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Convergence of AI and Urban Emergency Responses: Emerging Pathway toward Resilient and Equitable Communities

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Abstract: Urban communities have long been pivotal in wealth creation and technological innovation. In the contemporary context, their modus operandi is intricately tied to a diverse array of critical infrastructure systems (CISs). These systems—encompassing utilities, transportation, communication, and more—are indispensable for daily life; however, historical lessons underscore that the ever-growing interdependence among modern CISs has sapped their robustness. Furthermore, this vulnerability is compounded by the intensifying natural hazards catalysed by climate change, leaving urban communities with eroded resilience. Against this backdrop, pilot studies have harnessed breakthroughs in artificial intelligence (AI) to chart a new course toward resilient urban communities. This paper illuminates AI-driven resilience by reviewing the latest research in key aspects including (1) the limitation of state-of-the-art resilience assessment frameworks; (2) emergency response as a novel blueprint featuring swift response following catastrophes; (3) efficient loss assessment of CISs using AI algorithms; and (4) machine-learning-enabled autonomous emergency response planning. The remaining challenges and hardships faced on the journey toward resilient urban communities are also discussed. The findings could contribute to the ongoing discourse on enhancing urban resilience in the face of increasingly frequent and destructive climate hazards.

Keywords: urban community; critical infrastructure system; natural hazard; resilience; emergency response; artificial intelligence; deep reinforcement learning

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1. Introduction

The ongoing global urbanization has led to a majority of the world's population residing in urban communities [1,2]. Modern urban communities serve as engines driving economic growth and technological advancement for each nation [3]; furthermore, the urban sprawl is perpetuated by socio-economic developments, creating a cycle of growth and expansion [4].

Modern urban communities function as intricately woven systems comprising people, organizations, and patterned relationships [5]. Their operational dynamics hinge upon the inflow and outflow of goods and services facilitated by a network of Critical Infrastructure Systems (CISs). These cybernetically engineered and interdependent CISs maintain the socio-economic fabric of urban life [6]; however, amidst the boom of urbanization, recurring challenges persist. Pollution, violence, and pandemics cast shadows on the edges of thriving urban communities [7]; in particular, the global impact of the COVID-19 pandemic that has caused unprecedented human and economic losses [8] underscores the vulnerability of modern urban systems.

A series of studies have highlighted the intricate interplay within networked CISs. As their complexity increases, the controllability of cascading effects and repercussions diminishes [9]. Those intra and interdependencies (the concept of interdependence denotes a bidirectional relationship between two CISs, wherein the state of each system significantly influences or correlates with that of the other) amplify the potential consequences of localized damage to individual CIS components, potentially triggering full-blown failures [10–12].

Comprehensive studies have explored effective approaches to bolster urban communities against a spectrum of catastrophes [13–15]; however, stakeholders and engineers increasingly recognize that expecting future urban areas to remain immune to hazard-induced disruptions is generally unfeasible, even when mitigation methods are implemented [16,17]. The inherent vulnerability of these communities arises from the intricate interplay among diverse CISs, compounded by the escalating risks posed by climate-related hazards [18,19]. Research endeavours have consequently converged on the resilience of CISs and urban communities. It is self-evident that robust and swift recovery following hazard events plays a role as pivotal as disaster preparedness in ensuring the survival and sustainability of impacted communities [20–22]; besides, over the past decade, attention has shifted from isolated CIS components (such as bridges within transportation systems) to examining how interdependencies—particularly looped ones [23]—reshape the multi-dimensional resilience of modern, interconnected communities [24–26]. Justifiably, the new insights generated from those research endeavours have laid a solid foundation for resilience amelioration and risk governance for stakeholders and decision-makers [27].

While existing resilience assessment frameworks emphasize essential aspects, they often fall short of providing a comprehensive view of community resilience, as recent real-world lessons underscore the necessity for a more nuanced approach [28]. Overall, most of these frameworks primarily quantify the gross functionality losses sustained by networked CIS–communities throughout hazard events. These losses are assessed using physical, economic, or societal indicators [29,30]; however, the criticality across different temporal windows during these events has been indiscriminately characterized. This contrasts with the reality of real-world hazards, where initial localized damage can rapidly propagate, sometimes uncontrollably [9].

In response to this deficiency, post-hazard emergency response has emerged as a promising pathway toward resilient urban communities; however, devising optimal plans for these emergency responses immediately after real-world hazards presents significant challenges. The available information at this stage is often incomplete and inaccurate; furthermore, emergency response activities can be hindered by widespread damage and potentially inhabitable environments following such hazards [31]. Against this backdrop, very recently, researchers have harnessed advances in artificial intelligence (AI) to enhance emergency responses [32–34]. These efforts focus on rapid damage classification using deep learning and autonomous decision-making driven by (deep) reinforcement learning. Inspired by the prospect of AI-driven, resilience-oriented emergency response of future urban communities, this paper aims to shed light on the progress achieved by reviewing recent developments in this field while also emphasizing the ongoing challenges. To maintain generality, this paper primarily delves into research related to community resilience in the context of earthquake hazards. Accordingly, the subsequent sections are organized as follows: Section 2 traces the historical development of hazard resilience and examines the approaches devised thus far for engineering resilient communities; Section 3 elaborates on the newly established concept of post-shock emergency responses following seismic hazards; Section 4 delves into the latest studies concerning the rapid assessment of earthquake-induced damage and losses. In parallel, it also explores learning-based planning of post-shock emergency responses; Section 5 discusses the pathway forward for enhancing community resilience while addressing the challenges that need to be overcome; Finally, Section 6 summarizes the main findings and draws conclusions.

2. Development of Seismic Resilience of Modern Urban Communities

2.1. Establishment of a Resilience Assessment Framework for Integrated CISs–Communities

Earthquakes have long posed a grave threat to modern communities situated in earthquake-prone regions worldwide [35–37]. Statistical studies consistently reveal the devastating impact of earthquakes on urban communities, resulting in significant loss of life and socio-economic damage [38–42]; additionally, recovery from such events is often challenging [43,44]. In response, the concept of earthquake-resilient communities has assumed greater importance. These communities are expected to remain robust even during seismic hazards and have the capacity to restore functionality afterwards; therefore, they have been widely recognized as the cornerstone for the sustainable development of their respective regions [45].

The concept of resilience, initially rooted in the study of ecosystems, has gained prominence since the early 1970s [46]. In recent years, community resilience has emerged as a critical focal point, particularly within the context of disaster risk mitigation. This shift was underscored during the 2005 World Conference on Disaster Reduction (WCDR), where community resilience was positioned as a pivotal element in shaping the future sustainability of communities [47]. In continuation, Cutter [48] underscored that achieving the goal of resilience and sustainability for urban communities necessitates concerted efforts across diverse societal sectors from a political perspective.

