as key actors in risk communication, alternating between the roles of sender and receiver. Through the existing literature four distinct communication patterns have been identified (Fig. 2).

Emergency management authorities generally approach social media with caution, primarily due to concerns about data security and privacy (Plotnick & Hiltz, 2016). Inter-organizational communication remains largely traditional, with an emphasis on standardized channels and communication protocols to ensure interoperability [9]. Platforms such as X (formerly Twitter) and Facebook facilitate top-down communication, through which emergency agencies can disseminate alerts, guidelines, and official updates [10]. However, the limitations of this one-directional approach have been increasingly scrutinized. A systematic review by Vandrevala et alii [11] examined the relationship between emergency communication and community resilience, emphasizing that effective strategies require high citizen engagement and feedback. Their findings indicate that top-down interactions often fail to foster trust and collaboration, highlighting the need for inclusive communication models that integrate citizen-generated content rather than relying solely on authoritative messaging.

Groups of citizens that spontaneously form to address disaster-related challenges at a local level have been defined as emergent groups [12]. In nowadays digital World, numerous platforms facilitate these self-organized networks, enabling them to collect and distribute real-time crisis information, such as reports on missing persons, available shelters, and resource needs [8]. During the recent pandemic emergency, communities mobilized at an unprecedented scale, organizing mutual aid efforts to support vulnerable individuals [13]. However, these digital emergent groups often lack legal institutional support and long-term financial sustainability, which can result in sporadic or fragmented responses [14].

Bottom-up communication, where individuals provide real-time updates and observations, plays a key role in enhancing information accuracy by complementing institutional communications. Crowdsourcing mechanisms contribute valuable insights into hazard locations, resource availability, and evacuation routes, just to cite a few examples [15]. Several studies highlight the practical applications of social media in disaster management. Domalewska [16] analyzed social media use during the 2019 floods in Poland, illustrating how Facebook and Twitter facilitated public information dissemination, citizen mobilization, and emergency coordination. Similarly, during Hurricane Irma, Hu et alii [17] found that private citizens played a dominant role in shaping the information landscape, often surpassing official sources in terms of volume and engagement.

Despite undeniable advantages, like, for example, improved response times and enhanced access to real-time data, government agencies have yet to fully integrate citizen-generated data into their crisis management frameworks. Indeed, effectively leveraging social media information requires advanced Big Data processing tools and specialized personnel trained in emergency communication and crisis informatics [18]. Emergency managers also face technical challenges in ensuring the reliability of retrieved information and managing large-scale data streams that exceed human processing capacity [19]. Additionally, the credibility of emergency messages depends on source verification and protection against misinformation, disruption, or abuse [20]. Another key challenge remains the geospatial analysis of user-generated content, as only a small percentage of social media posts are natively geotagged [21,22]. Research seeks to address this issue through algorithmic approaches [23,24], artificial intelligence and machine learning models [25].

As previously mentioned, while social media platforms provide a decentralized and dynamic space for crisis communication, they lack standardized mechanisms for verifying and structuring citizen-generated information [26]. In contrast, calls to emergency-number services (i.e. 112) follow a regulated structure for real-time reporting, and information is systematically processed and integrated into standardized workflows. This structured interaction aligns with the *Citizens-to-Authorities* quadrant of the Crisis Communication Matrix (Fig. 2) in which individuals play an active role in transmitting emergency-related data to institutional actors.

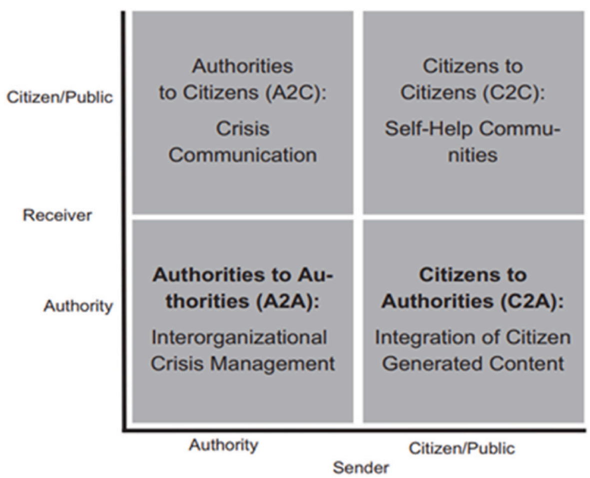

Fig. 2. Crisis Communication Matrix [8].

To ensure consistency in emergency-number services, European countries have structured their 112 systems choosing from five possible macro-models [27]. These models, adapted to the specific national characteristics, are designed to optimize the call management process, from initial call intake to the dispatch of emergency teams. In Model 1, law enforcement agencies, fire departments, and emergency medical services – collectively referred to as Emergency Response Organizations (EROs) – coexist with 112. In this model, emergency calls are managed directly by one of these EROs, which takes full responsibility for the process, from call filtering to resource dispatch (or forwarding the call to the most appropriate service). This model is implemented in Germany, Austria, and France. Model 2 and Model 3 introduce a two-stage process, where emergency calls are first received and filtered by a Public Safety Answering Point (PSAP) before being transferred to an ERO to dispatch response teams. PSAPs are emergency response centers managed either by public entities (e.g., regional health services) or private organizations (e.g., telecommunications companies). In this model, the initial call-taker is generally not a member of law enforcement, fire services, or emergency medical teams, but rather a call center operator from a public or private organization. In Model 2, adopted by Ireland and Norway, the PSAP identifies the caller's location and directs them to the appropriate ERO without conducting a detailed data collection process. Conversely, Model 3, used in Italy, ensures that all emergency calls – regardless of the "legacy-national-emergency number" dialed (e.g., 113, 115, or 118) – are automatically rerouted to the 112 PSAP. Here, operators collect key details, including caller identification, geolocation, and emergency classification. Subsequently the request is forwarded to the appropriate ERO, which determines which response to dispatch. Model 4 represents a hybrid system, where calls to 112 are processed by PSAPs and then redirected, while calls to legacy-national-emergency numbers continue to be handled directly by their respective EROs. This system is currently used in Spain and Greece. Finally, Model 5 centralizes all emergency call processing within PSAPs, where highly trained operators filter calls and directly dispatch emergency resources. Some PSAPs in this model integrate specialists from law enforcement, fire, rescue, or medical services to assist in real-time decision-making. This advanced and fully integrated system has been adopted in Estonia, Finland, and Iceland.

3. Research framework, Methodology and testbed

The main hypothesis to be tested is that crowdsourced information from emergency calls to the European emergency number 112 may provide superior situational awareness compared to the content posted on social media during critical events. The research questions that drive this study are as follows.

- RQ.1: What key information from social media supports emergency response, and how is it extracted?
- RQ.2: What key information from 112 calls is essential for effective response, and how is it extracted?
- RQ.3: How do 112 calls and social media content compare in terms of information accuracy and reliability?

Four methodological phases have been devised to answer these research questions: (I) Defining a model for extracting actionable emergency information from social media; (II) Defining a model for extracting emergency information collected through the 112 European Emergency Number; (III) Testbed (application of these information extraction models to a real case study); (IV) Comparative analysis of the extracted information to assess the quality of the two types of crowdsourced data.

