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Review

The Use of Decision Support in Search and Rescue: A Systematic Literature Review

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Abstract: Whenever natural and human-made disasters strike, the proper response of the concerned authorities often relies on search and rescue services. Search and rescue services are complex multidisciplinary processes that involve several degrees of interdependent assignments. To handle such complexity, decision support systems are used for decision-making and execution of plans within search and rescue operations. Advances in data management solutions and artificial intelligence technologies have provided better opportunities to make more efficient and effective decisions that can lead to improved search and rescue operations. This paper provides findings from a bibliometric mapping and a systematic literature review performed to: (1) identify existing search and rescue processes that use decision support systems, data management solutions, and artificial intelligence technologies; (2) do a comprehensive analysis of existing solutions in terms of their research contributions to the investigated domain; and (3) investigate the potential for knowledge transfer between application areas. The main findings of this review are that non-conventional data management solutions are commonly used in land rescue operations and that geographical information systems have been integrated with various machine learning approaches for land rescue. However, there is a gap in the existing research on search and rescue decision support at sea, which can motivate future studies within this specific application area.

Keywords: artificial intelligence; data management; decision support; disaster management; geographical information systems; search and rescue operations; spatial analysis; systematic review

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1. Introduction

Natural and human-made disasters, including hurricanes, floods, bushfires, avalanches, droughts, epidemics or pandemics, and terrorist attacks, have drastic effects on human beings, societies, economies, and the environment. According to the International Federation of Red Cross and Red Crescent Societies (IFRC) World Disaster Report 2020, disasters caused by climate change have surged by 35 percent over the last decade. A total of 400,000 people have died in these calamities, and 1.7 billion people have been affected [1]. According to the United Nations University—The Institute for Environment and Human Security (UNU-EHS) Interconnected Disasters Report 2020/2021, the world has witnessed several record-breaking disasters during the year 2020, including the COVID-19 pandemic, Texas cold wave, Amazon wildfire, Vietnam heavy storms, and Amphan cyclone on India–Bangladesh border [2]. These global disasters have affected or killed hundreds of people and caused billions of US dollars in damage. This scenario has fostered an increasing interest in the development of systems designed to support Search and Rescue (SAR) processes.

Whenever a disaster strikes, SAR services responsible for handling emergencies are required to respond. SAR services refers to the process planned by authorities to save people from death or injuries in the case of serious disasters that are not handled by specifically established agencies or under specific measures [3]. The SAR process establishes coordination between representatives from different organizations, such as the police, fire department, medical authorities, port authorities, armed forces, communication companies, air traffic services, civil defence, and voluntary organizations [4]. Collaboration across organizations makes SAR processes extremely complex, and often includes a set of interdependent assignments with many degrees of detail [5].

Typically, the SAR process is categorized into the following four phases, as shown in Figure 1: mitigation, preparedness, response, and recovery. Disaster mitigation is a continual process designed to decrease or eliminate risk. Risk identification, analysis, appraisal, and risk mitigation through spatial planning, technical measures, public awareness, and education, are all part of mitigation [6]. Preparedness is the process of deciding how to react to a disaster. Emergency planning and training, as well as the installation and operation of monitoring, forecasting, and early warning systems, are all included in this phase. In the case of a disaster, emergency response includes SAR activities and measures to meet the affected population's basic humanitarian requirements. Finally, the process of repairing living conditions in disaster-stricken areas is known as emergency recovery. This entails prompt damage assessment, rehabilitation, and reconstruction.

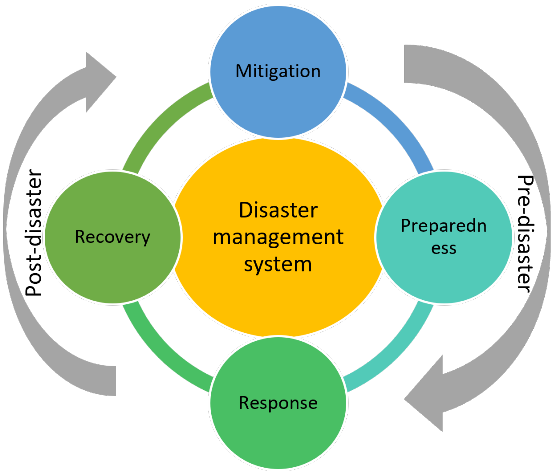

Figure 1. Disaster management system, inspired by [7].

To handle this level of complexity, it is necessary to utilize efficient and effective decision support. DSSs, data management solutions, and AI have been used extensively to help reduce the impacts of disasters. These technologies have received considerable attention in recent years and are being adopted by many different sectors, including business, healthcare, banking, telecommunications, government, and SAR, to gain a competitive edge [8].

In the context of SAR, these technologies can be used to optimize time and cost by providing valuable insights and support to disaster management experts. This can help them to make more informed decisions and respond more quickly and effectively to emergencies. Data management solutions such as Information Systems (ISs) and Geographical Information Systems (GISs) can be used to collect, store, and analyze large amounts of data from various sources, such as sensor networks, social media, and satellite imagery. This information can be used to gain a better understanding of the situation and to identify patterns and trends that can help inform decision-making. AI, on the other hand, can be used to analyze data and make predictions about potential hazards or risks. For example, machine learning algorithms can be used to analyze satellite imagery to identify potential flood or wildfire hazards. Similarly, Natural Language Processing (NLP) can be used to analyze social media data to identify areas where people are in need of assistance.

The development of suitable DSSs requires the utilization and integration of several state-of-the-art technologies, such as information and communication technology (ICT) and telecommunications, to support SAR operations. Government authorities, researchers, and practitioners involved in SAR processes have been working to enhance these concepts by considering new ideas from research fields such as computer science, information technology, cybernetics, environmental sciences, and decision sciences. The goal is to improve the data collection, management, processing, and visualization phases of SAR processes for timely and precise decision-making.

Motivated by the significance of these concepts in the field of SAR, in this review we aim to systematize existing knowledge about the use of DSSs, data management solutions, and AI in SAR processes.

We formulated our overarching research question as follows: How do SAR processes use DSSs, data management solutions, and AI?

To address this question, we performed a bibliometric mapping and systematic literature review. More specifically, we investigated the literature to identify research patterns, as described in detail in Section 4.3. The objective of our study was to identify existing solutions used for SAR operations and to provide practitioners with insight into knowledge transfer possibilities within SAR application areas.

We used Web of Science (WoS) for the bibliometric mapping and systematic literature review. Bibliometric mapping explores the data sample retrieved from a data source with the goal of characterizing the evolutionary dynamics of the research area by displaying evidence of the field's emerging areas [9]. In turn, a systematic literature review analyzes data while summarizing the existing evidence concerning an overarching research question. The results of this study can be beneficial for practitioners and researchers in the field of SAR by providing them with a comprehensive overview of the current state of the art in the use of DSSs, data management solutions, and AI in SAR operations. In addition, it can help to identify knowledge transfer possibilities and guide future research in this field.

The remainder of this paper is organized as follows. Section 2 discusses related works presented by various authors in this domain over the years. Section 3 defines and describes the concepts used in this study, specifically, the SAR process, DSSs, data management solutions, and AI technologies. The research methodology is presented in Section 4. Moreover, protocol development, inclusion and exclusion criteria, dataset preparation, research questions, and bibliometric mapping are explained in detail. In Section 5, we synthesize the bibliometric analysis and systematic review. Section 6 addresses the research questions using the synthesis provided in the previous section, and discusses with the potential future work. Finally, the study's conclusions and limitations are presented in Section 7.

2. Related Work

To the best of our knowledge, papers by [7,10–17] have previously reviewed the literature related to SAR processes using various methodologies.

Hair Zaki et al. [7] investigated existing flood disaster management systems by analyzing the incorporation of the system based on sentiment analysis and system-oriented architecture. In addition, they performed a comparative analysis of studies related to flood disastermanagement frameworks. Kaur et al. [10] performed a scientometrics analysis of ICT use for disaster management. In their study, the authors investigated research activities from 2009 to 2019. For the scientometrics analysis, the authors utilized the Scopus database to examine the annual increment in publications, contributions to several domains, and the cooperation of different countries and authors. According to Kaur et al. [10], the analysis showed that natural disasters such as floods and earthquakes were always at the forefront, with the maximum number of research articles, and that the USA, Japan, China, and India had the most remarkable collaboration with other countries in creating systems with the help of ICT. Nunavath and Goodwin [11] presented a systematic literature review of the applications of AI, machine learning (ML), and deep learning (DL) in disaster management from 2009 to 2019. Their work relied on the Scopus database to identify the relevant articles. In their review, the authors categorized disasters as natural or human-made disasters in order to analyze the types of techniques used for prediction and classification in the mentioned categories. According to the authors [11], the most common algorithms used for natural disasters are support vector machine (SVM), naïve Bayes (NB), convolutional neural networks (CNNs), Natural Language Processing (NLP), artificial neural networks (ANNs), reinforcement learning (RL), random forest (RF), decision tree (DT), logistic regression (LR), latent Dirichlet allocation (LDA), and k-nearest neighbor (KNN). In addition, they pointed out that the techniques most used for human-made disasters are RF, DT, CNN, NLP, KNN, genetic algorithms (GA), and multi-layered feed-forward networks (MLFFN). Ray et al. [12] presented state-of-the-art technologies in Internet of Things (IoT) for disaster management. Their survey focused on the approaches used to provide early warnings or awareness, notifications, and support for data analytics related to disasters. The authors discussed IoT-supported protocols for wireless sensor networks and the deployment of these protocols on different operating systems. In addition, they provided research on IoT-enabled market-ready products for disaster management systems. These products use various sensors and communications protocols to provide early warnings about future natural disasters, such as earthquakes, tsunamis, and landslides.

In another article, Shah et al. [13] conducted a thematic taxonomy of the importance of big data analytics (BDA) and IoT for disaster management. The designed taxonomy categorizes relevant concepts and essential parameters for BDA and IoT-based disaster management. The authors presented a conceptual reference model for BDA and IoT-based disaster management as a roadmap for future realistic applications. Another article by Minas et al. [14] presented a survey with the goal of improving the theoretical foundation of modeling emergency response and enhancing the research in that domain. The authors performed a bibliometric analysis by adopting unsupervised learning and citation network analysis methodologies. Through a bibliometric approach, they classified the literature related to emergency response operations management into different clusters and indicated the types of modeling used for emergency response, including analytic models, decision analysis, stochastic models, and queuing models. Their findings revealed relationships between the diversity of emergency response models. Prasanna [15] discussed the emergency response to fire emergencies. In their study, they carried out a survey on the outcomes of two previous preliminary studies on information and human–computer interaction based on discussions between end users, system architects, and designers. They evaluated the performance of Information Systems (ISs) architectures developed in previous studies using scenario-based action research. Based on their survey, the authors proposed an ISs architecture with particular key elements that were missing in previous studies; the overall objective of their study was to provide firefighters with better situational awareness through the use of ISs architectures. Shahrah and Al-Mashari [16] conducted a preceding study on emergency response systems and the related challenges. They classified the research directions in the investigated domain into design principles and frameworks, standardization, agent-based simulations, web technologies, business process management, IoT, case-based reasoning, and expert systems. For each research direction, they described the existing research until 2017 and the shortcomings in each domain. Alotaibi et al. [17] performed a review study of coordination in emergency response using agent-based simulation. The authors categorized the study field into three different parts in order to analyze the role of agent-based simulations. They concluded that the work carried out in connection with the coordination of multiple organizations in emergency response was limited in terms of agent-based simulation.