Bruneau et al. [20] significantly advanced the pursuit of resilient communities by proposing a comprehensive definition of hazard resilience in urban areas. Their framework involves diverse strategies aimed at minimizing losses from hazard events, including mitigation and recovery efforts; additionally, the concept of resilience can be delineated across four key dimensions: technical, organizational, societal, and economic. Notably, the technical and economic dimensions directly impact the resilience of CISs, whereas the remaining two dimensions provide valuable insights into the overall community resilience.

Building upon the foundation laid by Bruneau et al. [20], Ouyang et al. [21] established a general assessment framework for hazard resilience of CISs. Within this framework, the gross functionality losses throughout the entire event serve as a direct measure of the resilience of CISs of interest. To that end, hazard events are temporally divided into three distinct phases: hazard prevention, damage absorption, and post-hazard recovery. Additionally, Sun et al. [22] extended this research by proposing a supply–demand resilience assessment framework. This framework tracks both the functionality supply from CISs and the corresponding demand from the community in which these CISs are embedded. Throughout the three aforementioned phases, the deliverable functionality of CISs (abbreviated as "DF," essentially the supply) and the community demand (abbreviated as "D") evolve. After a shocking event like an earthquake, both the supply and demand take time to reach their minimum levels, signifying the end of the absorption phases, as shown in Figure 1.

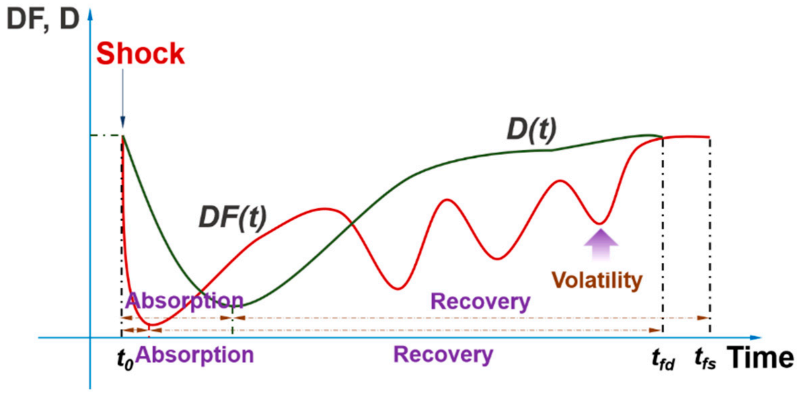

Figure 1. The supply–demand resilience assessment framework for CISs–community under hazard events.

Subsequently, they begin to recover until they reach a new post-shock equilibrium at time points t_{fs} and t_{fd}, respectively. Notably, in urban communities affected by calamitous earthquakes, post-shock recovery can span years [49], significantly surpassing the duration of their absorption phases. Meanwhile, as depicted in Figure 1, the recovery trajectory of the CIS–community need not follow a monotonic pattern; instead, it may exhibit volatility due to various additional disruptions (such as aftershock sequences related to earthquake hazards). Notably, the recovery rate of both supply and demand may vary radically based on case-specific political and economic governance structures and the coordination among different sectors following hazard events; therefore, following such a framework, the system-level functionality deficit (abbreviated as "*FD*") of the CIS–community is quantified by aggregating the corresponding deficits at each individual node k (k = 1: N, where N denotes the number of nodes in a particular CIS), denoted as $FD_k(t)$. Mathematically, $FD_k(t)$ is obtained by comparing the deliverable functionality ($DF_k(t)$) with the community demand ($D_k(t)$) during both the absorption and recovery phases, as shown in Equation (1):

$$FDk\ (T) = \sum_{l=1}^{m} \int_{t_{l,0}}^{t_{l,f}} (D_k(t) - DF_k(t))dt \quad (1)$$

In this context, the variable m stands for the cumulative count of intervals during which D_k(t) exceeds $\mathrm{DF_k}$(t). These intervals span from the initial occurrence of the shock to a designated "milestone" time point T—for example, when both supply and demand have fully recovered to their pre-shock levels; additionally, $t_{l,0}$ and $t_{l,f}$ correspond, respectively, to the start and end points of each individual interval among the m ones. For every node k, the value of D_k(t) is derived from the aggregated functionality demand across all users served by that node [50].

Importantly, this supply–demand assessment framework not only gauges the physical resilience of the networked CIS–community, but also provides insights into its socio-economic resilience. By doing so, it has laid a foundation for resilience-oriented risk governance policies, which are especially pertinent for CIS–communities subjected to various hazards.

2.2. Research on Seismic Resilience of Modern CISs

2.2.1. Seismic Resilience of Individual CISs

Extensive research has investigated the seismic behaviour of various modern CISs. These systems span diverse domains, including healthcare, gas, and water infrastructure systems [51–53]. Notably, considerable attention has been paid to two pivotal systems: Electric Power Supply Systems (EPSSs) and transportation systems (TSs). These two CISs play a strategically crucial role in ensuring the continuity of functionality and the robust recovery of all the other interconnected systems.

Specifically, regarding EPSSs, Shinozuka et al. [54] established a link between the seismic robustness of EPSSs and the fragility behaviour of their most critical components under damaging earthquakes. Their proposed modelling framework allows the quantification of the system-level cost of seismic damage, along with corresponding socio-economic losses.

Dueñas-Osorio and Vemuru [55] proposed a framework for modelling the impact of cascading failures across EPSSs. Within this framework, the overload resulting from cascades is characterized by a tolerance parameter, which assesses the element flow capacity relative to flow demands in real-world EPSSs. The study indicates that enhancing component tolerance alone does not guarantee EPSS robustness in the face of disproportionate cascading failures. Simultaneously, topological upgrades play a crucial role in enhancing the cascade robustness of the system, particularly when operating at viable tolerance levels.

Within the framework of game theory, Casari and Wilkie [56] employed mechanism design to introduce an economic model specifically targeting the post-shock recovery of EPSSs. Their research underscores that the prolonged restoration time of EPSSs, as well as other CISs, may stem from insufficient coordination among system operators. As a result, the adoption of incentive-compatible contracts emerges as a strategic approach for shaping effective emergency restoration plans, thereby significantly enhancing social welfare.

Sun et al. [57] established an agent-based model (ABM), a bottom-up and adaptive computational approach to large-scale socio-economic systems [58], to address the post-shock recovery of earthquake-damaged EPSSs. This study highlights the emergence of potentially conflicting interests between the community and the EPSS operator. Resolving such conflicts would reshape the recovery dynamics of the integrated EPSS–community. Additionally, this study demonstrates the importance of the development of seismic contingency dispatch strategies and contingency demand regulation measures to enhance the societal resilience of EPSS–communities.

Vis-à-vis TSs, Mackie et al. [59] introduced a comprehensive framework aimed at quantifying both the repair cost and repair time of bridge structures. These structures play a pivotal role in modern TSs, particularly highway networks. In such a framework, these two measures are obtained by linking the amounts of repair materials, to damage states requiring the repair, to structural response causing the damage, and eventually to the intensity measure of seismic hazards. By disaggregating these components, the framework provides detailed insights into the damage and failure of individual bridge members. Consequently, it facilitates informed decision-making regarding both structural design and retrofit strategies.

