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Digital post-disaster risk management twinning: A review and improved conceptual framework

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ABSTRACT

Digital Twins (DT) are the real-time virtual representation of systems, communities, cities, or even human beings with the substantial potential to revolutionize post-disaster risk management efforts and achieve resilient communities against the adverse effects of disasters. However, this potential remains largely unrecognized and poorly understood in disaster risk management. This study explores current achievements, existing challenges, and the untapped potential of DT in disaster risk management, and accordingly, proposes an improved Digital twin-based post-disaster risk management framework. This paper employs a systematic literature review approach focusing on digital post-disaster risk management twinning (DPRMT) and smart early warning systems derived from two databases: Scopus and Web of Science. After a screening process with exclusion criteria, the final analysis synthesizes findings from a selected set of 96 papers. The results revealed that previous studies are not beyond only providing general statements about DT. There is a need for diverse data collection methods, considering demographic and financial aspects, understanding social dynamics, employing dynamic models, recognizing interconnected systems, and giving due attention to the often-neglected recovery phase. This study proposes a comprehensive DPRMT concept framework leveraging decision-makers with a holistic and efficient approach that offers real-time, detailed, and data-driven modeling solutions to achieve insights into disaster-affected areas and communities. It is also helpful to optimize response planning, resource allocation, and scenario testing by capturing the dynamic and complex human behaviors and understanding interconnected systems and entities that are often overlooked in previous disaster risk management studies.

1. Introduction

Despite all the advancements in disaster risk reduction policies and technologies, disasters with escalating frequency continue to pose a significant threat to humanity and the surrounding built environment, resulting in tremendous financial damage [1,2]. The total damage caused by disasters around the world between 2000 and 2010 amounted to around US$ 890 billion. This figure witnessed a dramatic increase, surpassing US$ 1.7 trillion for the period between 2010 and 2020 [3]. Nevertheless, the consequences of disasters are not solely confined to financial effects on communities and their surrounding built environment. They affect built infrastructures such as power, water, and transportation networks and social infrastructures such as hospitals and educational buildings [4,5]. These hazards can reduce the functionality of the systems and their interconnected systems, causing discomfort and, at times, displaced people [6]. The total number of people affected by disasters in the world between 2000 and 2023 was almost 4.5 billion [7].

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Up to now, pivotal organizations such as the United Nations (UN), the World Bank, and the International Federation of Red Cross and Red Crescent Societies (IFRC) have made substantial efforts to enhance awareness and motivate many countries to take preventive measures to protect humanity and built resilient communities against disasters [8]. IFRC announced and adopted a Disaster Risk Management Policy to build resilience communities against existing and future risks through disaster risk management strategies [9]. On the other hand, numerous countries have established national organizations for disaster risk management. Examples include the United States' Federal Emergency Management Agency (FEMA), established in 1979, and China's Ministry of Emergency Management, established in 2018 [8].

Resilience is the ability of a community to reduce the adverse effects of disasters resulting in capacity loss at the city level, and it aims to minimize the time needed for the community to reach again to the same, acceptable, or better functional level [10]. United Nations Office for Disaster Risk Reduction (UNDRR) announced the Sendai Framework for Disaster Risk Reduction 2015–2030 and emphasized the significance of building resilient communities to prevent future risks and minimize the existing ones to reduce the detrimental effects of disasters, extreme weather conditions, and climate change [11]. These achievements desire to mitigate the adverse effects of disasters, be prepared for emergencies, respond to disasters effectively, and recover from disruptions quickly [12,13]. However, existing tools and methods have proven to be inadequate to achieve these defined goals and have not met expectations, hampering effective disaster response, creating severe recovery delays or resulting in a failure to achieve full recovery due to lack of capturing dynamic and evolving nature of disasters with dynamic data flow and predicting future scenarios to inform decision makers [2,14]. This study aims to contribute to these goals and enhance community resilience by integrating DT in post-disaster risk management (PRM).

Recently, there has been a paradigm shift to DT with the help of emerging technologies such as communication and information technologies (CIT) and artificial intelligence (AI) in smart cities [15]. Smart cities became a data source and a testbed for these technologies by collecting data with various data collection methods [16,17]. The main difference between smart cities and digital twins is that smart cities generally have the ability to collect and disseminate data in real-time; however, they lack the capability to generate insights or predict future scenarios for decision-makers, as digital twins can [18]. The utilization of DT extends beyond smart cities; they are also broadly used in other industries, like manufacturing, transportation, and construction, thanks to the conveniences DT offers, such as operational productivity and process optimization in the supply chain, risk management, and resource allocation [19]. Therefore, an increasing demand arises for data-driven disaster management solutions to overcome the complexity and dynamic nature of disasters [20].

DT poses a significant potential in the transition from data-driven smart cities to informed and data-driven PRM by analyzing and representing complex urban systems realistically and offering informed decision-making as a solution to disaster-related multifaceted challenges [6,21]. Uninterrupted and accurate data flow from various elements and agents in the aftermath of disasters is of vital importance in PRM, considering the complex and chaotic nature of post-disaster situations. AI can facilitate data processing to extract valuable information thanks to its computational power in terms of scale and time [22]. Despite the advancement of CIT and AI technologies in this data flow, progressing and integrating this much big data and extracting meaningful outcomes in response and recovery periods is another big challenge that DT can solve [2,23]. However, the existing body of research on DPRMT is currently limited.

DT has become a popular field in recent years, leading to various review studies on how DT can be adopted in different application areas. To exemplify, Hou et al. [24] reviewed the literature to examine how DT can enhance construction workforce safety. Furthermore, there have been similar efforts to explore the integration of DT into disaster risk management to improve overall outcomes. Yu and He [8] carried out a literature review on the use of DT in disaster prevention and mitigation by focusing specifically on pre-disaster risk management. Cheng et al. [12] conducted a systematic literature review on how DT can facilitate civil and infrastructure emergency management. Ariyachandra and Wedawatta [25] conducted a systematic literature review to explore evolving concepts and technologies in DT-driven disaster risk management. Despite these efforts, previous studies have fallen short of providing an inclusive explanation of digital twins' potential contributions and application domains in PRM. They also did not consider the socio-economic and demographic features of the communities that affect the overall PRM outcomes, relying on limited data collection methods and data types. Furthermore, studies investigating how AI and machine learning (ML) techniques can improve PRM efforts are limited.

Consequently, our study conducted a systematic literature review to investigate current achievements, existing challenges, and gaps in DT-driven PRM and early warning (EW). Even though early warning is a component of pre-disaster risk management, it is included in the systematic literature review since it plays a crucial role in the overall post-disaster response and recovery outcomes [26]. By analyzing previous case studies, review papers, and concept models with this systematic literature review and reviewing other papers from other similar areas (e.g., smart cities), our study proposes a conceptualization of a comprehensive digital post-disaster risk management twinning (DPRMT) platform to enhance post-disaster response and recovery efforts by considering a variety of entities at risk such as human lives, critical and social infrastructures, and post-disaster resources. Our study further emphasizes the integration of ML and AI within the proposed DPRMT framework. Our proposed platform can be used for damage assessment, casualty prediction, resource allocation, resilience assessment, scenario testing, hazard spread prediction, evacuation, policymaking, lessons learned, decision-making, community engagement, and recovery.

The remainder of the paper is organized as follows: Section 2 provides background information on disaster risk management and DT. Section 3 outlines the methodology for the systematic literature review of DPRMT and EW. Moreover, section 4 encapsulates the results obtained and the key points discussed. Furthermore, section 5 retrieves the conceptual design of DPRMT. Finally, section 6 concludes the paper.

2. Background

2.1. Disaster risk management

Disaster risk is the exposure to a scenario or situation with potential adverse outcomes that are not definitively known or entirely predictable, encompassing the potential loss of life, injury, and damage to assets, systems, or communities within a specific timeframe [27,28]. Disaster risk is mainly shaped by hazard, vulnerability, and exposure [29–32]. Hazard or natural hazard refers to extraordinary events or phenomena originating from natural processes and potentially harming or damaging the environment [28,29]. Exposure is the total number of entities in the hazard-prone area and is expressed through demographic, socioeconomic, and infrastructure data [33,34]. These entities are called entities at risk, indicating any element or component vulnerable to the potential impacts of disasters. Vulnerability is the possibility of entities in the hazard-prone area getting harmed or damaged due to lack of resilience [35,36]. Fig. 1 shows the disaster risk equation, which is the multiplication of hazard, vulnerability, and exposure.

Disaster management or disaster risk management usually covers prevention and mitigation, preparation, early warning, response, and recovery processes [35]. Prevention refers to the idea or objective of entirely preventing the potential adverse outcomes of disasters [28]. In contrast, mitigation refers to the measures taken to reduce risk and protect the community to minimize the potential consequences of disasters when full prevention is unachievable [11,35,37]. EW is a comprehensive system that empowers individuals, communities, or other entities to promptly take measures in anticipation of hazardous events to mitigate disaster risks by encompassing hazard monitoring, forecasting, risk assessment, communication, and preparedness activities [11]. Preparation means planning and taking action to reduce the potential damage or loss in the hazard-prone area before disaster [11,35]. Furthermore, response is the actions aiming to save lives and rescue affected individuals by ensuring public health and safety before, during, or immediately following the disaster to cope with the adverse effects of disasters [11,35]. Finally, recovery refers to the actions taken to repair or reconstruct a variety of dimensions of disaster-affected communities, such as livelihood, well-being, and other dimensions interrupted by disasters, to achieve acceptable, the same or a better functionality by using "build back better" and sustainable development guidelines [11,28,38].

Disaster risk management can be divided into two main time steps: pre-disaster and post-disaster risk management (Fig. 2). While the pre-disaster period covers EW, prevention and mitigation, and preparation steps, the post-disaster period covers response and recovery phases [28]. Despite the progress in disaster risk management, several challenges persist and hinder a successful process, such as knowledge sharing and management [39,40]. Even though the achievements in learning from previous disasters and disaster testing environments such as Natural Hazard Engineering Research Infrastructure (NHERI) Experimental Facility, it is still a challenging task due to the limited number of high-intensity disasters available for learning and the variability in the characteristic features of these events; disaster risk management-related strategies may need to be redeveloped in some cases [40,41]. Moreover, information flow during and post-disaster periods is vital to coordinating resources and agents in the emergency response and recovery phases [42]. This is crucial because almost every infrastructure, such as transportation and energy networks or system such as education and healthcare at the community level is connected, and any disruption in one quickly affects the other systems, resulting in critical de-

Fig. 1. Disaster risk equation (Equation source [28]).

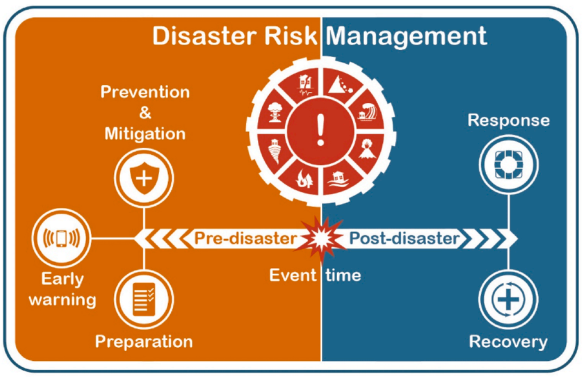

Fig. 2. Components of disaster risk management: pre-disaster and post-disaster.

lays [43]. Conversely, data collection is challenging in the aftermath of disasters [17]. Extracting valuable insight from various data types collected from various sources is another challenging task [2].

2.2. Digital twin

DT is a dynamic virtual counterpart of its physical or virtual twin that is continually updated through a multifaceted process with various data collection, data processing, and sophisticated simulation methods [2,12]. This comprehensive approach allows DT to mirror real-world entities and events, enabling informed decision-making about future scenarios without costly real-life experiments [6,44]. Fig. 3 shows the data flow and information flow in DT. Data is initially gathered from its physical twin using diverse methods, then processed and transformed into information within the DT, which is subsequently shared back with the physical twin [17].