In addition to these reviewed articles, Cumbane et al. [18] addressed the potential of big data sources and advances in data analytic techniques to extract geospatial information critical for rapid and effective disaster response. They compared processing frameworks and established a link between big data and processing frameworks for critical tasks in the disaster management response phase. Bomi et al. [19] investigated ways to improve the efficiency of disaster management in South Korea through the use of a spatial database and image information combined with information regarding nuclear power plants. Jessin et al. [20] analyzed the use of UAVs as a tool for data acquisition in coastal monitoring on island territories, highlighting the available platforms, sensors, software, and validation methods. They focused on operationalizing the concept of resilience as a risk management technique with the goal of linking analyzed data to a spatial decision support system, and used the French Polynesian islands as a case study.

Moreover, Gil et al. [21] presented a bibliometric analysis and systematic literature review of shipboard DSSs for accident prevention. The authors selected studies from the WoS database to increase understanding of the structure and contents of the academic domain. They reviewed the top articles based on a standardized technology readiness level (TRL) of systems provided by NASA, showing how previous researchers have categorized DSSs in the context of preventing accidents at sea, for example, in collision-avoidance, ship maneuvering, and ice navigation.

Although these reviews present relevant results for researchers in the investigated domain, we observed the following limitations. First, none of the existing reviews have focused specifically on the "use of DSSs, data management, and AI for SAR processes". The studies in [14–17] focused on "emergency response systems", while others such as [7,10–13] concentrated on "disaster management". The main difference between disaster management systems and an emergency response systems is that the former target large-scale disasters, whereas emergency response systems are mostly focused on small-scale emergencies. In our review, we consider both terms, namely, disaster management and emergency response systems, with respect to SAR operations, thereby broadening our perspective. Furthermore, we use terminology for both natural and human-made disasters. Existing reviews have characterized "the use of advanced technologies for SAR operations", which takes into account fewer dimensions. In our review, eight dimensions are considered, including, among others, AI, data management solutions, DSSs, disaster management, emergency response, SAR operations, and type of disaster. Another difference is that each previous study compared articles using different reviewing methods, and only Nunavath and Goodwin [11] carried out a systematic literature review using fewer dimensions and fewer tables and charts. Our review provides a bibliometric analysis of the investigated domain along with a systematic literature review. We believe that adopting these methods in our comparison of existing research allows us to identify the research patterns and trends in the area along with any existing gaps. In addition, we presume that there are opportunities for knowledge transfer among the different application areas involving SAR processes.

3. Definitions and Background

Our research study focuses primarily on the concepts of SAR operations, DSSs for SAR, data management solutions for SAR, and AI technologies for SAR. These concepts are defined below.

3.1. Search and Rescue (SAR)

According to the book Fundamentals of Search and Rescue by Cooper [22], the term "SAR" has had several definitions presented over the years. This term was first defined in the *1946 Air Sea Rescue Bullet* titled "Evolution of SAR: An Editorial", where it was defined as "the act of finding and returning to safety the survivors from an emergency incident". Another definition described by [22] is that of the *The International Aeronautical and Maritime Search and Rescue (IAMSAR) Manual (1999)*, which defined "search" and "rescue" separately, with search operations entailing the use of available personnel and facilities to locate people experiencing difficulties and rescue operations involving retrieval of people in distress, meeting their immediate medical or other requirements, and transporting them to a safe location. SAR includes SAR operations on land (ground SAR, mountain SAR, and urban/city SAR), in the air, and at sea.

As mentioned in Section 1, SAR is normally divided into four phases: mitigation, preparedness, response, and recovery [6]. Each phase has different responsibilities for handling a disaster, usually represented as a disaster management cycle, as shown in Figure 1. For instance, the mitigation phase focuses on reducing the risk of a disaster by identifying an upcoming crisis, while preparedness pertains to the planning and training of SAR experts. These two phases are mostly related to pre-disaster activities, whereas the response and recovery phases are considered post-disaster phases. The response phase includes measurements and actions taken to conduct SAR operations in the case of a disaster. The recovery phase includes activities regarding the assessment of damage due to a disaster and the conclusion of the SAR operations carried out in the response phase.

3.2. Decision Support System (DSS)

The DSS concept describes the role of computers in decision-making processes. Owing to the general growth of the concept over time, there is no exact definition of the term DSSs. According to Shim et al. [23], DSSs are computer-based solutions that can be used for decision-making and problem-solving. Cummings and Bruni [24] presented a general idea of DSSs as supporting the decision-making process by improving human and system performance, that is, by reducing the workload [24]. In our study, we refer to DSSs according to the definition of Keen [25]. According to Keen, DSSs are characterized by an “implementation approach” for making computers helpful to managers, along with responsive services and humanized software interfaces. The most well known types of DSSs are data-driven, knowledge-driven, communication-driven, model-driven, and document-driven [26], as described in Table 1.

Table 1. Description of types of Decision Support Systems (DSSs).

Types	Description
Data-driven [26]	Data-driven DSSs mainly target administrators, workforces, and product/service providers. They can be used to query a database or data warehouse to seek specific answers for specific purposes. Decisions made using data-driven DSSs can be influenced by factors irrelevant to the data; thus, great consideration needs to be paid to how data are structured and displayed as part of the system’s architecture.
Communication-driven [26]	Communication-driven DSSs emphasize network and communications technologies for decision-making relevant to collaboration and communication. Communication technology is the major architectural component in these systems.
Document-driven [26]	Document-driven DSSs provide facilities such as document retrieval and analysis by utilizing computer storage and processing technologies. They can consist of scanned documents, images, audio, and videos.
Knowledge-driven [26]	Knowledge-driven DSSs are human–computer systems that help in problem-solving by suggestion actions. The suggestions are based on the knowledge of a specific domain, an understanding of difficulties within that domain, and the ability to solve these problems.
Model-driven [27]	Model-driven DSSs are complex systems that help in decision-making processes. They are used to create models of present events to anticipate the consequences of future events. These models can include many states or external circumstances that the decision-makers may not be aware of, and they have the ability to simulate scenarios without harming any real-world entities.

The role of DSSs in SAR processes is to provide an interactive computer system that can help SAR personnel in decision-making, expand situational awareness in emergencies, and aid in the rescue of distressed people. With the emergence of advanced technologies and efficient solutions, SAR processes are in the process of being equipped with multiple supportive data sources as well as fast and cost-effective data processing tools that can be utilized to assist potential end users such as first responders, victims, volunteers, SAR team experts, and researchers in all phases of SAR processes.

3.3. Data Management Solutions

Increasing amounts of data have become a major asset in numerous organizations and businesses, and can be used to make informed decisions that improve operations and reduce costs. Data management normally refers to the process of sorting, inserting, organizing, and managing data generated and collected by an organization [28].

Efficient data management is a critical component in establishing IT systems that run business applications and provide analytical data to help executives, managers, and other end-users make operational and strategic decisions. An overall data management system covers a number of steps, from data processing and storage to data integration and usages in operational and analytical systems.

In our study, we perceive the term "data management solutions" from a broad perspective, inspired by [29,30]. A wide range of available data management tools and techniques can be implemented as part of such solutions. Among them, we include articles that contain either one of the following categories and subcategories: data mining and analytics (subcategories: data warehouse, data lake, and information retrieval); graph, network, and semi-structured data (subcategories: NoSQL); distributed database systems; data acquisition; data analysis and presentation (subcategories: visualization, user-centered design, and interaction design); big data systems (subcategories: cloud computing, and fog computing); novel database architectures (subcategories: Internet of Things (IoTs)); and programming, data structures, and algorithms (subcategories: algorithms, programming, and numerical methods). Table 2 provides an overview of the definitions we have found for subcategories identified in our study.

Table 2. Definitions of subcategories of data management solutions.

Subcategories	Definition
Data warehouse [31]	Enormous historical databases used for decision-making, where new data are updated on a periodic basis and have evolved to necessitate specific query processing support. These are related to the data mining and analytics domain of data-centric subjects.
Data lake [32]	A storage repository that stores a large amount of raw data in its original format until it is required for analytics applications. It is incorporated in the same category as a data warehouse; however, it differs from a standard data warehouse in the way that it stores data in a flat architecture, mostly in files or object storage, rather than in hierarchical dimensions and tables. This provides the user with more control over data management, storage, and usage.
Information Retrieval [33]	Information retrieval is concerned with the representation, storage, organization, and retrieval of information. Information elements should be represented and organized in a way that enables users to find relevant information in an organized database. Information retrieval belongs to the data mining and analytics category. Traditionally, information retrieval systems refer to textual data retrieval, however, modern information retrieval deals with text, audio, video, and image data.
NoSQL [34]	Commonly distributed databases that prioritize semi-structured data storage, high performance, availability, data replication, and scalability over rapid data consistency, strong query languages, and structured data storage.
Distributed database [35]	A database in which components on networked computers communicate and coordinate their operations solely through the transmission of messages. These databases have properties that are independent of one another, such as component concurrency, the lack of a global clock, and component failures.
Data acquisition [36]	A process of extracting data from around the world in the form of various parameters for analysis, display, and storage on a computer.

Table 2. *Cont.*

Subcategories	Definition
Information Systems (ISs) [37]	A network of interrelated components that work together to collect, analyze, store, and disseminate data to assist decision-making, coordination, control, analysis, and visualization.
Geographical Information Systems (GISs) [38]	A computer-based system used for capturing, storing, checking, manipulating, analyzing, and displaying geo-referred data.
System-of-systems [39]	A collection of systems that emerges from the integration of separate systems into a larger system that provides unique features.
Knowledge Repository [40]	An online database that systematically captures, organizes, and categorizes knowledge-based data.
Cloud computing [41]	A set of network-enabled services that provides on-demand and scalable QoS-guaranteed low-cost computing infrastructures; these are generally personalized, and can be accessed in a simple and ubiquitous manner. Both cloud computing and fog computing belong to the category of big data systems.
Fog Computing [42]	A decentralized computing infrastructure or process in which computing resources are distributed between a data source and a cloud or other data center. Fog computing is a computing paradigm that caters to user requests at the network edge.
Internet of Things (IoTs) [43]	An open and comprehensive network of intelligent objects that have the capacity to automatically organize, share information, data, and resources, and act or react to different situations and changes in the environment.

