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Research Article

Humanitarian Smart Supply Chain: Classification and New Trends for Future Research

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Abstract

During the crisis, relief supply chain management (also known as humanitarian supply chain management) has received great attention these days. The core questions facing many humanitarian organizations are: where are their strengths/weaknesses? Are they positioned to be effective in their supply chain system? What challenges do you need to overcome? What do they need to do to take advantage of the technological opportunities offered nowadays? These questions have been addressed them extensively during the past two decades. This paper tries to review and classify some of the papers carried out in key areas of the humanitarian supply chain such as location, certainty and uncertainty, relief teams and injured (patient) classification, machine learning, queue theory, the employed research methods, solution methods, and the type of objective functions. The paper begins first to define what the "humanitarian" ecosystem may include, and which actors play important roles. After, certain critical views of the humanitarian relief supply chain are examined. The critical views of the humanitarian relief supply chain would help researchers to introduce further research orientations and areas to overcome crises in the real world.

Keywords: Humanitarian Supply Chain; Location; Machine Learning; Patient Classification; Queue Theory; Relief Team and Patient Classification.

1. Introduction

According to various global surveys, many crises have been caused by bad climate conditions, such as floods and storms over the recent decade. Such crises have led to the death of 410,000 people and affected 1.7 billion people globally. The international federation of the Red Cross has reported 2.850 crises due to natural hazards, the most common of which is floods. Recent statistics indicate that 147 million people will be at risk of floods by 2030 (https://www.redcross.org.uk/). The average over the past decade indicates 45,000 people globally died from natural disasters, representing 1% of global deaths (https://ourworldindata.org/natural-disasters#citation). An appropriate crisis management system can reduce life and financial losses. Humanitarian logistics is divided into three phases: pre-disaster logistics (prevention and mitigation preparedness), relief logistics (alert, impact, and emergency relief), and post-disaster logistics (transport, rehabilitation, reconstruction, development, assessment, and learning) (Wei et al., 2015). The main purpose of humanitarian logistic processes is to deliver the right supplies to the right people in the right place and time during the crisis (Budak et al., 2020). Cooperation in the supply chain is complex due to uncertainties caused by intensity, impact probability, infrastructure failure, and definitive injury (Chakravarty, 2014). Evidence has indicated that humanitarian organizations have been recently interested in using supply chain management frameworks in their operations (Gatignon et al., 2010).

In the case of crisis management, the supply chain can be defined as activities done in goods flow and converting them from raw materials to deliver goods to injured people (Pfeiffer et al., 2017). A supply chain network established in the crisis phase provides three features: agility, flexibility, and alignment (Fontainha et al., 2020). Supply chain and social welfare have specific attributes during a crisis. These features, that collaborate to the survival of a sustainable system, include density, effectiveness, adaptability, and coherence. Density means the presence of various behaviors, and effectiveness means performance with medium consumption of resources. Adaptability means flexibility for change in response to new pressures, and coherence means unifying forces of connections (Sharma and Srivastava, 2016). Traditional supply chain management problems, such as allocation of resources, transportation, and inventory management, have developed a new level of sophistication in the relief area. The decisions must be made rapidly based on limited information (Ergun et al., 2010).

The complexity of decision-making is not only limited to a lack of prior information, but also thanks to the presence of many actors in the big picture. In aid work the term "humanitarian" is often used synonymously with emergency activities; however, these are not the only actors

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in the extended ecosystem definition. Therefore, we need to include all activities which are undertaken to improve the human condition in case of an unexpected event. Building on this broad definition of the humanitarian term, we consider the actors who support and orchestrate every level of field relief operation, locally, nationally, and internationally. They include governmental organizations, Red Cross, Red Crescent, the military, non-governmental NGOs, relief aids, (university) research centers, private donors to humanitarian organizations, more importantly, the people affected by crises. The dynamic that defines the relationship among actors in the human ecosystem is like a traditional supply chain (goods, information, and flow of money). However, the flow of money depends on the actors providing it and their power positions and it is difficult to have a comprehensive picture in the humanitarian ecosystem. Therefore, humanitarian organizations deal with two challenges; time and budget shortages due to unexpected maturity of demand, the sudden occurrence of needs, high human costs, and lack of resources due to lack of sufficient funds.

The convoluted challenges reveal how strategic long-term supply chain operations and logistics decisions are substantial in humanitarian relief and rescue operations. These key decisions include locating various structural activities that would determine the efficiency and effectiveness of rescue operations and disaster response. The relief/recovery supply decisions include locations of major distribution centers, warehouses, shelters, medical service centers, and blood donation centers. Therefore, smart planning and a network management framework are needed to address the entire ecosystem. Figure 1 suggests such a framework. This smart framework blends the elements of digitalization, classical optimization, and machine learning into making the best decisions for all logistical activities to supply the relief field. When a large-scale disaster occurs, the local emergency services become weak and ask other countries for help; therefore, relief locational decisions are multi-level (local, national, and international). For this reason, an information exchange platform is needed to establish the coordination and optimization of activities. This platform impacts disaster response efficiency and can alleviate injury and mortality, relax victims and suffering from accidents (Wel et al., 2015).

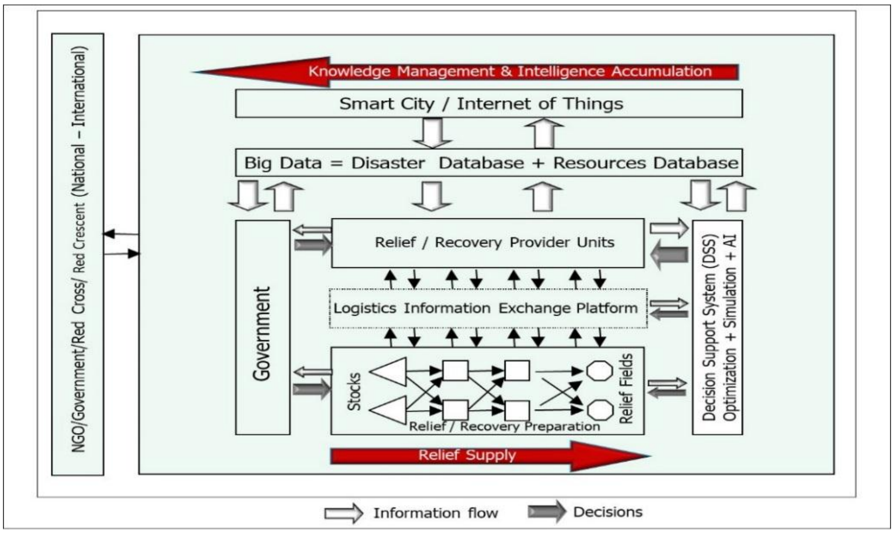

Fig. 1. Humanitarian smart planning and network management framework

Without thinking in the long-term, humanitarians cannot support communities and address the structural dimensions of the crisis. Therefore, a big data repository is required to not only carry historical data on previous disasters and resources but also be fed in real-time through the Internet of Things and smart city sensors. Many natural disasters occur all around the world annually. The notion of humanitarian relief logistics is an attempt to reduce the consequences of natural disasters, which have recently increased (Budal et al., 2020). There are different needs in each crisis response phase considering the injured people, religion, food habits, and climate (Upadhyay et al., 2020). All are captured in the big database. There are five key elements for relief and humanitarian organizations' preparedness: human resources to choose individuals' training, knowledge management to learn from past disasters, knowledge transfer, operations, and processing management to rapidly transport resources, financial resources for preparedness and initiate the operations and society for cooperation (Harke and de Leeuw, 2015). We did not include the financial flows here as it is very complicated and out of the paper scope. Emergency location of large-scale disasters is a key element of an effective response to major large disasters for instant access to resources in emergency centers, which have received less attention in previous studies (linLuet al., 2010) is included in the proposed framework. In the post-disaster phase at the early stages (first 72 hours), the predetermined relief items must be distributed among disaster centers to save people's lives and mitigate the negative effects of the crisis; however, lack of some resources such as predetermined relief items may create some problems (Doodman et al., 2019). Estimating demand in the humanitarian chain using natural disaster specifications (Gobaco et al., 2016) can be achieved using the big database through various traditional and recent Artificial Intelligent (AI) techniques.

During a crisis that damages the life of people, infrastructures, constructions, and the natural environment, those responsible for relief aids must rapidly start the relief process (Oloruntoba et al., 2010). The timely and accurate post-disaster evaluation and some strategies, such as dynamic evaluation and relief process modification during the relief operations, can effectively contribute to general health aid and general health prevention system (Shen et al., 2012). This would be feasible by a decision support system in the framework.

Recovery activities continue until the system reaches a normal or better level. These activities have two types: short-term system recovery activities with a standard minimum (e.g., cleaning the place and providing temporary warehouses), and long-term activities done for years after the disaster to recover the life of injured people giving them a normal life (renovation of houses, legal aids, and society planning) (Mu and Liang, 2014). Transportation planning and logistics can be described as the main drivers for effective relief operations. These two drivers are interconnected in decision-making operations and are done based on the personal experiences and intuitions of staff (Widera et al., 2017), and more importantly through machine learning, which is a part of the AI in Figure 1. Land, sea, air, and rail transportation are the most common transportation in the crisis response phase. Most organizations cope with different problems in transporting relief items (e.g., clothes, food, drugs, and relief resources) during a crisis (Mushanyuri & Ngcamu, 2020).

Regarding the increasing number of studies on crisis logistics and its application for planners, it is necessary to summarize, classify, and identify those cases and indicate the neglected issues in order to develop a suitable decision support system for the above framework.

One of the best advantages of reviewing papers is subjects categorizing and providing suggestions for future research which readers can use them for their research. Therefore, in this paper as well as classification of the paper related to the humanitarian supply chain papers, we try to the answer these questions: where are their strengths/weaknesses? Are they positioned to be effective in their supply chain system? What challenges do you need to overcome? What do they need to do to take advantage of the technological opportunities offered nowadays? Therefore, the present paper reviewed the relevant studies and offers some recommendations for further development. Papers' search scope covered 2006-2021. Because the extant paper was written in 2022, the studies conducted this year were ignored due to inaccessibility to accurate information. In total, 180 papers were obtained from searches through Science Direct, Scopus, and Google Scholar databases, of which 129 papers were used in this research. Sixty-four studies were systematic reviews, and the rest of them were general studies. Papers were searched by using some keywords: “location problem in disasters”, “machine learning in crisis”, “relief team classification in an earthquake”, “relief team classification in an earthquake”, “patient classification in a disaster”, “supply chain in a disaster”, and “uncertainty in disasters”.

Figure 2 depicts the countries in which systematic reviews have been carried out.

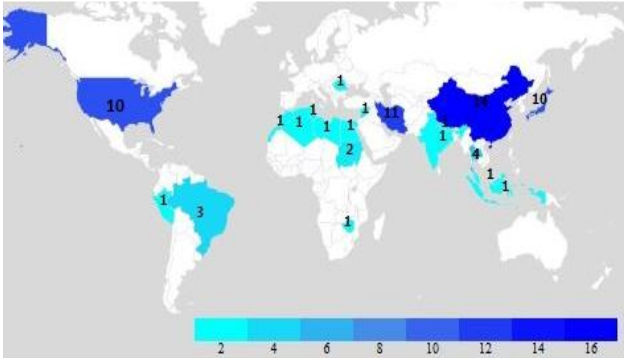

Fig. 2. Countries with case studies on crisis

According to Figure 2, China is at the first rank with 14 reviews in papers, followed by Iran (11 reviews), the USA (10 papers), and Japan (10 papers).

Figure 3 indicates how frequently each crisis has been studied in all 129 papers.

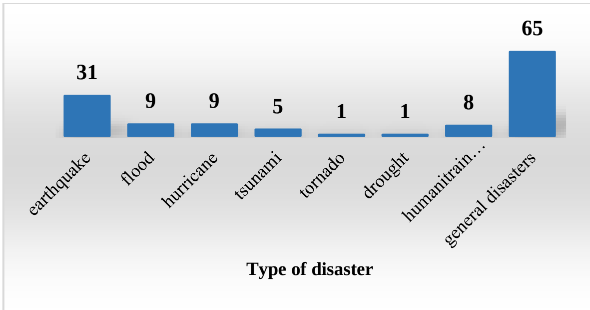

Fig. 3. Number of crises examined in reviewed studies

Figure 3 shows that earthquake (31 times) has been the most common crisis examined in reviewed studies in different countries. Floods and storms (9 times each) were the second crises mostly considered in research. The term "general disasters" covers those papers that did not examine any specific crisis and addressed their problems during a crisis.