The design and fine tuning of information extraction model from social media (phase I) was developed using specialized literature from the past ten years, with an emphasis on recent advancements in data extraction, analysis, and real-time processing techniques applied to social media platforms. Older studies were excluded due to outdated methodologies and tools that may not reflect current practices. The criteria guiding the selection and analysis of data sources were defined as follows.

➢ *Relevance of Data Sources:* Articles were selected based on their focus on social platforms recognized for their effectiveness in public information dissemination, user engagement, and real-time crisis reporting. Particular attention was given to studies on Facebook and Twitter due to their demonstrated ability to rapidly collect and share critical information [28,29]. Additionally, the selection prioritized research that examined the applicability of these platforms to emergency response scenarios and the use of state-of-the-art data management technologies to enhance information processing and decision-making.
➢ *Compliance with Ethical and Privacy Standards:* Information collection methodologies were assessed to ensure adherence to the latest platform policies and data protection regulations.
➢ *Structured Data Processing:* Given the unstructured nature of social media data, various processing techniques were examined, with a specific focus on textual and semantic analysis. Special attention was given to methods for deriving actionable insights from tweets, including coding strategies for event detection and classification [30].
➢ *Assessment of Information Reliability:* Geolocation was identified as a crucial factor. Since many social media posts lack explicit geolocation data [31], different georeferencing methodologies were explored to improve spatial accuracy and contextual relevance. Additional credibility indicators, such as user engagement patterns and posting behaviors, were also considered to distinguish reliable sources from misleading or irrelevant information.

The extraction model for the information gathered through the 112 calls (phase II), was developed using technical grey literature, including reports and case studies. A specific focus was placed on the Italian 112 infrastructure, as it provided the context for applying the collected data in a real-world scenario. The methodological approach was structured around the following key criteria.

➢ *Authority of institutional sources:* Only documentation from recognized Italian institutional sources, such as the Ministry of the Interior, the Department of Civil Protection, and regional emergency management authorities, was considered to ensure alignment with official emergency response frameworks.
➢ *Operational relevance:* The analysis focused on emergency call center workflows that directly impact data collection, processing, and communication with response teams, prioritizing procedures that enhance efficiency and reliability.
➢ *Information reliability:* A key factor in this assessment was geolocation, as precise location data is essential for effective emergency response coordination. Since not all callers explicitly provide location details, different georeferencing technologies were examined to improve spatial accuracy.

To test the functionality of the developed information extraction models (phase III), they were run on a real-world case, the Vaia Storm. This was an extreme weather event, which struck northern Italy between October 28 and 30, 2018, causing severe coastal flooding in Liguria, massive tree uprooting in Veneto and Trentino-Alto Adige, along with widespread power outages [32]. The rationale to choose the Vaia Storm was that it generated the highest volume of 112 calls recorded by the Liguria emergency response center since its activation in 2017 (9897 calls on October 29 and 6628 on October 30). As a matter of fact, recognizing the significance of this analysis, the Ligurian 112 Response Center partnered in this project, granting access to the emergency database on this specific disaster. Hosted by San Martino Hospital in Genoa, this 112 Center facilitated data sharing through a formal agreement.

The final step of this research (phase IV) involved a comparative analysis of social media content and 112 emergency calls, assessing the quality and reliability of these two types of crowdsourced data. The evaluation focused on information accuracy, verification, and operational usability, aiming to identify the relative advantages and limitations of each source in supporting emergency response efforts. To ensure a consistent and meaningful comparison, the social media data analyzed (e.g., tweets and Facebook posts) were collected using the same time frame of the incoming 112 emergency calls, specifically during the peak hours of the storm on October 29 and 30, 2018. This alignment allowed for a direct assessment of how both sources contributed to real-time crisis communication and the extent to which they provided actionable information.

3.1. The Vaia Storm disaster

The Vaia Storm developed from an intense low-pressure system that developed over the North Atlantic and rapidly deepened as it moved towards southern Europe. By late October 2018, a combination of exceptionally strong Scirocco winds, extreme rainfall (Fig. 3A), and a sudden drop in atmospheric pressure gave rise to one of the most destructive storms in Italy's recent history [33]. Wind gusts exceeded 200 km/h, and up to 850 mm of rain fell in some areas within just 36 h, leading to catastrophic flooding, landslides, and severe infrastructural damage [34]. The environmental and economic impact was particularly severe across northern Italy. In Veneto and Trentino-Alto Adige, hurricane-force winds uprooted an estimated 8 million cubic meters of trees, drastically altering entire mountain landscapes and devastating centuries-old forests [35]. In Liguria, the storm's impact was particularly devastating along the coast. Storm surges exceeding 4 m resulted in severe coastal flooding (Fig. 3B), heavily damaging ports, roads, and buildings [32]. The violent sea conditions completely destroyed several coastal structures, including a century-old coastal road and part of the breakwater wall of the Rapallo dam. The estimated damage in this area alone amounted to several tens of millions of euros [36].

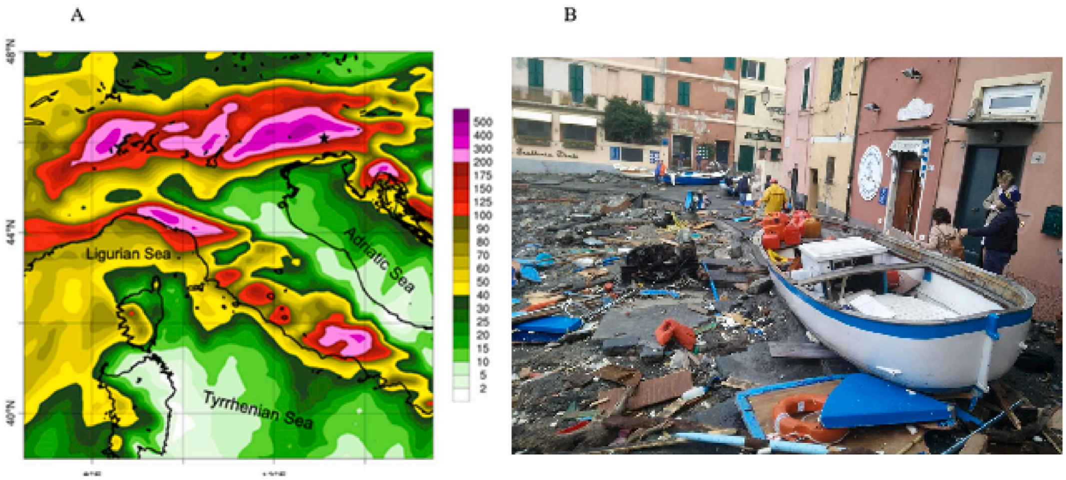

Fig. 3. Impacts of Vaia Storm in Liguria (A) The 72-h accumulated precipitation (0000 UTC 27–0000 UTC Oct 30, 2018). Source: [37]. (B) Damages caused by storm surges in Genova-Boccadasse: (Picture. Paolo Robiglio).

4. Results

4.1. *Defining information extraction models for crowdsourced data*

4.1.1. *Extracting information from social media sources*

Built upon the analysis of the existing literature, the model proposed below conceptualizes the process of extracting actionable information from social media to support emergency responders in crisis scenarios (Fig. 4). Previous research has identified key computational tasks, including message collection, filtering, classification, ranking, and data aggregation, all of which contribute to higher-order objectives such as situational awareness and crisis mapping. Drawing on these insights, the model structures these processes into a systematic framework aimed at enhancing the identification, validation, and dissemination of critical information.