3.4. AI Technologies

Although AI has received a great deal of coverage in recent years because of developments in computer hardware, computer network speeds, availability of massive volumes of data, and processing algorithms [8], there remains a considerable amount of vagueness about what it means and what it includes. Therefore, it is necessary to clarify the distinctions between the core concepts in AI and how these concepts are considered.

From the definitions in Table 3, it is clear that AI refers to computers with human-like capabilities, which means computers that are capable of performing activities that would ordinarily require human intelligence. This covers tasks such as comprehension, thinking, and problem-solving. It can be stated that AI does not necessarily replace humans, instead serving as a supplement for complex and time-sensitive activities [44].

Table 3. Definitions of Artificial Intelligence (AI).

Reference	Definition
Enholm et al., (2021) [8]	AI is an applied discipline that aims to enable systems to identify, interpret, make inferences, and learn from data to achieve predetermined organizational and societal goals.
Nunavath and Goodwin, (2019) [11]	AI is the study and development of software and machines that can imitate human-like intelligence to capture high-level abstractions in big data, providing significant improvement for various tasks and processes and finding patterns in enormous quantities of data.
Mikalef and Gupta, (2021) [44]	AI is the ability of a system to identify, interpret, make inferences, and learn from data to achieve predetermined organizational and societal goals.
Kolbjørnsrud et al., (2017) [45]	AI refers to IT systems that sense, comprehend, act, and learn.

AI definitions can be grouped based on two different perspectives. One perspective defines AI as a tool that can solve assigned tasks, while the other regards AI as a system that imitates human intelligence for interpreting, making decisions, and learning [44]. In our study, we adopt the stance that AI is a system that can emulate human-like intelligence to identify, interpret, make decisions, and learn from data to achieve predetermined SAR goals. The different definitions of AI provide a broader picture of this concept. However, our focus is on the next level of definition that encompasses the techniques used to capture the essence of AI. Our review of the existing literature reveals that this can be accomplished using a variety of methods, most of which focus on scenarios in where ML is used.

Machine Learning and Deep Learning

ML has gained considerable attention from researchers worldwide, particularly with increases in data availability and advanced computational power. ML is defined as a subset of AI comprising complex statistical approaches that allow computers to progress over time when performing tasks [11]. The objective of ML is to learn from data, make assumptions and predictions, and identify associations that can guide the process. It can be further subdivided into the following categories used in the investigated literature: supervised learning, unsupervised learning, and RL. The supervised learning approach is defined as a class of systems that classifies data and predicts outcomes using labeled datasets for training algorithms [8]. In our study, researchers mostly use supervised learning in applications involving UAVs [38,46]. In unsupervised learning, algorithms are trained using unlabeled datasets. Instead of relying on labels, the system identifies previously unnoticed patterns and information [8]. RL approaches, in turn, are not trained on past datasets; rather, they learn in an interactive environment through trial and error using feedback from their own actions and experiences [8].

ML approaches can be implemented in two ways, namely, with shallow structure or a deep structure. Shallow-structured architectures learn from data described by predefined features, whereas deep-structured architectures have a multi-layered structure that is derived from data. Deep-structured architectures, known as DL, are a subset of ML, and its use of neural networks differentiates it from more traditional ML approaches. ANNs aim to mimic the functionality of the human brain by imitating human neurons.

DL techniques are extremely complex, and different types of ANNs are used to solve particular tasks or datasets. For instance, in our study, we found that several researchers used CNNs to solve SAR-related problems. CNNs are widely used in computer vision and image classification applications that can recognize the characteristics and patterns within an image, allowing tasks such as object detection and recognition to be performed. In addition to CNNs, distributed DL was used in the reviewed literature; this refers to multi-node ML techniques and systems aimed at improving performance, increasing accuracy, and scaling SAR decisions to larger input datasets [47].

Table 4 provides definitions of other technologies used in the reviewed literature, such as serious games, Petri nets, multi-objective optimization, and NLP.

Table 4. Definitions of other technologies.

Reference	Definition
Serious Games [48]	The oxymoron of serious games unites seriousness of thought and the problems that require it with the experimental and emotional freedom of active play. Serious games combine the analytic and questioning concentration of the scientific viewpoint with the intuitive freedom and rewards of imaginative and artistic acts.
Petri nets [49]	A Petri net is a mathematical language tool used for analyzing concurrent processes that occur in multi-component systems (distributed systems).
Natural Language Processing (NLP) [50]	NLP employs a collection of computational techniques for making human languages accessible to computers, particularly with the goal of enabling computers to interpret and generate human language.
Multi-objective Optimization [51]	A multi-objective optimization problem is a problem dealing with more than one objective function.

4. Research Methodology

This section describes the research methodology used in this review to identify and analyze relevant papers. The procedure and typical methods used are illustrated in Figure 2. First, a systematic and repeatable approach was used to gather and filter data samples. Subsequently, bibliometric mapping was applied to the selected data samples. The bibliometric method provides an overview of SAR operations at the global level. According to Donthu et al. [9], bibliometric analysis is a prominent and comprehensive method for exploring and analyzing vast volumes of scientific data which enables the discovery of the evolutionary complexities of a particular domain. The data of a bibliometric analysis are usually massive and objective in nature, for example, the number of citations and publications or the occurrence of keywords and topics [52]. Finally, a literature review of the selected sample data was conducted. The articles aggregated during the selection process were categorized according to the research questions raised in order to address the investigated domain. When assigning a particular paper, the purpose of each presented solution (i.e., the type of decision it aims to support) was considered. We identified relevant articles from WoS, as shown in Figure 3. These articles described research on the use of DSSs, data management solutions, and AI technologies for SAR processes. We focused on studies published from 2017 to 2021. Following an assessment of the articles' eligibility and quality, irrelevant retrieved articles were excluded. The remaining articles were analyzed and synthesized, resulting in a discussion with the goal of understanding how existing systems use advanced technologies and manage data. The included articles directly address SAR processes in the context of the investigated areas. We categorized AI technologies as ML and RL, with DL as a subcategory of ML. The categories of data management solutions are perceived in a broad range, as described in Section 3.3.

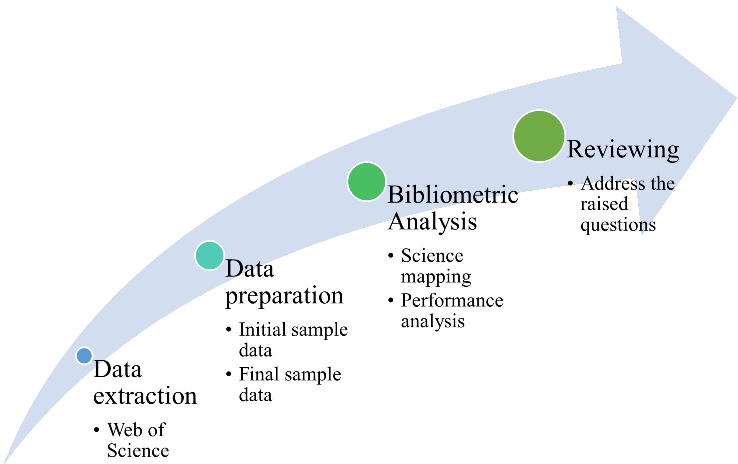

Figure 2. The performed process and method in the study.

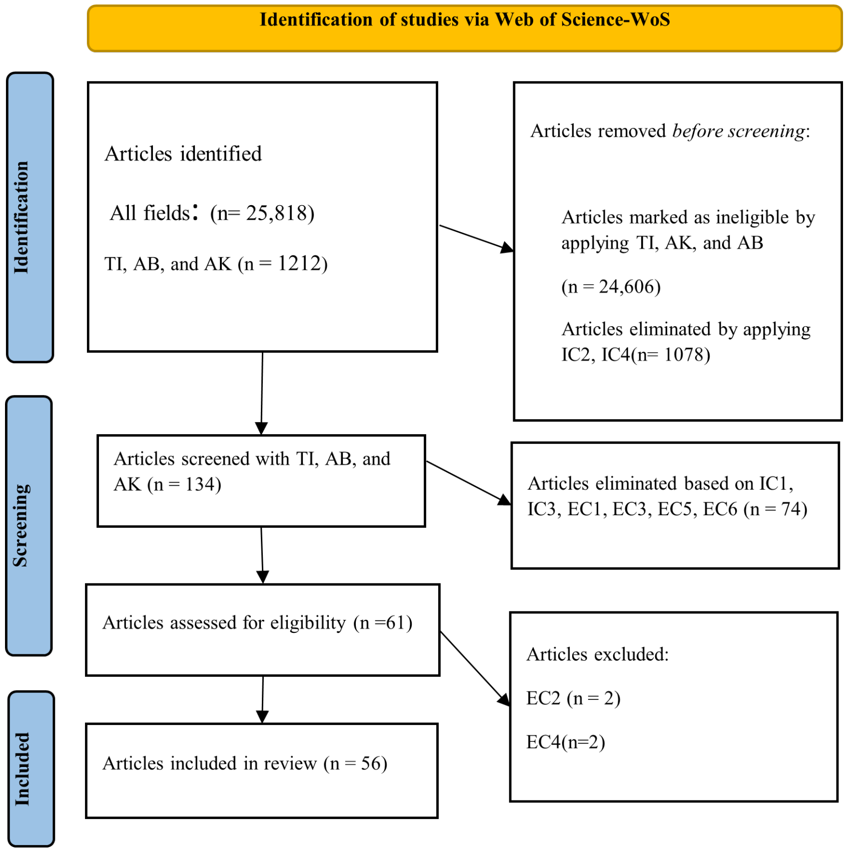

Figure 3. Flow chart outlining the four-stage procedure adopted in our systematic literature review based on PRISMA [53].

The systematic literature review was conducted based on the guidelines on systematic literature reviews in software engineering proposed by [54] (p. 45).

4.1. Protocol Development

The review protocol identifies the methods to be used in undertaking a systematic review of the investigated field; a predefined protocol can help to reduce research bias [54]. In this study, we started our systematic review by developing a protocol following the guidelines for performing a systematic literature review [54]. The primary research questions, search strategy, and inclusion, exclusion, and quality criteria were specified according to the protocol. Additionally, the synthesis process was determined using the protocol. This review was prompted by the overarching research question, which served as a foundation for determining how to proceed.