The extant study aimed to examine a part of different studied areas in the supply chain for natural disaster conditions. This study allows researchers to identify those approaches and techniques used in papers over recent years, as well as those methods increasingly used. The present paper has been structured as follows: Section 2 reviews the study conducted on the crisis and classifies the papers. The reviewed studies have been divided into areas, including location in crisis conditions, certainty and uncertainty in disaster, patient classification in disaster, relief team classification in disaster, the queuing system in disaster, and machine learning in disaster. Furthermore, it classified papers based on the research method (analytical, empirical, conceptual, and applied), number of objective functions (single-objective and multi-objective functions), solution methods (exact, heuristic, metaheuristic, simulation, multi-criteria decision-making, game approach, questionnaire and statistical analyzes, and learning techniques). Finally, Section 3 concludes and suggests some approaches for further research orientations and tries to answer the questions which asked before. Figure 4 illustrates an overview of the research structure.

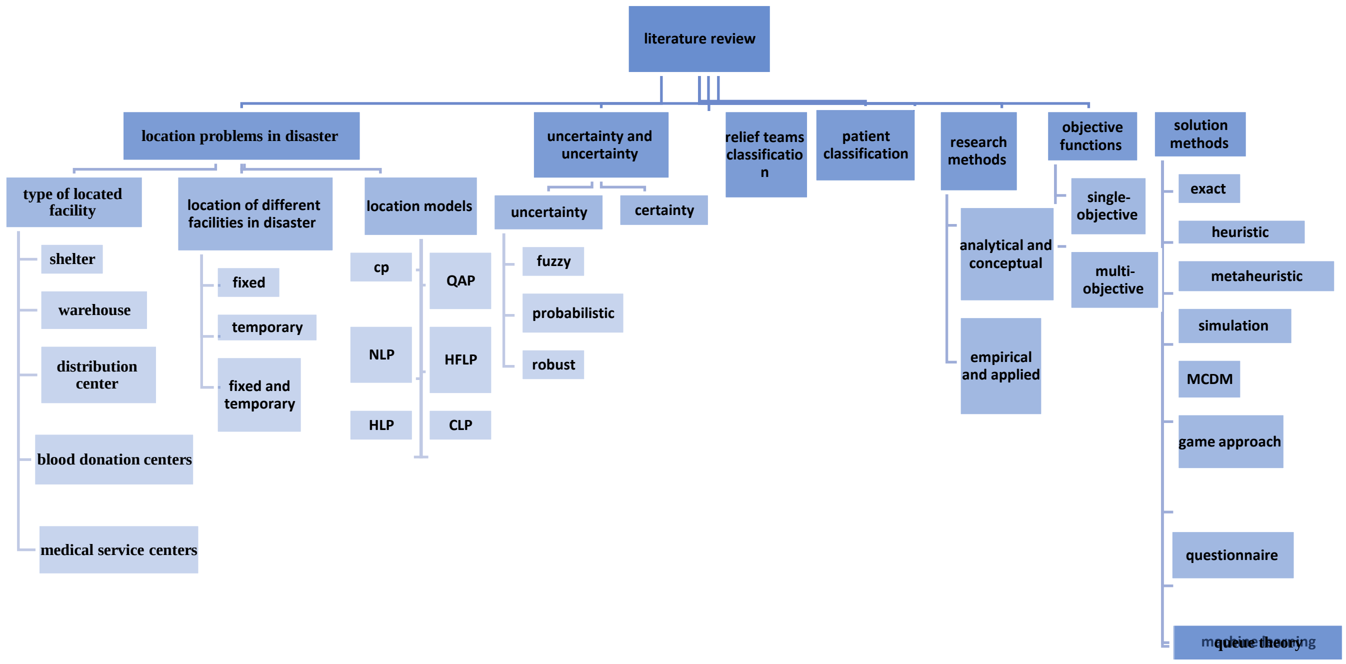

Fig. 4. Research structure of relief/recover logistical decisions

2. Literature Review

This section examines the reviewed studies on the crisis at different levels of location, solution techniques, certainty, uncertainty, relief team classification, patient classification, number and type of objective functions, and research method. Each level mentioned above has been divided into some subsets, and their relevant papers have been analyzed. The studies on location have been addressed regarding the mathematical model, location of facilities (fixed and temporary), and type of facilities (shelter, warehouse, distribution center, factory, medical service centers, and blood donation centers). The papers about certainty and uncertainty were examined in terms of certainty and different types of uncertainty (fuzzy, stochastic, and robust). The studies on patient classification were reviewed based on the acuity degree and intensity, patient coloring, and type of injury (urgent, non-urgent, normal). The papers related to research methods were examined in terms of methods, including analytical and conceptual, empirical and applied. Studies related to objective functions were divided into single-objective and multi-objective objective functions. Regarding solution methods, studies were reviewed based on the exact techniques, heuristic and metaheuristic methods, simulation, multi-criteria decision-making (MCDM), game approach, questionnaire, scientific-statistical analyses, machine learning, and queuing systems.

The reviewed studies have examined pre-disaster, post-disaster, or both periods. Figure 5 indicates the number of studies conducted on pre-disaster, post-disaster, or both.

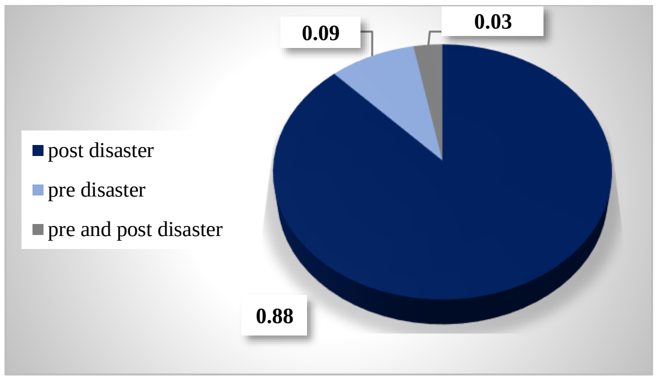

Fig. 5. Planning outlooks considered in papers

As seen in Figure 5, most papers reviewed in the present study have considered the post-disaster period.

Figures 6, 7, and 8 depict the frequency of papers per year, the number of papers published in each journal, and the number of papers written by each author.

Figure 6 indicates that most studies have been conducted in two recent years, and this ascending trend implies this subject has received great attention from researchers in recent years.

Figures 7 shows that most papers have been published in the International Journal of Production Economics (12 papers), followed by Transportation Research (8 papers), Transportation Research (8 papers), and Lecture Notes in Logistics (5 papers).

Figure 8 shows Tavakkoli-Moghaddam. R has carried out the most studies in this field (4 papers), followed by authors with 3 and 2 papers. The majority of authors, however, have published only one paper.

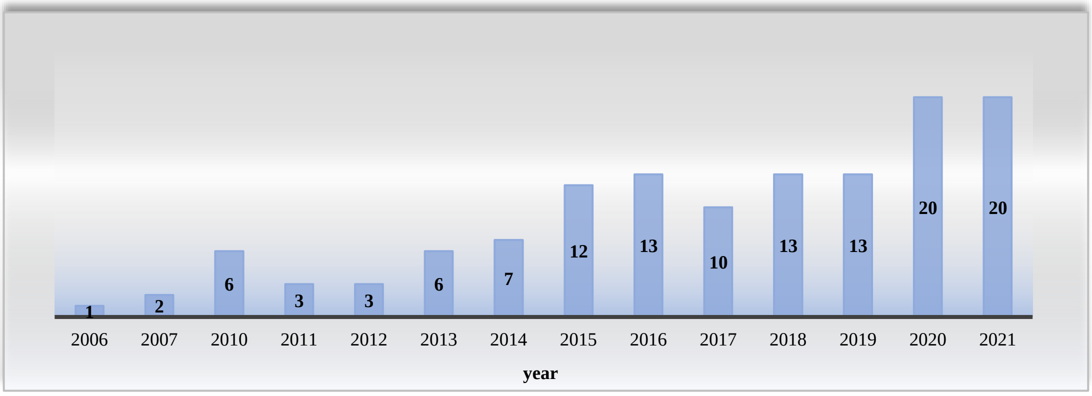

Fig. 6. Number of papers carried out per year

Fig. 7. Number of papers reviewed in each journal

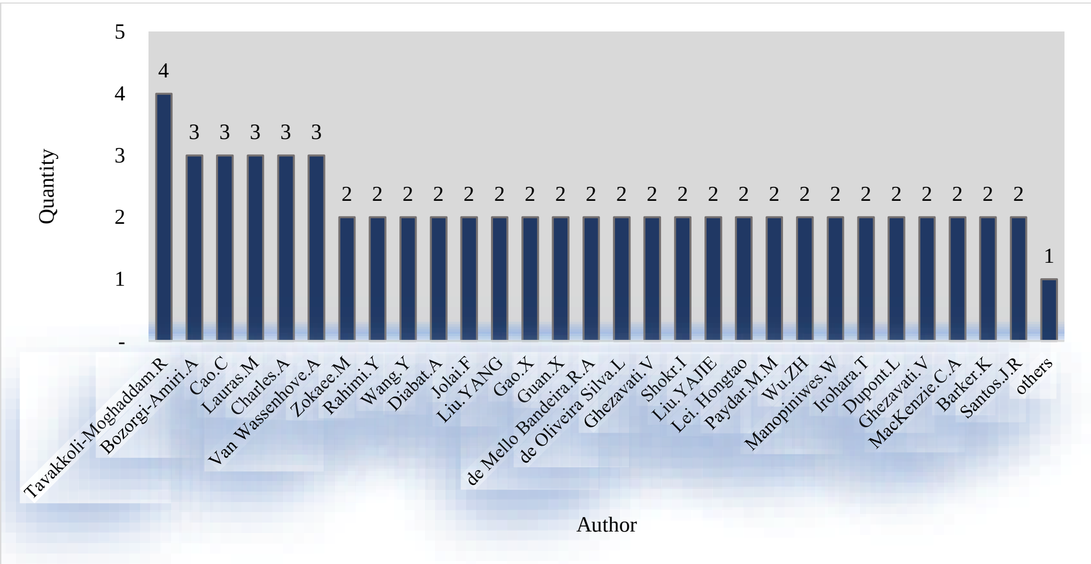

Fig. 8. Number of papers conducted by each author

2.2. Location problems in disaster

Location problem under disaster conditions is an important case that improves the relief process for victims. It is challenging when planning in a disaster to find the best place for shelter, warehouse, distribution center, medical service, and blood donation centers. Selection of the best location based on the researchers' goals and problem conditions can be done based on the different criteria. The best location for a medical service center is a place with a minimum distance from damaged areas. In this way, injured people and patients can be taken to the relief center within the shortest time. The best location for building a warehouse or shelter is a place with the lowest risk, far away from the points on the fault, or at risk of aftershocks. Sometimes, some constraints in the problem cause choosing a suitable location based on several criteria. For instance, a limited budget does not allow medical service centers in all potential locations and affects the distance criterion.

2.2.1. Location Models

Location problems have been divided into several categories in terms of their mathematical models: 1- center problem (CP), 2-network location problem (NLP), 3-Covering location problem (CLP), 4-quadratic assignment problem (QAP), 5-hub location problem (HLP), and 6-hierarchical facility location problem (HFLP), which have been examined individually.

2.2.1.1. Center Problem (CP)

The purpose of these problems is to minimize the risk of worse conditions. These problems are used to find the location of the clinic in rural areas, the location of fire stations in a large urban area, telecommunication applications, such as the location of a multi-wave station (TV, radio, and cellphone), and the location of delivery systems' facilities (delivery, post, and food). These problems ate widely used in urgent facilities (emergency and firefighting) or easy access (access to the warehouse), or other cases that require investment in far distances (Francis & White, 1974). Some authors have conducted studies in this field: Saatchi et al. (2021), Praneetpholkrang et al. (2021), Gutierrez and Mutuc (2018), Charles et al. (2016), and Budak et al. (2020).

Saatchi et al. (2021) designed a round-trip supply chain network. In their model, central warehouses provided materials required for hospitals and commodities on the forward route. They transported injured people to hospitals using transportation facilities on the backward route to warehouses. Praneetpholkrang et al. (2021) carried out a study on shelter location-allocation in humanitarian relief logistics. The difference between their study and other papers was the idea of minimizing the distance between affected areas and candidate shelters protected from aftershocks. Gutierrez and Mutuc (2018) designed a model to determine the minimum time and cost of the optimum location of a temporary relief center and meet victims' needs instantly.

2.2.1.2. Network Location Problem (NLP)

In these location problems, a new facility can be located on a network called an advanced center location or network location. It is assumed in these problems that several facilities exist, and one or more facilities are supposed to be located on the network (Francis & White, 1974).