Social media data analysis begins with an opportunistic sensing approach, where publicly available event-related messages are collected using predefined keywords, hashtags, or metadata. This process is typically facilitated by data extraction via Application Programming Interfaces (APIs), which allow for the automated retrieval and filtering of relevant posts based on specific parameters such as time frame, geographic area, and content relevance. However, access to APIs may be restricted due to platform policies, rate limits, or sudden changes in data availability. When API access is unavailable or limited, manual extraction via Advanced Search Tools becomes an alternative, but this method presents significant challenges during crisis situations. Unlike API-based extraction, which enables systematic and large-scale data retrieval, manual searches require a human operator to iteratively refine queries, manually review retrieved posts, and document relevant findings. While tools such as X's (formerly Twitter) Advanced Search and Facebook's filtering functions allow for targeted searches based on keywords, hashtags, and geographic areas, the overwhelming volume of social media posts during an emergency can complicate the process. The sheer number of posts, misinformation, and redundant content can make it difficult to efficiently identify relevant information in real time. Despite these limitations, when automated methods are not feasible, manual extraction remains a valuable approach to ensuring that critical event-related content is captured, supporting situational awareness.

In automated systems, message filtering plays a crucial role in managing the vast amount of social media data collected during emergencies. Given the potential for information overload, particularly when manual search methods are used, automated approaches leverage artificial intelligence to streamline the identification of relevant content. A key technology in this process is Natural Language Processing (NLP), which enables the efficient analysis and categorization of large volumes of textual data. NLP algorithms are designed to interpret and understand human language, allowing messages to be classified as relevant or irrelevant based on their content. A common approach involves training a binary classifier on a labeled dataset, enabling it to automatically assess new messages by analyzing textual features such as keywords, sentiment, and context. By applying NLP, nonessential content is filtered out, ensuring that messages containing critical information – such as damage reports, safety alerts, and eyewitness accounts – are prioritized. This automated filtering process enhances situational awareness, providing emergency management teams with real-time, actionable insights to support decision-making and response efforts.

Witness detection involves identifying posts from individuals who have directly witnessed the events of a disaster, with the goal of prioritizing firsthand accounts over second-hand information. To achieve this, several key attributes of social media posts are analyzed: geolocation, temporal data, post content, and user history. Geolocation plays a significant role in this process. By analyzing spatial metadata, it is possible to determine whether a post originates from within the affected area. This helps filter posts from individuals who are not on the disaster scene, ensuring that the information comes from those who are more likely to have direct knowledge of the situation. In addition to geolocation, temporal data is another crucial factor. The timestamp of a post helps assess its immediacy and relevance. Posts made shortly after the disaster strikes are often more urgent and provide critical, real-time information, while older posts may be less timely and potentially less relevant to the ongoing situation. Another key factor is the content of the post itself. Posts are categorized based on the type of information they provide, such as emergency warnings, safety advice, casualty reports, and damage assessments. This classification ensures that posts containing urgent or actionable information are prioritized for emergency responders. Lastly, the social media history of the user is also considered. Posts from verified accounts or trusted users are given more weight, as these sources are more reliable than those from unverified or unknown individuals.

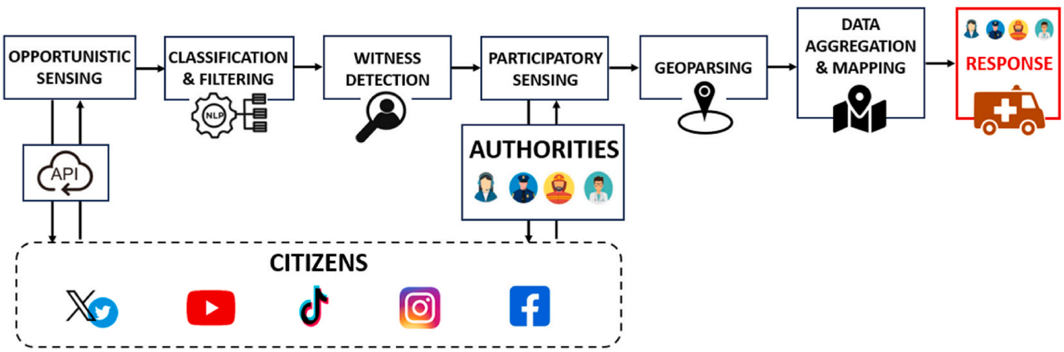

Fig. 4. Proposed social media information extraction model.

Once posts that are from witnesses are identified, the next step is to extract key data or prompt further interaction through participatory sensing. This approach allows for engaging with selected users to gather more focused and detailed information. Targeted interactions with individuals who have direct knowledge or additional insights about the ongoing emergency can enhance the accuracy and depth of situational awareness. In practice, when enough preliminary data is collected, the process may involve reaching out to identified users to ask specific questions and gather additional evidence. This is often done using automated tools, such as chatbots, which simulate human conversation. These tools can prompt witnesses to clarify certain details, like the extent of damage, safety conditions, or the status of affected areas. This method of direct interaction ensures that the information gathered is aligned with the specific needs identified by emergency responders. By targeting users with relevant insights and encouraging more detailed reporting, the quality and timeliness of the data are improved, providing emergency management teams with the most accurate and up-to-date information for decision-making and response.

As mentioned earlier, geographic references are vital for information extraction in the aftermath of a disaster, as they help emergency management teams gain situational awareness and coordinate effective response efforts. However, a significant challenge is that only a small proportion of social media posts inherently contain geospatial data, limiting the scope of real-time analysis. Geotagging, the process of appending geographic coordinates (latitude and longitude) to posts based on metadata from GPS (Global Positioning System) sensors in mobile devices, is one way to address this challenge. When enabled by users, geotagging allows the automatic inclusion of location data, which can be invaluable for understanding where an event is taking place. However, geotagging is not universally applicable. It depends on users' willingness to share their geolocation information, and many posts – particularly those from individuals who have disabled location services – may lack geospatial metadata altogether. This limitation highlights the importance of geoparsing, which plays a pivotal role in addressing the gaps left by geotagging. Geoparsing helps by extracting location information from unstructured text. Unlike geotagging, which relies on metadata, geoparsing identifies location-related terms (such as place names or landmarks) within the content of social media posts and maps them to geographic coordinates. The process of geoparsing can be broken down into several key steps.

1. Location Detection: The first step involves identifying location-related terms within the post. This is achieved using NLP techniques, such as Named Entity Recognition (NER), which automatically detects references to locations.
2. Disambiguation: One of the challenges in geoparsing is the ambiguity of location names. To resolve these ambiguities, contextual clues are utilized, including nearby landmarks, event descriptions, and external geographic databases, to accurately identify the intended location.
3. Geocoding: After identifying and disambiguating the location, geocoding is used to convert place names or references into geographic coordinates.
4. Validation: The last step involves validating the geographic coordinates by cross-referencing them with additional data sources to confirm that the location is relevant to the disaster event. For instance, posts referencing locations far outside the affected area can be flagged as irrelevant.