4.2. Inclusion and Exclusion Criteria

To define the scope of the systematic review, a number of inclusion and exclusion criteria were used [55]. A paper was included if it met the following inclusion criteria:

(IC1) It provided insight into SAR processes in the context of the investigated field
(IC2) It was published in the years from 2017 to 2021
(IC3) It covered studies related to the overarching research question described in Section 1
(IC4) The paper belonged to the "Computer Science (CS)" research area

- In the WoS database, the CS research area is categorized into several domains; we only considered those categories that conformed to the scope of our study, specifically, CS Information Systems (ISs), CS theory methods, CS AI, CS interdisciplinary applications, CS software engineering, and CS cybernetics.

On the other hand, papers described by the following exclusion criteria were excluded:

(EC1) The paper was written in a language other than English
(EC2) The paper had an objective that was outside the scope of our study
(EC3) The paper was only published as an abstract
(EC4) The paper was a poster paper or a pre-print
(EC5) The paper was not accessible online
(EC6) The paper presented a solution in the context of telecommunications, health sciences, or chemical incidents.

4.3. Review Questions

To enable an unbiased selection process, the selected articles were reviewed based on the following questions to analyze the findings and discuss future possibilities [56].

Q1 When and where was the literature published?
This question provides researchers with a perception of the breadth and novelty of this literature review new by providing an overview of where and when the reviewed papers were published. In this regard, we employed a performance analysis and scientific mapping to perform bibliometric mapping of the extracted original dataset. Additionally, a review of the final data sample is provided in Section 5.2.

Q2 What are the targeted disasters considered in the study?
This question describes the crisis events addressed in the selected studies. We categorized disasters as natural disasters (e.g., floods, bushfires, earthquakes, droughts, tsunamis, and hurricanes) or human-made disasters (e.g., fire emergencies and day-to-day emergencies). This question can be helpful for researchers who intend to accomplish new initiatives for SAR processes based on the type of emergency or disaster.

Q3 What are the major purposes of DSSs for the SAR processes used in this study?
This research question investigates the major purposes of presenting the DSSs in SAR processes. This question presents researchers' ideas that might be helpful in the development of all phases of the SAR process (i.e., mitigation, preparedness, response, and recovery).

Q4 What is the scope of this study in terms of the specified spatial dimensions?
This question investigates which countries are presented in the study (i.e., demographic locations) and what types of emergency areas (land, sea, air) are presented in the papers. This question can help researchers to analyze and compare the presented case studies and to determine the most common emergencies based on geographical location.

Q5 What are the main data management solutions employed for the SAR processes described in this study?
This question is related to **Q**3, and asks which data management solutions are usually employed with respect to DSSs in the literature when investigating the topics covered by DSSs for SAR? The aim of this question is to characterize the most common data-centric solutions employed in the investigated domain.

Q6 What kinds of data are managed in the considered SAR processes?
This question is related to **Q**3 and **Q**5, and aims to characterize the types of data that have been managed in different studies.

Q7 What are the main AI solutions employed in the SAR processes described in this study?
This question refers to the AI solutions embedded in the literature. This question can aid in understanding the AI technologies (e.g., ML, DL, and RL) adopted in different studies.

Q8 Who are the potential end users of the presented methods?
This search question looks into the end users for whom the methods are presented (e.g., SAR experts, first responders, victims, government officials, and volunteers). This question can help researchers to identify the clear intentions of the authors of the study.

4.4. Dataset Preparation

Dataset preparation comprises a four-phase procedure based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) [53]. In the initial stage, the search strategy was defined and the data records were identified (phase 1). The obtained sample was then screened and filtered based on the title, abstract, and author keywords (phase 2). Additionally, we screened the articles based on the inclusion and exclusion criteria (phase 3). Finally, articles were included using full-text analysis (phase 4). The entire data sample determination process is presented in Figure 3.

Motivated by Kitchenham and Charters [54], Kitchenham et al. [55], and Gil et al. [21], who state that WoS is a well-known platform of multiple databases providing broad access to citations and abstracts from reputable and significant scientific articles, we chose it as our source for identifying relevant articles.

Documents were obtained from three main core collections: the Science Citation Indexed Expanded (SCI-EXPANDED), Social Sciences Citation Index (SSCI), and Conference Proceedings Citation Index-Science (CPCI-S). To ensure that the search string was properly designed and conformed to the vocabulary used in the search and rescue domain, the wording used in the IAMSAR manual [3] was applied. The search string was divided into four parts: DSSs, data management solutions, AI, and SAR, as shown in Table 5. The search was conducted on 10 November 2021 on the WoS database, and the search string was as follows: ((“DSS” OR “Decision Support Syst*”) AND (“Search and Rescue Operat*” OR “Emergency respons*” OR “Disaster Manag*”)) OR (“Database syst*” OR “Data manag*” OR “Information syst*”) AND (“Search and Rescue Operat*” OR “Emergency respons*” OR “Disaster Manag*”)) OR (“Artificial Intellig*” OR “Intelligent algo*”) AND (“Search and Rescue Operat*” OR “Emergency respons*” OR “Disaster Manag*”) OR (“Search and Rescue Operat*” OR “Emergency respons*” OR “Disaster Manag*”).

Table 5. Search String.

Search Area	Search Term
DSSs	“DSS”OR “Decision Support Syst*”
Data management solutions	“Database syst*” OR “Data manag*” OR “Information syst*”
AI	“Artificial Intellig*” OR “AI” OR “Intelligent algo*”
Search and Rescue (SAR) operations	“Search and Rescue Operat*” OR “Emergency respons*” OR “Disaster Manag*”
((“DSS” OR “Decision Support Syst*”) AND (“Search and Rescue Operat*” OR “Emergency respons*” OR “Disaster Manag*”)) OR (“Database syst*” OR “Data manag*” OR “Information syst*”) AND (“Search and Rescue Operat*” OR “Emergency respons*” OR “Disaster Manag*”)) OR (“Artificial Intellig*” OR “Intelligent algo*”) AND (“Search and Rescue Operat*” OR “Emergency respons*” OR “Disaster Manag*”))	

Wildcards were utilized to consider various forms of inflection. In our case, we used the * symbol as a wildcard character at the root of words to extract the maximum data sample. The initial data sample after execution of the search string contained 29,145 documents from WoS. For data sample preparation, all articles retrieved from WoS were investigated by focusing on the title, abstract, author keywords, and the aforementioned inclusion and exclusion criteria. After applying the title, abstract, and author keywords to the data sources, 24,606 documents were marked as ineligible. By applying IC2 and IC4, 1078 documents were removed. Articles that passed the screening phase were classified as eligible for the subsequent procedure (134 articles). These articles were included in a new dataset that was analyzed in the filtering step, which led to a final data sample comprising 56 articles. In the final phase of dataset preparation, all articles were examined to verify whether they met the required criteria. If they did, the articles were assigned suitable thematic categories. The breakdown of categories with the general aim of addressing the raised review questions is described in Section 5.

4.5. Bibliometric Mapping

Bibliometric research mapping is a scientific domain involving the quantitative analysis of books, journals, articles, and other forms of written literature [57]. Bibliometric mapping is of significant interest in the bibliometric domain. The goal of bibliometric mapping is to provide visual representations of the relationships between various units of interest. The units of interest can be documents, authors, or keywords, and the connections between them can be based on citations, co-citations, co-authorships, or keyword co-occurrences.

Donthu et al. [9] illustrated bibliometric mapping using two techniques, namely, performance analysis and science mapping. Performance analysis includes publication-related metrics (i.e., the total number of publications, number of describing authors, number of active years of publications), citation-related metrics (total citations and average citations), and metrics related to both citation and publication (collaboration index, number of cited publications, citations per cited publication). Science mapping, on the other hand, includes citation analysis, co-citation analysis, bibliographic coupling, keyword co-occurrence, and co-authorship analysis. In our study, a bibliometric analysis was conducted using both techniques. The performance analysis focused on identification of the total number of articles, the number of describing authors, and the number of active years of the investigated field, while science mapping was concerned with citation analysis, bibliometric coupling, and keyword co-occurrence.

5. Synthesis of Bibliometric Analysis and Literature Review

In this section, we address the overarching question defined in Section 1. To do this, we address all the review questions from Q1 to Q8 and then present the findings in the form of tables and charts.

5.1. Synthesis of Bibliometric Analysis

A bibliometric analysis was conducted considering two aspects, namely, performance analysis and science mapping. Data processing in this part of the study was performed by using VOSviewer [58].

5.1.1. Performance Analysis

Performance analysis of bibliometric mapping involves examining the contribution of researchers to the investigated domain. In this study, the performance analysis of the investigated bibliometric includes the total number of publications, number of describing authors, and number of active years of publications.

In accordance with the dataset preparation described in Section 4.4, 1212 articles were identified as relevant based on their title, abstract, and author keyword criteria, then processed using scientific mapping methods. Among these documents, 508 stemmed from proceedings papers, 675 from journal articles, and 43 from review articles published over the course of three decades, as illustrated in Figure 4a. Figure 4b shows that from the selected time span the year 2019 had the highest number of publications.

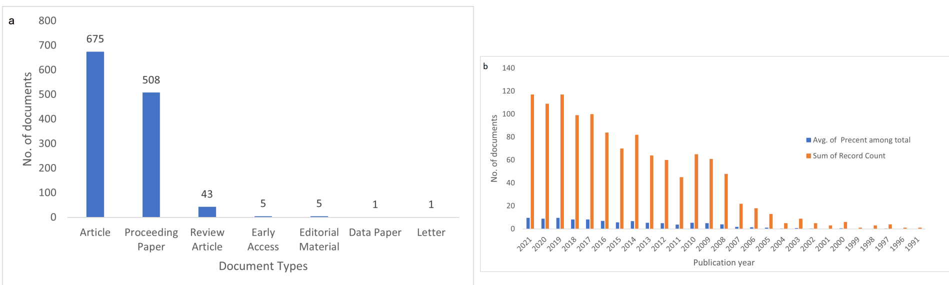

Figure 4. Document distribution of articles (**a**) per category and (**b**) over the full study period.

There were approximately 3500 authors who published work on search and rescue processes that used decision support systems, data management solutions, or artificial intelligence technologies.The countries with the most publications in this area were China and the USA, as depicted in Figure 5b. The most active research area was computer science, with 206 out of 1212 papers, or about 517% of the total, as shown in Figure 5a. The authors with the most publications in this area were Zeng QT, Li J, and Liu C, as shown in Figure 6.