Decò et al. [60] proposed a probabilistic model to evaluate the seismic resilience of bridges. This model utilizes fragility functions to assess the earthquake-induced physical damage of a specific bridge. Subsequently, considering varying levels of initial damage and different rates of rehabilitation, a probabilistic six-parameter sinusoidal-based function is established. This function shapes the recovery trajectory of bridge structures, enabling risk-informed decision-makings.

Regarding the post-shock recovery of TSs, Hu et al. [61] investigated the impact of various recovery strategies on the seismic resilience of those systems following catastrophic earthquakes. Three distinct strategies were considered: the greedy recovery (GR), the preferential recovery based on nodal weight (PRNW), and the periphery recovery (PR). Specifically, GR prioritizes the sequential restoration of damaged links, aiming to maximize network functionality recovery at each time step; on the contrary, PRNW focuses on restoring edges that connect isolated nodes with the largest population to the functional components within the TS; finally, PR prioritizes the restoration of isolated nodes related to the largest population. The case study revealed that both PRNW and PR effectively contribute to TS recovery after damaging earthquakes; notably, PRNW emerged as a recommended strategy for resource allocation, significantly reducing the time needed to restore TS functionalities.

Most recently, Wu et al. [62] introduced a comprehensive modelling framework for the long-term recovery of TSs following earthquake hazards. In such a framework, both travel time and safety have been included to track and measure the time-varying functionality of TSs during the course of recovery; in particular, the framework generates a restoration criticality index for each bridge. This index informs the formulation of effective long-term recovery strategies for TSs in the aftermath of seismic events.

2.2.2. Seismic Resilience of Interdependent CISs

In the early 2000s, a series of unprecedented cascading failures of CISs on a global scale prompted renewed research into their hidden vulnerabilities [63–66]. These systems, which play critical roles in various domains, exhibited a significant lack of resilience even when faced with seemingly minor initial disruptions. Researchers turned to complexity theory to revisit the behaviour of these CISs. The findings consistently pointed to the inherent vulnerability of modern CISs, stemming from their intricate intra and interdependencies. These dependencies create a delicate balance, making the systems susceptible to failures [10–12].

The CIS vulnerability induced by interdependencies also extends into real-world hazard events, such as destructive earthquakes. To safeguard the resilience of modern urban communities, it is imperative to deepen understanding of these vulnerabilities and actively work toward effective mitigation strategies.

Krishnamurthy et al. [67] conducted a comprehensive study on EPSS resilience under two significant real-world earthquake events: the 2011 M_W 9.0 Tohoku earthquake in Japan and the 2010 M_W 8.8 Maule offshore earthquake in Chile. Their research specifically investigated the interdependencies between EPSSs and telecommunication systems. To that end, this study analysed time series data related to damage, outages, and service restoration of both the two CISs throughout the respective earthquakes. The findings revealed a strong coupling between the restoration of the EPSS and telecommunication systems in both Japan and Chile. In particular, the restoration of mobile communication networks was more closely tied to EPSS restoration than that of landline telephony systems. This consistent pattern underscores the significant and asymmetric dependence of telecommunication systems on EPSSs. Consequently, the study highlights the urgent need for innovative technological solutions, such as microgrids, to enhance the resilience of telecommunication systems and safeguard the entire community under catastrophic earthquakes.

It is noteworthy that modern CISs exhibit interdependencies that extend beyond the conventional, “unidirectional” relationships. Both the operation and post-shock recovery of CISs are often mutually reliant, as observed under real-world scenarios [6]. Researchers have begun investigating the impact of this looped interdependence on CIS resilience. In a recent study, Zhao and Sun [26] explored the resilience behaviour of an interwoven system comprising an EPSS and a TS, as well as the urban community that they serve, under seismic hazards. Following damaging earthquakes, the restoration of EPSSs becomes contingent upon the functionality of TSs. Specifically, EPSS components can only be repairable if accessible via the TS; conversely, the restoration of TSs is also reshaped by the time-varying functionality of EPSSs, as many TS repair equipment rely on the energy supply. To model these complex and dynamic interactions between the two CISs, an agent-based model (ABM) was developed. This ABM incorporates two key agents: the operators responsible for the recovery campaigns of the TS and the EPSS. Sensitivity analysis was run to explore how post-shock recovery is influenced by the looped interdependence between these two systems, considering various earthquake scenarios. The simulation outcome reveals a nonlinear relationship between the degree of interdependence and system-level resilience, particularly under strong shocks. When the interdependence degree surpasses a critical threshold, the resilience of the EPSS–TS–community system undergoes a sharp deterioration, especially when viewed from a societal perspective.

3. Emergence of Resilience-Oriented Post-Shock Emergency Responses

3.1. The Concept of Post-Shock Emergency Responses

Despite considerable advancements in resilience assessment research, it is increasingly acknowledged that state-of-the-art frameworks fall short of capturing the dynamics of contemporary urban communities, as highlighted by recent real-world hazard events [28]. In particular, existing frameworks exhibit a critical limitation: they fail to adequately characterize the criticality of different time windows during post-shock recovery [68]. In the context of real-world catastrophes such as damaging earthquakes, the immediate physical, economic, and societal losses resulting from the mainshock can be substantially exacerbated in the subsequent short time frame. These cascading effects have far-reaching implications for the society as a whole. For instance, the functionality losses or deterioration of local hospital and road networks significantly impact earthquake-injured inhabitants. Those who cannot be promptly evacuated face a heightened risk of mortality within days or even hours after the seismic event due to the limited access to life-saving treatments [69,70]. Meanwhile, in the absence of well-planned disaster management, the societal consequence of earthquake-initiated releases of radioactive contamination or other toxic chemicals become both financially burdensome and irreparable over the subsequent years and decades [71–73]. Additionally, the potential aftershock sequences following the mainshock could even further amplify these consequences [74,75]. Moreover, the ever-growing interdependencies among CISs would accelerate the propagation of earthquake-initiated disruptions. Consequently, planning and executing effective post-shock restorations face increasingly complex challenges.

Against this backdrop, emergency response—incorporating an array of actions that the operators and stakeholders responsible for post-earthquake restorations can take immediately after the shock—has emerged as a new pathway toward future earthquake-resilient urban communities [76]. Conceptually, the emergency response (ER) empowers each operator of a single CIS or networked CISs to mitigate the functionality deficit in the immediate aftermath of earthquakes (IAoEs), as mathematized in Equation (2):

$$ER = arg\ \underset{a}{min}\left(\int_{t_0}^{t_{er}} (D(t) - DF(t,a))\, dt\right) \tag{2}$$

In this context, $DF(t, a)$ stands for the deliverable functionality of those CISs, conditioned on the action a taken by their operators; additionally, t_{er} denotes the time point when the deliverable functionality has been restored to an acceptable level, ensuring that the emergency functionality demand from the community can be met (which essentially signifies the end of IAoEs), as illustrated in Figure 2.