Mansoori et al. (2020), Velasquez et al. (2021), Stauffer et al. (2016), Rezaei-Malek et al. (2016), Harke and de Leeuw (2015), and Manopiniwes et al. (2015) have been conducted studies on NLP. Velasquez et al. (2021) introduced mixed-integer linear programming in which damage and demand points were assumed exactly. Stauffer et al. (2016) formulated the vehicle supply chain of an international humanitarian organization using a dynamic hub location model. They derived vehicle data from the International Federation of Red Cross Society. Rezaei-Malek et al. (2016) formulated disaster relief logistic problems at two echelons: the location of warehouses and the location of hospitals. They formulated the problem as a multi-objective mixed-integer linear programming model.

2.2.1.3. Covering Location Problem (CLP)

In CLP, customers can receive service from all facilities if the distance between the customer and the provider facility is less than a predetermined value, the covering radius (Francis & White, 1974).

Zokaee et al. (2021), Guan et al. (2021), Barzinpour and Esmaeili (2014), Memari et al. (2018), Moeen-Moghadas et al. (2013), and Lu et al. (2010) have carried out studies based on CLP. Zokaee et al. (2021) developed a three-tier multi-resource model and capacitated location routing to identify the suppliers of the most reliable resources, the most advantages in facilities, and optimal routes for procurement and transpiration of resources from suppliers to damaged residential areas.

2.2.1.4. Quadratic Assignment Problem (QAP)

In QAP, there are some locations. We want to assign some new facilities to them to connect new facilities, such as assigning factories to a certain number of locations (Francis & White, 1974).

Zavvar Sabegh et al. (2017) and An et al. (2015) are the authors that have used this method. Zavvar Sabegh et al. (2017), for example, formulated a new multi-objective model to assign a drug supply chain in a natural disaster. They considered some objectives: minimizing production costs considering the cost of low quality, minimizing negative environmental effects, and maximizing social responsibility, such as enhancing humanitarian forces in their model.

2.2.1.5. Hub Location Problem (HLP)

This problem is based on the network location problem and aims to consider some nodes as central cores used for collection and distribution. This problem uses a set of nodes as hub nodes instead of a direct connection between two nodes (Francis & White, 1974). Ismail (2021), Boostani et al. (2021), Lauras et al. (2014), and Chakravarty (2014) can be named as authors who have used this problem in their studies.

Ismail (2021) proposed a mathematical stochastic programming model to control relief items flow in the humanitarian supply chain. This model assumed that responsible people for relief distribution had sufficient information about demand locations, the number of stakeholders in each location, transportation network, consumption rate, volume, and required items. Boostani et al. (2021) formulated a stochastic mixed-integer programming model to achieve a humanitarian relief logistic network. This model tended to minimize the total cost of logistics, maximize the minimum rate of satisfaction, and minimize the environmental effects of the humanitarian supply chain. Lauras et al. (2014) designed a network that could deliver all required goods most effectively.

2.2.1.6. Hierarchical Facility Location problem (HFLP)

A hierarchical system is a system in which facilities are connected in a one-way method (top-down or bottom-up) at different service phases. The medical center is at the lowest level and clinic at a higher level, and the hospital at the highest level of customers, for instance. In these problems, the higher levels provide services of the lower level and some other services (Francis & White, 1974).
Sun et al. (2021), Saghehei et al. (2021), Haghjoo et al. (2020), Beiki et al. (2010), Liu and Song (2019), Ghasemi (2019), Habibi-Kouchaksaraei et al. (2018), Fahimnia et al. (2017), Fereiduni and Shahanaghi (2016), Ghezavati et al. (2015) have used this problem in their studies.
Saghehei et al. (2021) divided the disaster emergency network into three phases. The first phase included national warehouses; the second phase covered regional warehouses; and the third phase included demand locations. Haghjoo et al. (2020) examined temporary facility locations and blood supply chain networks and facility and relief assignments in disasters. Beiki et al. (2010) designed a model for location during the earthquake in Tehran, Iran. They considered some assumptions: fixed and exact number of supplier locations in damaged and relief areas, and certain potential locations for building distribution centers. Liu and Song (2019) suggested a linear mixed-integer multi-objective model using several vehicles, blood groups, and periods that allowed decision-makers to determine the required blood volume for collection of blood dispatching strategy and blood volume existing in each blood bank and center.
Ghasemi (2019) designed a model for assignment location problems in the post-disaster phase. This model comprised eight blood donators, five locations for temporary facilities, and three proposed locations for fixed facilities. Habibi-Kouchaksaraei et al. (2018) considered blood facilities in two forms: temporary facilities with low capacity and the ability to be deployed in different areas and fixed facilities with higher capacity, such as hospitals and clinics. Fahimnia et al. (2017) formulated a stochastic multi-objective model to design a sustainable blood supply chain for different disaster scenarios. This model could determine the number of temporary blood centers in each scenario.
Thirty-three papers reviewed in this study examined the location problem. Figure 9 indicates the frequency of different location types. It indicates HFLP has been mostly used in the reviewed models.

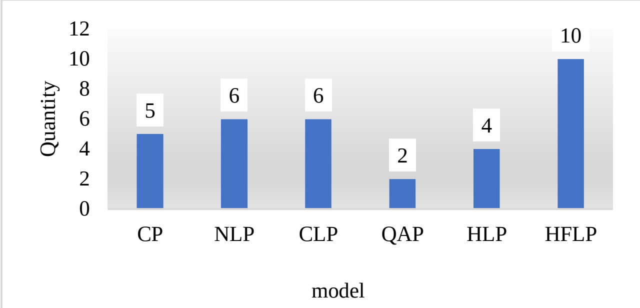

Fig. 9. Frequency of location problems in disaster

2.2.2. Location of different facilities in disaster

This part of the study examines fixed and temporary facility locations. It has strived to consider fixed facilities and temporary facilities to minimize costs and deal with demand uncertainties regarding budget shortage, time limitations, and demand uncertainty. This classification of facilities has been examined herein. Table 1 reports the papers related to the type of facility location.
Figure 10 illustrates the percentage of papers related to fixed, temporary, and facilities compared to all reviewed location studies.

Table 1.
Type of located facilities

Facilities	**Author and year**
Fix	Saghehei et al. (2021); Moeen-Moghadas et al. (2013); Barzinpour and Esmaeili (2014); Budak et al. (2020); Boostani et al. (2021); Manopiniwes et al. (2015); Lauras et al. (2014); Lu et al. (2010); Velasquez et al. (2021); Ismail (2021); Mansoori et al. (2020); Harke and de Leeuw (2015); Chakravarty (2014); Rezaei-Malek et al. (2016); Charles et al. (2016); Ghezavati et al. (2015); Guan et al. (2021); Praneetpholkrang et al. (2021); An et al. (2015); Liu and Song (2019); Saatchi et al. (2021); Zavvar Sabegh et al. (2017)
Temporary	Memari et al. (2018); Zokaee et al. (2021); Fahimnia et al. (2017); Stauffer et al. (2016)
Fix and temporary	Gutierrez and Mutuc (2018); Habibi-Kouchaksaraei et al. (2018); Fereiduni and Shahanaghi (2016); Ghasemi (2019); Sun et al. (2021); Haghjoo et al. (2020); Beiki et al. (2020).

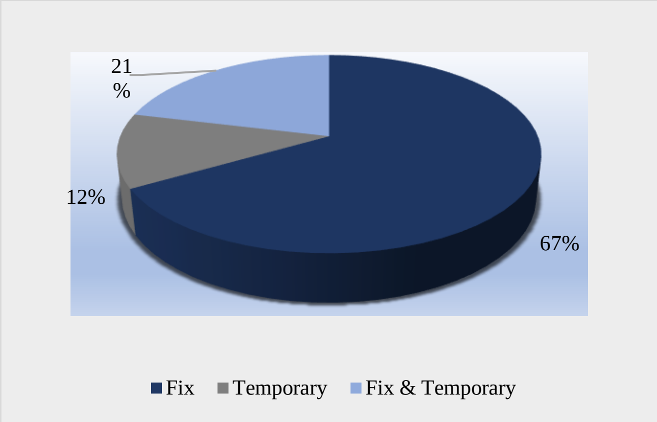

Fig. 10. Frequency of facility types in studies related to location in disaster

Figure 10 indicates that 67% of reviewed studies addressed fixed facility location, 22% examined fixed and temporary facilities, and the rest was related to temporary facility location.

2.2.3. Type of located facility

In location problems, the type of located facilities can be different based on the crisis and the problem's objectives. The problems reviewed in this study considered the location of the shelter, warehouse, distribution center, medical service centers, and blood donation centers, which have been assessed herein. Table 2 reports the papers related to the type of located facility.

Table 2.
Type of location facilities

Facility	Author and year
Shelter	Mansoori et al. (2020); Praneetpholkrang et al. (2021)
Warehouse	Lauras et al. (2014); Budak et al. (2020); Manopiniwes et al. (2015); Harke and de Leeuw (2015); Rezaei-Malek et al. (2016); Charles et al. (2016); Saghehei et al. (2021); Saatchi et al. (2021); Guan et al. (2021).
distribution center	Barzinpour and Esmaeili (2014); Zavvar Sabegh et al. (2017); Chakravarty (2014); Ghezavati et al. (2015); Stauffer et al. (2016); Mansoori et al. (2020); Zokaee et al. (2021); Ismail (2021); Boostani et al. (2021); Velasquez et al., (2021); Beiki et al. (2020); Gutierrez and Mutuc (2018).
medical service centers	Lu et al. (2010); An et al. (2015); Sun and et al. (2021); Saatchi et al. (2021); Sun et al. (2021); Beiki et al. (2020); Memari et al. (2018); Moeen-Moghadas et al. (2013).
blood donation centers	Fahimnia et al. (2017); Fereiduni and Shahanaghi (2016); Habibi-Kouchaksaraei et al. (2018); Ghasemi (2019); Liu and Song (2019); Haghjoo et al. (2020)

Figure 11 indicates the frequency of different location facilities in all reviewed studies on location.

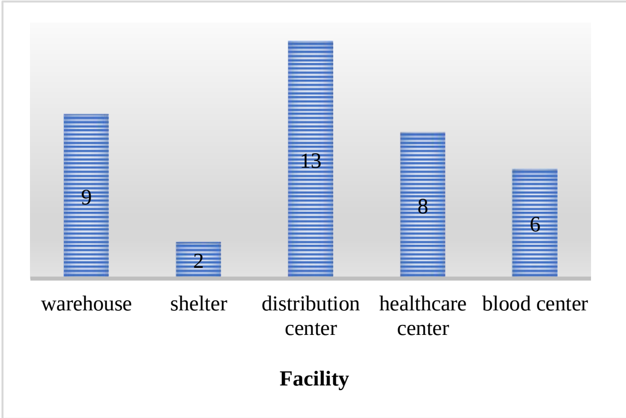

Fig.11. Frequency of types of facilities located in the disaster

As seen in Figure 11, the locations of distribution centers have had the highest location frequency indicating the frequency of different types of location facilities in all reviewed studies.

Figure 12 depicts the number of studies conducted in various locations in different years. It indicates the increasing number of studies on the location problem.

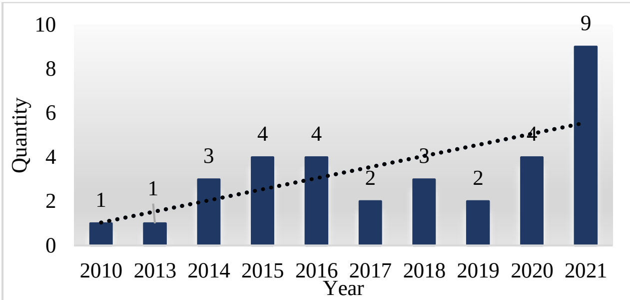

Fig. 12. Number of studies conducted on location in different years among all reviewed location papers

2.3. Certainty and uncertainty under disaster conditions

Problems' parameters can be certain or uncertain (definitive or probabilistic) under different conditions and information. Because the exact time of the disaster is unclear and the number of injured people is unpredictable, some parameters will be definitive or probabilistic. This part of the study reviews the papers in cases of certainty and uncertainty, dividing the uncertainty cases into three categories: fuzzy, stochastic, and robust.

2.3.1. Uncertainty in disaster

In this section, those studies conducted on uncertainty under disaster conditions have been examined. These papers have been divided into three categories: fuzzy approach, stochastic or probabilistic approach, and robust approach. Fuzzy logic is the opposite of the 0 and 1 logic. Fuzzy numbers provide each parameter with values between zero and one, the membership degrees of numbers in the fuzzy membership function. These numbers indeed indicate the probability of a state as a number between 0 and 1. In the stochastic approach, all or some parameters are probabilistic with a specific probability distribution. A robust approach is not just looking for an optimum solution; it tends to find a solution that remains constant in possible change. Table 3 reports the studies conducted on different uncertainty approaches.