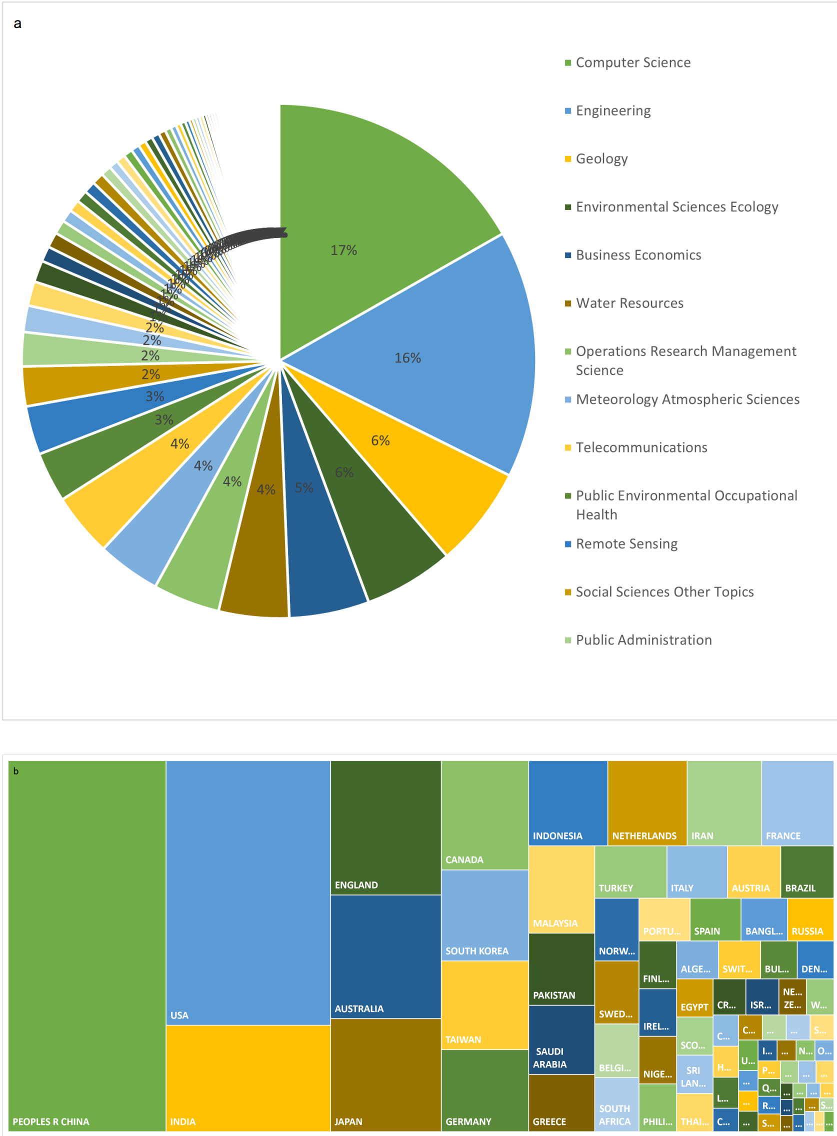

Figure 5. Distribution of publications (**a**) across different domains and (**b**) across countries.

5.1.2. Science Mapping

In bibliometric analysis, science mapping explores the relationships between researchers, including citation analysis, bibliographic coupling, and keyword co-occurrence. Citation analysis assumes that citations reflect intellectual linkages among publications [9]. In this review, we performed mapping to examine the relationships among cited articles in order to better understand the development of initial ideas in the investigated domain. Figure 7 shows the linkage between the publication sources in the literature. This linkage among the publication sources illustrates the development of the investigated domain over time.

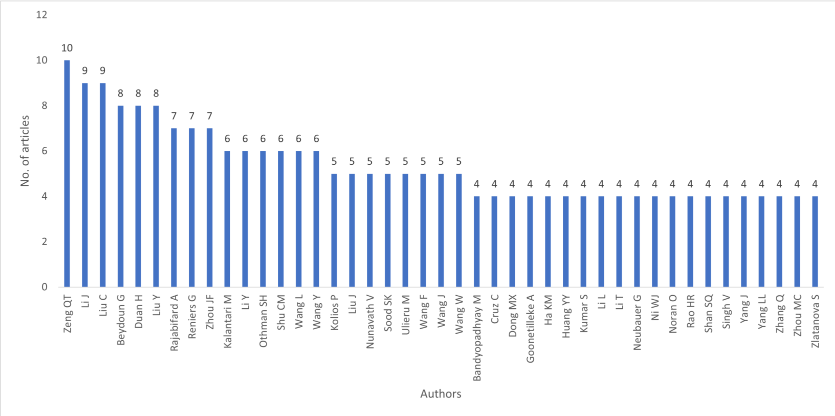

Figure 6. The most relevant authors over the study period (minimum four publications).

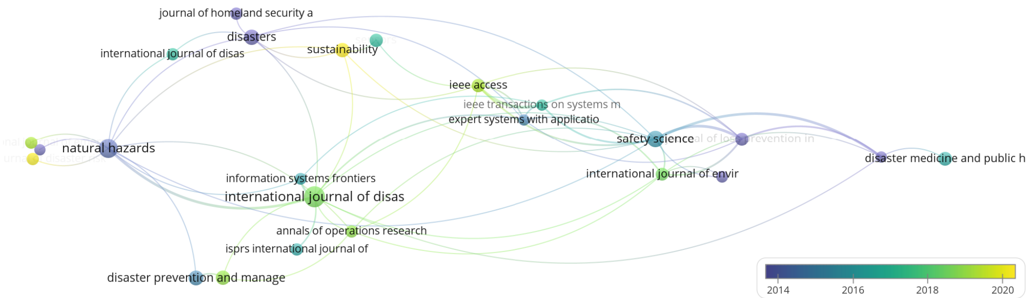

Figure 7. Collaboration relationships among sources: citation analysis.

The citation analysis focus on publications, while keyword co-occurrence analysis focuses on the content of the publication itself. The words that appear most frequently together indicate the thematic coverage of the investigated study, as shown in Figure 8. This analysis tells us the existing association of topics in the investigated domain; in our review, the vast majority of identified topics were related to disaster management. We have taken away the main keywords, namely, disaster management and emergency response, in order to better visualize the links among the other keywords with a minimum of three occurrences. In addition, the most relevant keywords, which indicate researchers' interest in SAR processes, were DSSs, ISs, information management, knowledge management, AI technologies, ML, UAVs, cloud computing, IoTs, and big data.

5.2. Synthesis of Systematic Literature Review

In this study, we describe the systematic literature review performed according to the guidelines described in Section 4. The initial data samples were identified and obtained using the procedure presented in Figure 3; 42 percent of the initially collected papers (56 out of 134) were included in the review. The literature review was conducted with the aim of systematically investigating the targeted field of study to answer the formulated questions (Q1–Q8).

5.2.1. When and Where Was the Study Published? (**Q**1)

Figure 4 shows that research on SAR processes that used DSSs, data management solutions, or AI technologies has been quite active, with a very large number of papers published from 2017 to 2021. The distribution of papers among conferences and journals is approximately equal, as shown in Tables 6 and 7, respectively.

The final data sample accounted for only 42 percent of the initial data. Table 8 and Figure 4 present the distribution of papers published over the years. With regard to the final data sample, the number of articles from 2017 is higher than in other years, and IEEE ACCESS remains the most influential source of publications for these articles [12,13,59–62].

With regard to conference proceedings, the International Conference on Information and Communication Technologies for Disaster Management has the highest number of articles [11,63,64].

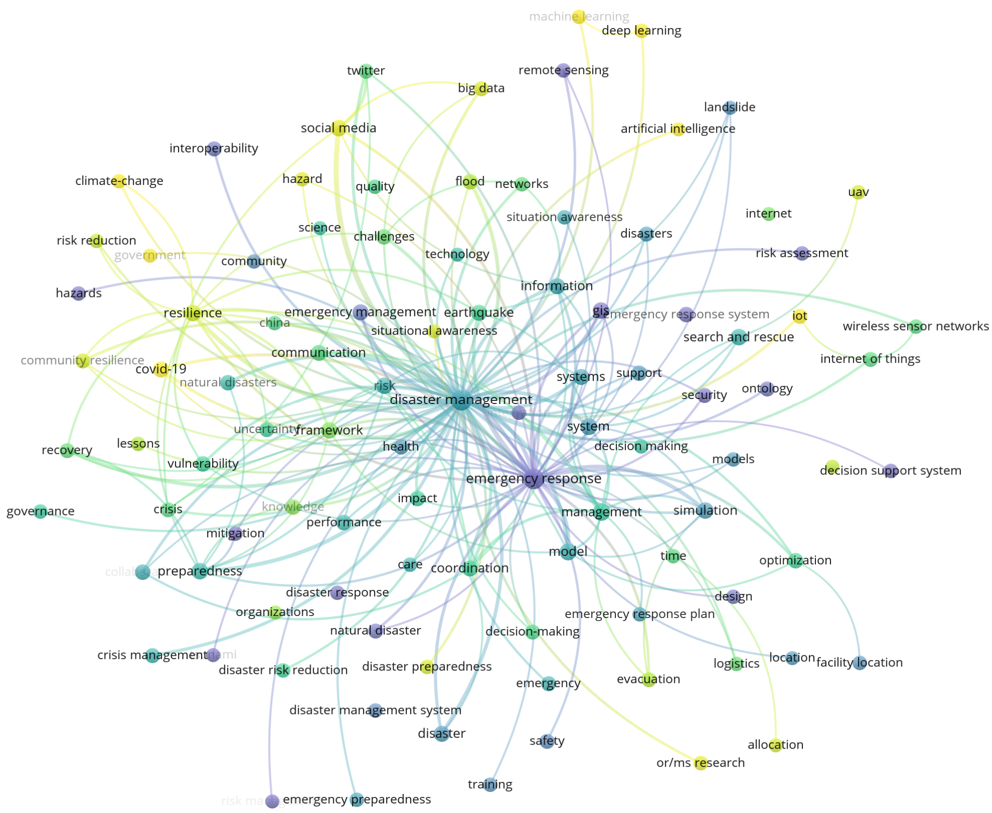

Figure 8. Co-occurrence of words analysis.

Table 6. List of conference venues from final data sample.