Innovations in big data technologies, the Internet of Things, 5G technologies, smart devices, cloud-based platforms, machine learning, and deep learning algorithms have fueled a shift toward a data-driven world [45–47]. The COVID-19 pandemic further accelerated this transformation, highlighting the importance of digital transformation [48]. In alignment with this, DT has gained more attention as a critical concept due to this data boom and digital transformation. DT is not a new technology but a significant technology with a longstanding history.

"Twins," as a concept, originated in NASA's Apollo program in 1970, which involved creating two or more identical spacecraft. The one that stayed on Earth was named a twin and used for training before the flight to replicate mission conditions during the flight thanks to available data and to assist orbiting astronauts in critical situations and return to Earth safely [49]. For example, after the tank explosion during the flight, the twin was used to simulate and find an improvised air purifier solution [50]. However, this twin was a physical twin at this stage [51].

In 2002, Michael Grieves informally introduced DT as a concept in his presentation titled "Conceptual Ideal for Project Life-cycle Management (PLM)" [50]. His DT model consisted of three primary components: 1) a tangible space containing a physical object; 2) a virtual space containing a digital object; 3) the bridge for data flow from the tangible space to the virtual space as well as for information exchange from the virtual space to the tangible space [50,52,53]. These developments elucidate why the initial research on DT focused on PLM [51].

In 2010, NASA introduced "Digital Twin" for the first time within its integrated technology roadmap named "Modeling, Simulation, Information Technology and Processing Roadmap" [49,54]. DT was defined as a comprehensive simulation of a vehicle or a system employing the most accurate physical models, sensing real-time data, and more to mirror the operational lifespan of its real-world counterpart [49]. Besides, a significant advancement has occurred for DT as the U.S. Air Force Research Laboratory (AFRL) introduced the concept in a published paper, aiming to predict aircraft structure lifespan and improve maintenance decisions in 2011 [51,55]. The following year, AFRL introduced the concept of the Airframe Digital Twin, starting a new phase for individualized aircraft management [56]. In the following years, DT has become a hot topic for various industries for various purposes.

One of the primary industries utilizing DT is manufacturing. The manufacturing DT enables comprehensive simulation, optimization, and visualization of the production system, ranging from individual components to assemblies, integrating crucial aspects such as production planning, maintenance, and layout planning to increase competitiveness, productivity, and efficiency [57]. Previous studies discussed the DT-driven manufacturing solutions in shipyard optimization, energy system prediction, and improved retail service in many industries such as shipbuilding, automotive, energy, and retail [58].

Furthermore, DT enhances the supply chain, using real-time simulation, production, and historical data processes, by offering services such as program verification, process optimization, quality prediction, and intervention control [59]. Previous studies highlighted the advantages of the DT concept in supply chain management: enhanced connectivity, improved end-to-end visibility, increased agility and resilience, and the ability to tackle complexity [60].

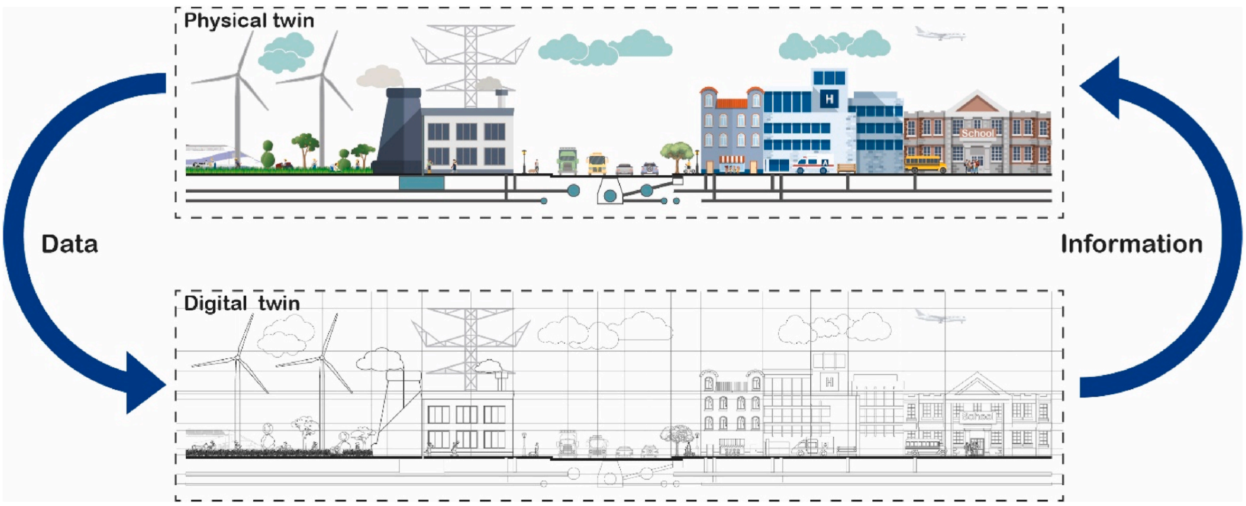

Fig. 3. Data flow and information flow in digital twin.

To summarize, DT has been applied to various fields and continues to penetrate different domains. Healthcare management [61], military [62], agriculture [63], cyber-security [64], farming [65], construction [66], and energy sector [67] are the other fields where DT technology has been applied. The main and subcomponents of DT exhibit differences because of the variations in the application areas and implementation purposes and lack of standardization [68]. Fig. 4 demonstrates the common main components of DT.

Every DT model begins with the data collection from its physical twin. The data sources can be singular or multiple based on the intended goals. For example, Park and You [19] collected different types of data from various sources, such as electricity and gas consumption, household waste, and the number of vehicles, to evaluate carbon emission levels in Jeonju City, South Korea. Subsequently, the collected data undergoes processing within the data processing module as required. Hristov et al. [69] proposed collecting the Light Detection and Ranging (LiDAR) data with sensors and processing it with node boxes before modeling.

Sophisticated models and simulations are applied to the processed data to derive insightful outcomes from the model. For example, Basaglia et al. [70] employed a discrete-event simulation to model the hospital patient flows in central Italy following an earthquake scenario. These insights can be presented as 2D and 3D visuals and graphs or virtual reality formats for better comprehension, particularly for stakeholders without expertise in the field. Yavo-Ayalon et al. [71] conducted several bus tours for households from Roosevelt Island and introduced a variety of climate change scenarios by using VR glasses. Ultimately, these insights are vital in guiding the decision-makers concerning potential future outcomes and scenarios. Kim and Ham [72] constructed a DT model to inform the decision-makers about the current situation of the power infrastructure in Houston, TX, by collecting crowdsourced data to update the 3D DT model. Finally, collected data is sent back to the physical twin to inform it, and this uninterrupted cycle is a continuous process. This ongoing loop ensures that DT model remains up to date, dynamic, and realistic by providing a constantly evolving representation of the physical component.

3. Methodology

This section demonstrates a comprehensive methodology derived from Kitchenham et al. [73] for a systematic literature review to examine DPRMT and EW by adapting a structured procedure to mitigate biased results. For this, we formulated a set of research questions as the initial step of the procedure to review and analyze DPRMT and EW. A search string was created to find the relevant studies. This string was finalized after a trial-and-error refinement process to find the most accurate and effective search string for DPRMT and EW. Subsequently, the studies were selected based on a series of exclusion criteria after reading titles, abstracts, and full papers. A comprehensive data extraction form was developed to collect general information such as publisher's name and specific information such as machine learning algorithms (Appendix Table 43). Finally, the collected data was analyzed and categorized based on the research questions, allowing for a structured presentation of results, key insights, conclusions, and future recommendations.

3.1. Research questions

We employed five research questions (RQs) to address the primary goals of this study. These RQs were selected to facilitate a comprehensive exploration of the state-of-the-art within this research domain to uncover significant achievements and potential gaps. This methodological analysis of the Structured Literature Review is anchored upon the following RQs:

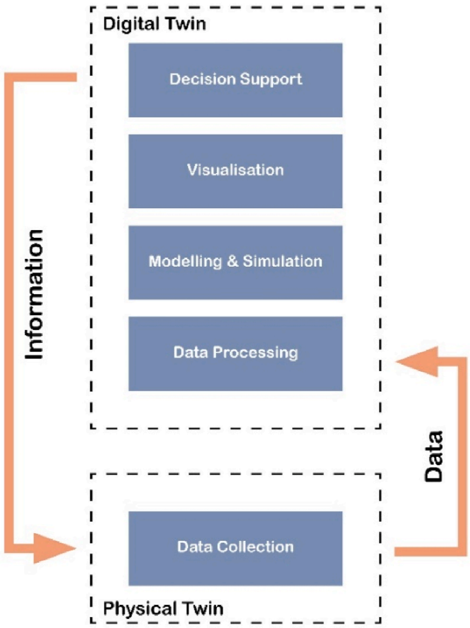

Fig. 4. Main components of DT.

RQ1. Which countries and case studies contributed to the use of DPRMT and EW?
RQ2. What are the disaster types and domains those studies are focusing on?
RQ3. What are the data collection methods, and what types of data have been used to address DPRMT and EW?
RQ4. What machine learning algorithms have been used to address DPRMT and EW?
RQ5. What are the existing research directions, achievements, and challenges?

3.2. Search strategy

This search was conducted on Scopus and Web of Science, which are well-known and highly accepted databases. The search was conducted in April 2024 without any publication date limitation. The following search string was formulated and executed on the search engine of the two databases to search for title, abstract, and keywords of the papers:

((“disaster risk management” OR recovery OR relief OR damage OR impact OR post-disaster OR response OR evacuation OR reconstruction OR rehabilitation OR “early warning”) AND (earthquake OR typhoon OR tsunami OR flood OR hurricane OR tornado OR volcano OR landslide OR wildfire OR drought OR cyclone OR avalanche OR hailstorm OR blizzard OR heatwave OR bushfire OR “forest fire” OR pollution OR “climate change” OR disaster OR “natural hazard” OR storm) AND (“digital twin” OR “smart city” OR “digital city”))

The search string is the combination of three parts separated by “AND”. The first part aimed to find the relevant publications concerning the PRM components and EW. The second part aimed to find relevant studies focusing on disasters. Finally, the last part aims to find relevant papers focusing on digital twins.

3.3. Study selection criteria

In the initial phase, the papers retrieved through the execution of the search query were manually filtered to find the most appropriate studies. During this process, a set of exclusion criteria (EC) was applied to address the objectives of the study. Papers not written in English and without available full text were excluded. Moreover, papers not about DT, only mentioning DT shortly, not directly focusing on disasters, or not directly contributing to PRM or EW were also excluded. Moreover, papers focusing on the performance of one building or infrastructure were not selected since this study focuses on community-level DPRMT and EW.

Furthermore, our study excluded papers focusing on the long-term effects of climate change, such as air pollution, as it emphasizes immediate post-disaster response and recovery. Finally, studies focusing on building specific hazardous events such as fire and studies not focusing on urban areas were excluded. Our study includes review papers and concept model papers, unlike the conventional practice of excluding them. The objective of the study is to gain insights into the current achievements of existing review papers using DT in PRM and EW to create a conceptual design of DPRMT. Those ECs are listed in Table 1.

3.4. Data extraction

Data Extraction is of vital importance in order to extract the necessary data from selected papers. To facilitate this, we created a data extraction form (Appendix Table 3) to comprehensively address the defined research question. This form consists of attributes to gather general and specific information from the papers. Those general attributes are publication year, publisher database, type of publication, publisher journal, and country of the author. The specific attributes are focused disaster type, domain of the paper, data type, data collection method, case study of the paper, case study country, and which machine learning algorithms were used. After general data extraction while screening the papers, we reviewed the papers in detail with careful reading and examination to ensure the quality of our data collection.

3.5. Data synthesis

The final step of the systematic literature review process is synthesizing the extracted data to address the research questions and present the results. This step summarizes and visualizes the selected data according to each research question. This process helps reveal the key insights of the results through the process, make comprehensive conclusions, and formulate future recommendations.

Table 1
Exclusion criteria (EC) for paper selection.