Finally, the information becomes structured and can be visualized on maps. This enriched information can be aggregated and summarized visually using data visualization techniques such as heatmaps, point maps, and cluster maps. Heatmaps display the intensity of posts in specific areas, with color gradients indicating the density of messages. Point maps show individual post locations as discrete points, while cluster maps group posts in regions of high interaction to help identify hotspots of activity. By producing maps that illustrate the locations of relevant posts, emergency managers can identify areas with the highest density of interactions, thereby highlighting geographic regions that may have sustained more severe damage. These visual summaries should enable responders to prioritize resource allocation and ensure a more efficient response.

4.1.2. Extracting information from 112 emergency calls

The information extraction model for emergency calls is derived from an in-depth analysis of the Italian 112 system, offering a structured representation of call processing within Public Safety Answering Points (Fig. 5). It outlines key operational phases,

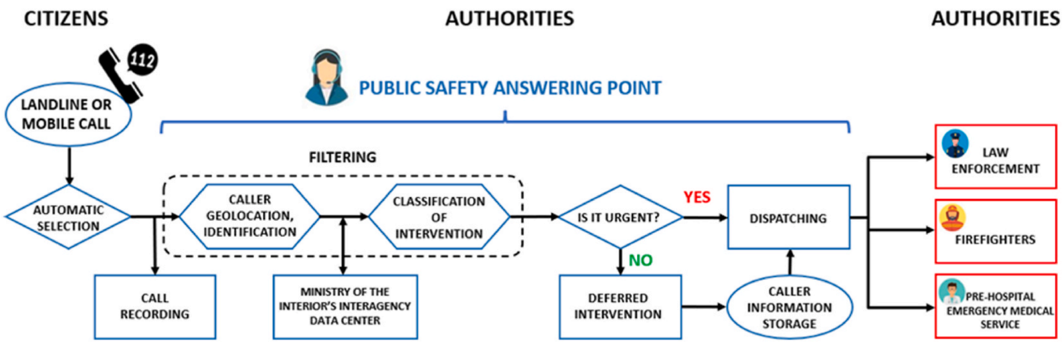

Fig. 5. Information extraction model from emergency calls – processes involved in handling and processing 112 emergency calls in the Italian system. (Adapted from Ref. [38]).

including call reception, caller identification, request classification, and urgency analysis. Based on this assessment, emergency responses are either initiated immediately or postponed, with caller information securely stored for further action. This model serves as a foundation for understanding how critical information is identified, processed, and transmitted to enable timely and effective emergency operations. The following sections provide a detailed explanation of each phase.

When a citizen dials 112, they are immediately connected to an operator who initiates an information triage procedure. This process is crucial for gathering essential data, determining the nature of the emergency, and prioritizing the intervention. Simultaneously, the system automatically identifies and geolocates the caller, while the conversation is recorded and archived to ensure it remains available for judicial authorities if needed.

The geolocation process is overseen through the Ministry of the Interior's Interagency Data Center. This center operates in connection with Public Safety Answering Points (PSAPs) and telecommunications providers, who are required by law to share their subscribers' location data with the Ministry of the Interior to facilitate rescue operations. For landline calls, the emergency system directly accesses the service providers' databases, ensuring immediate and precise location tracking based on the registered address. For mobile calls, which account for the majority of emergency requests, the process is more complex. Since the Global System for Mobile Communications (GSM) network does not automatically transmit location data, the system initially relies on cell tower triangulation. This method provides an approximate area rather than an exact position, and its accuracy depends on various factors, such as.

- The density of cell towers – in rural or remote areas with fewer towers, accuracy decreases,
- Physical obstacles such as tall buildings, hills, or electronic interference, which can further impact the precision of the caller's location.

However, in recent years, location accuracy has significantly improved with the introduction of Advanced Mobile Location (AML) technology [39]. AML automatically activates during an emergency call, transmitting the precise coordinates of the caller's location without requiring any manual input. This system integrates Global Navigation Satellite System (GNSS) technology and Wi-Fi positioning, allowing the PSAP operator to pinpoint the caller's position within a few meters, even in rural areas. AML has been widely adopted across EU member states following Directive 2018/1972/EC [40], ensuring that emergency services have access to the most accurate geolocation data available. This advancement enhances the speed and effectiveness of emergency responses by reducing errors and improving overall system efficiency.

Beyond geolocation, an essential component of the 112 system is call-classification, which determines the urgency of each emergency report and ensures appropriate response prioritization. At a ministerial level, standardized procedures are used to categorize incoming calls based on specific criteria. These procedures rely on a structured telephone interview, where the 112 operator follows a predefined script to collect key information from the caller. The operator then assigns the call to a category using an algorithm that considers.

- The nature of the emergency (e.g., medical, fire, police intervention),
- The caller's responses to specific questions,
- Keywords or indicators that suggest the presence of immediate danger.

If the 112 operator detects a life-threatening situation, the call is immediately classified as urgent and forwarded to the appropriate emergency response organization (law enforcement, firefighters, or medical services). The Computer-Aided Dispatch (CAD) system transmits all relevant information, including geolocation data and the digital contact card, which contains structured details about the emergency.

If the emergency is not classified as urgent, intervention may be deferred, or the report may be stored for future verification. The classification system also plays a vital role in filtering calls, blocking hoax reports, managing multiple reports of the same incident, and ensuring that operators focus solely on cases involving real danger.

4.2. Applying the information extraction models to the Vaia Storm

The following section presents the results of the analysis of crowdsourced information conducted on the Vaia Storm case study in the Liguria region applying the two modes described above.

4.2.1. Analysis of posts published on social media

The extraction of social media posts was performed on Twitter (in this paper we retain this name, because although this platform at the time of writing is called X, at the time of the study events it was known as Twitter) and Facebook platforms, which were selected on the base of their large use in Italy in 2018 [41]. Due to restrictions on API access, a manual retrieval process was implemented to enable a more targeted selection of relevant content. The extraction was based on key themes associated with the event. Frequently used hashtags included *#maltempo* (bad weather), *#mareggiata* (storm surge), and *#vento* (wind), which captured general discussions on adverse weather conditions. Additionally, *allertarossa* (red alert) and *#allertameteo* (weather alert) facilitated the identification of posts directly linked to the official emergency alert. Geographic specific hashtags *(#genova*, *#rapallo*, *#laspezia*) further refined the search, allowing for the localization of affected areas. The extraction process continued iteratively until retrieval saturation was reached. Successively, a textual analysis of the collected posts enabled the classification of content relevant to emergency management. In total, 132 tweets and 96 Facebook posts were sieved as containing real-time situational updates, shared by users reporting localized storm impacts.

The categorization of social media posts illustrates how users engaged with crisis-related information on Twitter (Fig. 6A) and Facebook (Fig. 6B). Approximately 50 % of the posts on both platforms contained updates on the evolving situation, such as real-time reports on rainfall accumulation or wind gust intensity. Meanwhile, 17 % of Twitter posts and 23 % of Facebook posts specifically focused on damage reports, detailing infrastructure collapse, fallen trees, and power outages. Authorities predominantly used twitter to share safety recommendations (12 % of tweets), including warnings about hazardous road conditions, instructions to stay indoors, and emergency contact numbers. Facebook, on the other hand, became a platform for emotional support, with 19 % of posts expressing personal distress, solidarity, and community-driven recovery efforts. Additionally, a smaller proportion – less than 10 % on both platforms – included complaints and satirical content, reflecting citizens' frustrations over delayed responses or infrastructure failures, as well as humor as a coping mechanism. While different in nature, these messages also played a role in capturing the public's emotional state and the social dynamics that emerged during the crisis.