Conferences	Reference
Int. Conference on New Trends in Intelligent Software Methodologies, Tools and Techniques	[7]
Int. Conference on Information and Communication Technologies for Disaster Management	[11,63,64]
Int. Conference on Internet of Things, Data and Cloud Computing	[16]
Int. Conference on Computer Applications and Information Security	[17]
IEEE Int. Conference on Electro Information Technology	[38]
IEEE Int. Conference on Mobile Cloud Computing, Services, and Engineering	[42]
IEEE Int. Advance Computing Conference	[65]
Int. Conference on Computer and Information Sciences	[66]
Int. Conference on Advances in Computing, Communications and Informatics	[67]
IEEE Int. Conference on Cyber, Physic and Social Computing	[68]
Int. Conference on Emerging Technologies	[69]
Int. Conference on Digital Government Research	[70]
IEEE Int. Humanitarian Technology Conference	[71]
Int. Conference on Human Factors and Systems	[72]
IEEE Global Communications Conference	[73]
Int. Conference on Information Management	[74]
IEEE Int. Conference on Industrial Engineering and Applications	[75]
IEEE SoutheastCon Conference	[76]
European Conference on Free and Open Source Geospatial Technologies	[77]
IEEE Int. Conference on Internet of Things and Intelligence System	[78]

Table 6. *Cont.*

Conferences	Reference
IEEE Int. Conference on Automation and Computing	[79]
Experiment Int. Conference	[80]
Int. Conference on Web Research	[81]
IEEE Int. Conference on Mobile Data Management	[82]

Table 7. List of journals from the final data sample.

Journals	Reference
Earth Science Informatics	[10]
IEEE Access	[12,13,59–62]
Computers & Operations Research	[14]
Journal of Enterprise Information Management	[15]
Int. Journal of Ad Hoc and Ubiquitous Computing	[36]
IEEE Systems Journal	[39]
Information Systems (ISs) Frontiers	[40]
ISPRS Int. Journal of Geo-Information	[46,83]
Communications in Computer and Information Science	[84]
IEEE Transactions on Systems, Man, and Cybernetics-Systems	[85,86]
Computers in Industry	[87]
IEEE Internet of Things Journal	[88]
IEEE Transactions on Parallel and Distributed Systems	[89]
Computers & Industrial Engineering	[90]
Computer Communications	[91,92]
Multimedia Tools and Applications	[93]
Neurocomputing	[94]
Computers Materials & Continua	[95]
Decision Support Systems	[96]
Journal of the Association for Information Systems (ISs)	[97]
Software and Systems Modelling	[98]

Table 8. Distribution of final data sample over years.

Year	Publications per Year
2017	15
2018	12
2019	13
2020	13
2021	3
Total number of publications	56

5.2.2. What Are the Targeted Disasters Considered in the Study? (**Q**2)

Disasters are usually categorized into two types: natural disasters, which include floods, hurricanes, earthquakes, volcanos, avalanches, and bushfires, and human-made disasters, which include day-to-day emergencies (traffic accidents and industrial accidents) and fire emergencies. Figure 9 shows that ≈41 percent of the studies focused on both types of disasters, ≈32 percent on human-made disasters, and ≈25 percent on natural disasters. Figure 10 illustrates the categories of natural disasters analyzed in the papers. Detailed descriptions of each type, including references to articles, are presented in Table 9. Additionally, Xu et al. [68] did not describe the type of disasters considered by the authors.

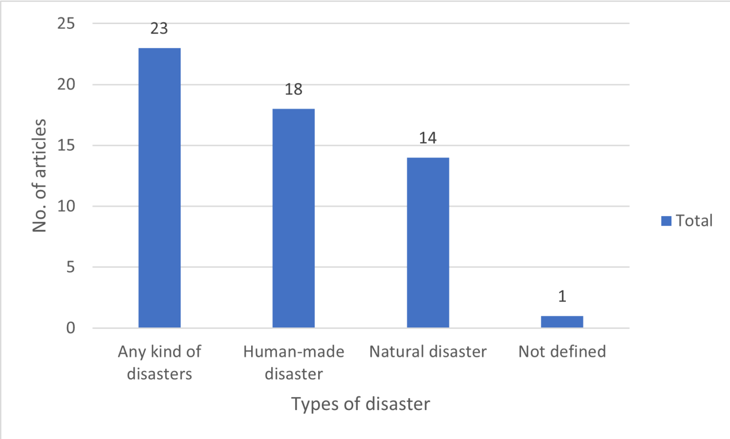

Figure 9. Distribution of categories of disasters discussed in the studies.

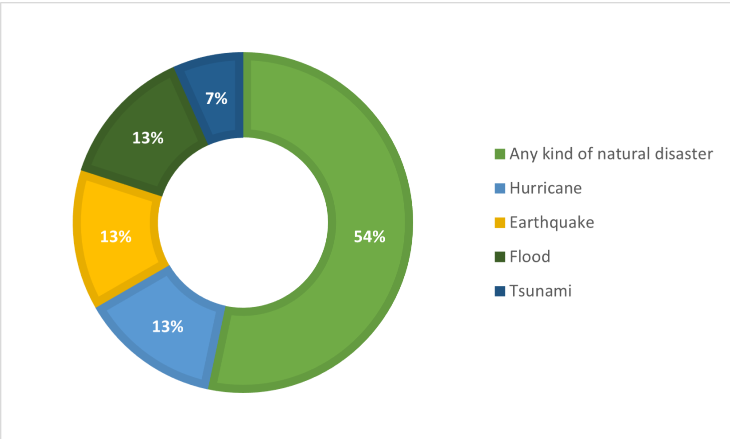

Figure 10. Distribution of natural disasters discussed in the studies.

5.2.3. What Are the Major Purposes of the DSSs for the SAR Processes Used in the Study? (**Q**3)

Disaster management systems are a key factor in reducing the effects of disasters. They are categorized into four phases: mitigation, emergency preparedness, emergency response, and emergency recovery. The distribution of articles on the disaster management system and its phases is described in Table 10 and illustrated in Figure 11. Additionally, there were a few articles with the objective of presenting solutions for two phases, specifically, emergency planning and recovery (3 percent) and emergency response and recovery (2 percent). We observed that most of the investigated literature focused on the emergency response phase for day-to-day emergencies, as shown in Figure 12.

5.2.4. What Is the Scope of the Study in Terms of Specified Spatial Dimensions? (**Q**4)

Figure 13 shows that most of the articles focused on the investigated problem instead of defining any demographic location. In the articles where the demographic location was specified, the authors were more interested in solving problems related to a particular area. The USA appears the most among all countries (seven articles), followed by China (six articles). It was observed that most of the articles addressed disasters related to land, as shown in Figure 14.

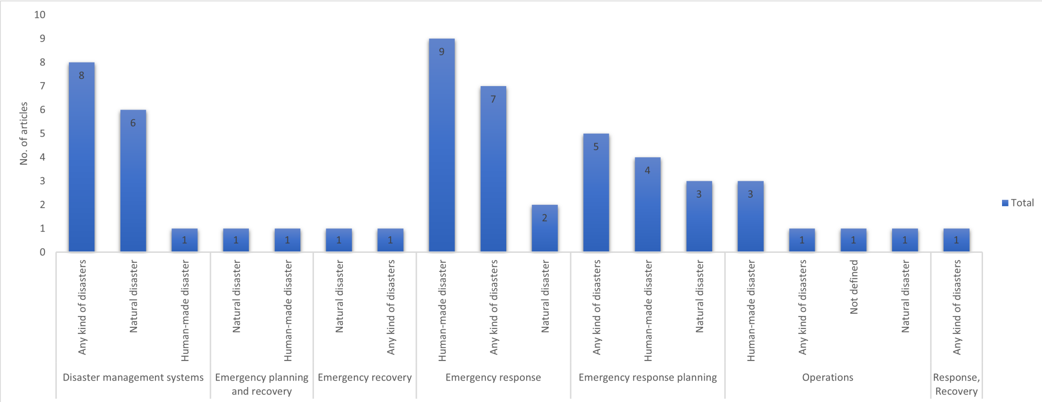

Figure 11. Distribution of disaster management system phases among the different types of disasters in the studies.

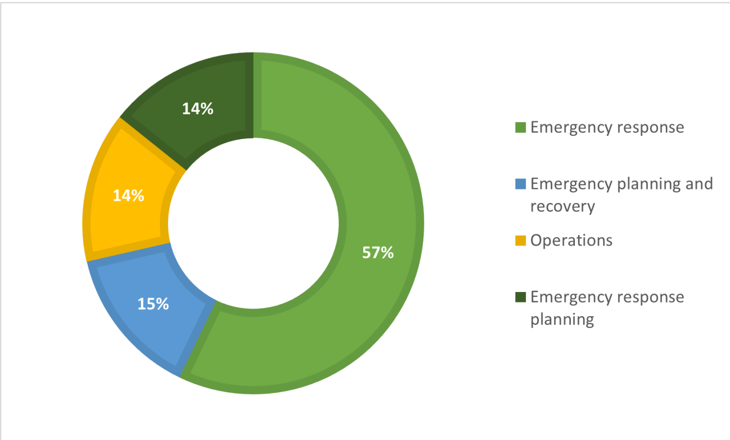

Figure 12. Distribution of day-to-day emergencies in the studies.

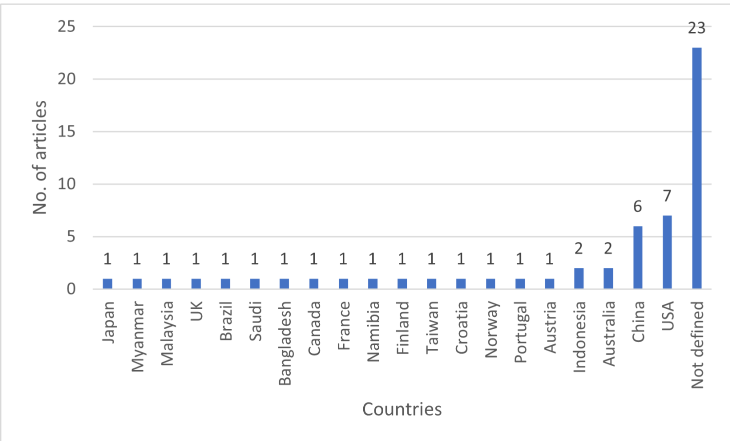

Figure 13. Distribution among countries.

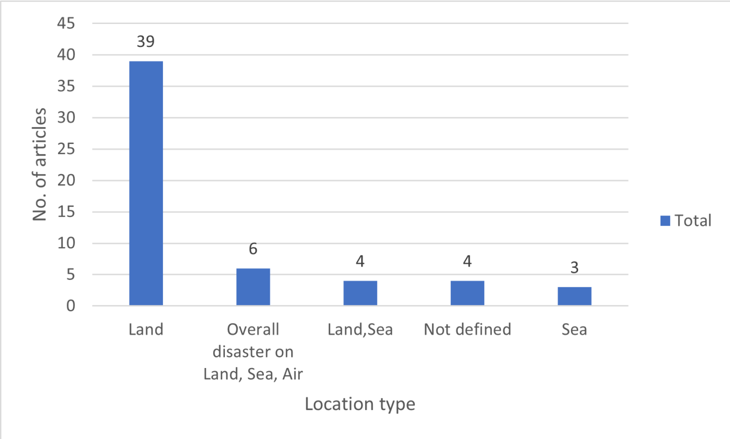

Figure 14. Scope of study based on application.