Table 3
Types of uncertainty in reviewed papers

Type	Author and year
fuzzy	Ismail (2021); Cao et al. (2021); Guan et al. (2021); Budak et al. (2020); Doodman et al. (2019); Liu and Song (2019); Torabi et al. (2018); Ganguly et al. (2017); Deng et al. (2016); Wei et al. (2015); Li et al. (2021); Tian et al. (2011); Memari et al. (2018); Kondo Lu et al. (2018)
probabilistic	Zokaee et al. (2021); Zhang et al. (2021); Boostani et al. (2021); Cheng et al. (2021); Patil et al. (2021); Diaz et al. (2020); Kaur and Singh(2020); Mora-Ochomogo et al. (2020); Gao and Cao(2020); Beiki et al. (2020); Alaswad and Salman (2020); Doodman et al. (2019); Nozhati et al. (2019); Naghipour and Bashiri (2019); Cui et al. (2019); Song et al. (2018); Torabi et al. (2018); Sun et al. (2018); Wang et al. (2018); Cao et al. (2018); Javadian et al. (2017); Fahimnia et al. (2017); Hu and et al. (2017); Manopiniwes and Irohara (2017); Gobaco et al. (2016); Anjomshoae et al. (2016); Ghezavati et al. (2015); Alem and Clark (2015); MacKenzie et al. (2014); Kelle et al. (2014); Lauras et al. (2014); Chakravarty(2014); Davis and et al. (2013); Kumar and Havey (2013); Han and et al. (2010); Ozbay and Ozguven(2007); Sayarshad et al. (2020); Memari et al. (2018); Moeen-Moghadas et al. (2013); MacKenzie et al. (2013); Rahimzadeh Dehaghani et al. (2021); Lu et al. (2010); Xiang and Zhuang (2016); An et al. (2015); Lee and Lee (2021); Bravo et al. (2019); Nie and et al. (2020); Azimi et al. (2019); Yu et al. (2018); Hashemipour et al. (2018); Bune et al. (2016); Iizuka and Iizuka (2015); Ni et al. (2015); Edrissi et al. (2013); Taskin and Lodree (2010); Kaddoussi et al. (2013); Gamage and Olapiriyakul (2020).
robust	Mansoori et al. (2020); Kamyabniya et al. (2021); Sun et al. (2021); Velasquez et al. (2021); Haghjoo et al. (2020); Hamdan and Diabat (2020); Liu et al. (2019); Safaei et al. (2018); Habibi-Kouchaksaraei et al. (2018); Liu et al. (2018); Fereiduni and Shahanaghi (2016); Connelly et al. (2016); Zokaee et al. (2016); Rezaei-Malek et al. (2016); Tal et al. (2011);

Cao et al. (2021) designed a fuzzy multi-level optimization model for pre-disaster relief distribution in a sustainable humanitarian supply chain. Ganguly et al. (2017) modeled the performance of the relief system in a disaster in terms of preparedness and suddenness of the model situation.

Zhang et al. (2021) studied a reliable closed-loop supply chain design under facility-type-dependent probabilistic disruptions. They considered some assumptions in their research: normal distribution of demand for new goods of the retailer, the independent failure probability of separate distribution centers in the forward route that was not in the same place as the backward path, and unlimited capacity of distribution centers in the round-trip path. Cheng et al. (2021) modeled an effective and fair distribution problem in humanitarian relief logistics using ideal robust programming. They considered some assumptions in their study: increased demand due to increased poverty, different poverty levels in countries, and transportation between food banks. Nozhati et al. (2019) presented a probabilistic framework for evaluating the food security of households in the aftermath of a disaster. They introduced three conditions of food availability, accessibility, and affordability to take a house or urban area as a place with food security in society. Sun et al. (2018) proposed a bi-level model concerning storage levels for emergency resources and the distribution of resources in different post-disaster demand locations. They considered uncertain demand, predetermined reserves survival, and post-disaster transportation network. Mora-Ochomogo et al. (2020) suggested a Markov model that simulated specific operations in collection locations and helped decision-makers with inventories to determine the optimal volume and time of entering the donated items. Alaswad and Salman (2020) designed a game for humanitarian aid and relief distribution, which allowed researchers to derive humanitarian supply chain management notions by learning from classroom activities. Cui et al. (2019) considered the operational risk of emergency resource locations and apparent resilience as problem factors. Song et al. (2018) designed a model to optimize system design and operations to minimize total programming delay. Javadian et al. (2017) designed a multi-objective linear mixed-integer programming to determine the location of central warehouses and local distribution centers simultaneously, the corresponding inventory volume for relief items, the number of distribution of items sent from the supplier to central warehouses, from central warehouses to local distribution center in damaged areas, and from strategic storage to local distribution centers.

Kelle et al. (2014) considered three decision criteria: expected cost and reliable regret criteria with different max-min regret probabilities. Liu et al. (2018) presented a robust optimization approach to demand programming and uncertain transportation time. Safaei et al. (2018) designed a multi-objective robust optimization model for urgent logistic operations. Zokaee et al. (2016) designed a three-tier robust supply chain model that included suppliers, item distribution centers, and affected locations. Connelly et al. (2016) designed an analytical method to enhance humanitarian logistic management for disaster preparedness and responsiveness. Their model allows decision-makers to assess priorities change. Tal et al. (2011) designed a robust optimization framework for optimal dynamism traffic allocation in disaster. Gamage and Olapiriyakul (2020) focused on different supply chain parameters under the possible disruption in the supply chain.

2.2.1.4. Uncertain parameters

Various uncertain parameters have been reviewed in this part of the study. Uncertain or probabilistic parameters include demand, number of injured people and patients, time (travel or waiting), capacity, number of vehicles, cost, damage level, service level, inventory level, risk, efficiency, and profit. Table 4 reports the classification of uncertain parameters.

Table 4.
Classification of uncertain parameters

parameter		Author and year
demand	**Total relief items without mentioning a specific type**	Mansoori et al. (2020), Zhang et al. (2021), Boostani et al. (2021), Velasquez et al. (2021), Diaz et al. (2020), Mora-Ochomogo et al. (2020), Gao and Cao (2020), Beiki et al. (2020), Alaswad and Salman (2018), Doodman et al. (2019), Liu et al.(2019), Song et al(2018), Torabi et al. (2020), Sun et al. (2018), Safaei et al. (2018), Liu et al. (2018), Wang et al. (2018), Cao et al. (2018), Javadian et al. (2017), Hu et al.(2017), Manopiniwes and Irohara (2017), Gobaco et al. (2016), Zokaee et al. (2019), Rezaei-Malek et al. (2016), Wei et al. (2015), Alem and Clark (2015), Ni et al. (2015), Lauras et al. (2014), Li et al. (2013), Davis et al. (2013), Tal et al. (2011), Han et al. (2010), Ozbay and Ozguven (2007), Taskin and Lodree (2010), Lu et al. (2010)
	Blood items	Haghjoo et al. (2020), Hamdan and Diabat (2020), Naghipour and Bashiri (2019), Liu and Song (2019), Fahimnia et al. (2018), Fereiduni and Shahanaghi (2016)
	medical items	Memari et al. (2019)
	Water, food and clothing	Kaddoussi et al. (2013)
time	**time of travel**	Mansoori et al. (2020), Sun et al. (2021), Guan et al. (2021), Cui et al. (2020), Liu et al. (2018), Rezaei-Malek et al. (2016), Tian and et al. (2011), Memari et al. (2018), An et al. (2015), Javadian et al. (2017), Edrissi et al. (2013)
	waiting time	Moeen-Moghadas et al. (2013)
	Time of distributing items	Liu and Song (2019)
	Relief time	Manopiniwes and Irohara (2020), Hashemipour et al. (2018)
capacity	**Warehouse**	Zokaee et al. (2021), Mora-Ochomogo et al. (2020), Lauras et al. (2014)
	Road	Zokaee et al. (2021)
	Supplier	Cheng et al. (2021), Kaur and Singh (2020), Javadian et al. (2017), Gobaco et al. (2016), Zokaee et al. (2016)
	Distribution center	Doodman et al. (2019)
	Facilities for collecting, storing and donating blood	Liu and Song (2019), Habibi-Kouchaksaraei et al. (2021)
	The capacity of blood donors to donate	Fereiduni and Shahanaghi (2016)
	Capacity of relief centers	Liu and et al. (2019)
cost	**Deprivation**	Ismail (2021)
	Budget	Cheng et al. (2021), Torabi et al. (2018), Zokaee and et al. (2016), Chakravarty (2014)
	Storage of relief items	Doodman and et al. (2019), Torabi et al. (2018)
	Providing relief items	Doodman and et al. (2019, Torabi et al. (2018), Fereiduni and Shahanaghi (2016)
	Distribution of items	Doodman and et al. (2019), Torabi et al. (2018), Javadian et al. (2017), Manopiniwes and Irohara (2017).
	Shortage	Torabi et al. (2018), Zokaee and et al. (2016), Rezaei-Malek et al. (2016)
	Surplus	Javadian et al. (2017)
	Construction of facilities	Habibi-Kouchaksaraei et al. (2018)
	Facility relocation	Fereiduni and Shahanaghi (2016)
	Transportation of relief items	Ghezavati et al. (2015)
	Service level of medical centers to the injured	Xiang and Zhuang (2016)
	Power disruption	Nie et al. (2020)
	Delay	An et al. (2015), Kaddoussi et al. (2013)
	Evacuation	Manopiniwes and Irohara (2017)
Inventory level	**Distribution center**	Cao et al. (2021), Mora-Ochomogo et al. (2020), Liu et al. (2019), Javadian et al. (2017), Alem and Clark (2015), Davis et al. (2013)
	Blood collection and storage facilities	Hamdan and Diabat (2020), Liu and Song (2019), Fahimnia et al. (2017)
	Warehouse	Javadian et al. (2017)
	water level of River	Anjomshoae et al. (2016)
	Supplier	Kelle et al. (2014), MacKenzie et al. (2013)
	Remaining debris removal equipment	Sayarshad et al. (2020)
	Stored electricity	Nie et al. (2020)
Risk		Budak et al. (2020), Ganguly et al. (2017), Tian et al. (2011)
Efficiency		Deng et al. (2016), Connelly et al. (2016)
Profit		MacKenzie et al. (2014), Li et al. (2013)
Shortage		Gamage and Olapiriyakul (2020)
Damage level		Velasquez et al. (2021). Nozhati et al. (2019), Bune et al. (2016), Kumar and Havey (2013), Kondo (2018)
Service level		Memari et al. (2018), Lu et al. (2010), Xiang and Zhuang (2016), Rahimzadeh Dehaghani et al. (2021)
Number of injured people		Mansoori et al. (2020), Kamyabniya et al. (2021), Sun et al. (2021), Patil et al. (2021), Beiki et al. (2020), Liu et al. (2019), Habibi-Kouchaksaraei et al. (2018), Liu et al. (2018), Kelle et al. (2014), Lu et al. (2010), Lee and Lee (2021), Bravo et al. (2019), Azimi et al. (2019), Yu et al. (2018), Iizuka and Iizuka (2015)

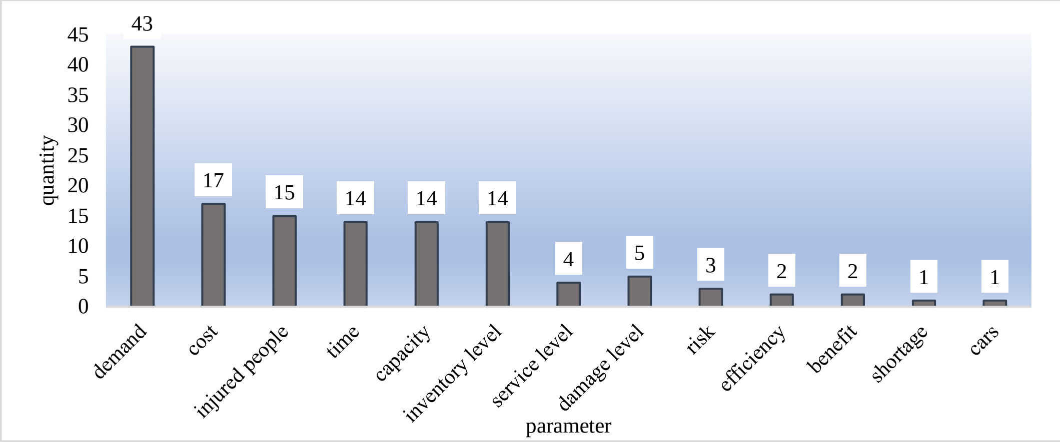

Fig. 13. Frequency of uncertain parameters in papers

Figure 13 indicates the frequency of uncertain parameters in studies conducted on uncertainty.