ID	Exclusion Criteria
EC1	Papers are not written in English
EC2	Papers in which the full text is unavailable
EC3	Papers are not about DT or only mention DT shortly
EC4	Papers are not directly focused on disasters
EC5	Papers do not directly contribute to post-disaster risk management or early warning
EC6	Papers are focusing on one building or infrastructure's performance
EC7	Papers focus on the long-term effects of climate change, such as air pollution
EC8	Papers are not focusing on urban areas
EC9	Papers are focusing on building-specific hazardous events such as fire

4. Results and discussion

In total, 1483 papers were identified in two databases: 842 in Scopus and 641 in Web of Science (Fig. 5). In the initial stage, the papers not written in English and not having DT context were excluded. The number of studies was filtered to 185 and 127 in two databases after reading their titles, keywords, and abstracts, respectively. Then, the screened papers from the two databases were merged by removing duplicates. In the final stage, 96 papers were selected based on the ECs for detailed review.

Fig. 6 shows the yearly distribution of selected papers in DPRMT and EW between 2014 and April 2024. The number of studies in this area is limited since it is an emerging research area. Notably, there is a significant increase in the number of studies in 2023.

Fig. 7a represents the publishers' names of the selected 96 papers. IEEE is the most popular publisher with 33 papers, and MDPI is the second with 16 papers. These two are followed by Elsevier with 15 papers. Springer and ASCE Science have 7 and 4 papers, respectively. Besides, the results showed that 50 of the selected papers are journal articles, 42 are conference papers and 4 are book chapters (Fig. 7b). The most frequently published journals are Water (5 publications), Sustainable Cities and Society (4 publications), and International Journal of Disaster Risk Reduction (3 publications).

Fig. 8 shows the distribution of these papers by paper type. The figure indicates that majority of the papers are case studies: DT-driven PRM papers (58) and DT-driven EW papers (5). Only 7 out of 96 papers are review papers: 5 for DT-driven PRM and 2 for DT-driven EW. This distribution indicates that an emphasis should be placed on concept and review papers.

4.1. RQ1. Which countries and case studies contributed to the use of DPRMT and EW?

Fig. 9 illustrates the worldwide distribution of the selected 96 papers. The figure highlights the involvement of 28 distinct countries utilizing DPRMT and EW, with the geographical distribution based on the locations of the first authors' organizations. The

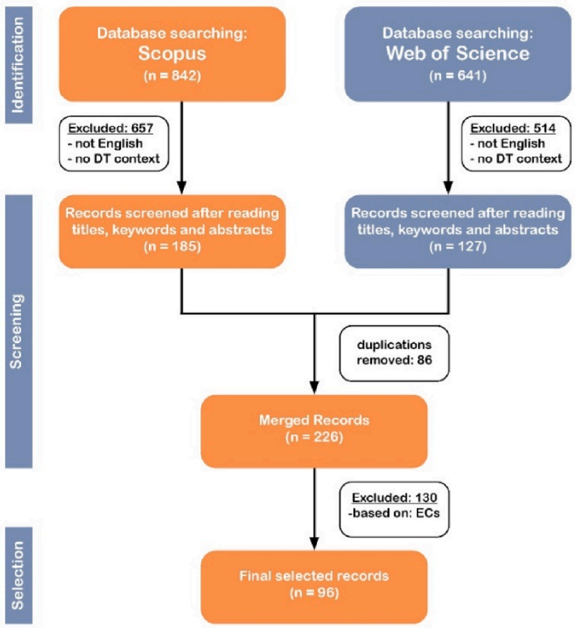

Fig. 5. Paper selection process.

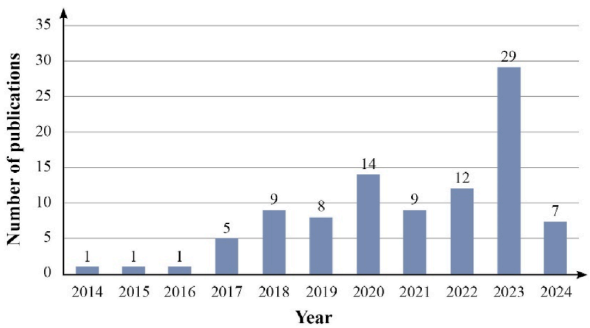

Fig. 6. Yearly distribution of the selected papers.

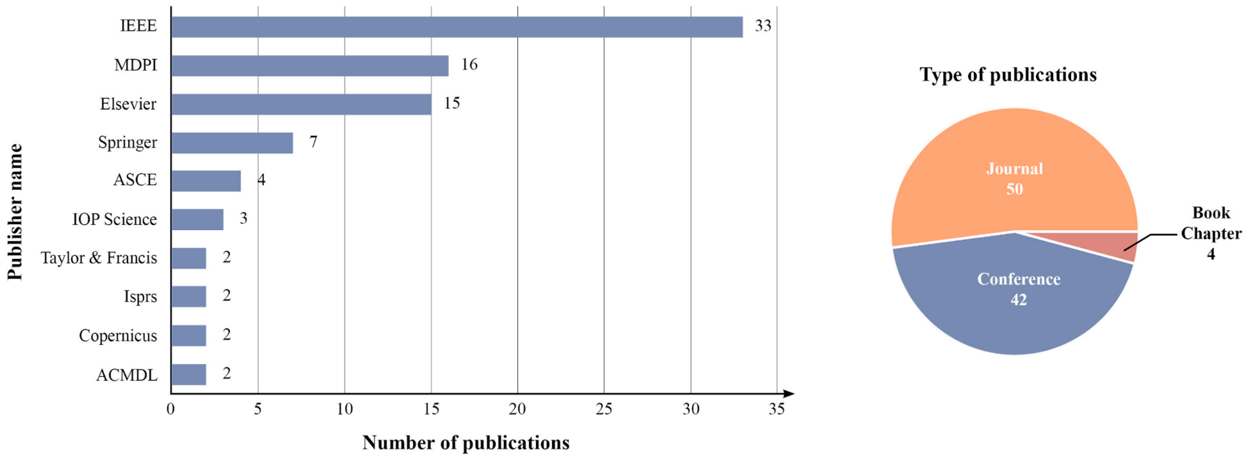

Fig. 7a. Publishers of the selected papers, b: Type of the publications.

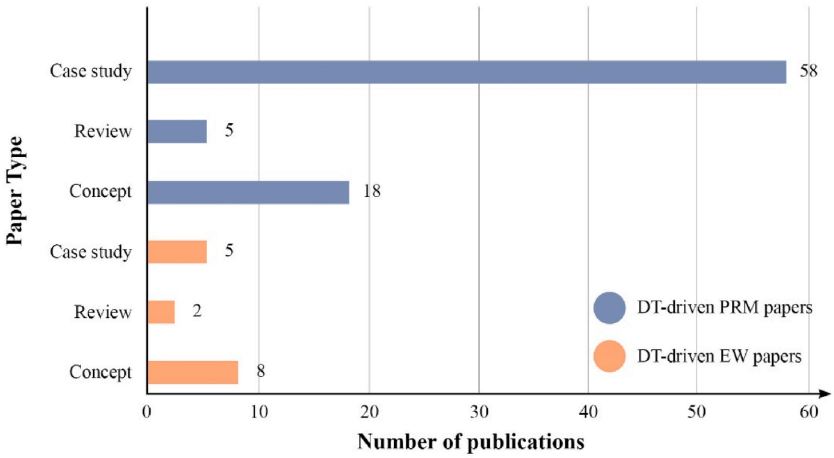

Fig. 8. Distribution of DT-driven PRM and DT-driven EW papers by paper type.

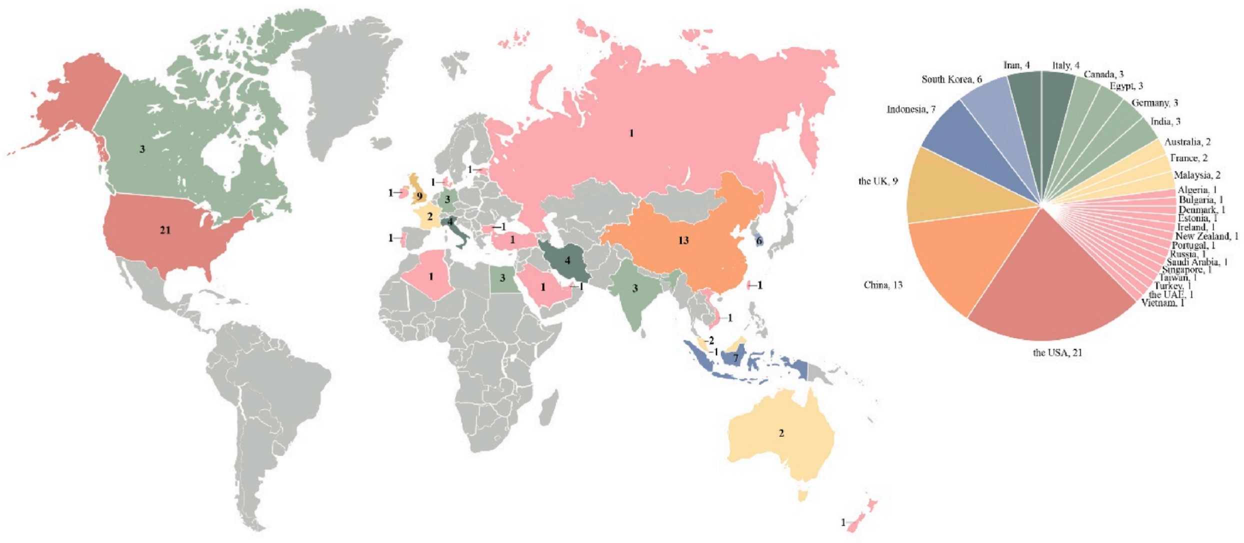

Fig. 9. Worldwide distribution of the selected papers based on the locations of the first authors' organization.

United States leads with 21 papers, contributing most among the other countries. China and the UK followed with 13 and 9 papers, respectively. Furthermore, Indonesia and South Korea have 7 and 6 papers, respectively.

Fig. 10 presents the worldwide distribution of the selected papers with case study applications. The results showed that the USA with 14 times is the most popular country regarding case study applications. Besides, 13 papers utilize a generic approach without focusing on one specific country. Moreover, 7 of the selected papers are review papers, and 26 are concept models.

4.2. RQ2. What are the disaster types and domains those studies are focusing on?

Fig. 11 represents insight into the distribution of research domains and disaster types of the selected 96 publications. Many papers took a general approach, with 32 focusing on more than one disaster type. This generic approach indicates that the concept DT or DT model considered multiple hazard types. Flood, among others, drew significant attention and were addressed in 32 papers. Additionally, wildfire and earthquake hazards were addressed in 13 and 10 papers, respectively. Hurricane and landslide were also topics of discussion in 6 and 3 papers, respectively.

Regarding the domains of the publications, 21 papers concentrated on disaster management. 15 of the remaining studies focused on EW. Situational awareness and evacuation were the topics of 11 and 10 studies, respectively. Notably, only three studies focused on post-disaster recovery.

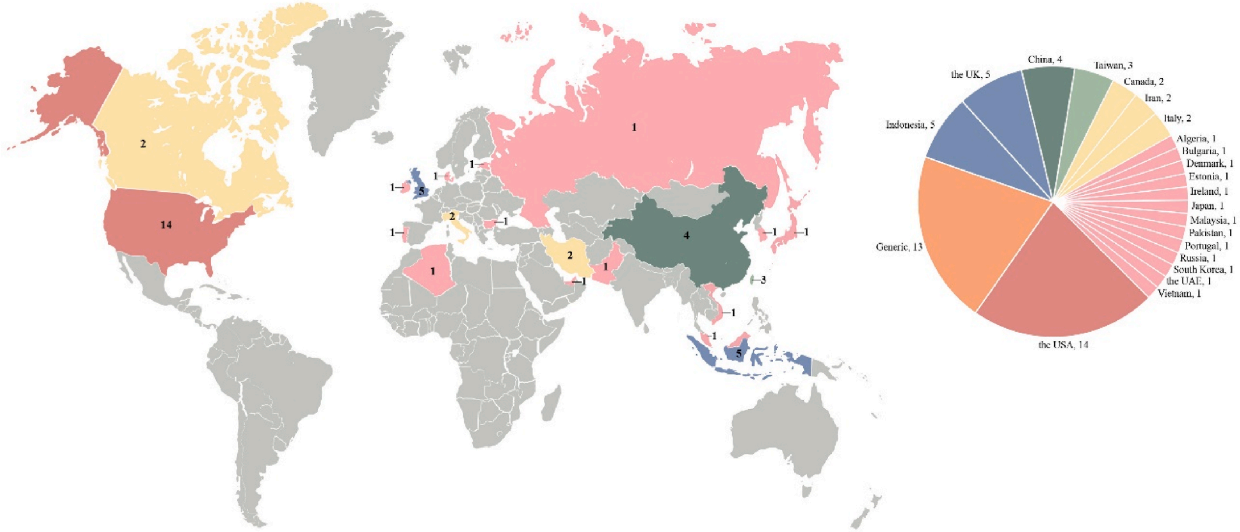

Fig. 10. Worldwide distribution of the case study areas.