Fig. 7 shows the distribution of communication types between citizens and authorities across both Twitter (Fig. 7A) and Facebook (Fig. 7B). It was found that the flow of communication was balanced on both platforms. However, on Facebook, interactions from citizens slightly outnumbered those from authorities (54 % of messages from citizens and 46 % from authorities). The further breakdown, based on the selection of the posts from citizens containing operationally relevant information – such as damage reports, warnings, safety advice, and updates on affected areas – revealed that such content remained limited on both platforms. Specifically, only 16 % of Twitter posts and 10 % of Facebook posts were considered potentially useful for authorities.

Fig. 8 shows whether the geolocation of the posts' content was obtainable or not. Geolocation data played a pivotal role in identifying direct witnesses of the event. The results indicate that, both on Twitter (Fig. 8A) and Facebook (Fig. 8B), no posts published by citizens were natively geolocated. However, a significant percentage of posts contained useful information that allowed for the deduction of an approximate location, such as place names mentioned in the text and references to locations in images or videos. In particular, a higher proportion of posts on Twitter (58 %) were potentially linked to geographic coordinates, while only 36 % of posts on Facebook showed this possibility, suggesting that more content on Twitter could be indirectly geolocated.

Out of the initial dataset of 132 tweets and 96 Facebook posts, only 21 tweets and 10 Facebook posts – published by citizens who directly witnessed the emergency event – were identified as relevant and contained deducible geographic information. This content provided valuable data for approximate mapping, offering potentially significant insights for authorities (Fig. 9). More than half (52 %) of the posts submitted by direct witnesses documented Damage Reports. A significant portion of the posts (42 %) provided Updates on the weather (e.g. rainfall intensity), while a smaller percentage of the posts (6 %) provided Warnings about ongoing or worsening conditions. The majority of these posts were concentrated along the Ligurian coastline, particularly in the province of Genoa. This area, the most densely populated in the region, also experienced the most significant storm impacts.

Fig. 10 specifically highlights social media posts related to the Rapallo port area (in the province of Genoa) that sustained considerable damage. The mapped content was geolocated using hashtags with clear geographic references, along with textual and visual cues, such as images mentioning and key landmarks at the port (i.e. the castle and the main pier). The timestamps associated with these posts confirmed that they were shared in real time, thus enhancing local situational awareness during the emergency.

4.2.2. Analysis of emergency calls to 112

The dataset, provided by the 112 Ligurian emergency Response Center, comprised 9304 calls that were examined to determine the type of intervention requested (e.g., medical emergency, technical rescue). The spatial distribution of these calls over the 48-h period of the Vaia Storm is visualized in Fig. 11, highlighting the areas most affected. The calls were concentrated along the coastline of the Liguria region, indicating that the population was calling primarily to signaling impacts of heavy storm surges. In terms of calls content, the standardized procedures of the European Emergency Number 112 allow for detailed classification of calls to provide useful information about the requested rescue. This classification entails dividing the request in: *Technical Rescue*, *Pre-Hospital Emergencies and Medical Services*, *Discovery or Reports*, *Crimes or Violations*, *Marine Search And Rescue*, *Hazard situations*, *Non-Urgent calls*. Of all 9304 emergency calls, almost half were classified as Technical Rescue requests directed to the fire department to manage situations like

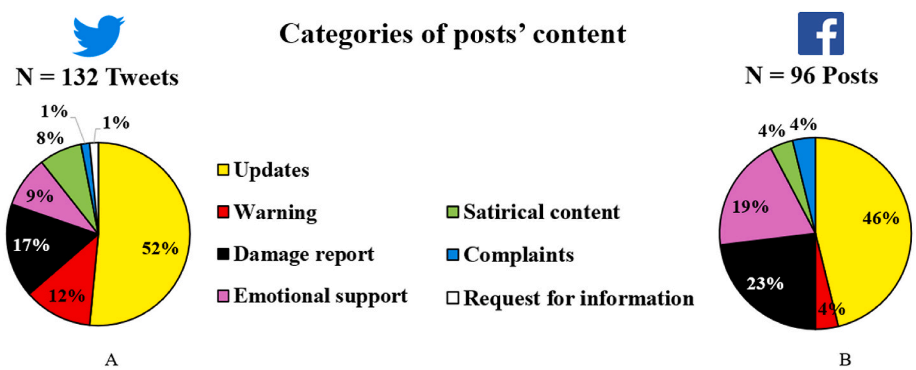

Fig. 6. Different categories of content shared via social media posts (A) Twitter and (B) Facebook.

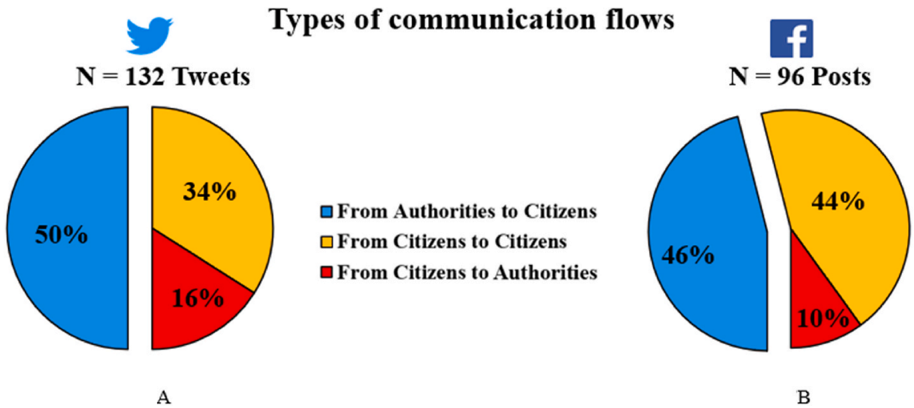

Fig. 7. Different types of communication flows (A) Twitter and (B) Facebook.