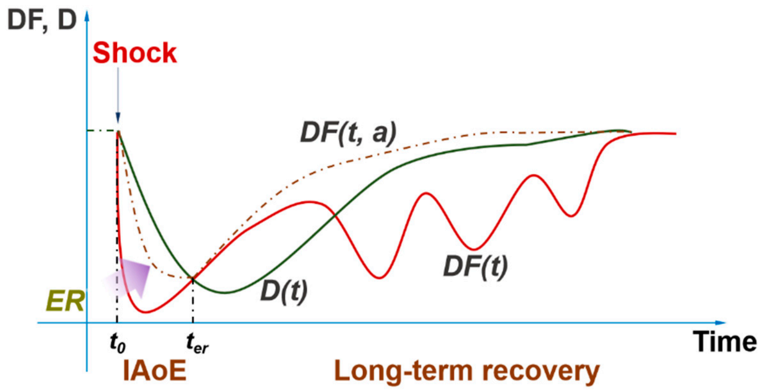

Figure 2. Modelling framework for resilience-oriented emergency response of modern CISs.

3.2. Challenges Faced by Post-Shock Emergency Responses

Despite the potential advantages highlighted above, planning, optimizing, and executing emergency responses during real-world catastrophes remain challenging. Specifically, when dealing with seismic events, it is crucial to assess the severity and geographic distribution of earthquake-initiated losses and disruptions across the whole community immediately after the shock. This assessment should consider the knowledge of exposed assets and their seismic vulnerabilities [77]. As illustrated in Figure 2, a comprehensive set of emergency response actions must be planned and executed in the IAoEs. Given the severity of losses sustained by earthquake-disrupted CISs, the emergency response may encompass a wide range of viable actions, spanning physical, economic, and societal restoration efforts. Practically, local Civil Protection Agencies and CIS operators should incorporate the following elements into their emergency toolkit: emergency shelters, emergency food and medical assistance, emergency repair of CISs, and emergency functionality dispatch [50,76,78–80]; however, the complexity of each enumerated action, especially the coordination among them, poses significant challenges. Even when the severity and geographic distribution of the initial damage have been precisely assessed (which is rarely the case in real-world earthquake events), strategic planning on the emergency response campaign remains extremely demanding. In principle, there are, at least, three challenges to be addressed by the decision-makers, as outlined below:

1. Challenges from a computational perspective: In the case of widespread earthquake-initiated damages, potential permutations for restoring a single CIS alone can be massive due to the scale and heterogeneity of modern CISs [81]. Brute-force search algorithms are thus computationally unaffordable for discovering the optimal sequence of restoration actions [81,82];
2. Challenges from a technical perspective: In light of the potentially pervasive damage in the wake of damaging earthquakes, the emergency response associated with any single CIS could be hindered not only by the damage to the other CISs, but also by self-inflicted ones [76]; furthermore, damage to a set of different CISs providing critical services can render an affected area uninhabitable or inaccessible to human beings [83], significantly affecting community restoration efforts;
3. Challenges from a socio-economic perspective: In the context of hazard-impacted communities, top-down planning is commonly favoured. These planning approaches emphasize centralized decision-making and coordination, which are crucial for efficient resource allocation, streamlined communication, and rapid deployment of emergency measures; however, top-down planning can also lead to a lack of transparency and accountability. Consequently, emergency response campaigns may be influenced by biases and misconceptions, inadvertently exacerbating environmental and societal disruptions [78].

4. Resilience-Oriented Emergency Responses Driven by Machine Learning

Section 3 delves into the strategic criticality of post-shock emergency responses concerning the resilience of urban communities under seismic hazards. More importantly, it highlights the comprehensive challenges that hinder the practical implementation of the responses of real-world CISs. In parallel, thanks to the significant advances in the domain of machine learning throughout the past decade [84,85], it has been demonstrated that AI-capable machines can surpass human experience-based decision-making, even without prior human knowledge [86–91]. Justifiably, their integration into modern societies holds the potential to revolutionize post-hazard emergency responses. Overall, the machine-learning-driven approach to post-shock emergency responses offers distinct advantages. Its generalization capability enables adaptive decision-making in an expeditious manner. Furthermore, these AI-capable machines promise to mitigate the impact of the emotional and irrational behaviour exhibited by humans during emergencies.

Pilot research in this area has primarily focused on rapid damage assessment and learning-based decision-making on post-shock restorations. The remainder of this section will review and provide insights from these research endeavours.

4.1. Rapid Damage Assessment

The effectiveness and timeliness of emergency responses following damaging earthquakes critically depend on an accurate assessment of earthquake-induced damages. Traditionally, post-shock damage assessments rely on manual inspections, which are often time-consuming and struggle to inform agile decision-making; moreover, these manual inspections yield inherently subjective outcomes, potentially misleading decision-makers [92]. To address these challenges, recent research efforts have capitalized on the latest advancements in deep learning (DL) techniques to rapidly identify earthquake-induced damages. DL leverages computational models, i.e., artificial neural networks with multiple layers capable of handling complex learning tasks by processing large datasets. These models employ hierarchical representations with multiple levels of abstraction and are trained using gradient-driven optimizers in conjunction with the backpropagation algorithm [84]. A pivotal moment in DL for computer vision was the development of convolutional neural networks (CNNs), exemplified by the influential AlexNet. AlexNet's victory in the 2012 ImageNet Large Scale Visual Recognition Challenge convincingly surpassed classical approaches [93]. Subsequent advancements in hardware, software, and algorithms (such as GPUs and DL frameworks like TensorFlow 2.17.0 and PyTorch 2.4.0) have solidified

CNNs as powerful tools for image classification [94], object detection [95,96], and semantic segmentation [97–99].

The architecture of CNNs encodes certain prior assumptions that are usually met in many computer vision problems. Because of such inductive biases, CNNs are especially suitable for problems from this domain. Beyond the deep model's hierarchical representation, which includes both low-level and high-level features, CNNs also exhibit a certain translational invariance in the learned features. A simple CNN architecture for binary damage classification is depicted in Figure 3. It illustrates a model that classifies input images based on whether they include damaged or undamaged objects. Denoted as $NN_\theta(x)$, this model has some trainable weights θ and yields the probability $p_\theta(damage \,|\, x)$ that a given input image x contains a damaged object. The complementary probability, $p_\theta(no\ damage \,|\, x)$, is straightforwardly calculated as $1 - p_\theta(damage \,|\, x)$. The map from the input image to the probabilistic output usually consists of a convolutional feature extractor and a fully connected classifier. The feature extractor contains convolutional and downsampling layers, typically several. Moreover, nonlinear activation functions such as the rectified linear unit (*ReLU*) are applied to the feature maps, usually directly after the convolution. The flattened features are then further processed in the final classifier. It contains dense linear layers, each followed by an activation function. A sigmoid function is applied to the single output of the last layer so as to ensure that the predicted damage probability is properly normalized.