Table 9. Description of categories of disasters.

Disasters	Description
Natural disasters [7,39,40,59,60,69,71,75–78,82,87,88,96]	The articles where the category encompasses disasters caused by nature. e.g., floods, hurricanes, earthquakes, avalanches, and bushfires.
Human-made disasters [15,38,46,61,62,65–67,69,70,74,85,86,93–95,97]	The articles in which the category of disaster involves the calamities caused by mankind. For instance, fire emergencies such as fire in a building or urban fire emergencies, and day-to-day emergencies that can be traffic accidents, and industrial accidents.
Natural and human-made disasters [10–14,17,36,42,63,64,72,73,80,81,83,84,89–92,98,99]	The articles where the authors contemplate both types of disasters. It means that the presented solutions in these articles work in both types of disasters.

Table 10. Description of categories of SAR processes.

Categories of SAR Process	Coverage	Description
Disaster Management System	27%	A management system of administrative decisions, organization, capabilities, and skills to enact policies, plans, and adaptation of society or individuals to mitigate the effects of natural and human-made disasters.
Emergency Response Planning	21%	Emergency response planning is a part of the preparedness phase where the SAR teams and personnel make a plan for handling a disaster.
Emergency Response	32%	It can be considered as the third phase of a disaster management system which includes the SAR activities and providing the victims with necessities.
Operations	11%	It is part of emergency response but consists of only SAR activities.
Emergency Recovery	4%	It is the final phase of the whole process where the SAR teams conclude the emergency response.

5.2.5. What Are the Main Data Management Solutions Employed in the SAR Processes Described in the Study? (**Q**5)

We have observed that those articles that describe studies involving relational databases mainly focus on post-disaster management and recovery, whereas those articles based on NoSQL refer to solutions involving situational awareness in an emergency as shown in Figure 15. Most of these articles focused on land disasters, and most authors presented solutions for SAR processes based on UAVs and data. For example, Ni et al. [59], Widagdo et al. [78], and Sarma et al. [87] presented post-disaster solutions using various relational databases for the redistribution of resources and estimation of damages. Simoes-Marques et al. [72] used the UCD approach to employ a data warehouse as a disaster management support system. Similarly, Fleischhauer et al. [77] utilized OpenStreetMap and GIS with a data lake for disaster management. Sulaiman et al. [38] and Almuraykhi et al. [66] presented solutions with the help of information retrieval for UAVs and an Android app to manage small emergencies, such as fire emergencies in buildings [38] or road accidents [66]. Lopez et al. [60] and Li et al. [89] proposed distributed databases for training of decision-making agents and situational understanding using a view-invariant CNN model for emergency scenarios. Nunavath and Prinz [65], Kabir et al. [82], and Toujani et al. [84] all addressed fire emergencies using NoSQL. Kumar et al. [36] and Zhang et al. [46] presented data acquisition based on UAVs for emergency response and recovery.

It can be noticed that most of the relevant articles propose solutions based on data analysis and presentation techniques. Lwin et al. [64], Puspita et al. [75], Gokaraju et al. [76], Fontes et al. [80], and Peng et al. [83] designed GISs that can help to improve the efficiency and decision-making of emergency response in various scenarios. Preinerstorfer et al. [63], Ahmed et al. [71], Valecha et al. [97], HoseinDoost et al. [98], and Agrawal et al. [99] developed ISs for emergency response in various scenarios, mainly focusing on land SAR. Ghasemi et al. [81], Mouradian et al. [88], and Ejaz et al. [91] focused on IoT applications and their characteristics for disaster management. On the other hand, Inan et al. [40] presented a knowledge repository for disaster management for better communication among stakeholders. Fan and Mostafavi [39] addressed the lack of heterogeneity among systems and stakeholders, and proposed a system of systems for disaster management.

Moreover, many authors have presented research in the big data systems and programming, data structures, and algorithm categories to solve their defined problems. Gu et al. [74], Bai et al. [92], and Lv et al. [93] presented a platforms for disaster management based on IoT and cloud computing [74], mobile cloud computing [92], and cloud computing and GIS [93]. Horita et al. [96] addressed the challenge of alignment in decision-making for disaster management systems employing big data applications. Maharjan et al. [42] and Dar et al. [69,79] employed fog computing for a disaster management system to spread situational awareness [42], reduce cost [69], and provide notification of daily life accidents via mobile app [79]. Sambolek and Ivasic-Kos [61], Kumar et al. [67], Xu et al. [68], Fragskos et al. [73], Muhammad et al. [94], and Gong et al. [95] proposed solutions for SAR phases utilizing DL and various algorithms. Zeng et al. [85], Duan et al. [86], and Li and Cao [90] developed and designed SAR processes using Petri nets with time and resource factors [85], workflow nets with time, resource, and message information factors with hierarchical modelling [86], and multi-attribute risk decision analysis for disaster management [90].

5.2.6. What Kinds of Data Are Managed in the Considered SAR Processes? (**Q**6)

Different types of data were used in the studies depending on the solutions provided in a particular article. Figure 16 shows the distribution of data types in the different studies. It was observed that the most commonly used data in the investigated articles were geographical data (16/47) and textual data (11/47), with the latter including reporting and social media. For historical data, time series data, images, and all sortss of data cover there were 4/47 articles each, whereas 2/47 articles focused on maps.

5.2.7. What Are the Main AI Technologies Employed in the SAR Processes Described in the Study? (**Q**7)

In this study, we have looked into the solutions using AI technologies, observing that the studied articles consider AI, ML, and DL technologies separately, rather than considering ML as a subset of AI or DL as a subset of ML, as presented in [11]. Based on this observation, we have divided technologies into the following categories: AI, ML, DL, and miscellaneous.

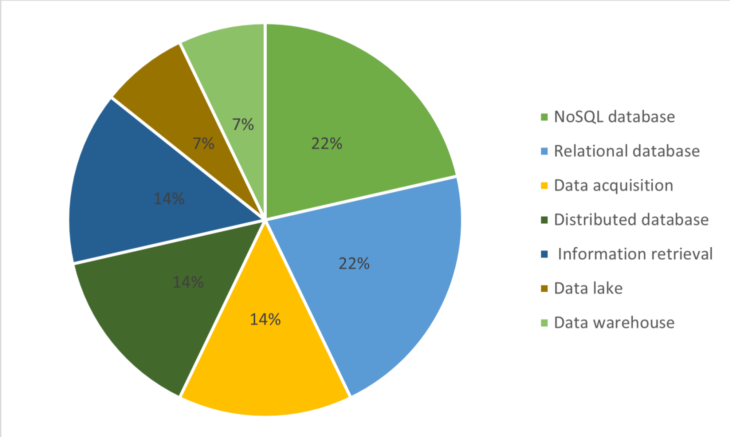

Figure 15. Distribution of data management solutions in the studies.

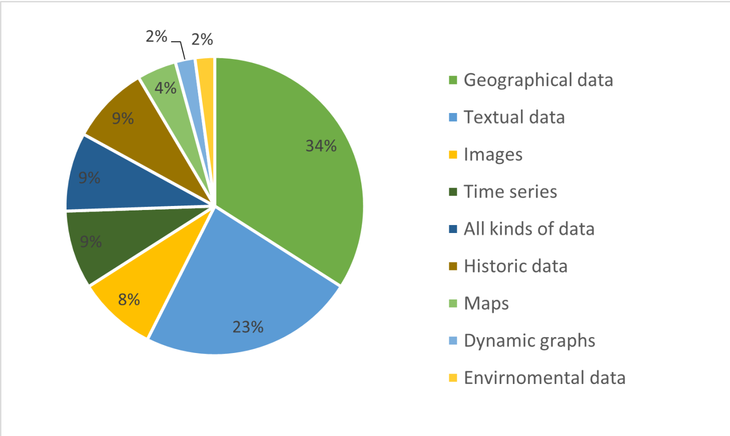

Figure 16. Distribution of different kinds of data in the studies.

We observe that several articles describe or present solutions using AI techniques [11,17,40,42,98]. However, few studies specifically use ML and DL techniques. Thus, we note that the majority of the selected articles belong to the miscellaneous category, as described in Table 4. For example, Nunavath and Prinz [65] presented solutions based on serious games to visualize and analyze data collected from smart glasses and cameras, whereas Zeng et al. [85], Duan et al. [86], and Li et al. [90] used Petri net models for emergency response modeling in fire emergencies. Sarma et al. [87] proposed the concept of resource redistribution among affected areas in an emergency with the help of a multi-objective optimization model, and Ni et al. [59] presented textual emergency response plans based on NLP.

Figure 17 illustrates the types of ML techniques presented in the studies, specifically, supervised learning, unsupervised learning, RL, and other ML techniques. The studies by [36,38,46] utilized supervised learning, whereas the study by [67] used unsupervised learning. The articles by [60,66,73] proposed solutions based on RL to address emergency response processes, and the ones by [71,76,84,91,92,99] employed other ML techniques. Ahmed et al. [71] used ML for multiple regression analysis to visualize the preparedness of emergency response and medical care. Gokaraju et al. [76] implemented ML with statistical methods to collect sensor data and increase the performance efficiency of emergency preparedness and disaster management in cases such as landslides and tornadoes. Toujani et al. [84] used ML in Microsoft Power BI to analyze data in order to address situational awareness during fire emergencies. Ejaz et al. [91] implemented an ML algorithm for energy-efficient task scheduling of UAVs to find the optimal path with the lowest energy consumption. Bai et al. [92] utilized ML to develop a dynamic tracking mathematical model for the safe evacuation of victims after a disaster. Agrawal et al. [99]

used ML for UAVs to address situational awareness in fire emergencies and deployed a scenario-based participatory design process.

The studies presented by [61,68,79,82,89,94] used DL techniques for SAR processes.