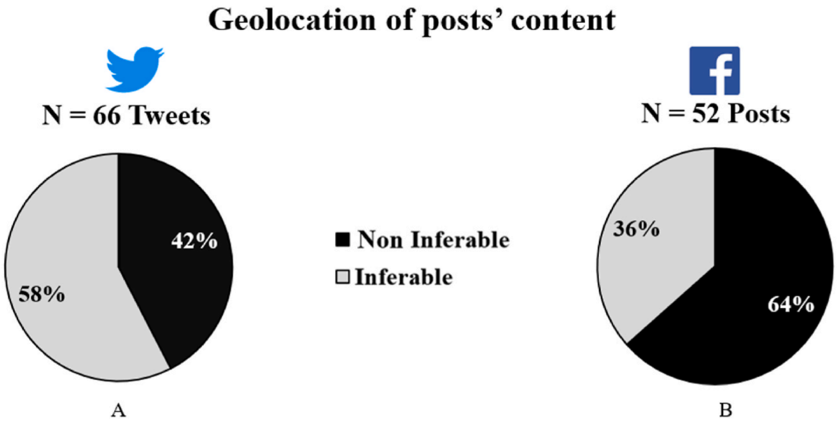

Fig. 8. Percentage of posts with inferable geolocation based on content references (A) Twitter and (B) Facebook.

fallen trees, damaged buildings, and floodwater. Within these 4508 Technical Rescue calls about 45 % were categorized as *other interventions*, (which included, for instance, damaged infrastructure or evacuations), 39 % referred to *building collapses*, while 9 % concerned *flooding*. As a matter of fact, the storm generated violent waves, as high as 7–10 m, that struck the coastlines of Savona and Genoa, causing almost complete destruction of the beachfront infrastructures (piers, lighthouse, breakwater, outdoor seating areas, etc.) and the erosion of large sections of sandy and pebble beaches. The second largest group of emergency calls, totaling 2,267, was classified as Non-Urgent. These calls primarily consisted of information requests and were filtered out to avoid overloading the phone lines of emergency response organizations' call centers. The third group, comprising 1303 calls, was related to Pre-Hospital Emergencies and Medical Services. These included rescue operations for individuals injured in collapsed buildings, as well as cases requiring immediate medical care or transportation to hospitals. The fourth group of emergency calls, 837, involved Discovery/Reports (e.g. reporting downed power lines, trees blocking roads, and other damage related to the storm). Finally, 376 emergency calls accounted for Crimes/Violations.

The detailed analysis of 112 emergency calls, particularly those related to the Rapallo harbor area, provides valuable insights when compared to relevant social media posts. By overlaying precisely geolocated 112 emergency calls with the posts from Tweets and Facebook, the volume of useful information significantly increases (Fig. 12). This was not only from a quantitative perspective (more information), but also qualitative (more detailed and comprehensive data). The integration of social media content with information from 112 emergency calls offers a more complete picture of how the emergency is unfolding, significantly enhancing situational awareness.

5. Discussion

This section discusses the similarities and differences between the information extraction models from social media and emergency calls. Both social media and 112 emergency calls serve as sources of crowdsourced information during crises, yet the processes through which relevant data is extracted differ significantly. In both cases, emergency situations trigger the flow of information from individuals, but while social media relies on opportunistic sensing, emergency calls follow a structured, participatory approach. These differences have substantial implications for informing emergency responses.

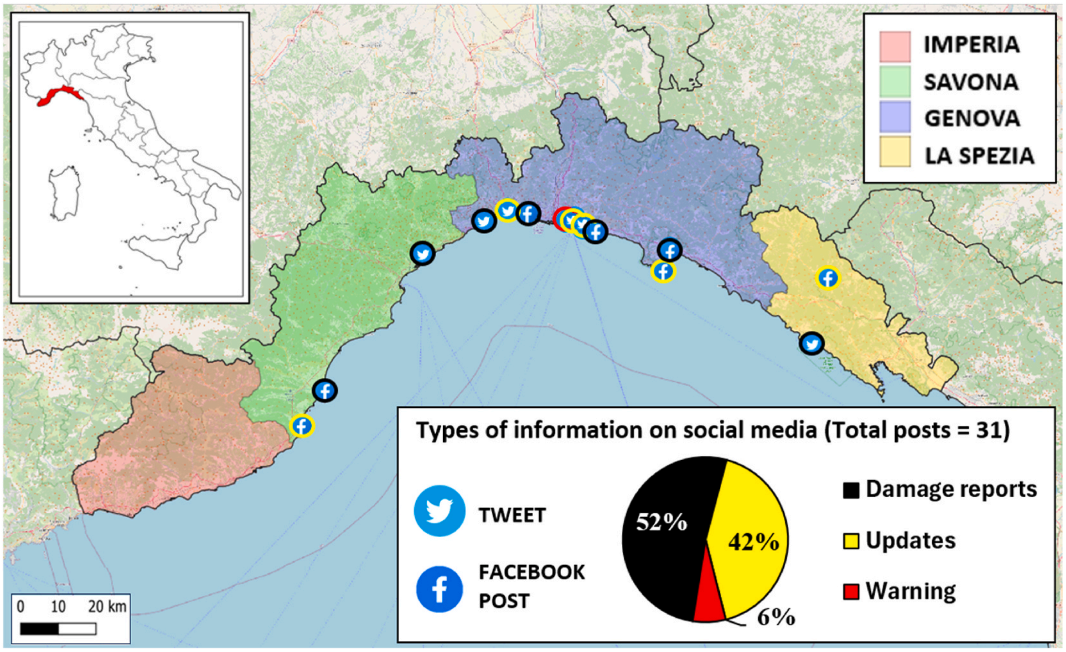

Fig. 9. Geographical distribution and content types of social media posts by Ligurian citizens.

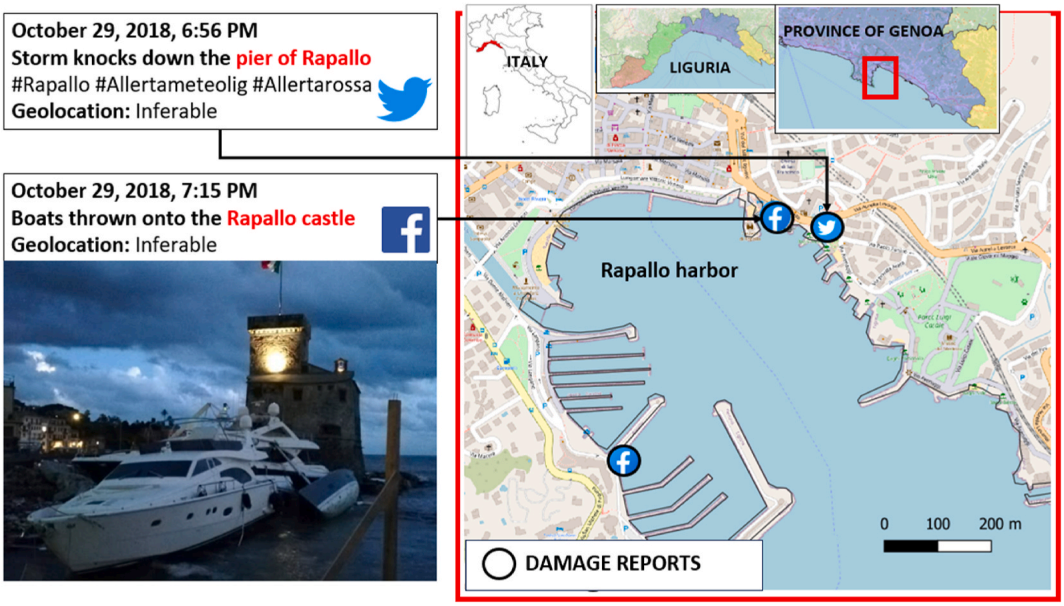

Fig. 10. Social media Posts in the Rapallo Port Area with useful information for emergency services.