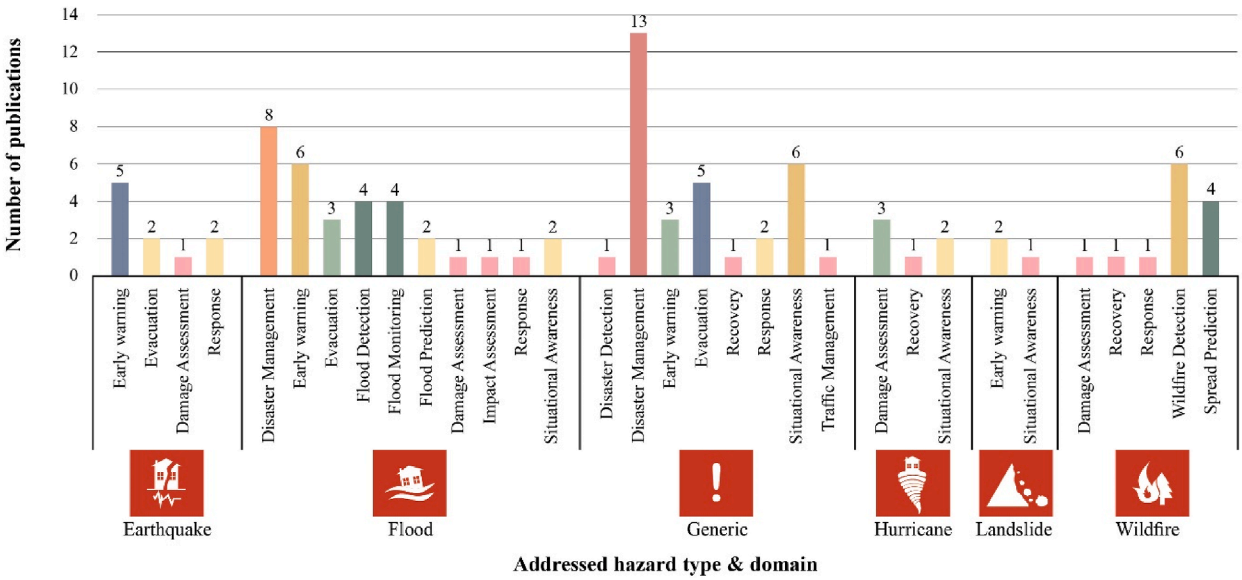

Fig. 11. Addressed disaster types and domains in DPRMT studies.

The results underscore the potential of landslides and hurricanes for future research focus, as they were the focus of limited number of studies compared to hazard types. No study focused on tsunami, typhoon, and volcano. Even though 6 studies examined the direct effects of the disasters on the physical environment and focused on post-disaster damage assessment, only one study examined the indirect impacts of disasters by specifically focusing on the flood impact scenarios on the house prices [74]. It is significant to note that only three of the selected studies focused on the recovery phase within DRM although recovery is one of the main components of post-disaster risk management, representing a significant potential for future research [75–77].

In the realm of PRM, a paradigm shift has occurred towards a broader perspective considering multi-hazard scenarios and cascading effects [25,78]. This shift is because considering disaster in isolation and ignoring the interaction between hazards and cascading effects are unrealistic [79]. For example, the 2011 Tohoku Earthquake in Japan and the 2018 Palu Tsunami in Indonesia were both strong earthquakes that triggered tsunamis, leading to severe flooding in coastal and nearby areas [80,81]. Modern PRM approaches, including the Sendai Framework for Disaster Risk Reduction, integrate multi-hazard risk assessments and cascading effect analysis into their planning process to achieve a holistic approach [11,82]. The use of technologies like the remote sensing imagery and GIS following the 2015 Nepal Earthquake was crucial in landslide impact assessment triggered by the earthquake to enhance better response strategies [83]. Although existing DPRMT models have not adopted the perspective of multi-hazard scenarios and cascading effects of disasters, which holds immense importance for having realistic scenarios, they can model how various disasters, such as earthquakes, floods, and wildfires, interact and amplify each other's effects. In addition, the adverse effects of disasters extend beyond the direct impact on human lives. On the contrary, disasters can bring about cascading effects such as infrastructure damage, resource scarcity, social and economic impacts, humanitarian crises, and displacement [84,85]. These effects can deepen the harmful effects of disasters by making them more challenging to manage. This approach can help decision-makers to have robust, effective, and comprehensive resource allocation and response coordination to reduce existing and future risks, prevent secondary disasters, and build long-term recovery planning [86].

4.3. RQ3. What are the data collection methods, and what types of data have been used to address DPRMT and EW?

The most common data collection method employed in the selected papers is secondary data. Secondary data in this context means data already collected by other individuals or organizations for similar or different purposes. When a model solely based on secondary data or manual data collection without dynamic data collection capabilities, this static representation of the physical environment is digital model [87]. A model that incorporates dynamic data flow and displays real-time changes of the physical environment but cannot reflect changes in digital environment to physical counterpart is digital shadow [87]. In contrast, a digital twin dynamically gathers data and enables bidirectional synchronization between the digital model and its physical counterpart [88]. This synchronization allows changes in either the physical or digital representation to be reflected instantaneously in the other.

Truu et al. [89] used historical rainfall data as secondary data to calibrate their models for flooding scenarios in their case study areas in Estonia and Sweden. Basaglia et al. [70] did a comprehensive literature review to collect the necessary parameters for their discrete event simulation model to demonstrate the post-earthquake response emergency response of different hospitals in Italy.

Remote sensing is another data collection method used most frequently in the selected papers. For example [90], collected images of a case study forest with unmanned aerial vehicles (UAV) in Russia for hazard assessment following a wildfire. Furthermore, Park and You [19] employed light detection and ranging (LiDAR) technique and drone images to create a comprehensive 3D geometry of a case study river in South Korea for flooding scenarios. The other data collection methods used in the selected papers are 3D modeling, crowd sourcing, manual collection, remote sensing, secondary data, sensor networks, and social sensing. Fig. 12 shows the data collection methods employed in the selected papers.

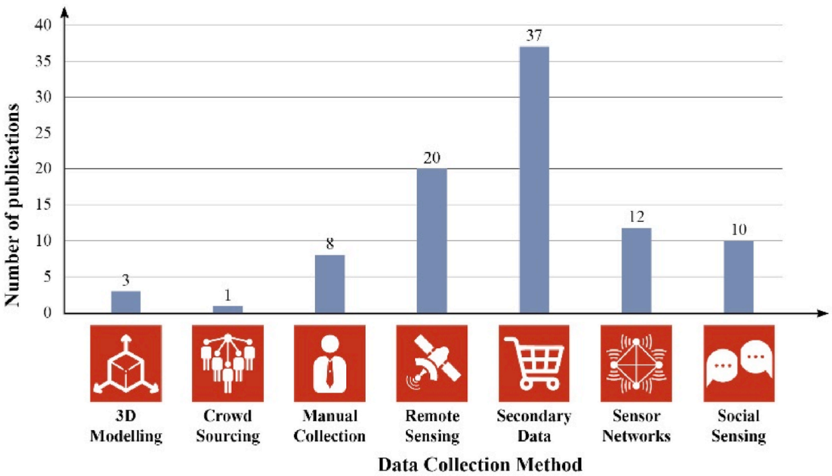

Fig. 12. Data collection methods of the selected papers.

4.4. RQ4. What machine learning algorithms have been used to address DPRMT and EW?

Several ML and DL algorithms have been used in the selected DT-driven PRM and DT-driven EW papers (comprehensive list of the used ML and DL methods are provided in Appendix - Table 3). For example, Fan et al. [2] investigated the situational awareness of the citizens following built environment disruptions after Hurricane Harvey in 2017. The study collected social media data from Twitter and employed a kernel density approach to determine the scales of the disruptions in the event. Yun et al. [91] in another study applied the Convolutional Neural Network (CNN) algorithm for feature extraction from the input data in their DT model for wildfire spread prediction. Moreover, the study created a hybrid model and used a CNN-based model to refine the prediction of the physics-based model. Zhong et al. [92] proposed a global wildfire prediction method with the help of a deep-learning-based DT model that combines three ML algorithms. They used a Convolutional Autoencoder (CAE), combining autoencoder and CNN, for feature extraction and dimensionality reduction and Recurrent Neural Networks (RNNs) for prediction. Other ML algorithms used to facilitate the use of DT in PRM include support vector machine (SVM) [93], Artificial Neural Network (ANN) [94], Random Forest and Gradient Boosting [95], Long Short-Term Memory (LSTM) [92,96], Decision Tree [97], K Nearest Neighbors [98], FireNet [99], Yolov8 [100], and DeepLabv3 [101] to address different disasters including earthquake, flood, hurricane, wildfire. Only two DT-driven EW studies employed ML algorithms. Kuyuk and Susumu [102] presented a methodology for real time classification of earthquake vibrations into near-source and far-source employing LSTM to enhance rapid warnings even in the blind zones without earthquake EW systems. Liu et al. [103] employed various ML algorithms: SVM, ANN, extreme learning machine (ELM) and gaussian process regression (GPR), and developed an EW system for rainstorm-induced landslides to improve post-disaster response of mountainous areas and their resilience. Overall, the results showed that only one study with dynamic dataflow employs Machine Learning algorithms [103] while others lack dynamic data flow and rely on static data.

Integrating XAI with DPRMT poses excellent potential to enhance the decision-making process and disaster risk management outcomes by providing transparency, accountability, and decision support, improving community engagement, and mitigating bias and ethical concerns [104,105]. The power of XAI lies in its ability to offer a transparent process showing how decisions are made, which is crucial to building trust and collaboration among various stakeholders, including government agencies, NGOs, and affected communities [101]. This transparent and interpretable process supports decision-makers in being involved in the process and tracing these decisions instead of adopting them as black-box decisions [105]. Moreover, it is also crucial to mitigate any bias about the fairness of response and recovery strategies, such as resource allocation in the aftermath of disasters, by building public trust and acceptance [99].

XAI also leverages the explanations behind the predictions made about disasters. Furthermore, XAI can explain the potential impact of disasters to individuals and help them take informed actions [104,106]. This ability is also helpful for them to follow the proposed recovery actions by government agencies. XAI-driven models can improve their accuracy based on the comments and explanations provided by stakeholders, and this also helps to improve disaster policies for the future [99].

4.5. What are the existing research directions, achievements, and challenges?

DPRMT is promising regarding response, and recovery phases of disaster risk management; however, studies in this field have limitations. This systematic literature review revealed that existing studies rely on only one or two data collection methods or sources, which might not be comprehensive enough to represent post-disaster situations successfully. Each data collection method can reveal different insights about post-disaster situations and help decision-makers to have diverse perspectives [107]. In addition to capturing different aspects of post-disaster situations, different data sources can help verify data from multiple sources to ensure data accuracy and reliability [108]. Specific data may lose its validity or become insufficient in time due to temporal and spatial coverage, which require a multi-source data collection to capture the dynamic nature of disasters [109,110].

Existing case studies did not consider the affected communities' demographic and financial aspects, which have a crucial impact on the outcome of post-disaster response and recovery policies [111]. Different demographic groups in the same affected community might experience different recovery patterns since some groups are more vulnerable than others [112]. For example, elderly and disabled people might require extra help during their evacuation in the aftermath of the disasters, which requires more specialized evacuation plans [113]. A successful resource allocation plan following a disaster requires resource optimization based on accurate and comprehensive demographic data [114]. Furthermore, vulnerable income groups might have lifelong effects after disasters due to the lack of financial capacity to cope with its consequences [115]. For example, people from high-income groups recovered quickly after the 2018 Lombok earthquake, although financially disadvantaged people experienced a longer recovery process [116]. Therefore, financial support is vital in short-term and long-term disaster recovery, and financial data is critical to manage these processes.