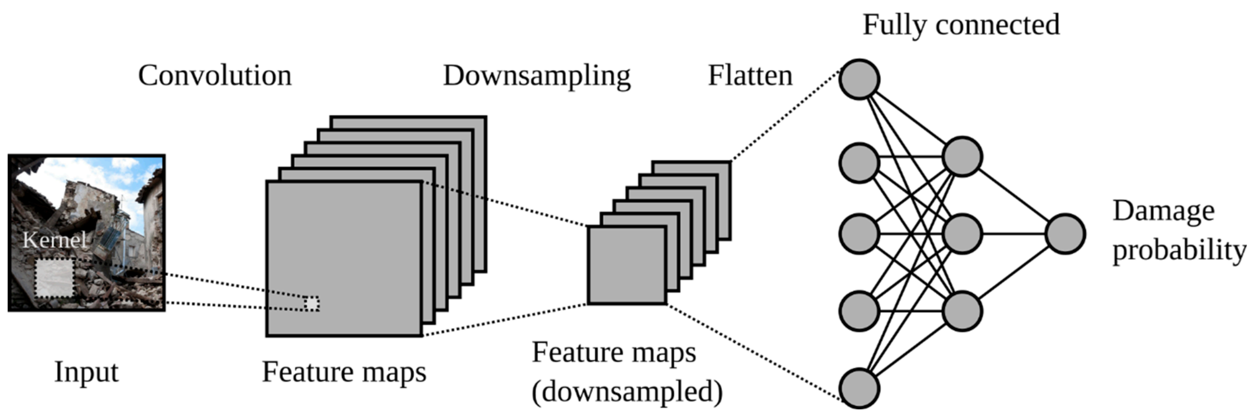

Figure 3. Illustration of a simple CNN architecture with regard to (binary) damage classification.

In the context of emergency responses, researchers have already started to leverage the advances in CNNs to develop adaptive models for identifying damage in structures and CISs following destructive earthquakes. Specifically, the CNN-based image classification, object detection, and semantic segmentation for damage identification and localization have undergone comprehensive scrutiny by Sony et al. [100] and Zhang et al. [92], respectively.

Notably, Mondal et al. [101] employed region-based object detection methods to localize earthquake-induced damage in building structures and distinguish between various damage types. To facilitate autonomous, robot-led damage inspections, pretrained models were fine-tuned using manually annotated data collected through in situ observations of earthquakes over the past two decades. Similar detection approaches have also been proposed by Pan and Yang [102], as well as Liang [103], who utilized image segmentation (pixel-wise classification) for post-disaster damage assessment.

Meanwhile, Chachra et al. [104] proposed a classification approach for detecting damaged buildings immediately after earthquakes using images from social media platforms. Their method leverages transfer learning with a pretrained feature extractor and customizes a classifier using a small manually labelled dataset; additionally, they explored model interpretability techniques to visualize and gain insights into the decision-making process of the "black-box" model based on specific features.

Most recently, Braik and Koliou [105] introduced an end-to-end model that establishes a direct connection between satellite imagery and large-scale damage maps. The primary objective of this model is to facilitate near-real-time decision-making on post-shock emergency responses. To achieve this, the model seamlessly integrates satellite imagery, geographic information systems (GIS), and DL techniques. The case study demonstrated that leveraging GIS enables the automated extraction of sub-images with remarkable accuracy; meanwhile, fine-tuning further enhances the robustness of damage classification, resulting in highly accurate building damage maps at a regional level.

It is worth noting that vision transformers (ViTs) have recently emerged as an alternative to CNNs. They have also been adopted for the automated and rapid damage assessment of engineering structures and CISs. For instance, Shamsabadi et al. [106] developed a ViT-based model specifically designed for crack detection in concrete and asphalt—the two most commonly used materials in structures and roadways. The ViT was demonstrated to outperform classical CNNs in their study.

4.2. The Reinforcement Learning-Driven Emergency Response and Recovery

Reinforcement learning (RL), a subfield of machine learning, centres around how independent agents can make decisions in dynamic environments to maximize cumulative rewards [107]. Unlike other machine learning approaches, RL closely mirrors the learning behaviour observed in humans and other animals. Many recent RL algorithms draw inspiration from biological processes [85]. In RL, an agent interacts with an environment, typically modelled as a Markov decision process (MDP). To address this interaction, dynamic programming techniques are commonly employed [107,108]. Due to its versatility, RL has found successful applications across various domains, including autonomous vehicles [109] and board games; notably, it played a pivotal role in the development of AlphaGo and AlphaZero [87,110].

Post-hazard recovery, including emergency responses in urban communities, is an area where RL can be particularly effective. Its unique ability to balance long-term rewards against short-term gains makes it well-suited for such critical tasks [107]. When real-world hazards strike, the overarching objective becomes minimizing human and socioeconomic losses throughout the entire event. To fulfil that objective, decision-makers must meticulously weigh the criticality and recoverability of the damaged components within those hazard-impacted CISs. Factors like accessibility, based on the real-time topology of the system, and the ease of repair play a pivotal role in their decision-making. This balancing act persists sequentially and adaptively throughout the whole emergency response campaign. RL, in theory, holds the promise of discovering optimal policies for these campaigns. These policies translate observations on the status of CIS components into specific recovery actions—such as determining which damaged components should be prioritized for restoration. However, practical implementation faces challenges. The MDPs governing post-shock emergency responses are inherently high-dimensional, rendering traditional RL algorithms inadequate for their resolution. In response to this limitation, a new subfield termed deep reinforcement learning (DRL) has emerged. Inspired by the increasing generalization capacity of deep neural networks, DRL leverages these networks as nonlinear function approximators [85] for policies (π (a | s) {\displaystyle \pi (a | s)} or other learned functions). Despite their successful application in various domains, limited research has been conducted to date on harnessing advancements in RL (including DRL) for post-hazard emergency response and urban community recovery.

Nozhati et al. [111] introduced a discrete optimization approach to the sequential decision-making on the recovery management of urban communities affected by hazards. This approach integrates approximate dynamic programming with heuristics specifically tailored for post-shock recovery planning, effectively addressing the challenge posed by the curse of dimensionality. The approach was applied to inform decision-making regarding the post-earthquake recovery of the EPSS within a testbed community coarsely modelled after Gilroy, California, United States. By considering recovery policies from both public and private institutions, the simulation demonstrated a significant enhancement in post-earthquake recovery performance. Most importantly, the approach facilitates the identification of near-optimal recovery strategies aligned with multiple objectives in an efficient manner.

Tao and Wang [112] developed a Markovian framework for determining optimum post-earthquake restoration strategies for highway networks, with a focus on life-cycle costs (LCCs). Within this framework, seismic hazards are considered over an infinite time horizon, and the optimal restoration strategy for each individual bridge in the network is determined using a continuous-time MDP. Additionally, the framework accounts for indirect economic losses resulting from earthquake-induced traffic congestion. This framework has been applied to guide the post-shock restoration of a virtual highway network consisting of seven nodes and 12 links. The simulation results demonstrate that an optimal post-shock restoration policy can be obtained through policy iterations. Importantly, the optimal restoration of a single bridge depends not only on its own state but also on the states of other bridges within the whole network.