As seen in Figure 13, demand has been the most used parameter among uncertain parameters, while the number of vehicles and shortage had the lowest frequency. Figure 14 indicates the number of studies conducted on uncertainty in disasters during different years.

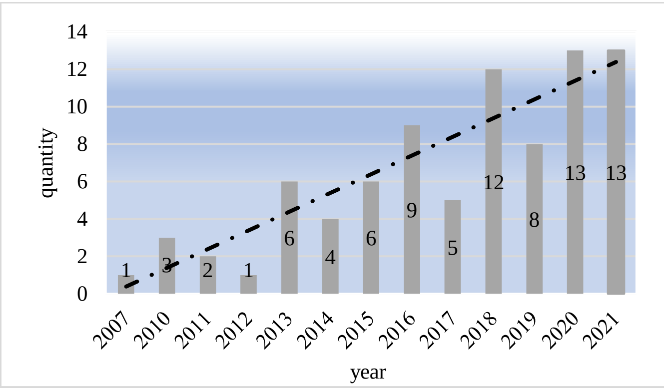

Fig. 14. Frequency of papers considering uncertainty per year

As seen in Figure 14, most studies on uncertainty have been carried out in 2018, 2020, and 2021.

2.3.2. *Certainty in disaster*

The papers related to this scope have defined parameters. The following authors used certain parameters in their studies: Gulzari and Tarakci (2021), Mousa et al. (2021), Saatchi et al. (2021), Islam et al. (2021), Xavier et al. (2021), Praneetpholkrang et al. (2021), Saghehei et al. (2021), Rezaei et al. (2020), Ren et al. (2020), Ghaffari et al. (2020), Guo and Peng (2019), Behl et al. (2019), Ghasemi (2019), Hong and Jeong (2019), Gökçe and Ercan (2019), Gutierrez and Mutuc (2018), Zavvar Sabegh et al. (2017), Baraka et al. (2017), Widera et al. (2017), Baharmand et al. (2017), Ransikarbum and Mason (2016), Charles et al. (2016), Stauffer et al. (2016), Abidi et al. (2015), Harke and de Leeuw (2015), Gil and Mcneil (2015), Manopiniwes et al. (2015), Barzinpour and Esmaeili (2015), Ji and Zhu (2012), Hu (2011), Mushanyuri and Ngcamu (2020), and Horner and Downs (2007). Mousa et al. (2021) conducted a study to optimize the supply chain under natural disaster conditions; they developed a multi-objective optimization algorithm. Islam et al. (2021) proposed a predictive model for fuel shortages during a hurricane evacuation. Xavier et al. (2021) developed a mathematical model to minimize operation time and deployment of helicopters and people to optimize distribution during the last path of the humanitarian supply chain. Rezaei et al. (2020) suggested a framework that required flexibility for sync with other natural disasters, like floods, volcanic eruptions, storms, tsunamis, and tornadoes. They claimed that natural disasters have many points in common despite their differences. Ren et al. (2020) introduced a model to compensate for the damages caused by Coronavirus in Wuhan, China. Behl et al. (2019) introduced ten critical success factors for humanitarian supply chain management. Panned emergency relief systems, technology applications, and reasonable organizational structures were the most important success factors. In the pre-disaster preparedness phase, Hong and Jeon (2019) designed a two-phase framework for humanitarian supply chain network design. They introduced two four-objective programming models for the configuration of a modified humanitarian supply chain network. Gökçe and Ercan (2019) designed a mixed-integer model to find those goods with replenishment requirements. Their model could determine replenishment strategies for several periods. Baraka et al. (2017) designed a single-objective model to minimize transportation costs. Ransikarbum and Mason (2016) designed a model to integrate the responsive phase of supply chain distribution operations and the network restoration decisions phase. Ji and Zhu (2012) studied an emergency supply chain in disasters and urgent relief decision-making. Horner and Downs (2007) developed a flow network model for programming relief item distribution to minimize allocation, relief, and facility location costs.

Among reviewed studies on certainty and uncertainty, 83 papers studied certainty, and 32 studies examined certainty parameters. In total, 115 studies conducted on certainty and uncertainty were reviewed; the rest were qualitative studies. Figure 15 shows the frequency of certainty and uncertainty approaches, including fuzzy, probabilistic, and robust cases compared to all studies conducted on certainty and uncertainty.

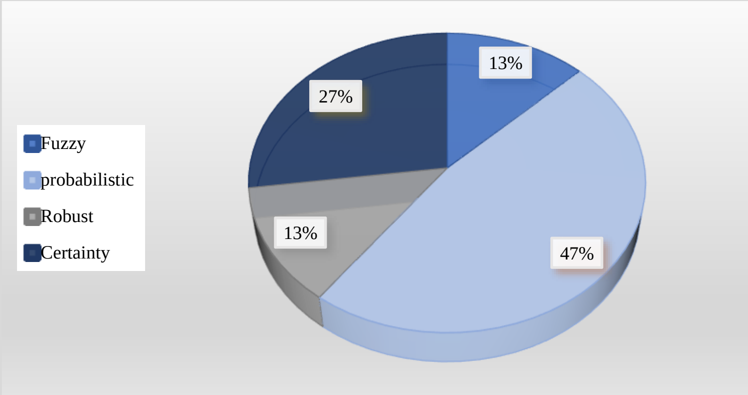

Fig. 15. Frequency of papers covering certain parameters and uncertainty approaches

Figure 15 depicts that the probabilistic approach has been mostly used for parameters, while the fuzzy approach has had the least application in reviewed studies. Moreover, 73% of studies used uncertainty, while 27% considered a certainty state. Figure 16 compares the number of papers considering certainty and uncertainty in each year.

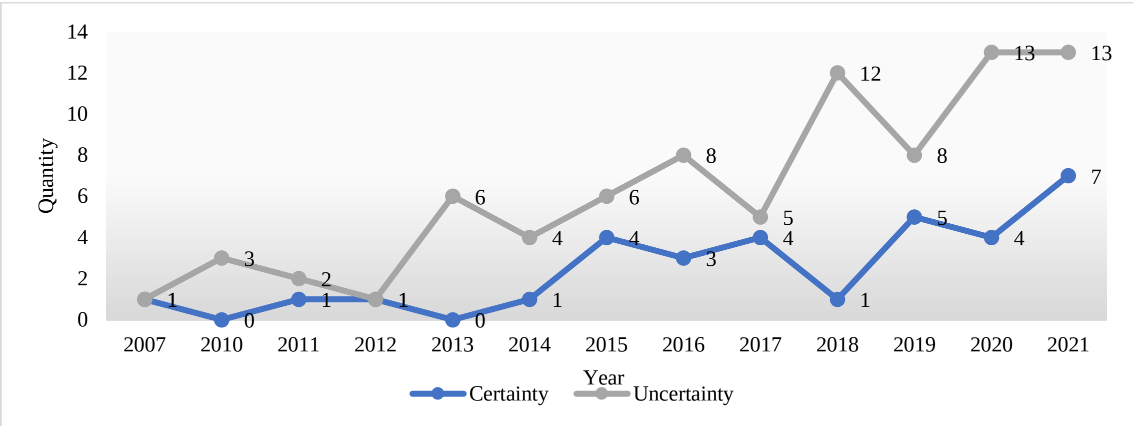

Fig. 16. Comparison of frequency of papers covering certainty and uncertainty in each year

Figure 16 indicates that papers considering uncertainty equaled or exceeded the number of papers with certainty approaches in all studied years. The most uncertain studies were carried out in 2021 rather than in other years.
The ascending trend of uncertainty studied in recent years implies authors' willingness to use uncertain (probabilistic) approaches to deal with unpredictable disaster conditions.

2.4. *Relief team classification in disaster*

relief team classification is one of the most appropriate methods of accelerating the relief process. Relief teams are responsible for participating in post-disaster response operations and delivering drugs, food, and clothes to injured people and patients. This classification is done in several forms: medical classification based on proficiency, teams based on their relief services, classification of different organizations in the relief process, and similar relief teams (regardless of their skills) assigned to affected locations. In general, the affected population starts within the first 30-min of the disaster to save their lives and others, assess the conditions of people buried or trapped under the rubble, and ask for dispatching medical and relief teams. Relief forces at the urban and state level, like armed police, traffic police, firefighters, and pharmaceuticals, must arrive at the scene within 2 hours to carry out rescue operations, while provincial forces must arrive and provide services within four hours (Guan et al., 2021).
Ghaffari et al. (2020) examined the dispatch of relief teams from their stations to hospitals through pre-positioned routes for relief providers and the initial evaluation of required relief items. They considered an agreement between the supplier and humanitarian organizations that persuaded suppliers to provide or produce required drug relief items. Abidi et al. (2015) carried out a study on sustainable supply chain optimization considering relief team classification. This study aimed to mitigate casualties and deaths, save people's lives, increase the number of survivors, fight against diseases, and promote gender equity in response and transportation phases. Gil and Mcneil (2015) conducted a study on post-disaster humanitarian logistics to find the role of outsourcing in the supply chain to identify available situations for improving performance and chance for optimization of storage, transportation, distribution capacity of relief teams, relief network, and humanitarian relief system. Table 5 reports the studies that have used relief team classification in their models.

Table 5
Studies with relief team classification

Title	Author(year)	classification
A healthcare location-allocation model with an application of telemedicine for an earthquake response phase	Gulzari and Tarakci (2021)	Medical team classification based on proficiency
Multilevel coverage location model of earthquake relief material storage repository considering distribution time sequence characteristics	Guan et al. (2021)	Level of relief services (high and low)
Emergency supply chain scheduling problem with multiple resources in disaster relief operations	Ghaffari et al. (2020)	Medical team
Sustainable humanitarian logistics optimization-a hub concept for Germany based on the shapley value	Abidi et al. (2015)	Different organizations in the relief process
Supply chain outsourcing in response to manmade and natural disasters in Colombia, a humanitarian logistics perspective	Gil and Mcneil (2015)	Similar relief teams

2.5. Patient classification in disaster

The patient classification system is a method that accelerates the relief process. Patient classification helps assign injured people to suitable medical teams based on their conditions. Patient classification can be done based on the injury severity and acuity within two forms of colors (red: severe injury, yellow: normal casualty, and green: a patient needs outpatient treatment) or urgent-nonurgent patient.

Kamyabniya et al. (2021) considered a multi-phase supply chain consisting of regional blood units, hospitals, and specific needs of emergency shelters in the affected locations. This model was considered a transportation model of multi-layer injury intensity of patients with sharing resources among relief facilities. Sun et al. (2015) proposed a multi-objective robust optimization model for disaster response programming under uncertainty.

This model classified patients based on their injury severity into two serious and lower injuries. Table 6 reports the studies conducted on patient classification based on their publishing years.

Table 6
Studies with patient classification

Title	Author and year	classification
A healthcare location-allocation model with an application of telemedicine for an earthquake response phase	Gulzari and Tarakci (2021)	Emergency and non-emergency patient
A robust multi-objective humanitarian relief chain network design for earthquake response, with evacuation assumption under uncertainties	Mansoori et al. (2020)	Different types of patients (without mentioning the specific type)
A robust integrated logistics model for age-based multi-group platelets in disaster relief operations	Kamyabniya et al. (2021)	Injury level
A bi-objective robust optimization model for disaster response planning under uncertainties	Sun et al. (2021)	Serious and non-serious injuries
Designing a bi-objective stochastic blood supply chain network in a disaster	Naghipour and Bashiri (2019)	Patient classification based on blood type
A robust model predictive control approach for post-disaster relief distribution	Liu et al. (2019)	Different types of patients (without mentioning the specific type)
Fuzzy dynamic location-allocation problem with temporary multi-medical centers in disaster management	Memari et al. (2018)	Classification based on injury severity (yellow-green-red-black)
A medical resource allocation model for serving emergency victims with deteriorating health conditions	Xiang and Zhuang (2016)	Different types of patients (without mentioning the specific type)

According to Table 6, classification was done based on the injury severity indicated in color categories (red: severe injury, yellow: normal casualty, and green: a patient who needs outpatient treatment) or urgent-nonurgent patient.

2.6. Research Methods

This part of the study reviews studies based on their research methods, including analytical, empirical, conceptual, and applied.

The authors choose different methods based on the research subject and available tools for data collection. Table 7 reports the research methods used in reviewed studies.