The affected communities' social dynamics are crucial in a successful post-disaster response and recovery process [2,117]. In the aftermath of a disaster, people rely on information from friends, family, and the community they feel they belong to, and this might result in collective behavior to secure themselves in this chaotic situation [118]. Additionally, family structures and relationships with their neighbors and friends shape their risk of perception and sense of belonging to the area, and these plans play a crucial role in the evacuation and relocation decisions of the households [119–121]. Moreover, individual decisions of the households in the aftermath of disasters might hinder the desired outcomes and result in severe delays and other losses [119]. Therefore, analyzing and understanding these dynamics is necessary to meet the social expectations of the community and design strategies and policies accordingly. However, existing studies in DPRMT did not consider the social dynamics of the affected communities and their effects on the PRM frameworks.

Existing studies shows that DPRMT studies employing dynamic models where the model is continuously updated with data flow are somewhat limited (Appendix Table 3) [25,122]. Disasters are not static processes; instead, disaster situations change quickly due to their dynamic nature, such as the progression of events, cascading and compounding effects, evolving conditions, and post-disaster response [123]. This continuous model update is crucial to understanding the current situation and making timely decisions during the response and recovery phases [21]. For example, how a wildfire is spreading, or an area is flooding should be captured to optimize emergency response, resource allocation, and evacuation planning [92,95].

While the very first impression of DT is to collect all data automatically through sensors, it is crucial to recognize the effectiveness of manual data collection such as surveys in understanding complex dynamics of the affected communities. Manual data collection methods can be instrumental in integrating the dynamics of the affected communities into digital twin by combining it with dynamically collected other data to achieve more holistic views of disasters. This method is particularly valuable when other data collection methods are limited due to post-disaster disruptions [70]. Even though the potential delays are due to the human involvement in manual data collection, this manual data feed may benefit from efficient data processing and analytics by leveraging Machine Learning models for rapid synthesis and integration [124]. Alternatively, this kind of deeper social impact analysis can be done in the critical phases of post-disaster recovery, while digital twins rely on other automatically collected data. This integrated approach supports decision-making processes by providing comprehensive understanding to enhance the effectiveness of disaster management strategies.

Current studies focus on only one or two elements at risk in isolation from others, which hinders understanding the complex and interconnected systems and subsystems within the study scale. A system or subsystem's failure in urban areas directly affects others since they are highly interconnected [125]. To exemplify, power outages after disasters hinder successful emergency response and recovery processes since many systems, such as transportation, communication, and water supply, need electricity to function appropriately [126]. After the 1995 Kobe earthquake, the response phase could not achieve the desired outcomes due to massive telecommunication outages [127]. Similarly, affected people could not get the necessary supplies and services promptly due to the severe damage to the transportation network following the 2008 Wenchuan earthquake [5]. Besides, analyzing only one system in isolation can bring about an underestimation of the cascading effects of disasters, resulting in inadequate emergency response [128,129].

It was discussed in Fig. 2 that PRM covers emergency response, and recovery processes. Studies focusing on the recovery part of PRM are limited, although they shape the overall outcome. The recovery phase encompasses a series of activities to retrofit, repair, and reconstruct damaged entities to achieve desired or acceptable functionality in the aftermath of a disaster [130]. This phase can be described as dynamic and complex due to involving a series of parties, including clients, contractors, suppliers, and subcontractors in construction projects, to achieve a common goal [131]. However, the post-disaster conditions make this process more difficult than regular times. For instance, more than 600,000 buildings collapsed, and 300 buildings were damaged following the Nepal Earthquake in 2015 [132]. In addition to the complexity level, limited resources, supply chain disruptions, and highly skilled labor availability hinder timely recovery [133,134]. These are the challenges to be addressed in digital twin-driven PRM studies.

One of the immense potentials of DPRMT is the ability to interact with stakeholders and people from various disciplines and even decision-makers. It is challenging to have a common understanding of the same case, especially with people from different backgrounds. DT is suitable for interdisciplinary collaboration and working collectively to achieve common goals [135,136]. A dynamically updated DT model ensures that decision-makers or end users make decisions based on more accurate and coherent data. The interaction with the end users also provides an ability to test different scenarios and select the best alternative not only before the event but also in the post-disaster period [12]. This interaction with end users is not limited to web or mobile terminals; disasters or disaster scenarios can be tracked with Virtual Reality technologies [71].

Data and model integration/fusion stands at the core of DPRMT, enabling adequate risk management strategies with a comprehensive understanding and improved situation awareness. Nevertheless, this process presents challenges as it necessitates integrating disaster-related data from various sources, each bearing dissimilar formats, scales, and standards [137]. Model integration can pose further challenges as various models may operate on disparate assumptions and parameters, demanding meticulous alignment [138]. Overall, successful data and model integration in the realm of DPRMT depends on considerable effort, interdisciplinary collaboration, and a methodological approach to overcome the challenges.

Table 2 presents the aims and key findings of review papers highlighted in Fig. 8. These studies provided results similar to our study in terms of the need for explainability of AI and ML models, the importance of understanding human behaviors in the aftermath of disasters, and ongoing data management and privacy concerns [2,12,25]. These review papers collectively agreed that existing DT-driven PRM and DT-driven EW studies need further conceptual development and should generally be improved by providing diverse data [15,25,139]. Moreover, our study highlights that current studies lack dynamic data flow and primarily rely on secondary or static data, reducing them to digital shadows and, in some cases, only digital models. It also indicated that the recovery phase of PRM, the social and demographic dynamics of the communities, and the integration of manual data collection with DT have been neglected. Importantly, our study proposes an improved conceptual Digital Twin-based Post-Disaster Risk Management framework, which will be thoroughly explained and discussed in the next section.

5. Conceptualization of DPRMT

After analyzing previous studies with a systematic literature review, a concept model of DPRMT was designed based on the insights, achievements, and literature gaps encountered during this review. Since studies focusing on directly DT-driven PRM are limited, the model's design was supported by studies focusing not only on digital twin but also post-disaster risk management to achieve a comprehensive model that may improve overall post-disaster response, and recovery efforts. The model aims to minimize the adverse effects of disasters and facilitate timely, effective, and optimal post-disaster response and recovery. This section presents a conceptualization of the components of DPRMT, which takes the main components of DT in Fig. 4 as basis, as follows: 1) entities at risk, 2) data

Table 2
Aims and key findings of review papers (the seven review papers highlighted in Fig. 8).

Ref.	Aim of the study	Key findings
Cheng et al. [12]	To review and analyze the applications of DT in civil and infrastructure emergency management (EMCI), identify current progress and limitations, and propose a framework for their use across different stages of EMCI.	AI in predicting disaster dynamics faces challenges with prediction explicability. National security concerns and commercial competitiveness restrict access to crucial infrastructure data, leading to incomplete disaster data. Current research focuses more on strengthening infrastructure capabilities, with less attention to human emergency behavior and responses.
Fan et al. [2]	To present a vision for the Disaster City Digital Twin, integrating AI for disaster management, enhancing situation assessment, decision-making, and coordination among stakeholders, and identifying current progress and limitations.	Rapid situational data collection from satellites, crowdsourcing platforms, and social media, often noisy and unreliable, requires the integration of machine learning and crowdsourcing techniques for improved data labeling and rumor detection. Advancing AI-based multi-actor decision-making models through automated multi-agent systems with deep learning is crucial for understanding and modeling relief actors' decision-making processes in emergency responses.
Ariyachandra and Wedawatta [25]	To review the evolving concepts of Digital Twin Smart Cities (DTSCs) for DRM, clarify their potential in disaster mitigation, preparation, response, and recovery, and identify current progress and limitations in this field.	Despite preliminary attempts to establish DTSCs worldwide, developing a 'DTSC for Disaster Risk Management' as a collective system is still in its early stages. While DTSCs offer significant potential benefits, they also introduce additional complexity and challenges, including the need for advanced technical solutions and concerns about data management and privacy.
Bakhtiari et al. [122]	To conduct an integrated critical review of cutting-edge digital visualization tools (CDVT) and assess their contribution to DRM stages of urban flood risk management.	Integrating real-time data for infrastructure and environmental conditions with data-driven modeling offers unique opportunities for CDVTs. This integration can significantly enhance real-time flood forecasting, improving early warning, preparedness, and resilience to floods for stakeholders and the public.
Mei et al. [139]	To review the current state of IoT applications and technologies for geohazard prevention, assess their integration into smart cities and DT frameworks, and identify challenges and opportunities for enhancing urban resilience and disaster management.	There is a need for robust data management systems, integration of heterogeneous data sources, ensuring data privacy and security, and standardized protocols for sensor data. Future research should focus on enhancing the accuracy and reliability of IoT sensors, developing machine learning models to process collected data, and improving interoperability within smart city frameworks. The study calls for more pilot projects and real-world applications to validate the theoretical benefits of IoT and DT technologies in disaster risk management.
Hernaningsih et al. [140]	To analyze and propose the integration of smart city and smart water management (SWM) concepts, aiming to create an efficient, sustainable, and technologically advanced urban water management system.	There is a need for an online water quality monitoring system to continuously monitor water quality in real-time. This system ensures water quality is maintained and issues are promptly addressed.
Macatulad and Biljecki [15]	To explore and highlight the potential of urban digital twins (UDTs) in enhancing DRM, building upon the progress and opportunities identified in the midterm review of the Sendai Framework.	Effective use of urban digital twins (UDTs) requires robust data management practices and addressing privacy concerns to ensure data accuracy, security, and ethical use. Further research is needed on integrating UDTs with emerging technologies, such as AI and IoT, to enhance their capabilities in disaster risk management. Implementing UDTs encourages collaboration among sectors like urban planning, emergency services, and public health, fostering a more integrated approach to disaster management.

collection and pre-processing, 3) data processing, 4) digital modeling, 5) information decoding, and 6) user interaction and application Fig. 13.

This DPRMT model starts by identifying entities at risk during disasters in the first component. This step is crucial since previous studies generally focus on one or limited number of entities during disasters such as only buildings [141] or human lives [142] in isolation by ignoring the interconnectedness of these entities with each other [19,143]. Next, it systematically collects data about these entities before, during, and after disasters using various data collection methods and preprocesses this dynamically collected data for further steps. The reviewed studies generally used one or a limited number of data collection methods such as remote sensing [95,144], social sensing [145,146], and sensor networks[91,147]; therefore, the types of data and data collection methods found in the literature have been presented comprehensively. In the next component, collected data is prepared for the digital modeling phase in the subsequent stage through a series of additional processes [2,148]. One or multiple models are established to generate information for this process such as AI-based modeling [100,101], BIM [17], and agent-based modeling [149,150]. User interaction component is facilitated through various tools such as Virtual Reality [71] or web portal terminal [19] to interact with different groups of people such as decision makers, authorities, or residents, allowing this model to be applied in various areas such as evacuation [142,151], damage assessment [152,153], hazard spread prediction [92,154]. In the model, all components are interconnected; this active process is a continuous cycle.