The use of social media as a source of crisis-related information has introduced new opportunities and challenges for emergency response efforts. Users share updates on ongoing emergencies through text, images, and videos, often without being fully aware that their contributions may assist emergency responders. However, not all social media platforms contribute equally to emergency data extraction, as they cater to different communication styles and user engagement patterns. X (formerly Twitter) is predominantly used for official updates, making it a key source for institutional communications from emergency agencies. In contrast, Facebook and Instagram are more suited for personal narratives and community-driven reports. Since no single platform provides a comprehensive representation of a crisis, relying solely on one data source may result in biased or incomplete assessments. This limitation underscores the necessity of a multi-platform approach when leveraging social media for emergency response. Beyond platform-specific characteristics, accessibility constraints further impact the effectiveness of social media-based crowdsourcing. Individuals lacking internet

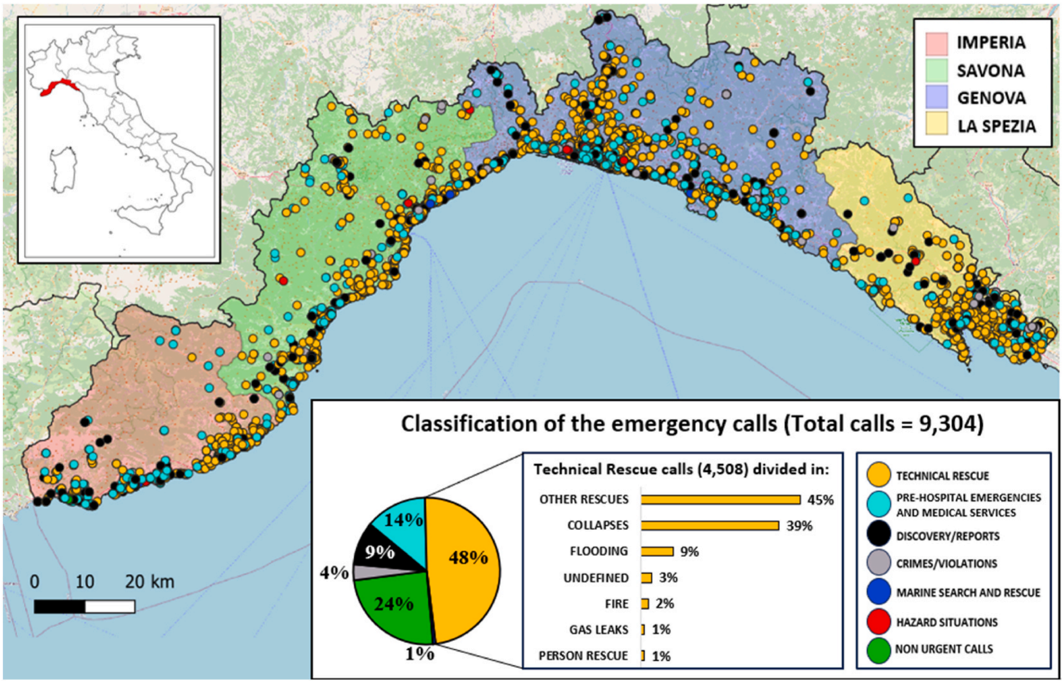

Fig. 11. Geographical distribution and content types of emergency calls to the 112 number.

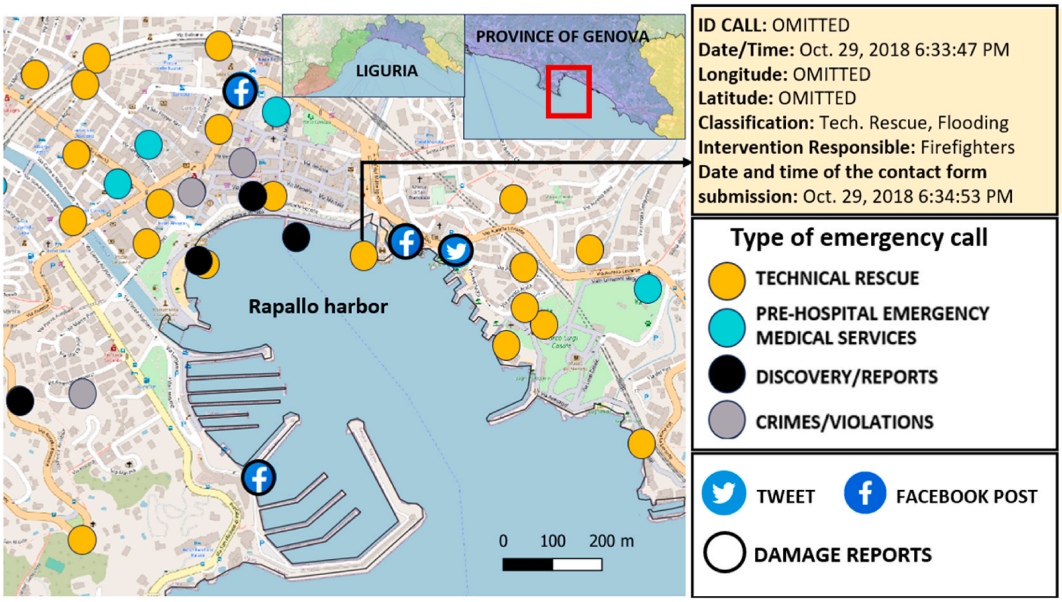

Fig. 12. Merging 112 Emergency Calls and relevant Social Media Posts in the Rapallo port area during the Vaia Storm.

access, digital literacy, or smartphones – such as the elderly or low-income populations – are often excluded from these communication processes. As a result, the information collected may not fully represent the experiences and needs of all affected individuals, leading to potential gaps in situational awareness. Extracting relevant data from social media presents additional challenges, particularly due to the overwhelming volume of user-generated content during emergencies. To manage this complexity, automated methods are typically employed, relying on Application Programming Interfaces (APIs) that facilitate data collection from platforms such as X and Facebook. However, APIs impose several constraints, including limited access to real-time data, privacy regulations, and platform-specific filtering biases. Additionally, the sheer volume of social media posts can obscure critical insights, making it increasingly difficult to distinguish valuable information from noise. Temporal inconsistencies further complicate the use of social media for crisis response.

Delays in both content posting and subsequent extraction can lead to the dissemination of outdated or inaccurate information, potentially undermining decision-making. Similarly, geoparsing and geotagging, commonly employed to assign a geographic location to social media posts, present accuracy and reliability issues. A key limitation is the voluntary nature of geotagging, which relies on users choosing to share their location information. While GPS coordinates or location tags can be embedded in posts, a significant portion of social media content lacks such data, requiring validation through participatory sensing. This necessity to cross-verify location data with external datasets prolongs processing times, increasing the likelihood of discrepancies between reported and actual conditions. These limitations hinder the ability of emergency services to use social media data to rapidly develop an accurate situational awareness framework in dynamic crisis scenarios. To mitigate these challenges, artificial intelligence (AI) models are frequently employed to filter, classify, and rank social media content. These models must be trained on diverse and comprehensive datasets to ensure reliability across different emergency contexts. However, despite extensive training, their performance can remain inconsistent due to the highly dynamic nature of crisis-related content, the ambiguity of natural language, and the prevalence of misinformation, all of which can distort situational assessments. Given these limitations, the use of automated information extraction systems must be complemented by human operators with specialized training for data analysis and decision support. Addressing these limitations requires a hybrid approach that integrates automated extraction techniques, human validation processes, and multi-platform data aggregation, thereby enhancing the accuracy, reliability, and operational applicability of social media information in real-time crisis management.