Most recently, Sun et al. [113] established an autonomous planning system specifically designed to address the post-hazard emergency response of modern road networks (RNs) by leveraging the latest advancement in DRL, particularly the breakthroughs associated with AlphaGo [87]. In this research, the partial yet rapid repair of those hazard-decimated bridges has been adopted as a viable approach to the emergency response of modern RNs under hazard events. In particular, the system employs a deep neural network trained on a wealth of hypothetical earthquake and damage scenarios. By learning from these experiences, the neural network guides the search process within the newly developed planning system. Notably, the system's generalization capacity is examined through an iterative process. Initially, a neural network (i.e., the first generation) is purposefully trained using experiences associated with a naïve heuristic—without sophisticated domain knowledge. Subsequent generations build upon this foundation, each expected to yield an improved training dataset for the next iteration. A case study conducted on a real-world RN in Luchon, France, demonstrates the system's applicability. Remarkably, even without domain-specific knowledge, the post-shock emergency response campaign guided by this autonomous planning system significantly outperforms strategies informed solely by engineering heuristics.

Figure 4 presents a comprehensive summary of the latest research, detailing various approaches employed during decision-making for post-hazard recovery of CISs.

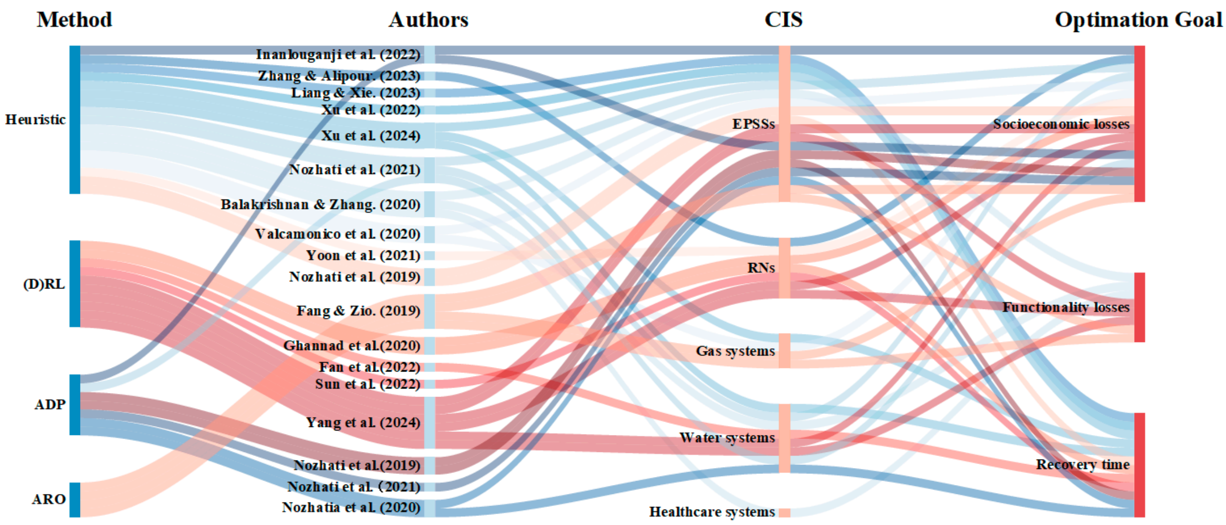

Figure 4. Summary of the state-of-the-art research undertaken (ADP and ARO stand for approximate dynamic programming and adaptive robust optimization, respectively) [76,111,114–127].

5. Prospects and Challenges

5.1. Holy Grail—Autonomous, Grouped, and Humanoid Recovery Robots

In recent years, significant scientific advancements, as discussed in Section 4, have laid a foundation for assessing the damage and informing decision-making for emergency responses across hazard-affected urban areas. These developments are crucial for safeguarding communities subjected to crises. Humanoid robots, driven by breakthroughs in research, are increasingly poised to play a pivotal role in shaping the modus operandi of urban communities. Their capabilities extend beyond routine tasks; they are now entrusted with critical functions such as constructing large-scale engineering structures, managing complex transportation systems, and even performing surgical procedures [128–132]. In particular, humanoid robots have already been deployed as sophisticated tools for disaster management in modern urban settings. Their applications include firefighting, emergency search and rescue operations, and other critical interventions [133–135].

Justifiably, the convergence of cutting-edge AI techniques and advancements in robotics engineering heralds a new era of autonomous and adaptable humanoid recovery robots, which has long been the holy grail of the scientific community [136]. It is particularly highlighted that the deployment of these recovery robots promises a paradigm shift in emergency response and resilience of future urban communities in the following sense:

1. Instead of human beings, these autonomous recovery robots will "bear the brunt" in the wake of catastrophes. Traditionally, human responders have borne the initial risks during catastrophes; however, the severity of natural or man-made disasters often renders affected areas uninhabitable and inaccessible to humans. For instance, in major fire accidents, smoke inhalation and extreme temperatures pose fatal threats to firefighters themselves [134]. Similarly, the release of radioactive materials triggered by hazardous events like earthquakes will substantially jeopardize the well-being of first responders [137]; consequently, not only can post-hazard emergency responses be significantly delayed and thwarted, but additional human and societal losses may also occur. To address this challenge, humanoid recovery robots—operating autonomously and cooperatively—can venture into affected zones, bearing the initial brunt of danger [136];
2. The adaptivity of decision-making, as well as the agility (and manoeuvrability) of autonomous recovery robots. In urban communities facing hazardous events, post-hazard restoration decisions typically adhere to top-down, experience-based protocols; however, real-world observations reveal that restoration campaigns often suffer from sluggishness and poor management due to a lack of adaptivity in decision-making processes (i.e., decision-making lacks the agility needed to respond swiftly to dynamic situations; additionally, uncertainties and evolving conditions also challenge traditional protocols), ambiguity in stakeholder roles (can be both public and private institutions), as well as coordination gaps between them [73]; on the contrary, as manifested and inspired by a series of substantial successes in the pursuit of AI-capable agents [86,88,90], grouped and humanoid recovery robots would be able to serve as full-fledged first responders in future urban communities. Leveraging state-of-the-art AI algorithms, they can explore vast state-action spaces within hazard-impacted CISs, allowing them to chart coordinated restoration pathways, even amidst uncertainties and noise. It is therefore expected that these robots could outperform human responders, even without domain-specific knowledge [88,90]. In parallel, they could effectively mitigate the negative impact of panic and irrationality inherent in human responders and decision-makers; additionally, with quality maintenance, the robots would be readily available on-site, agile, and manoeuvrable across harsh terrains.