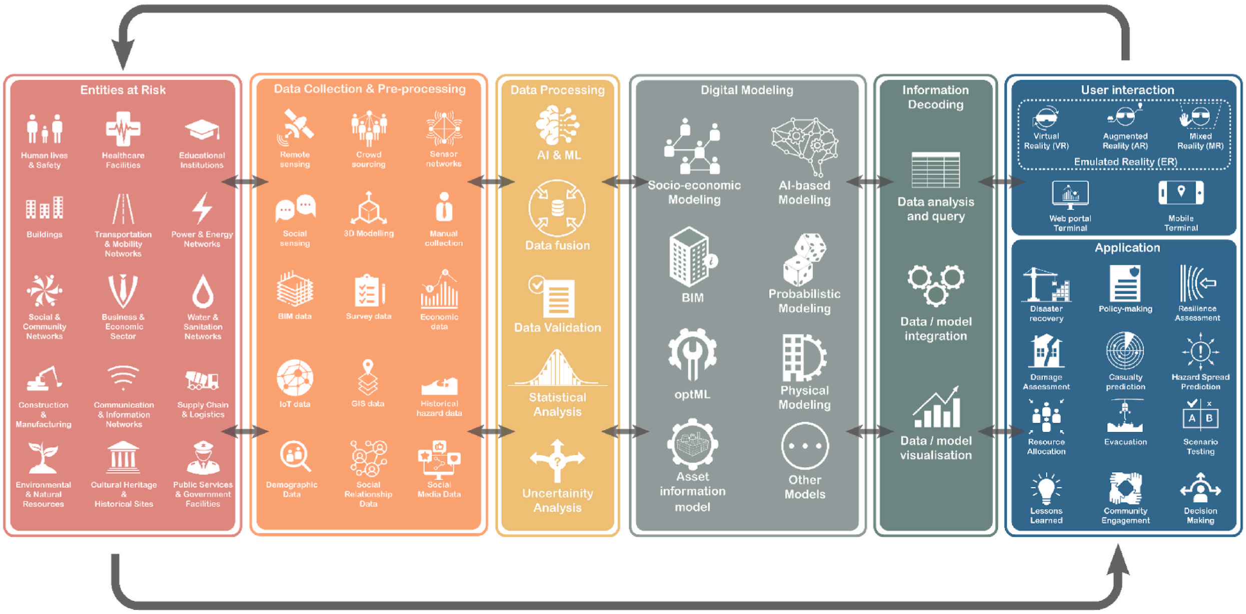

Fig. 13. Conceptualization of components of DPRMT.

5.1. *Entities at risk*

This section provides an overview of entities at risk during disasters, depicted in DPRMT framework, and explain their significance in PRM. Regarding entities at risk, human lives are the primary concern of authorities during and after the event in PRM to minimize the loss. In 2004, the Indian Ocean earthquake and tsunami, an earthquake of 9.1–9.3 followed by a tsunami, hit Indonesia, Sri Lanka, India, and many other countries, resulting in more than 280,000 deaths [155].

Moreover, buildings are another significant entity at risk during disasters since damaged or collapsed buildings result in forced displacement or voluntary relocation to reduce the existing and future risks and human losses due to collapsed buildings. These buildings are also the primary sources of financial loss during disasters that cause social, technical, and organizational problems. It was reported that more than 300,000 buildings were damaged (including collapsed and other damage states) in the 2010 Chile earthquake [156].

Following the event, healthcare facilities are stressed not only structural-wise but also organizational-wise. After the event, these facilities should rearrange their organizational procedures and increase their capacities to meet the post-disaster patient demand [70]. Due to the limited opportunities and time constraints to test the preparedness of hospitals for emergencies, disasters might turn into more profound crises, and both disaster-affected and existing patients may experience casualties [70]. Following Hurricane Katrina, vulnerable people, especially those over 75 years old, died due to unpreparedness for evacuation and medical care [157]. Therefore, these facilities are critical to successful PRM and require additional effort in the response and recovery phases.

Educational institutions hold significant importance in society since student spend most of their time in these buildings and receives education [158]. Moreover, education and educational institutions become more critical during the response and recovery phases. These structures and surrounding areas become emergency shelters for disaster-affected people since they are designed accordingly [159]. Furthermore, continuation of education is critical for students' psychological health and adaptation in the recovery process. During the 2008 Cyclone Nargis in Myanmar, the affected children's education was disrupted due to over 4000 collapsed school buildings [160].

The following entities at risk in the context of PRM are critical infrastructures: transportation and mobility networks, power and energy networks, water and sanitation networks, and communication and information networks. Transportation networks are fundamental in today's societies to facilitate the movement of people and goods. Moreover, they are crucial for evacuating the affected people, transferring them to emergency shelters, and post-disaster recovery steps [161]. Therefore, transportation disruptions shape the outcomes of the response phase and the overall post-disaster recovery performance of the affected communities. These disruptions also affect other infrastructures, creating financial and organizational problems. In the 2010 Chile earthquake, transportation infrastructure was severely affected, and around 300 bridges were damaged, resulting in almost US$ 1 billion in total to repair [162].

Power and energy networks are the lifeblood of other infrastructures since they depend on energy to function correctly during disasters. Since supplies such as electricity cannot be stored and are required to produce other goods, they affect the overall PRM outcomes [163]. Following the 1999 Turkey earthquake, a widespread electrical blackout hampered the prompt emergency response, including efforts to suppress fires and prevent chemical leaks [164]. Using and drinking safe water is necessary for life, health, and hygiene. Otherwise, it results in serious health problems and diseases among the affected community [165]. Hence, post-disaster prompt response and successful recovery of water and sanitation networks is a milestone in disaster risk management and reduction to minimize the adverse effects [166]. Communication and information networks focus on effective and accurate information-sharing during and after disasters to manage post-disaster efforts to achieve the desired outcomes. Accordingly, authorities rely on these channels to communicate with affected people and the responders to guide them correctly and get prompt and accurate information from them to make decisions accordingly [167].

Supply chain is a process where suppliers, manufacturers, distributors, and retailers collaborate to produce raw or specified end products and transfer them to retailers [168]. Supply chains have become more vulnerable to disaster due to the interdependency level among their components [169]. Post-disaster supply chain disruptions threaten the communities and may take longer to restore to the pre-disaster conditions [170]. Accordingly, supply chain continuity is fundamental to meeting the urgent needs of the affected people and ensuring long-term recovery [171].

Disasters also affect social and community networks, hindering post-disaster effective relationships, interaction, and support systems among households. Due to the mental disorders caused by physical damage, displacement, and the loss of loved ones following disasters, households tend to isolate themselves, resulting in weakening social bonds [172]. Cultural heritage and historical sites are also affected by disasters directly and indirectly, bringing about the loss of cultural identity and historical knowledge and resulting in the loss of a sense of belonging [173,174]. Moreover, the post-disaster environmental and natural resources conditions are crucial for people to continue to live in the affected areas and may result in abandonment of the area to find alternative resources [175]. Public services and government facilities can be subject to disasters, bringing about emergency service delays [176]. All in all, the disruption of these entities can hinder the overall PRM outcomes and pose cascading adverse effects.

Disasters threaten the business and economic sectors leading to operation interruptions, financial losses and enduring economic impacts [177]. These developments impact the overall economic activities in the region, reducing the job opportunities and leading to unemployment [178]. It was reported that the unemployment in the affected community in some areas exceeded 25 % following the 2013 Lushan earthquake in China, although this number was only 10 % before the event [179]. Furthermore, people with income tied to the affected area prefer to stay in their original places to continue to income generation [180]. These different preferences hinder the inclusive recovery policies creating barriers for authorities to yield the desired outcomes. Such disasters increase the existing economic disparities, creating more devastating and long-lasting effects for lower-income people [181,182].

Following the event, the built environment, including buildings, critical infrastructures, supply chains and others, can be damaged or collapsed, including construction and manufacturing industries. These industries might not be prepared for a complex post-disaster recovery process, and this might bring about severe recovery delays. Their capacity is also limited by supply chain disruptions and material and highly skilled labor availability [183,184]. These limitations create competition for resources and lead to construction price inflation in the affected community [185]. This price inflation might trap some households and delay their recovery [186].

5.2. Data collection and pre-processing

This section delves into data collection and pre-processing methods within DPRMT framework. These methods are pivotal in shaping the quality, precision, and utility of information utilized in DPRMT applications. There are a variety of data collection and pre-processing methods that can be used to fulfill that purpose. Remote sensing is used in DPRMT, which collects information on objects, regions, or occurrences remotely, generally utilizing aircraft, satellites, or UAVs [187,188]. It utilizes sensors attached to those devices to detect electromagnetic energy emitted or reflected to capture the existing situations and ongoing changes [189]. The techniques used in remote sensing data collection can be listed as follows: satellite imagery, aerial photography, LiDAR (Light Detection and Ranging), and SAR (Synthetic Aperture Radar) [190,191]. Park and You [19] utilized LiDAR and drone photogrammetry to analyze a flooding scenario in a dam and watershed platform in South Korea. Moreover, Zhong et al. [92] employed two-dimensional image data to capture temperature, humidity, and rainfall in order to make a wildfire spread prediction. All in all, remote sensing is utilized to detect anomalies and changes in the natural and built environment with the help of satellite and UAV-based devices in disaster risk management [2]. Geometric and radiometric corrections are typically necessary for remote sensing data to eliminate distortions and enhance accuracy [192,193]. Moreover, satellite imagery sometimes requires atmospheric correction to rectify distortions and ensure data accuracy [194].

Social sensing is another data collection method used in DPRMT to extract information from social media platforms such as Twitter and Facebook with the help of Natural Language Processing (NLP) following disaster occurrences [195]. These platforms are preferred by a large number of users to reach to authorities, interact with others, and express their emotions in disaster phenomena [196]. Social sensing offers distinct advantages compared to other data collection methods since it is based on public-generated content with the potential of real-time updates on the post-disaster situations enhancing effective decision-making [2]. However, it is crucial to process the data to exclude noise and rumors in it so that to extract accurate information. The information obtained through this method is vital to deliver aid effectively, to conduct rescue operations and analyze human sentiments [197].

Crowdsourcing refers to the practice of leveraging a diverse group of people to report on an online or offline platform to collect data or information related to disasters [198]. This data collection method has significant potential during disasters, offering time-efficient and cost-effective solutions [2]. It is useful primarily when the sources of authorities to collect data is limited since it allows local residents and volunteers report from the site [199]. It is also effective for rapid real-time data collection since these people are already in the field and spread along the affected area. Similar to social media data, this information frequently encompasses noise, rumors, and inaccurate details [12]. Moreover, it was reported that the challenges related to the application of this data collection method was reliability of the resources, and policy and legislation in Canada [199]. ML and AI techniques can be used to filter and verify data in order to harness the potential of crowdsourcing and they can provide crucial contributions to the emergency and recovery phases if this method is implemented before disaster [200].

Sensor networks is a data collection method that employs interconnected devices equipped with sensors to collect data about environmental or physical phenomena before, during, and after disasters [201]. One of the most common data types collected with sensor networks is Internet of Things (IoT) which made a huge contribution to the development of DT [91,201]. It plays a significant role in updating the digital twin counterpart with real-time data collected from the field [17]. IoT devices facilitates the connection of physical entities by utilizing sensors, actuators, and networks that enable the interaction of a diverse range of devices including sensors, smart devices, mobile phones and cameras [202]. Nonetheless, sensor networks data may require data pre-processing for calibration, outlier detection, and noise reduction [203].

Manual data collection covers the processes of a human involvement gathering information and observation often from the field [204]. Furthermore, 3D modeling is another data collection method that is a cornerstone in smart city and digital twin concepts. 3D model is a fundamental tool to demonstrate any area to test any scenario before implementation decisions [17]. Building Information Modelling (BIM) is widely used as a 3D modelling method, and offers a standardized representation of building elements and systems [205]. While the various data collection methods mentioned earlier are used in DPRMT, secondary data becomes a viable option when the other methods are limited due to various reasons [70].

5.3. Data processing

Data processing has a crucial impact on the digital twins' success in PRM. This section explores the data processing techniques presented in DPRMT framework. These techniques encompass AI and ML, data validation, data fusion, statistical analysis, and uncertainty analysis. The involvement of AI and ML in disaster risk management has revolutionized data processing. These cutting-edge technologies possess a remarkable ability for pattern recognition, anomaly detection, and trend identification [20,206]. The validity of the data is vital in the domain of PRM to ensure data quality due to the limited resources and time constraints. Data validation ensures that the collected data is reliable, accurate, and appropriate for the intended purpose in the context of DPRMT to inform decision-makers [207].

Data fusion is another cornerstone in DPRMT, as relying on only one source in emergencies might be dangerous. Data fusion is the process of merging and aligning data derived from various sources [208]. This step empowers decision-makers to arrive at a more comprehensive and robust decision based on the available data. Moreover, disaster management professionals employ statistical analysis to calculate necessary descriptive statistics and to reveal the existing relationship in the collected data [209,210]. This step plays a vital role for them to gain a deeper understanding of the dynamics of disasters. Finally, uncertainty analysis allows quantifying data's uncertainty to ensure its trustworthiness [211]. This step is crucial in reliable data-driven predictions during and after disasters.