The 112-emergency call system offers a structured and highly reliable method for extracting crisis-related information, addressing many of the limitations associated with social media-based data collection. Unlike social media, where information is shared opportunistically, often lacking direct relevance, 112 calls represent an active and participatory form of crowdsourcing, where callers deliberately engage with emergency services to provide specific, real-time information. This structured interaction ensures that the data collected is immediately actionable, enhancing situational awareness and supporting effective decision-making in emergency response efforts. Beyond its structured approach, the 112 data gathering system ensures inclusivity, overcoming the digital divide that limits social media-based crowdsourcing. Every citizen can call 112 without needing specialized technological literacy or internet access, thus broadening the pool of participants and ensuring that individuals from all socioeconomic backgrounds can contribute to the emergency response process. The accessibility of the system can be further enhanced by Over-The-Top (OTT) applications, such as Italy's Where Are U app. This tool allows users to connect with emergency response centers through voice or simplified interactions, making emergency communication more inclusive for individuals with disabilities. Features such as a dedicated chat for deaf, deaf-blind, and hard-of-hearing users, automatic call forwarding to local emergency numbers abroad, and multilingual support through real-time interpretation in 14 languages reinforce the ability of the 112 system to accommodate diverse populations, ensuring that language barriers do not hinder access to critical services. Additionally, 112 operators are trained to provide real-time guidance, offering safety instructions, emergency protocols, and pre-arrival advice, further strengthening the system's effectiveness. Another key advantage of the 112-emergency system is its ability to efficiently manage information overload, a common challenge in social media-based crisis monitoring. While the high volume of social media posts can create delays in filtering and responding times, 112 call centers are designed to handle large-scale information flow in real time. Standardized interview procedures allow operators to classify emergencies quickly, prioritize cases based on urgency, and streamline resource allocation. Unlike social media, where data filtering requires significant computational resources and human intervention, the 112 system minimizes bottlenecks by enabling direct, structured communication between the caller and the operator, thus ensuring that emergency situations are assessed and addressed without unnecessary delays. The absence of lagging time in conveying critical data allows emergency responders to receive timely and verified information, significantly enhancing operational efficiency. Geolocation capabilities further distinguish the 112 system as a superior model for crowdsourced information extraction. While social media-based geolocation relies on voluntary user input, leading to inconsistent accuracy and the need for additional validation, 112 calls automatically integrate Advanced Mobile Location (AML) technology. This system precisely determines the caller's location without requiring manual input, using Global Navigation Satellite System (GNSS) and Wi-Fi data to pinpoint the caller's position within a few meters, even in rural areas. By combining structured information collection, inclusivity, real-time prioritization, and precise geolocation capabilities, the 112-emergency system appears more reliable and accurate of the social media-based extraction models.

The application of the two above-described information crowdsourcing models to the real-world case study of Vaia Storm over the Liguria region confirmed the preferability of emergency calls data over social media content crowdsourcing in providing structured, dependable, and actionable information for crisis management. A key finding in the Vaia Storm testbed is the substantial disparity in both the volume and quality of data generated by the two sources. Although social media produced a large quantity of content related to Vaia Storm, much of it constituted irrelevant noise, leaving a little quantity of useful information for emergency responders. In contrast, the Liguria 112 emergency response center processed over 9000 emergency calls during the Vaia Storm disaster, much of it containing useful information for emergency response. This discrepancy can be attributed to several factors. Firstly, the storm's primary impacts were confined to coastal areas, with damage limited to storm surges and localized flooding. Consequently, social media discussions were generated by individuals not in immediate need of assistance, centering on personal experience and peer-to-peer communication rather than the dissemination of critical, real-time updates for emergency authorities. Secondly, the demographic characteristics of Liguria might further explain the lower volume of relevant social media content. According to the Italian Institute of Statistics [42], Liguria has the oldest population in Italy, with a significant proportion of residents exhibiting lower engagement with digital communication platforms. This digital divide contributed to an underrepresentation of emergency-related information on social networks, reinforcing the non-inclusivity of social media-based crowdsourcing in crisis scenarios. Beyond the disparity in information volume, a fundamental distinction between the two crowdsourcing methods lies in the structure and reliability of the data collected. Social media content, inherently unstructured, necessitated extensive filtering, classification, and verification before extraction of actionable insights about the Vaia Storm. Conversely, the 112-emergency call system provides inherently structured data through standardized European protocols ensuring the collection of relevant and ready-to-use information.

The findings of this study empirically validate the theoretical models described in chapter 4, by demonstrating the limitations of social media-based crowdsourcing in a real emergency scenario, while concurrently highlighting the effectiveness of the 112 system in gathering structured, location-verified, and operationally relevant data. The results of the Vaia Storm testbed support the hypothesis of this study, that 112 emergency calls constitute a more reliable data source compared to the social media ones. Nonetheless, the study also underscores the potential for integrating multiple crowdsourced information to enhance conventional monitoring systems. Despite its inherent limitations, social media data can complement structured emergency call data by offering qualitative context, capable of capturing dimensions of the crisis that may not be immediately reported through formal emergency channels.

6. Conclusions

The findings of this study highlighted important variances in how different types of crowdsourced emergency information contribute to situational awareness, information accuracy, and emergency response decision-making. While social media provides a powerful open and decentralized channel for the dissemination of crisis-related information, its unstructured nature, lack of verification mechanisms, and demographic limitations, constrain its reliability as a primary information source for emergency operations. In contrast, the 112-emergency call system offers a structured, standardized, and highly accurate source of crisis-related information, effectively addressing many of the challenges associated with the extraction of relevant knowledge from social media.

The application of the two information crowdsourcing models to the real-world disaster Vaia Storm in Liguria confirmed the higher reliability of the 112 emergency calls system over the social media ones. A valuable finding of this study is the substantial disparity in both the volume and quality of information obtained from these two sources. While social media platforms produced a large amount of content, much of it was irrelevant noise, significantly reducing the proportion of useful information available to emergency responders. In addition, the Vaia Storm case study highlighted the non-inclusiveness of social media-based information in emergency situations, particularly in regions with an aging population, such as Liguria, where digital engagement is comparatively lower.

Beyond these differences in volume and inclusivity, the study also underscored the difficulties in geolocating information sources and the different level of accuracy achievable. Social media data, often lacking explicit geospatial references, necessitates extensive post-processing, including geoparsing and cross-verification, which can delay response times and introduce errors. Conversely, the integration of Advanced Mobile Location (AML) technology used with the 112 system ensures that caller locations are automatically transmitted with high precision.

The theoretical and empirical contributions of this study lays in the heightened understanding of citizen-generated information during emergencies and disasters. Future research should focus on refining methodologies for integrating social media and 112 emergency call data, developing standardized validation protocols, and testing these frameworks across various crisis scenarios. Additionally, further exploration is needed into the potential of artificial intelligence and machine learning models to enhance the extraction and verification of crisis-related information. Strengthening the interoperability between structured emergency call data and unstructured social media content could improve real-time crisis management, leading to more effective decision-making and resource allocation in emergency response efforts.

CRediT authorship contribution statement

Giuseppe Lelow: Writing – original draft, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Fausto Marincioni:** Writing – review & editing, Validation, Supervision.

Declaration of competing interest

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

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Data availability

Data will be made available on request.

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