Table 7
The research method of reviewed papers

	Author and year
Analytical and Conceptual	Zhang et al. (2021); Mousa et al. (2021); Saatchi et al. (2021); Patil et al. (2021); Kaur and Singh(2020); Ghaffari et al. (2020); Budak et al. (2020); Alaswad and Salman(2020); Guo and Peng(2019); Behl et al. (2019); Naghipour and Bashiri(2019); Cui et al. (2019); Gökçe and Ercan(2019); Song et al. (2018); Wang et al. (2018); Zavvar Sabegh et al. (2017); Fahimnia et al. (2017); Ganguly et al. (2017); Charles et al. (2016); Gobaco et al. (2016); Ni et al. (2015); Harke and de Leeuw(2015); Ghezavati et al. (2015); Chakravarty(2014); Li et al. (2013); Ji and Zhu(2012); Hu et al. (2011); Tal et al. (2011); Han et al. (2010); Taskin and Lodree(2010); (Ozbay and Ozguven(2007); Memari et al. (2018); Rahimzadeh Dehaghani et al. (2021); Lu et al. (2010); Xiang and Zhuang (2016); Lee and Lee (2021); Nie et al. (2020); Iizuka and Iizuka (2015); Edrissi et al. (2013); Kaddoussi et al. (2013); Azimi et al. (2019); An et al. (2015); Sutrisno et al. (2020); Upadhyay et al. (2020); Fontainha et al. (2020); Mora-Ochomogo et al. (2020); Pfeiffer et al. (2017); Sharma and Srivastava (2016); Schumann-Bölsche (2015); Syahrir et al. (2015); Mu and Liang (2015); Venkatesh et al. (2014).

Empirical and Applied	Ismail (2021); Velasquez et al. (2021); Islam et al. (2021); Ren et al. (2020); Ransikarbum and Mason (2013); Gil and Mcneil (2015); Davis et al. (2013); Shen et al. (2012); Gulzari and Tarakci(2021); Mansoori et al. (2020); Zokaee et al. (2021); Kamyabniya et al. (2021); Sun et al. (2021); Boostani et al. (2021); Cao et al. (2021); Cheng et al. (2021); Guan et al. (2021); Xavier et al. (2021); Praneetpholkrang et al. (2021); Saghehei et al. (2021); Rezaei et al. (2020); Diaz et al. (2020); Gamage and Olapiriyakul(2020); Haghjoo et al. (2020); Hamdan and Diabat (2020); Mushanyuri and Ngcamu (2020); Gao and Cao(2020); Beiki et al. (2020); Doodman et al. (2019); Liu and Song (2019); Nozhati et al. (2019); Ghasemi (2019); Hong and Jeong (2019); Liu et al. (2019); Torabi et al. (2018); Sun et al. (2018); Gutierrez and Mutuc(2018); Safaei et al. (2018); Habibi-Kouchaksaraei et al. (2018); Liu et al. (2018); Cao et al. (2018); Kondo(2018); Javadian et al. (2017); Baraka et al. (2017); Hu et al. (2017); Manopiniwes and Irohara (2017); Widera et al. (2017); Baharmand et al. (2017); Deng et al. (2016); Fereiduni and Shahanaghi (2016); Stauffer et al. (2016); Connelly et al. (2016); Anjomshoae et al. (2016); Zokaee et al. (2016); Rezaei-Malek et al. (2016); Abidi et al. (2015); Wei et al. (2015); Alem and Clark (2015); Manopiniwes et al. (2015); MacKenzie et al. (2014); Kelle et al. (2014); Lauras et al. (2014); Barzinpour and Esmaeili (2014); Kumar and Havey (2013); MacKenzie et al. (2012); Tian et al. (2011); Horner and Downs(2007); Sayarshad et al. (2020); Moeen-Moghadas et al. (2013); Bravo et al. (2019); Yu et al. (2018); Hashemipour et al. (2018); Bune et al. (2016); Ergun et al. (2010); Oloruntoba et al. (2010); Gatignon et al. (2010); Kwasinski et al. (2006).

This section examined the studies based on their research methods (analytical and conceptual, empirical and applied). Of 129 reviewed papers, 77 were applied and empirical, while 52 studies were analytical and conceptual. Figure 17 indicates the frequency of research methods in reviewed studies.

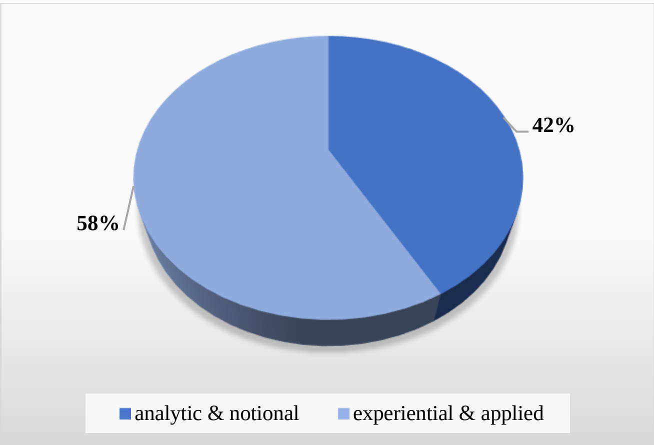

Fig. 17. Frequency of research methods

According to Figure 17, 58% of reviewed papers used empirical and applied approaches, and 42% employed analytical and conceptual approaches.

2.7. Number of objective functions

This part of the study reviews the papers based on their number of objective functions. Table 8 indicates the type and number of objective functions in single-objective problems.

Table 8
Type of objective functions in single-objective papers

type of objective function	Author and year	Quantity
Minimize the Cost	Zokaee et al. (2021); Ismail et al. (2021); Zhang et al. (2021); Velasquez et al. (2021); Gamage and Olapiriyakul(2020); Haghjoo et al. (2020); Mora-Ochomogo et al. (2020); Naghipour and Bashiri (2019); Ghasemi (2019); Torabi et al. (2018); Gutierrez and Mutuc(2018); Liu et al. (2018); Baraka et al. (2017); Hu et al. (2017); Charles et al. (2016); Fereiduni and Shahanaghi (2016); Stauffer et al. (2016); Zokaee et al. (2016); Wei et al. (2015); Ghezavati et al. (2015); Alem and Clark (2015); Kelle et al. (2014); Davis et al. (2013); Hu et al. (2011); Tal et al. (2011); Han et al. (2010); Taskin and Lodree (2010); Ozbay and Ozguven (2007); An et al. (2015); Iizuka and Iizuka (2015).	30
Minimize service delivery time	Xavier et al. (2021); Ghaffari et al. (2020); Song et al. (2018); Wang et al. (2018); Manopiniwes et al. (2015); Tian et al. (2011); Hashemipour et al. (2018); Kaddoussi et al. (2013).	8
Maximize demand satisfaction	Gulzari and Tarakci (2021); Cheng et al. (2021); Liu et al. (2019); Lauras et al. (2014); Sayarshad et al. (2020); Lu et al. (2010).	6
Maximize the number of rescued people	Moeen-Moghadas et al. (2013); Lee and Lee (2021); Bravo et al. (2019); Bune et al. (2016).	4
Maximize the Profit	Gökçe and Ercan (2019); Nie et al. (2020).	2
Minimize distance	Saghehei et al. (2021); Yu et al. (2018).	2

According to Table 8, minimization of costs is the most common type of objective function among other options in single-objective papers.

Multi-objective problems have more than one objective function. In most real cases, problems have more than one objective function, so researchers try to solve these problems with minimum conflicts between functions. Table 9 reports the papers that had multi-objective functions.

Table 9
Type of objective functions in multi-objective papers

Author(year)	Min Cost	Min time	Max demand satisfaction	Max number of rescued people	Min shortage	Min environmental effects	Min Risk	Max reliability	Max efficiency	Max quality of relief services
Mansoori et al. (2020)				✓	✓					
Kamyabniya et al. (2021)	✓		✓							
Sun et al. (2021)	✓			✓						
Mousa et al. (2021)	✓	✓								
Boostani et al. (2021)	✓		✓			✓				
Cao et al. (2021)	✓		✓				✓			
Guan et al. (2021)		✓	✓							✓
Saatchi et al. (2021)	✓							✓		
Praneetpholkrang et al. (2021)	✓	✓								
Rezaei et al. (2020)	✓		✓							
Hamdan and Diabat (2020)	✓	✓								
Gao and Cao (2020)		✓	✓							
Guo and Peng (2019)					✓				✓	
Doodman et al. (2019)	✓		✓							
Liu and Song (2019)	✓	✓								
Cui et al. (2019)	✓	✓								
Hong and Jeong (2019)									✓	✓
Cao et al. (2018)			✓	✓						
Zavvar Sabegh et al. (2017)	✓			✓						
Javadian et al. (2017)	✓	✓								
Fahimnia et al. (2017)	✓	✓								
Manopiniwes and Irohara (2017)	✓	✓								
Habibi-Kouchaksaraei et al. (2018)	✓				✓					
Ransikarbum and Mason (2016)	✓		✓							
Gobaco et al. (2016)	✓	✓								
Rezaei-Malek et al. (2016)	✓	✓								
Barzinpour and Esmaeili (2014)	✓			✓						
Ji and Zhu (2012)		✓								✓
Horner and Downs (2007)	✓			✓						
Memari et al. (2018)	✓	✓								
Rahimzadeh Dehaghani et al. (2021)	✓	✓								
Xiang and Zhuang (2016)		✓		✓						
Azimi et al. (2019)		✓		✓						
Edrissi et al. (2013)				✓					✓	
Total	24	17	9	9	3	1	1	1	3	3

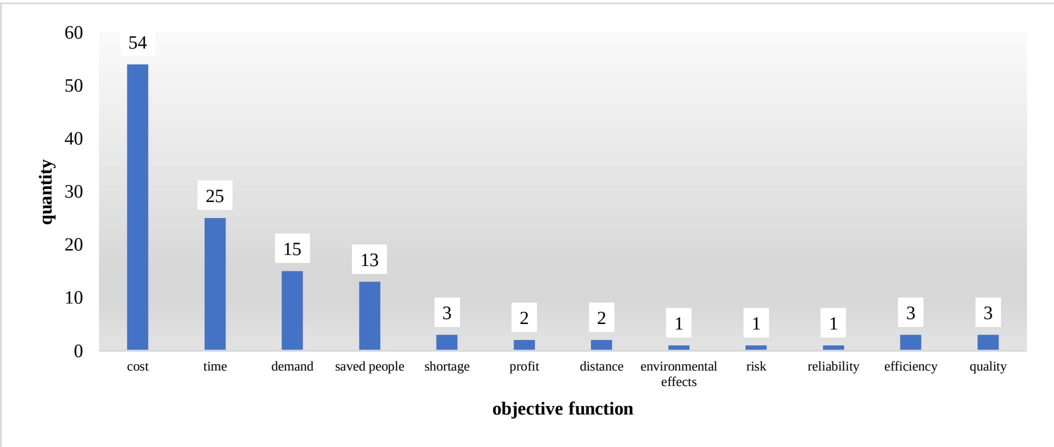

Fig. 18. Frequency of objective function types in both single-objective and multi-objective papers

According to Table 9, minimizing costs is the most common type of objective function among other options in multi-objective papers. Figure 18 depicts the frequency of objective function types in both single-objective and multi-objective papers.

Figure 18 shows that cost and time are the most common types of objective functions, while risk, number of manufacturing products, and quality have been less used as objective functions.

2.8. Solution methods

This part of the study reviews papers based on their solution methods. Solution methods are selected based on the number of objective functions, constraints, and problem data.

2.8.1. Exact

The exact solution method is about finding the optimal solution in a limited time. The exact solution is a classic method (Rao, 2009). Table 10 reports the studies that used the exact solution method and mentions the names of these methods.