Data processing plays a vital role in DPRMT's development of robust data-driven disaster management strategies. Employing the capabilities of AI and ML, data validation, data fusion, statistical analysis, and uncertainty analysis, researchers and practitioners can reinforce their digital twins with more accurate, validated, and trustworthy data. Nonetheless, post-disaster data processing is an inherently intricate task that requires a substantial computational capacity in terms of time and scale, given the complexity of post-disaster situations. AI can mimic human intelligence to perform tasks requiring learning, reasoning, problem-solving, and decision-making of human cognitive by using various algorithms and models [212]. This ability is substantial to achieve desired outcomes in post-disaster situations. Furthermore, the progress of robust hardware components such as CPUs, GPUs, and specialized AI accelerators equipped AI with high progressing power in speed and scalability to perform complex computations: rapid data processing, real-time decision-making, and handling large datasets [213,214].

5.4. Digital modeling

This section delves into the digital modeling techniques presented in DPRMT framework. Digital modeling is a process of creating a computer-based representation of any city, system, or entity at risk to demonstrate, analyze, and predict various aspects of disaster-related phenomena [215]. The digital modeling techniques that can be used in DPRMT are socio-economic modeling, AI-based modeling, BIM, probabilistic modeling, optML, physical modeling, asset information modeling, and other models. To begin with, socio-economic modeling investigates the effects of disasters on the affected community in terms of social and economic development [216]. This approach is crucial to understand those effects on the different socio-economic groups instead of only focusing on physical impact since these groups experience different response and recovery patterns in the aftermath of the disasters. The methods used in socio-economic modeling are agent-based modeling [217], social network analysis [218], and economic impact modeling [219].

AI-based modeling encompasses a diverse array of ML and AI techniques aiming to analyze the impact of disasters and create predictive models before and after the event. These techniques find application in the domain of damage assessment, disaster monitoring, post-disaster recovery, resource allocation, and decision-making [2,220]. In the realm of PRM, the literature has explored ML algorithms like random forest [221], K-nearest neighbor (KNN) [222], and SVM [223] for various purposes. Moreover, deep learning techniques such as convolutional neural networks (CNN) [224], LSTM [225], and recurrent neural networks (RNNs) [226] have been investigated for diverse applications within PRM.

BIM is a modeling process used widely for digital and information modeling in architecture, engineering, and construction industries, and it also poses a significant potential for PRM. BIM is a digital platform used for rapid damage assessment in digital twin-based PRM [227]. Moreover, it is a cornerstone, especially in smart city digital twins, thanks to its integration with other data models and various data collection methods [228]. Furthermore, Asset Information Modeling can be integrated into BIM to optimize the digital modeling process within various scales [229].

Probabilistic modeling relies on statistical analysis and probabilistic modeling to quantify the uncertainties related to disasters in order to inform decision-makers about phenomena such as risk assessment and scenario analysis. To do so, probabilistic modeling encompasses various methods and techniques to assess those risk-related uncertainties, such as Monte Carlo simulation [230], Markov chains [231], Bayesian modeling [232], and epidemic-type aftershock sequence (ETAS) model [233]. Physical modeling creates a scaled-down physical representation of real-world systems or phenomena to demonstrate the effects of disasters on the built environment. The methods used in physical modeling in the realm of PRM are hydraulic modeling [234], landslide and soil erosion models [235], and finite element analysis [236].

Optimized Machine Learning (optML) is a specialized approach in the domain of digital twins-based PRM for specific tasks in smart cities. The methods used in optML differ based on the specific task or challenge. For example, this method can be used to select the best alternative among machine-learning algorithms [237] or feature selection and engineering for a specific task [238].

In addition to the previously mentioned digital modeling techniques, several models find relevance in PRM. For example, geospatial models using geographic data and spatial analysis can be utilized in DT [239]. In addition, network models focusing the interconnectedness and interdependencies of critical infrastructure systems can be beneficial for post-disaster scenarios and building resilient cities [240]. Other digital modeling approaches such as supply chain and epidemiological models can also be integrated into the digital modeling layer of DPRMT [241,242].

5.5. Information decoding

This section provides an overview of information decoding techniques that can be used in DPRMT framework. Information decoding consists of data and model analysis, integration, and visualization steps within the context of PRM. As a crucial component of DPRMT, the information decoding component plays a significant role, encompassing timely response, resource efficiency, communication, transparency, adaptive planning, and informed decision-making. Data analysis and query cover the systematic effort to understand the current situation in general [243]. They are also essential for retrieving specific information when needed [244]. Data/model integration helps achieve a more holistic view of the current situation in the aftermath of disasters, combining various digital models [245,246]. In addition, this integration is also crucial in achieving improved accuracy and more efficient decision-making. Finally, data/model visualization aims to present complicated and disaster-related information visually and understandably [247]. This approach enables a variety of stakeholders, decision-makers, and households to communicate effectively. All in all, information decoding in digital twins serves as a powerful tool that facilitates the effectiveness of disaster risk management efforts by providing timely, accurate, and actionable information.

5.6. User interaction and application

This section presents user interaction methods and application areas within DPRMT framework. The user interactions layer enables the communication between DT models and end users in the realm of PRM. This interaction can be in various formats, such as web portal terminal, mobile terminal, and emulated reality (ER) [12]. Mobile and web terminals, such as smartphones, tablets, and web interfaces, provide real-time information about disasters. ER is a technology used to mimic a fictional or real-world within a computer-generated virtual environment by which users feel real. The most common examples of emulated reality technologies are virtual reality (VR), augmented reality (AR), and mixed reality (MR) [12]. Although VR provides an isolated virtual environment, AR enhances reality by overlaying digital elements in the real world [8]. MR creates a hybrid environment by integrating the real world with digital content by enabling the interaction of virtual objects with physical surroundings [8]. By engaging people with these events, ER technologies could drive public awareness and actions against disasters [71].

DT can be used in a variety of applications in the realm of PRM to ensure disaster response and recovery. To begin with, DT can help decision-makers with their disaster-related response and recovery strategies to minimize the adverse effects on the entities at risk by providing real-time information and capturing the dynamic nature of disasters [2,247]. DT can also support damage assessments in the aftermath of disasters and provide an inclusive synopsis of the current situation of entities at risk, such as buildings and critical infrastructures [248,249]. Moreover, DT can optimize resource allocation efforts by providing real-time insights into the most urgent needs in the aftermath of disasters [228]. It can also utilize real-time data and predict potential casualties during disasters, informing decision-makers on strategies for response and recovery efforts to prevent loss of lives [250].

DT can utilize real-time data to predict the trajectory of hazards such as flood, wildfire, and diseases and inform authorities to take necessary measures to prevent severe damages [17,92]. Furthermore, they can assist evacuation planning by capturing recent changes in disasters and determining the best evacuation routes and times inside and outside buildings to reduce the risk of harm in these processes [251,252]. Moreover, they are helpful tools for emergency services and organizations to test what-if scenarios, identify weaknesses, and refine the effectiveness of their strategies [247]. This approach is fundamental for system-level resilience assessment and improvement [253].

DT can play a significant role in post-disaster recovery efforts by providing critical data about damage assessment, resource allocation, and task prioritization [20]. They can also enhance collaboration among stakeholders, NGOs, governments, and decision-makers and community engagement in the aftermath of disasters [12]. All these efforts generated by DT before and after disasters enhance lessons learned and policy developments to optimize future efforts that help to minimize the adverse effects of disasters [254].

6. Conclusion

This paper envisions a digital post-disaster risk management twinning (DPRMT) paradigm to contribute to how we prepare for, respond to, and recover from disasters. This study offers a real-time, detailed, and data-driven modeling approach to improve post-disaster risk management efforts in affected areas, incorporating the use of DT. This new way of managing disasters combines technology and data-driven decision-making to minimize the adverse effects of disasters.

To present this vision, we conducted a systematic literature review to address the current state of DT for PRM and EW: the disaster types and domains those studies focus on, what data collection methods, data types, and ML algorithms they use to address DPRMT and EW. We also presented the existing research directions, achievements and challenges related to DPRMT. The systematic literature review showed that current studies often rely on limited and static data sources, which hinders fully capturing the dynamic nature of disasters. Moreover, they neglect the financial, social, and demographic aspects of communities, impacting the overall response and recovery efforts. Studies employing dynamically updated models are rather limited, and they overlooked the interconnected nature of systems and subsystems in the urban environment. On the contrary, they are focused on only one or limited components in isolation. These studies paid limited attention to the post-disaster recovery of the affected communities. The results revealed the need for pioneering approaches considering data and model integration challenges, the potential of multi-hazard scenarios and cascading effects, and the potential of explainable artificial intelligence (XAI) within disasters.

The presented DT-driven PRM framework offers a robust and integrated approach to address the challenges posed by disasters. The framework consisting of entities at risk, data collection and pre-processing, data processing, digital modeling, information decoding, and user interaction and application enables users with advanced tools and informed data-driven decisions to optimize the efforts in response and recovery processes following the disasters. The presented approach is expected to enhance and improve existing methods in disaster recovery, policy-making, resilience assessment, casualty prediction, hazard spread prediction, resource allocation, evacuation, scenario testing, lessons learned, community engagement, and decision-making to create a more effective post-disaster risk management.

CRediT authorship contribution statement

Umut Lagap: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Saman Ghaffarian:** Visualization, Supervision, Methodology, Investigation, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:Umut Lagap reports financial support was provided by the Ministry of Education of the Turkish Republic. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix

Table 3
Summary of selected DPRMT and EW papers: types, domains, data, machine learning models, and case studies.

Ref.	Disaster Type	Domain	Data type	Data collection	Dynamic model	ML model	Case study area
Ghaith et al. [13]	Flood	Response	Digital elevation model (DEM), Historical flood hazard data, OpenStreetMap data, Satellite images	Remote sensing, Manual Collection, Secondary data	No	–	Canada
Truu et al. [89]	Flood	Disaster Management	Historical rainfall data	Secondary data	No	–	Estonia
White et al. [17]	Flood	Evacuation	3D BIM data (terrain and Building information)	3D Modeling	No	–	Ireland
Basaglia et al. [70]	Earthquake	Response	Patient flow data from literature review, Emergency plans of the hospitals, Survey data	Manual Collection, Secondary data	No	–	Italy
Aleksandrov et al. [90]	Wildfire	Damage assessment	UAV images, Weather data (moisture, temperature)	Remote sensing, Sensor networks	No	–	Russia
Park and You [19]	Flood	Disaster Management	GIS data (LİDAR and drone photogrammetry), CCTV video data, Water management data (river water level and rainfall), Digital elevation model (DEM)	Remote sensing, Secondary data	Yes	–	South Korea

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Table 3 (*continued*)