5.2. Challenges Ahead

Despite the (potentially) revolutionary impact of autonomous recovery robots on post-shock emergency responses, it is crucial to acknowledge the significant challenges that lie ahead, potentially casting a shadow over their development and deployment. Overall, these challenges include (but are not limited to) the following:

1. The safety of deployment. Machine learning models, particularly deep neural networks, have showcased remarkable performance in controlled benchmarks; however, their safety and trustworthiness in real-world applications raise valid concerns, especially in safety-critical scenarios like post-hazard emergency responses [6]. The crux of the issue lies in the fact that minimizing a statistically motivated loss function during training does not guarantee optimal real-world performance. When these models encounter data during in situ deployment—data that significantly diverge from their training and testing datasets—their robustness against distribution shifts becomes compromised [138], exacerbated by the scarcity of hazard-related datasets. Furthermore, uncertainty compounds the challenge of ensuring model safety [139]. Inaccurate or false predictions can have severe unintended consequences during real-world hazard events. For instance, mischaracterizing the damage status of CISs using CNN-based image recognition may lead to significant disaster mismanagement; similarly, the uncertainty and dynamics surrounding the functionality of CISs during such periods can amplify the impact of unsafe actions of autonomous agents. These actions may trigger cascading failures whose consequences could, paradoxically, go substantially beyond the initial hazard [64,65]. Against this backdrop, in-depth research should be undertaken to institutionalize the certification of autonomous recovery robots [138]. It is also vital to develop a more interpretable and scalable DRL framework [140] to enable these robots to shun unsafe actions while still fulfilling the optimization objectives of post-shock emergency response campaigns [141,142];
2. Ethical decision-making. As AI penetrates modern societies, ethical questions arise regarding how AI-capable machines navigate complex decisions; for instance, autonomous vehicles, faced with unavoidable harm during crashes, must grapple with the difficult choice between running over pedestrians or sacrificing themselves and their passengers [143–145]. This principle of the "greater good" becomes even more intricate in the context of post-hazard emergency responses, or early warnings [146,147]. Recovery robots, deployed after disasters, face a delicate balancing act. Functionality gaps between supply and demand in hazard-impacted CISs, coupled with limited restoration resources, lead to critical decisions. These robots must prioritize certain neighbourhoods while "sacrificing" others [57]. Although well-intentioned, such decisions can evoke anxiety and discontent among local inhabitants, exacerbating societal inequality and sapping the long-term resilience of urban communities affected by hazards [148–152]. It is thus crucial for private and public sectors to collaborate to address such a thorny challenge by proposing an inclusive regulatory framework to guide recovery robots to select a strategy that reconciles widely recognized moral values with the self-interest of affected neighbourhoods.

6. Conclusions

The modus operandi of modern urban communities has been profoundly and increasingly reliant upon the enduring functionality supply from a diverse array of CISs; however, real-world hazard events have consistently revealed the vulnerabilities of these CISs in communities across the spectrum of wealth. Over the past two decades, extensive research has sought to establish resilient CISs capable of withstanding such events while swiftly recovering functionality. Notably, this research endeavour provides valuable insights into the impact of interdependencies among CISs. These intricate connections play a pivotal role in amplifying initial local damage or dysfunction on a global scale. Additionally, state-of-the-art assessment frameworks consider not only the physical resilience of networked CISs but also their multidimensional resilience from a socio-economic perspective. Despite these significant advances, recent extreme climate events have exposed the limitations of these frameworks, leading to the following conclusions:

1. The majority of the state-of-the-art resilience assessment frameworks indiscriminately characterize the criticality across different temporal windows during hazard events. Conversely, damage or dysfunction initiated by a hazard in any single CIS tends to propagate, potentially triggering a full-blown cascading failure in the immediate aftermath of such events;
2. In this context, post-shock emergency responses emerge as a promising pathway toward resilient urban communities. These responses aim to swiftly restore the functionality of hazard-impacted CISs to a minimal yet acceptable level immediately after shocking events. By effectively inhibiting potential cascading failures triggered by the initial damage, these emergency responses facilitate smoother long-term recovery;
3. Practical implementation of emergency responses faces obstacles from computational, technical, and socio-economic perspectives;
4. Pilot studies have utilized advanced machine learning techniques to enhance post-shock emergency responses of Critical Infrastructure Systems (CISs). These efforts underscore AI-driven strategies that can rapidly restore functionality and bolster resilience in the aftermath of disasters. Notably, deep learning has proven to be a powerful tool for swift damage assessment immediately following hazardous events. Progress in this field has established the groundwork for adaptive post-shock emergency responses, with (deep) reinforcement learning playing a crucial role;
5. By integrating state-of-the-art AI with robotics engineering, autonomous, grouped, and humanoid recovery robots could potentially revolutionize urban crisis management. These robots not only shield human responders from hazard-induced dangers but also devise strategies that may surpass traditional top-down, experience-based protocols.

Lastly, this paper also serves as a cautionary message to the scientific community and public regarding the potential risks associated with the convergence of AI and emergency responses. Amidst the intricate and dynamic interactions within urban communities throughout hazard events, any erroneous prediction or unsafe action by these AI agents could inadvertently exacerbate the damage sustained by hazard-impacted CISs, potentially exceeding the initial hazards themselves; furthermore, decision-making by these AI agents during emergency response campaigns may unintentionally perpetuate societal inequality across hazard-affected communities. Without vigilant oversight, their actions could unwittingly exacerbate existing disparities; therefore, comprehensive studies are imperative to regulate the behaviour of AI agents, ensuring alignment with ethical norms while contributing to the resilience of future urban communities imperilled by various natural and/or man-made catastrophes.

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References

1. Dunn, S.; Wilkinson, S.; Ford, A. Spatial structure and evolution of infrastructure networks. *Sustain. Cities Soc.* **2016**, *27*, 23–31. [CrossRef]
2. United Nations Department of Economic and Social Affairs. *World Population Prospects 2022: Summary of Results*; United Nations Fund for Population Activities: New York, NY, USA, 2023.
3. Bettencourt, L.M.A.; Lobo, J.; Helbing, D.; Kuhnert, C.; West, G.B. Growth, innovation, scaling, and the pace of life in cities. *Proc. Natl. Acad. Sci. USA* **2007**, *104*, 7301–7306. [CrossRef] [PubMed]