Table 10
Papers with the exact solution method

Solution method		**Author and year**	**Quantity**
Exact	Cplex solver	Gulzari and Tarakci(2021); Zhang et al. (2021); Gamage and Olapiriyakul(2020); Mansoori et al. (2020); Doodman et al. (2019); Hong and Jeong (2019); Liu et al. (2019); Torabi et al. (2018); Liu et al. (2018); Hu et al. (2017); Stauffer et al. (2016); Rezaei-Malek et al. (2016); Alem and Clark(2015); Kelle et al. (2014); Han et al. (2010); Rahimzadeh Dehaghani et al. (2021); Horner and Downs (2007); Zokaee et al. (2021); Cheng et al. (2021); Ghasemi (2019); Mason and Ransikarbum (2016); Fereiduni and Shahanaghi (2016); Zokaee et al. (2016); Lauras et al. (2014); Davis et al. (2013); Gökçe and Ercan (2019).	26
	Lagrangian relaxation method	Kamyabniya et al. (2021); Hamdan and Diabat (2020); An et al. (2015).	3
	ε - Constraint	Kamyabniya et al. (2021); Sun et al. (2021); Naghipour and Bashiri (2019); Fahimnia et al. (2017); Memari et al. (2018); Saatchi et al. (2021); Praneetpholkrang et al. (2021); Gao and Cao (2020); Gökçe and Ercan (2019).	9
	Branch and bound method	Guan et al. (2021); Cao et al. (2021)	2
	Lp-metric method	Boostani et al. (2021); Cao et al. (2021); Liu and Song (2019).	3
	Lingo solver	Barzinpour and Esmaeili (2014); Wei et al. (2015); Habibi-Kouchaksaraei et al. (2018); Guo and Peng (2019).	4
	Gurobi solver	Song et al. (2018); Manopiniwes and Irohara (2017); Manopiniwes et al. (2015).	3
	Lindo solver	Ji and Zhu (2012)	1

According to Table 10, CPLEX Solver is the widely used exact solution method in reviewed papers.

2.8.2. Heuristic

Heuristic algorithms provide some criteria or principles to decide on several policies and strategies to select the most effective option. The papers that used the heuristic method have been mentioned herein (Rao, 2009).

Ismail (2021) studied the allocation of relief items in the humanitarian supply chain. Zhang et al. (2021) addressed the location problem in a closed-loop supply chain under disaster conditions. Velasquez et al. (2021) examined relief item distribution problems in emergency conditions. Islam et al. (2021) studied fuel shortages during a hurricane evacuation. Xavier et al. (2021) examined the use of helicopters in relief resource distribution operations. Diaz et al. (2020) studied evacuation problems and sending patients to temporary shelters. Wang et al. (2018) assessed emergency transportation in supply chain response operations. Kondo (2018) examined the effects of disruptions on the supply chain in a disaster. Charles et al. (2016) studied location problems in relief networks. Anjomshoae et al. (2016) studied the flood evacuation problem. Gobaco et al. (2016) examined relief items distribution problems in humanitarian supply chain networks. Rezaei-Malek et al. (2016) studied the location and allocation of relief items in a disaster. Abidi et al. (2015) assessed the effect of relief organizations' cooperation in disasters on the reduction of the relief process' cost and time. Ni et al. (2015) proposed a method to evaluate the performance of various relief strategies in disasters. Chakravarty studied the relief process under disaster conditions. Kumar and Havey (2013) developed a model to evaluate the decisions made in the supply chain. MacKenzie et al. (2012) studied inventory management problems in disasters, and Tian et al. (2011) assessed relief items' distribution routing problems. Hu et al. (2011) examined transportation planning problems in emergency relief conditions. Taskin and Lodree (2010) studied the inventory control problem for emergency relief resources. Sayarshad et al. (2020) examined the debris clearance problem in a disaster. Moeen-Moghadas et al. (2013) studied relief centers' location problems. Torabi et al. (2018) examined procurement planning problems in the supply chain. Gutierrez and Mutuc (2018) assessed facilities' location problems in a disaster. Ozbay and Ozguven (2007) introduced an inventory control model under crisis conditions. Xiang and Zhuang (2016) studied medical resource allocation under emergency conditions.

2.8.3. Metaheuristic

The metaheuristic method is an algorithm that searches through a solution space to find a solution near to optimum within the shortest time (Rao, 2009).

Mousa et al. (2021) studied the blood supply chain problem. Guan et al. (2021) examined the coverage location model of relief materials. Gökçe and Ercan (2019) assessed inventory management problems in humanitarian logistics. Javadian et al. (2017) studied transportation in the humanitarian supply chain. Memari et al. (2018) examined the relief center's location and allocation problems. Rahimzadeh Dehaghani et al. (2021) studied the blood supply problem in the humanitarian supply chain. Saatchi et al. (2021) examined warehouse and hospital location problems and emergency relief vehicle routing. Saghehei et al. (2021) studied warehouse location problems in disasters, and Rezaei et al. (2020) designed a fuel supply chain network under crisis conditions. Haghjoo et al. (2020) studied the blood facilities' location problem. Ghaffari et al. (2020) studied relief items inventory management for disaster conditions. Cui et al. (2019) addressed relief items distribution in disaster.

Hong and Jeong (2019) examined relief items allocation in post-disaster conditions. Wang et al. (2018) studied transportation under disaster conditions. Cao et al. (2018) considered the relief items distribution problem in a disaster. Baraka et al. (2017) studied transportation in disaster relief. Zavvar Sabegh et al. (2017) examined relief facilities' location problems in a disaster. Ghezavati et al. (2015) evaluated relief facilities' locations in disaster. Table 11 reports the papers that used the metaheuristic method, introducing the name of each solution method.

Table 11.
Papers with the metaheuristic solution method

Solution method		Author and year	Quantity
Metaheuristic	Particle swarm optimization	Zavvar Sabegh et al. (2017); Ghaffari et al. (2020); Rezaei et al. (2020); Mousa et al. (2021)	4
	Non dominated sorting genetic algorithm II	Guan et al. (2021); Gökçe and Ercan (2019); Javadian et al. (2017); Memari et al. (2018); Rahimzadeh Dehaghani et al. (2021); Saatchi et al. (2021); Rezaei et al. (2020); Hong and Jeong (2019)	8
	Simulated annealing	Saatchi et al. (2021); Ghezavati et al. (2015)	2
	Neighborhood search algorithm	Saatchi et al. (2021); Saghehei et al. (2021)	2
	Imperialist competitive algorithm	Haghjoo et al. (2020),	1
	Invasive weed opt imization	Haghjoo et al. (2020)	1
	Ant Colony Algorithm	Lu and et al. (2010); Wang et al. (2018)	2
	Genetic algorithm	Ghezavati et al. (2015); Zavvar Sabegh et al. (2017); Baraka et al. (2017); Cao et al. (2018); Cui et al. (2019); Saghehei et al. (2021).	6

Table 11 indicates that the multi-objective genetic algorithm (GA) has been widely used in papers that employed metaheuristic methods.

2.8.4. *Simulation*

Simulation is an imitation of a real natural process. In the simulation, the actual effects of a phenomenon on a target are applied under controlled and determined conditions (Pido, 2004).

Nozhati et al. (2019) studied individuals' food supply after a disaster. Stauffer et al. (2016) examined temporary hubs' location problems in the humanitarian supply chain, and Tal et al. (2011) studied emergency evacuation and relief problems under disaster conditions.

2.8.5. *Multi-Criteria Decision-Making*

This decision-making assesses optimization using several criteria (Hwang and Lin, 1987).

Patil et al. (2021) evaluated the effectiveness of different relief activities. Kaur and Singh (2020) investigate the order allocation to suppliers in the supply chain. Behl et al. (2019) evaluated critical success factors for the supply chain. Ren et al. (2020) studied various criteria for first aid under crisis conditions. Baharmand et al. (2017) assessed the performance, efficiency, and effectiveness of transportation systems in disasters.

Connelly et al. (2016) studied relief items allocation to damaged locations based on different criteria. Budak et al. (2020) studied warehouse locations in disasters by using different criteria. Sun et al. (2018) investigated the inventory management problem in a disaster. Safaei et al. (2018) studied relief item distribution problems under crisis conditions. Beiki et al. (2020) examined the distribution center location problem. Ganguly et al. (2017) assessed the factors affecting supply chain management. Li et al. (2013) designed a decision model for relief item distribution. Deng et al. (2016) studied the performance of the disaster supply chain. Table 12 reports those papers that have used MCDM methods and mention the names of these methods.

Table 12
Papers with MCDM

Solution method	Author and year	
MCDM	Fuzzy ANP	Patil et al. (2021)
	Fuzz AHP	Deng et al. (2016)
	Dematel method	Kaur and Singh (2020); Behl et al. (2019)
	Weighting method	Ren et al. (2020); Baharmand et al. (2017); Connelly et al. (2016); Ganguly et al. (2017); Li et al. (2013)
	Topsis method	Budak et al. (2020); Sun et al. (2018); Safaei et al. (2018).
	Lexicographic	Beiki et al. (2020)

According to Table 12, the weighted method has been widely used among other MCDM methods.

2.8.6. *Game Approach*

The following authors used a game approach in their studies: Alaswad and Salman (2020) studied relief problems and relief item distribution in disasters. Harke and de Leeuw (2015) examined inventory management problems in disasters, and MacKenzie et al. (2014) assessed disruptions in the supply chain in disasters.

2.8.7. Questionnaire and scientific-statistical analyses

In the questionnaire method, the data are collected through a questionnaire distributed among a specific statistical society and then analyzed through statistical software.
Mushanyuri and Ngcamu (2020) studied the effectiveness of a humanitarian supply chain in Zimbabwe. Widera et al. (2017) studied integrated logistics and transportation planning in disaster relief operations. Gil and Mcneil (2015) examined the supply chain performance in response to the disaster.

2.8.8. Machine learning & intelligent systems in the crisis area

Machine learning and its algorithms are one of the substantial and practical techniques that have received great attention in crisis problems over recent years. This algorithm helps researchers solve dynamic problems and other cases requiring simulation. These algorithms are used based on the problem subject and the researcher's idea. Accordingly, various approaches, like machine learning, deep learning, and multi-agent learning, are the most popular techniques used in papers.
Lee and Lee (2021) formulated the disaster response problem as a decentralized-partially observable Markov decision process (dec-POMD); they used a multi-agent reinforcement learning algorithm (MARL) to solve the problem. Bravo et al. (2019) studied unmanned aerial vehicles (UAVs) in humanitarian relief. They used Markov decision process and a greedy algorithm to solve their problem. Comparing the results of the two solution methods indicated that the Markov decision process could rapidly find victims compared to the greedy search. Nie et al. (2020) investigated the energy supply optimization problem in the aftermath of the disaster using multi-agent deep reinforcement learning. Azimi et al. (2019) developed two multi-agent models for intelligent search and rescue operations. In one model, the priority was delivering drugs to victims, sending information about victims to hospitals to find urgent cases, and updating ambulance routes. The second model considered coordination between emergency vehicles and intersections' traffic lights and updating the route of emergency vehicles concerning their initial place. Yu et al. (2018) allocated the space of surrounding shelters by integrating multi-agent system techniques and multi-criteria evaluation. Compared to previous methods used for shelter allocation, their methods clarified the importance of dynamic emergency evacuation simulations for appropriate analyses of space allocation. Hashemipour et al. (2018) developed an agent-based simulation system using machine learning techniques and experimental methods to test different configuration setups and determine the effects of various factors on operation completion time. Bune et al. (2016) used a multi-agent system at the mesoscopic level to examine people's behavior during evacuation time in post-disaster emergency conditions. Iizuka and Iizuka (2015) suggested a system to evacuate people from dangerous places using multi-agent cooperation. The main feature of this system is that it does not require central servers. Edrissi et al. (2013) proposed an agent-based optimization approach to earthquake disaster prevention and management. They used a heuristic technique to solve different subproblems introduced in their study. Kaddoussi et al. (2013) proposed a method to solve multi-agent-based scheduling for delivering goods (food, water, clothes) to the affected areas.
Table 13 reports the studies conducted on machine learning in crisis and the approaches they used.

Table 13
Approaches used in machine learning studies in crisis scope

Author and year	**Machine learning approach**
Lee and Lee (2021)	Multi-agent Reinforcement,
Bravo et al. (2019)	Partially observable Markov decision process
Nie et al. (2020)	Multi-agent deep reinforcement learning
Azimi et al. (2019)	Multi-agent
Yu et al. (2018)	Multi-agent ,Simulation
Hashemipour et al. (2018)	Agent-based simulation
Bune et al. (2016)	Multiagent
Iizuka and Iizuka (2015)	Multi-agent
Edrissi et al. (2013)	Multi-agent optimization
Kaddoussi et al. (2013)	Multi-agent systems

Table 13 reports that used machine learning in disasters, and ten papers used machine learning. These studies used Markov chains, agent-based learning, reinforcement learning, deep learning, learner agent-based simulation, and multi-agent optimization.
The mitigation of the impact of a possible natural disaster is vital for a modern city. In the framework proposed, it is critical to identify and analyze the most vulnerable regions of the city and use intelligent systems to gather data or process it (Nefros et al. 2022). Various intelligent systems can contribute, from sensors to unmanned aerial vehicles (UAV), to Artificial Intelligence to the Internet of Things (IoT). Today, for example, UAVs are used as navigation and surveillance tools on the ground and in the air. More recently, the use of UAVs has been abundant in a wide range of rescue missions, and disaster management in line with the requirements of smart and intelligent cities and their management (Qadir et al. 2021). A smart cities concept, which is being implemented by many countries, are innovative solution for cities and municipalities but also for humanitarian needs (Gavurova et al. 2022). Remote sensing technology has been used for the short-term and imminent earthquake precursory which contains both inland and sea areas (Liu et al. 2020).
Sufi (2022) reported a K-Means clustering-based knowledge discovery methodology that discovered the similarity and dissimilarities among various disaster types. Gupta et al. (2022) investigated the role of AI-based cloud technologies during emergency and disaster relief operations through qualitative exploratory research. Based on organizational information processing theory, their study examined the deployment of AI and cloud-based collaborative platforms in different phases of the extreme weather and disaster life cycle, and several key themes

were identified through an axial, open, and selective coding process. Raza et al. (2020) established effective communications in disaster-affected areas and AI-based detection using social media platforms. Their proposed work effectively establishes communication infrastructure to facilitate communications in the affected areas. In addition, their proposed machine learning scheme assists in identifying critical regions in the affected areas by analyzing bulk information through social messaging platforms.