Ref.	Disaster Type	Domain	Data type	Data collection	Dynamic model	ML model	Case study area
Zhong et al. [92]	Wildfire	Wildfire spread Prediction	2D image data (Temperature, humidity, rainfall, and lightning)	Remote sensing	No	Autoencoder (AE) + Convolutional Neural Network (CNN) + Recurrent Neural Network (RNN)	the UK
Fan et al. [20]	Generic	Situational awareness	Twitter data (text, images, and geotags)	Social sensing	No	Kernel Density Estimate	the USA
Yun et al. [91]	Wildfire	Wildfire spread prediction	IoT data, Historical wildfire data, Climate data, Vegetation data	Sensor networks, Secondary data	No	Convolutional Neural Network (CNN)	the USA
Yavo-Ayalon et al. [71]	Generic	Situational awareness	3D VR data	3D Modeling, Secondary data	No	–	the USA
Kim and Ham [143]	Hurricane	Damage assessment	Drone videos and images data	Remote sensing	No	–	the USA
Fan et al. [197]	Generic	Situational awareness	Twitter data	Social sensing	No	–	the USA
Tei et al. [147]	Generic	Response	IoT data, OpenStreetMap data, Urban Mobility Data	Sensor networks, Secondary data	No	–	Algeria
Bai et al. [74]	Flood	Impact Assessment	Real time flood-monitoring API, Energy performance certificates, HM land registry open data	Secondary data	Yes	–	the UK
Allen et al. [255]	Flood	Disaster Management	Satellite data, Digital elevation models, IoT data, AWS open registry data cube	Remote sensing, Sensor networks, Secondary data	Yes	–	the USA
Nurwatik and Hong [142]	Earthquake	Evacuation	Earthquake simulation data, IoT data, Risk assessment data, Road network data	Secondary data, Manual collection	No	–	Taiwan
Alkhatibl et al. [93]	Generic	Situational awareness	Twitter data	Social sensing	No	Support Vector Machine	the UAE
Henriksen et al. [95]	Flood	Disaster Management	Hydrological conditions data	Secondary data, Remote sensing	No	Random Forest, Gradient Boosting, Long short-term Memory	Denmark
Braik and Koliou [78]	Hurricane	Hazard/Damage assessment	Electric power network data, Building inventories, Hazard model	Secondary data	No	–	the USA
Josephs et al. [75]	Hurricane	Recovery	Historical disaster data, Building related data, Flood simulation data, FEMA base flood elevation data	Secondary data, Manual collection	No	–	the USA
Alazawi et al. [256]	Generic	Evacuation	Transportation network data	Secondary Data	No	–	the UK
Tan et al. [146]	Generic	Situational awareness	Images for different disaster types	Social sensing	No	Convolutional neural network, Long short-term memory	Generic (various disasters)
Chen et al. [96]	Flood	Flood Prediction	The flow and water level data, Reservoir water level data, Historical rainfall data, IoT data	Sensor networks, Secondary data	No	Long short-term memory	China
Talaat and ZainEldin [100]	Wildfire	Wildfire Detection	Data of fire and non-fire images and videos	Remote sensing, Secondary data	No	Yolov8	Generic (various disasters)
Jiang [257]	Flood	Situational awareness	GIS data, IoT data, Video data	Remote sensing, Sensor networks	No	–	China
Ahmed et al. [101]	Flood	Flood Detection	Satellite and drone images	Remote sensing	No	DeepLabv3	Generic (various disasters)
Azimi et al. [150]	Generic	Evacuation	Emergency services data, Demographic data	Secondary data	No	–	Iran
Yao and Wang [145]	Hurricane	Situational awareness	Twitter data	Social sensing	No	Domain-adversarial neural network, Recurrent neural network	the USA
Basnyat et al. [97]	Flood	Situational awareness	Twitter data	Social sensing	No	Naive Bayes, Decision Tree	the USA

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Table 3 (*continued*)

Ref.	Disaster Type	Domain	Data type	Data collection	Dynamic model	ML model	Case study area
Munawar et al. [144]	Flood	Flood Detection	UAV images	Remote sensing	No	Convolution Neural Network	Pakistan
Chaudhuri and Bose [258]	Earthquake	Evacuation	Post-disaster images	Secondary data	No	Convolution Neural Network	Generic (various disasters)
Yu et al. [141]	Earthquake	Hazard/Damage assessment	Hazard simulation data, 3D building data	Manual Collection, 3D Modeling	No	–	China
Alboody et al. [259]	Wildfire	Wildfire Detection	Airborne visible/infrared Imaging spectrometer data, Sentinel-2 satellite data	Remote sensing, Secondary data	No	K-Nearest Neighbor, Support Vector Machines, Artificial Neural Networks, Convolutional Neural Networks	Generic (various disasters)
Shah et al. [260]	Generic	Disaster Management	Twitter data	Social sensing	No	–	Indonesia
Jung et al. [99]	Wildfire	Wildfire Detection	Data of fire and non-fire images	Secondary data	No	FireNet	Generic (various disasters)
Hofmeister et al. [261]	Flood	Disaster Management	Weather data, IoT data, Sensor data	Secondary data	No	–	the UK
Zuo et al. [262]	Hurricane	Situational awareness	Twitter data	Social sensing	No	–	the USA
Qadir et al. [263]	Wildfire	Bushfire Detection	UAV images	Secondary data	No	YOLOv5-s, Convolutional neural network, Long short-term memory	Generic (various disasters)
Mount et al. [264]	Flood	Evacuation	Transportation network data, LiDAR data, Critical infrastructures data	Secondary data, Remote sensing	No	–	the USA
Aqib et al. [94]	Generic	Traffic Management	Traffic data	Secondary data	No	Artificial Neural Networks	the UK
Susandi and Tamamadin [265]	Flood	Early Warning	Weather data, Rainfall data, Flood modeling data	Secondary data	No	–	Indonesia
Suquet et al. [266]	Flood	Flood Monitoring	Water level data, Satellite data, Drone data	Secondary data, Remote sensing	No	–	Generic (various disasters)
Ghaith et al. [267]	Flood	Flood Detection	Water flow data, Rainfall data	Secondary data	No	Convolutional neural network, Long short-term memory	Canada
Mishra et al. [268]	Earthquake	Response	Disaster regions and supply point locations, Transportation network data, Population data	Secondary data	No	–	Taiwan
Ugliotti et al. [86]	Generic	Disaster Management	Demographic data, Transportation network data, Land use and land cover, Hazard data, Critical infrastructures data	Secondary data	No	–	Generic (various disasters)
Sitinjak et al. [269]	Flood	Disaster Management	Survey data, Social media data, CCTV data	Crowd sourcing, Manual Collection, Remote sensing, Secondary data	Yes	–	Indonesia
Brito et al. [270]	Wildfire	Wildfire Detection	IoT data, Satellite images, Weather data	Sensor networks, Remote sensing	Yes	–	Portugal
Ud et al. [271]	Wildfire	Wildfire Detection	Data of fire and non-fire images	Secondary data	No	Att-MobileNetV2, Support vector machine, K-nearest neighbor, Random Forest, ResNet50, InceptionV3, VGG16	Generic (various disasters)
Meng et al. [152]	Flood	Hazard/Damage assessment	Images of flood scenes	Secondary data	No	Mask Region-based Convolutional Neural Network	Generic (various disasters)

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Table 3 (*continued*)

Ref.	Disaster Type	Domain	Data type	Data collection	Dynamic model	ML model	Case study area
Kuyuk and Susumu [102]	Earthquake	Early Warning	Historical earthquake vibration data	Secondary data	No	Long short-term memory	Japan
Yusoff et al. [272]	Flood	Early Warning	Water level data, GIS data	Secondary data, Remote sensing	No	–	Malaysia
Al Kindhi et al. [273]	Flood	Flood Monitoring	IoT data	Sensor networks	Yes	–	Indonesia
Hong and Shi [274]	Flood	Flood Monitoring	IoT data, CCTV data	Sensor networks, Remote sensing	Yes	–	Taiwan
Riyanto et al. [275]	Earthquake	Early Warning	IoT data	Sensor networks	No	–	Indonesia
Villegas and Martinez [153]	Hurricane	Hazard/Damage assessment	Twitter data	Social sensing	No	Latent Dirichlet Allocation	the USA
Stankova et al. [77]	Wildfire	Recovery	Satellite images	Remote sensing	No	–	Bulgaria
Azimi et al. [149]	Generic	Evacuation	Demographic data, Transportation network data	Secondary data	No	–	Iran
Chen et al. [276]	Generic	Situational awareness	Twitter data	Social sensing	No	Convolutional Neural Network	Generic (various disasters)
Vo et al. [277]	Generic	Disaster detection	IoT data	Sensor networks	Yes	–	Vietnam
Zhong et al. [92]	Wildfire	Wildfire prediction	Weather data (temperature, humidity, rainfall, and lightning)	Secondary data	No	Long short-term memory	Generic (various disasters)
Liu et al. [103]	Landslide	Early Warning	Rainfall data, Water level data, Water content data	Sensor networks	Yes	Support vector machine, Artificial neural network, Extreme learning machine, Gaussian process regression	China
Tarpanelli et al. [154]	Flood	Flood Prediction	Satellite data, 2D hydraulic model	Remote sensing, Manual collection	No	–	Italy
Subasinghe et al. [98]	Landslide	Situational awareness	Debris flow simulation, Demographic data	Secondary data, Manual collection	No	K Nearest Neighbor	the USA
Hyeong-Su et al. [278]	Wildfire	Wildfire spread prediction	–	–	–	–	Concept Model
Ford David and Wolf Charles [6]	Flood	Early Warning	–	–	–	–	Concept Model
Roh et al. [279]	Wildfire	Response	–	–	–	–	Concept Model
Zhang et al. [280]	Generic	Early Warning	–	–	–	–	Concept model
Ye et al. [148]	Flood	Early Warning	–	–	–	–	Concept model
Yang et al. [281]	Generic	Disaster Management	–	–	–	–	Concept model
Sharma et al. [282]	Generic	Early Warning	–	–	–	–	Concept model
Geihs [151]	Generic	Evacuation	–	–	–	–	Concept model
Hossain et al. [283]	Generic	Evacuation	–	–	–	–	Concept model
Abbasi et al. [284]	Flood	Evacuation	–	–	–	–	Concept model
Pradhan et al. [285]	Generic	Disaster Management	–	–	–	–	Concept model
Rotilio et al. [286]	Generic	Disaster Management	–	–	–	–	Concept model
Wolf et al. [287]	Generic	Disaster Management	–	–	–	–	Concept model
[288]	Flood	Disaster Management	–	–	–	–	Concept model

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Table 3 (*continued*)

Ref.	Disaster Type	Domain	Data type	Data collection	Dynamic model	ML model	Case study area
Abdalzaher et al. [289]	Earthquake	Early Warning	–	–	–	–	Concept model
Abdalzaher et al. [290]	Earthquake	Early Warning	–	–	–	–	Concept model
Ye et al. [148]	Flood	Early Warning	–	–	–	–	Concept model
Suri et al. [76]	Generic	Recovery	–	–	–	–	Concept model
Boukerche and Coutinho [291]	Generic	Response	–	–	–	–	Concept model
Hartama et al. [292]	Generic	Disaster Management	–	–	–	–	Concept model
Shrestha et al. [293]	Earthquake	Early Warning	–	–	–	–	Concept model
Nukavarapu and Durbha [294]	Flood	Flood Monitoring	–	–	–	–	Concept model
Kim et al. [295]	Generic	Disaster Management	–	–	–	–	Concept model
Pradhan [296]	Generic	Disaster Management	–	–	–	–	Concept model
Garcia et al. [297]	Flood	Flood Detection	–	–	–	–	Concept model
Li et al. [298]	Generic	Disaster Management	–	–	–	–	Concept model
Cheng et al. [12]	Generic	Disaster Management	–	–	–	–	Review Paper
Fan et al. [2]	Generic	Disaster Management	–	–	–	–	Review Paper
Ariyachandra and Wedawatta [25]	Generic	Disaster Management	–	–	–	–	Review paper
Bakhtiari et al. [122]	Flood	Disaster Management	–	–	–	–	Review Paper
Mei et al. [139]	Generic	Early Warning	–	–	–	–	Review Paper
Hernaningsih et al. [140]	Flood	Early Warning	–	–	–	–	Review Paper
Macatulad and Biljecki [15]	Generic	Disaster Management	–	–	–	–	Review Paper

Table 4
Data extraction form.

#	Extraction element	Contents
General Information		
1	ID	Unique ID for the study
2	Title	Full title of the article
3	Authors	The authors of the article
4	Year	The publication year
5	Publisher name	The publisher's name (e.g., MDPI)
6	Journal name	The journal name (e.g., Water)
7	Type of Publication	☐ Journal ☐ Conference ☐ Book chapter
8	Country	The country where the authors published the study in
Study Description		
9	Case study area	The location (country name) of the case study
10	Disaster type	The disaster type (e.g., Flood)
11	Domain	The addressed domain (e.g., Damage assessment)
12	Data collection method	The data collection method (e.g., Remote sensing)
13	Data type	The data type (e.g., IoT data)
14	Dynamic model	☐ Yes ☐ No
15	ML used	☐ Yes ☐ No
16	If ML used, which algorithm	The machine learning algorithm (e.g., CNN)
17	Additional notes	E.g., the opinions of the reviewer about the study

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