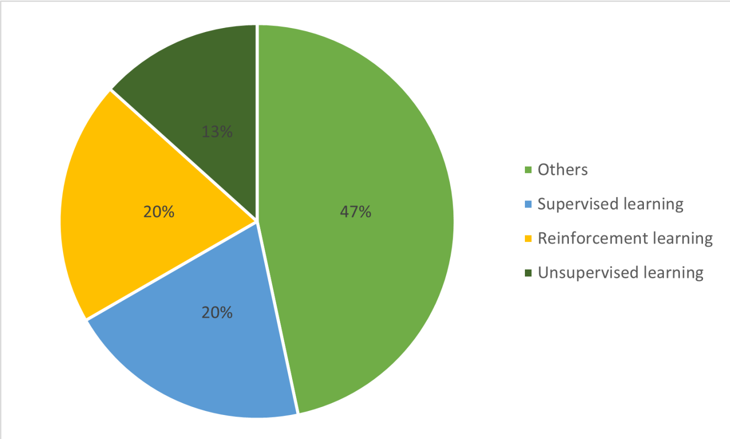

Figure 17. Distribution of machine learning (ML) techniques in the studies.

5.2.8. Who are the Potential End Users of the Presented Methods? (**Q**8)

Figure 18 shows the distribution of potential end users for the methods presented in the studies; ≈ 50 percent of articles focused on presenting solutions for SAR experts, whereas ≈ 20 percent of the articles were aimed at other expert actors such as researchers, first responders, victims, or volunteers. Many articles presented solutions for multiple groups of end users.

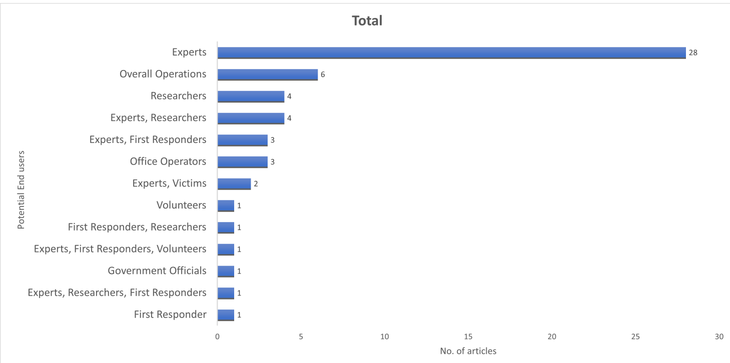

Figure 18. Potential end users.

6. Discussion and Future Work

This section provides answers to our overarching research question, i.e., how SAR processes use DSSs, data management solutions, and AI. Our discussion is based on the synthesis provided in Section 5, an includes a list of potential future work areas. The goal of the discussion is to identify and analyze the use of decision support in SAR. This includes identifying any gaps in the literature or areas where further research is needed. These results provide insight into the current state of the art in the use of these technologies in SAR operations as well as the potential future work that can be done to improve their effectiveness in decision-making and emergency response.

6.1. Discussions

In our study, we identified the existing studies in this domain and responded to eight questions (**Q**1–**Q**8) by comparing the existing studies.

Q1 aimed to understand the effectiveness of using DSSs, data management solutions, and AI in SAR processes. **Q**2 and **Q**3 presented the most common disaster events and proposed solutions based on the selected articles. We observed that most of the selected papers focused on both natural and human-caused disasters. We looked into the use of DSSs, data management solutions, and AI in SAR processes, finding that the reviewed articles tended to focus more on planning than on carrying out plans. **Q**4 explored the scope of the studies in terms of the specified spatial dimensions. Our observations show that research predominantly involved disasters occurring in the USA or China.

Most of the presented solutions in the investigated articles aimed at SAR operations on land (fire emergencies, mountain SAR, urban SAR, and small river SAR). Comparing the existing solutions, we observed that there are few studies focusing on DSSs for SAR at sea, potentially motivating further studies in this specific application area. Regarding the latter, we observed that few articles focusing on SAR at sea used AI technologies for data analysis and presentation to handle a disaster. Moreover, data-centric domains, such as novel database architecture and data analysis and presentation, constituted a significant portion of the investigated articles. The aforementioned categories are focused on overall disaster management systems, most of which involve the use of UAVs. These observations revolve around **Q**5, which explores the data management solutions provided in the studies.

Q6 emphasized the type of data managed in the reviewed articles. Based on our findings, the reviewed articles mainly focused on geographical data, with very few focusing on historical data. **Q**7 addressed which AI technologies were utilized. We observed that a very small percentage of articles integrated AI technologies and data management solutions for decision-making in SAR. In addition, we noted that AI technologies were used with data analysis and presentation (ISs) and to provide solutions for the emergency response planning phase. Most ML techniques, on the other hand, were used in semi-structured databases that provide situational awareness in an emergency. DL techniques were used in semi-structured databases and programming, data structures, and algorithms used to train UAVs models for SAR operations on land.

Additionally, other technologies such as NLP, serious games, Petri nets, and multi-objective optimizations were found to be utilized in different data-centric domain categories to address SAR processes. For instance, Ni et al. [59] used an NLP technique in developing an emergency response repository to build textual emergency response plans. Furthermore, Petri nets and workflow nets were presented in the context of cross-organizational emergency responsemodeling for better communication and resource distribution [62,85,90]. Finally, **Q**8 identified potential end users for the solutions provided in the investigated articles. We noticed that SAR experts were mainly the targeted users in the studied articles.

We found solutions presented in the literature for SAR processes on land that can be used in SAR DSSs at sea as well; for instance, Petri nets and workflow nets have been used to model DSSs for SAR processes on land [62,85,90]. Furthermore, a system-of-systems approach was used by Fan and Mostafavi [39] to develop a system able to identify and analyze the heterogeneity and complexity of SAR processes and develop plans accordingly. Big data systems such as cloud computing and fog computing have been used in SAR operations to aid disaster management [42,69,74,79,92,93]. Potentially, all the above-mentioned techniques are applicable within SAR operations at sea. The possibility of utilizing these techniques most likely depends on the problem description, that is, which phase of the SAR process is the focus.

6.2. Future Work

The research patterns observed in the literature are discussed in Section 6.1. Many researchers have provided enhancements and changes; in brief, all research goals require distinct techniques to accomplish the desired outcomes. However, the solution to each problem cannot be restricted to a single technique. We believe that there is a possibility of transferring knowledge among application areas of the SAR processes as the solution design process continues to grow.

For instance, as mentioned in Section 6.1, there are only a very small number of articles focusing on decision-making for SAR at sea. In the future, solutions provided for use on land SAR could be used for SAR processes at sea as well. Moreover, techniques that have been used only in a specific manner to date could be adapted for various other problems.

7. Conclusions

In the context of SAR, DSSs, data management solutions, and AI are all used to optimize time and cost by providing valuable insights and support to disaster management teams. This can help them to make more informed decisions and respond more quickly and effectively to emergencies. The main objective of our study was to identify and compare the existing systems that make use of DSSs, data management solutions, and AI in the field of SAR processes. To achieve this, we used two different research methods, namely, bibliometric mapping and a systematic literature review. Bibliometric mapping was used to generate a data sample, while the systematic literature review was used to answer the overarching research question.

The scope of the study was analyzed in relation to the research objectives and overarching research question. The types of SAR considered in the study were identified, and based on this the research contribution of different studies to SAR processes was described. The use of DSSs, data management solutions, and AI technologies in SAR processes was determined, and the potential end users of the presented solutions were identified.

The findings of this review have include the identification of research gaps in the investigated domains, including a lack of articles focusing on SAR operations at sea. In addition, we have discussed possibilities for knowledge transfer between application areas, recognizing that by implementing advanced DSSs, data management solutions, and AI technologies it is possible for SAR organizations to make better decisions about where they need to invest more effort and improve communications in order to utilize their resources to their fullest potential.

The present review has a number of limitations common to bibliometric mapping and systematic reviews [21,54], such as the year range, which only includes articles from 1 January 2017, to 10 November 2021, and the use of only WoS (Appendix A) as the platform for identifying articles based on a predefined search string.

In conclusion, our study highlights that significant efforts have been made to improve SAR processes using DSSs, data management solutions, and AI technologies. However, there is room for improvement; for example, decision-making solutions for SAR operations can be expanded, and knowledge can be further transferred among the application areas of SAR processes.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
SAR	Search and Rescue
CNN	Convolutional Neural Network
ANN	Artificial Neural Network
DSS	Decision Support System
DL	Deep learning
GIS	Geographical Information Systems
HRS	Hoverdredningsentralen

IS	Information System
IFRC	International Federation of Red Cross and Red Crescent Societies
IoT	Internet of Things
ICT	Information and Communications Technology
ML	Machine Learning
NLP	Natural Language Processing
RL	Reinforcement Learning
SQL	Structured Query Language
UNU-EHS	United Nations University–Institute for Environment and Human Security
UAV	Unmanned Aerial Vehicle
WoS	Web of Science

Appendix A

Search string in WoS database:

TI = (((“DSS” OR “Decision Support Syst*”) AND (“Search and Rescue Operat*” OR “Emergency respons*” OR “Disaster Manag*”)) OR ((“Database syst*” OR “Data manag*” OR “Information syst*”) AND (“Search and Rescue Operat*” OR “Emergency respons*” OR “Disaster Manag*”)) OR ((“Artificial Intellig*” OR “AI” OR “Intelligent algo*”) AND (“Search and Rescue Operat*” OR “Emergency respons*” OR “Disaster Manag*”)) OR (“Search and Rescue Operat*” OR “Emergency respons*” OR “Disaster Manag*”)) AND AB = (((“DSS” OR “Decision Support Syst*”) AND (“Search and Rescue Operat*” OR “Emergency respons*” OR “Disaster Manag*”)) OR ((“Database syst*” OR “Data manag*” OR “Information syst*”) AND (“Search and Rescue Operat*” OR “Emergency respons*” OR “Disaster Manag*”)) OR ((“Artificial Intellig*” OR “AI” OR “Intelligent algo*”) AND (“Search and Rescue Operat*” OR “Emergency respons*” OR “Disaster Manag*”)) OR (“Search and Rescue Operat*” OR “Emergency respons*” OR “Disaster Manag*”)) AND AK = (((“DSS” OR “Decision Support Syst*”) AND (“Search and Rescue Operat*” OR “Emergency respons*” OR “Disaster Manag*”)) OR ((“Database syst*” OR “Data manag*” OR “Information syst*”) AND (“Search and Rescue Operat*” OR “Emergency respons*” OR “Disaster Manag*”)) OR ((“Artificial Intellig*” OR “AI” OR “Intelligent algo*”) AND (“Search and Rescue Operat*” OR “Emergency respons*” OR “Disaster Manag*”)) OR (“Search and Rescue Operat*” OR “Emergency respons*” OR “Disaster Manag*”))

The above search string was used in addition to applying (**EC**1), (**EC**2), (**EC**4), and the WoS Core collection criteria, as described in Section 4.4.

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