Fan et al. (2021) presented a vision for a disaster city digital that could: (1) enable interdisciplinary convergence in the field of crisis informatics and information and communication technology in disaster management; (2) integrate AI algorithms and approaches to improve situation assessment, decision making, and coordination among various stakeholders; and (3) enable increased visibility into network dynamics of complex disaster management and humanitarian actions. Dubey et al. (2022) showed that AI-driven big data analytics capability was a significant determinant of agility, resilience, and performance of the humanitarian supply chain. Essam et al. (2021) suggested artificial neural network models predict earthquake acceleration, depth, and velocity, in Terengganu. Also, they compared the results of the artificial neural network with the random forest results.

2.8.9. Use of the queuing system in disaster

A queue (or queueing) system is one of the useful approaches widely used in the disaster response phase. This approach is used in papers in two forms: in the first case, transfer matrix and Markov chains are used in dynamic systems solved using machine learning methods or heuristic algorithms. In the second case, queuing systems are used in nondynamic systems as models with one or more servers with limited or infinitive capacities along with probabilistic conditions and distributions. The second problem is solved based on exact, heuristic, and metaheuristic methods. Sayarshad et al. (2020) studied debris clearance using two debris clearance and debris management strategies. They used machine learning, dynamic programming, and a heuristic algorithm. Memari et al. (2018) designed a relief center location and allocation model using queuing systems. They use a multi-objective genetic metaheuristic algorithm to solve this problem. Moeen-Moghadas et al. (2013) studied emergency location problems by using the queuing system to maximize population coverage. For this purpose, they used a heuristic algorithm. Rahimzadeh Dehaghaniand et al. (2021) designed a blood supply chain network optimization model. They used a multi-objective genetic metaheuristic algorithm. Lu et al. (2010) designed a facility location model with fuzzy data using the queueing system. They used the ant colony algorithm to solve their problem. Xiang and Zhuang (2016) designed a medical resource allocation model for serving emergency victims. They used a heuristic algorithm in this study. An et al. (2015) presented a model for emergency facility locations. They used the KNITRO solver in GAMS software and the heuristic method to solve the model. Mora-Ochomogo et al. (2020) designed a Markov decision model for inventory management in disasters. The use of queuing system depends on the problem conditions and researchers' detection. For instance, victims' arrival at and departure from relief vehicles, relief vehicles' arrival at and departure from damaged centers, services provided by medical relief teams for victims, and similar cases with limited capacity and labor that causes victims to wait can be considered queueing systems. Table 14 reports the studies that have used queueing systems.

Table 14
Papers with queueing systems

Author and year	**Queueing systems type**			**Markov chain**
	m/m/m	m/g/k	m/m/m/k	
Sayarshad et al. (2020)				✓
Memari et al. (2018)	✓			
Moeen-Moghadas et al. (2013)		✓		
Rahimzadeh Dehaghani et al. (2021)			✓	
Xiang and Zhuang (2016)				✓
An et al. (2015)				✓
Taskin and Lodree (2013)				✓

According to Table 14, seven papers used queuing systems in the disaster, of which three papers used the queue system, and four papers used the Markov chain. Figure 19 depicts the frequency of solution methods used in reviewing studies.

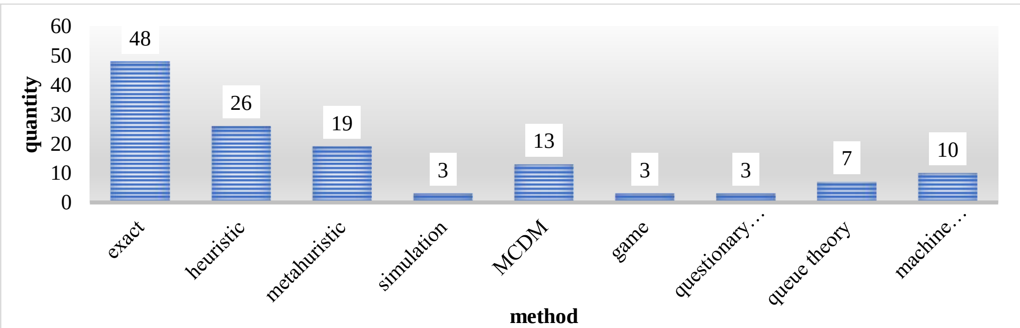

Fig. 19. Frequency of solution methods

As seen in Figure 19, the exact and heuristic methods had the most frequencies, while simulation, game theory, and questionnaire were less used in reviewing studies.

3. Conclusion

It is necessary to design efficient crisis management due to increasing natural and humanitarian crises causing the loss of lives and properties over recent years. The academic advances and the advent of state-of-the-art optimization techniques make us conduct novel studies in crisis management. Moreover, machine learning, queuing system, and simulation must be used more than before.

The systematic review of studies indicated that serving structure in the disaster is usually hierarchy, and hierarchical facility location was the most popular type in these studies. Moreover, the distribution center location had the most frequency among facilities located in reviewed studies. The widely used parameter used as uncertain (probabilistic) parameters in reviewed papers were demand, cost, and the number of victims. The probabilistic approach was the most popular uncertain approach used in reviewed studies. The number of uncertainty papers equaled or exceeded certainty papers in all reviewed years. Relief team and patient classification in disaster accelerate the relief process. In the reviewed studies, relief team classification was done as the classification of physicians based on their proficiency, relief team classification based on service levels, classification of different organizations involved in the relief process, and identical relief team classification. Patients were classified into two emergency and nonemergency categories, different types of diseases without naming any specific illness, injury severity of patients, serious and minor injuries, blood group-based classification, and classification using injury severity based on colors (green, yellow, red, and black). The Queueing system was one of the useful approaches employed in reviewed papers. Normally, we cannot fulfill all demands due to the unpredictable nature of the crisis and facility shortages in the early hours of the disaster. This case is more familiar to medical relief teams and debris clearance teams. Under such circumstances, victims must wait in queues to receive services. Markov chains are preferred to queueing systems in studies that used dynamic methods. Machine learning is a new approach that has received great attention from many researchers. This approach helps researchers solve dynamic problems and other cases requiring simulation. The reviewed studies were conducted in these countries: India, Iran, China, the United States, Brazil, Thailand, Syria, Zimbabwe, Japan, Nepal, Malaysia, Peru, Tunisia, Egypt, Libya, Morocco, Democratic Sahara, Algeria, Indonesia, Sudan, and Romania. Earthquakes, floods, tsunamis, hurricanes, droughts, and humanitarian crises were considered in the reviewed empirical and applied studies.

China was the country where most crises were examined, and earthquake was the most common disaster studied in the reviewed studies. Cost, time, and demand were three important factors for selecting the type of objective function, among other cases. The exact solution methods that were performed using GAMS, LINGO, CPLEX, and LINDO software, was the most common method employed in the reviewed papers. Heuristic and metaheuristic methods were at the next rank of the widely used techniques. Although the reviewed papers covered a wide range of scopes, they were inadequate. Because there are increasing problems in the world and modern technologies like machine learning are growing and developing, further studies must be done in this field. There are few studies about the failures and retrieval of remote communication systems and how their reliability depends on the stored energy in disasters (Kwasinski et al., 2006). Maximization of delivering cargo may seem a suitable objective, but this solution disrupts the area. Few logistic systems can manage a large volume of goods without having an appropriate infrastructure (Charles et al., 2016).

Although many studies were carried out about different disasters, none of them considered famine and starvation crises. Further studies can focus on famine and starvation crises in African countries. Moreover, crises caused by political changes can be an interesting subject for researchers. A few reviewed studies examined disasters caused by contagious diseases; hence, further studies on some crises, like the coronavirus, SARS, and other diseases. Another crisis that future studies can examine is the war crisis in some countries, such as Lebanon, Palestine, Iraq, and Afghanistan. Further studies can find how to evacuate people and provide medical items and food under such circumstances. Sanction is another crisis in that researchers can assess its impact on the industry and livelihood of people in the sanctioned country and find suitable solutions to cope with possible damages to industries. Facility location is another critical problem in crisis management issues. Hierarchical facility location was a model that was studied and used more than other location models. According to this systematic review, it is suggested that the researcher use center location models to build a shelter for immigrants from countries affected by war, food supply warehouses for countries with famine crisis problems, and deploy remote medical communication facilities. Covering location models can be used under epidemic circumstances (e.g., the Corona and SARS) that require reliving a large number of people and building field hospitals in the response phase. Researchers can use hub location models in problems associated with relief items collection and distribution in different countries and humanitarian organizations (Red Cross and Red Crescent Societies) and deliver them to the affected country. Furthermore, network location models can be employed to build temporary facilities, like hospitals, blood donation centers, and debris clearance equipment in the affected area. Further studies can examine a case in different disasters considered a cost-effective temporary facility location rather than fixed facilities. Future research can also investigate the different location models in studies on disasters to find their applications under various conditions. In reviewing studies, some parameters like demand, time, and cost were the most common uncertainty parameters. At the same time, the possible failure of debris clearance equipment, road closing, and relief items theft was unexamined in these studies. The probabilistic approach was the most common method used in papers; hence, further studies can develop the research scope by examining critical factors affecting the selection of the uncertainty approach and finding the efficiency of each approach. Few studies focused on relief teams and patient classification in disaster in their models. These classifications can be used under humanitarian crisis conditions, such as epidemics, wars, and political changes, which is a good subject for further studies. Future studies must develop the mentioned methods due to advances in existing sciences and methods and diversity in crises. Further studies can use queueing systems and Markov chains to evacuate victims, deliver relief services to injured people, distribute relief items, and clear debris. Moreover, using machine learning techniques with queuing systems and Markov chains in victims' search processes under the rubble by employing rescue dogs can be another research topic for further studies. Because modern technologies like machine learning have become popular, further studies can compare machine learning techniques with metaheuristic algorithms in the case of time efficiency, objective function optimality, and detection of the effective method based on the problem's constraints. Future studies can also consider some assumptions, including removal of debris in an affected area with equipment shortages, search for victims under the rubble by using rescue dogs and agent-based optimization, victims' arrival at and departure from relief vehicles in queueing systems, and the arrival of vehicles based on Markov chains. Another recommendation for further studies is queuing systems in post-disaster relief service centers, calculating victims' waiting time to receive relief services and the probability of the victim’s death when waiting in queues or receiving relief services. Researchers can use simulation-based optimization by using queueing systems and machine learning to imagine real conditions, compare the results with metaheuristic and exact techniques' outcomes, and analyze the strengths and weaknesses of this optimization approach. Further studies can consider communicational technologies, like remote medicine, to develop the research literature in further studies. The reviewed studies, mostly focused on some objectives, such as cost minimization, serving time immunization, and demand fulfillment maximization; therefore, further studies can increase the reliability of crisis management systems, evaluate the performance and coordination of relief and rescue organizations, reduce risk when relieving emergency patients, enhance the flexibility of the humanitarian relief system and mitigate the influence of possible disruptions over the relief system. If transportation of a large volume of relief items is managed and planned effectively, the relief items will be delivered to injured people very rapidly. Therefore, further studies must be done in this field due to the current technologies developed for this case and examine the role of artificial intelligence and machine learning in transportation systems during disasters. As well as the mentioned subjects, pay attention to the role of the NGO/government/Red Cross/Red Crescent in the field of knowledge management, intelligence accumulation, and relief supply are undeniable. They can use IoT and improve the city structures to have better smartness. Furthermore, using optimization, simulation, big data and AI for their DSS can save time, money, and resources which are very valuable in disaster situations.

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