4. Batty, M. The size, scale, and shape of cities. *Science* **2008**, *319*, 769–771. [CrossRef]
5. Alesch, D.J. Complex urban systems and extreme events: Toward a theory of disaster recovery. In Proceedings of the 1st International Conference on Urban Disaster Reduction, Kobe, Japan, 18–20 January 2005.
6. Kröger, W.; Zio, E. *Vulnerable Systems*; Springer: Berlin/Heidelberg, Germany, 2011.
7. Glaeser, E. Cities, productivity, and quality of life. *Science* **2011**, *333*, 592–594. [CrossRef]
8. World Health Organization. WHO Coronavirus (COVID-19) Dashboard. 2024. Available online: https://covid19.who.int/ (accessed on 31 March 2024).
9. Helbing, D. Globally networked risks and how to respond. *Nature* **2013**, *497*, 51–59. [CrossRef] [PubMed]
10. Buldyrev, S.V.; Parshani, R.; Paul, G.; Stanley, H.E.; Havlin, S. Catastrophic cascade of failures in interdependent networks. *Nature* **2010**, *464*, 1025–1028. [CrossRef]
11. Brummitt, C.D.; D'Souza, R.M.; Leicht, E.A. Suppressing cascades of load in interdependent networks. *Proc. Natl. Acad. Sci. USA* **2012**, *109*, E680–E689. [CrossRef] [PubMed]
12. Bashan, A.; Berezin, Y.; Buldyrev, S.V.; Havlin, S. The extreme vulnerability of interdependent spatially embedded networks. *Nat. Phys.* **2013**, *9*, 667–672. [CrossRef]
13. Bodenmann, L.; Galanis, P.; Broccardo, M.; Stojadinović, B. The role of risk measures in making seismic upgrading decisions. *Earthq. Spectra* **2020**, *36*, 1802–1822. [CrossRef]
14. Rosowsky, D.V. Projecting the effects of a warming climate on the hurricane hazard and insured losses: Methodology and case study. *Struct. Saf.* **2021**, *88*, 102036. [CrossRef]
15. Liu, C.; Ouyang, M.; Mao, Z.J.; Xu, X.L. A multi-perspective framework for seismic retrofit optimization of urban infrastructure systems. *Earthq. Eng. Struct. Dyn.* **2022**, *51*, 2771–2790. [CrossRef]
16. Fraser, S.; Raby, A.; Pomonis, A.; Goda, K.; Chian, S.C.; Macabuag, J.; Offord, M.; Saito, K.; Sammonds, P. Tsunami damage to coastal defences and buildings in the March 11th 2011 M_w 9.0 Great East Japan earthquake and tsunami. *Bull. Earthq. Eng.* **2013**, *11*, 205–239. [CrossRef]
17. British Broadcasting Corporation. Climate Change: Huge Toll of Extreme Weather Disasters in 2021. 2021. Available online: https://www.bbc.co.uk/news/science-environment-59761839 (accessed on 4 September 2024).
18. Milly, P.C.D.; Wetherald, R.T.; Dunne, K.A.; Delworth, T.L. Increasing risk of great floods in a changing climate. *Nature* **2002**, *415*, 514–517. [CrossRef] [PubMed]
19. Tellman, B.; Sullivan, J.A.; Kuhn, C.; Kettner, A.J.; Doyle, C.S.; Brakenridge, G.R.; Erickson, T.A.; Slayback, D.A. Satellite imaging reveals increased proportion of population exposed to floods. *Nature* **2021**, *596*, 80–86. [CrossRef] [PubMed]
20. Bruneau, M.; Chang, S.E.; Eguchi, R.T.; Lee, G.C.; O'Rourke, T.D.; Reinhorn, A.M.; Shinozuka, M.; Tierney, K.; Wallace, W.A.; Von Winterfeldt, D. A framework to quantitatively assess and enhance the seismic resilience of communities. *Earthq. Spectra* **2003**, *19*, 733–752. [CrossRef]
21. Ouyang, M.; Dueñas-Osorio, L.; Min, X. A three-stage resilience analysis framework for urban infrastructure systems. *Struct. Saf.* **2012**, *36–37*, 23–31. [CrossRef]
22. Sun, L.; Didier, M.; Delé, E.; Stojadinovic, B. Probabilistic demand and supply resilience model for electric power supply system under seismic hazard. In Proceedings of the 12th International Conference on Applications of Statistics and Probability in Civil Engineering (ICASP2015), Vancouver, BC, Canada, 12–15 July 2015.
23. Rinaldi, S.A.; Peerenboom, J.P.; Kelly, T.K. Identifying, understanding, and analyzing critical infrastructure interdependencies. *IEEE Control Syst. Mag.* **2001**, *21*, 11–25.
24. Sun, L.; Stojadinovic, B.; Sansavini, G. Resilience evaluation framework for integrated civil infrastructure-community systems under seismic hazard. *ASCE J. Infrastruct. Syst.* **2019**, *25*, 04019016. [CrossRef]
25. Blagojević, N.; Kipfer, J.; Didier, M.; Stojadinović, B. Scenario-based resilience assessment of communities with interdependent civil infrastructure systems. In Proceedings of the 17th World Conference on Earthquake Engineering (17WCEE 2020), Sendai, Japan, 13–18 September 2020.
26. Zhao, T.; Sun, L. Seismic resilience assessment of critical infrastructure-community systems considering looped interdependences. *Int. J. Disaster Risk Reduct.* **2021**, *59*, 102246. [CrossRef]
27. Linkov, I.; Bridges, T.; Creutzig, F.; Decker, J.; Fox-Lent, C.; Kröger, W.; Lambert, J.H.; Levermann, A.; Montreuil, B.; Nathwani, J.; et al. Changing the resilience paradigm. *Nat. Clim. Change* **2014**, *4*, 407–409. [CrossRef]
28. Galasso, C.; Opabola, E.A. The 2023 Kahramanmaraş Earthquake Sequence: Finding a path to a more resilient, sustainable, and equitable society. *Commun. Eng.* **2024**, *3*, 24. [CrossRef]
29. Hosseini, S.; Barker, K.; Ramirez-Marquez, J.E. A review of definitions and measures of system resilience. *Reliab. Eng. Syst. Saf.* **2016**, *145*, 47–61. [CrossRef]
30. Didier, M.; Broccardo, M.; Esposito, S.; Stojadinovic, B. A compositional Demand/Supply framework to quantify the resilience of civil infrastructure systems (Re-CoDeS). *Sustain. Resilient Infrastruct.* **2018**, *3*, 86–102. [CrossRef]
31. Saji, G. A post accident safety analysis report of the Fukushima Accident-Future direction of evacuation: Lessons learned. In Proceedings of the 21st International Conference on Nuclear Engineering (ICONE21), Chengdu, China, 29 July–2 August 2013.
32. Zhang, Y.; Burton, H.V.; Sun, H.; Shokrabadi, M. A machine learning framework for assessing post-earthquake structural safety. *Struct. Saf.* **2018**, *72*, 1–16. [CrossRef]

33. Lu, X.; Cheng, Q.; Xu, Z.; Xu, Y.; Sun, C. Real-time city-scale time-history analysis and its application in resilience-oriented earthquake emergency responses. *Appl. Sci.* **2019**, *9*, 3497. [CrossRef]
34. Xie, Y.; Sichani, M.E.; Padgett, J.E.; DesRoches, R. The promise of implementing machine learning in earthquake engineering: A state-of-the-art review. *Earthq. Spectra* **2020**, *36*, 1769–1801. [CrossRef]
35. Zhao, B.; Taucer, F. Performance of infrastructure during the May 12, 2008 Wenchuan Earthquake in China. *J. Earthq. Eng.* **2010**, *14*, 578–600. [CrossRef]
36. Goda, K.; Pomonis, A.; Chian, S.C.; Offord, M.; Saito, K.; Sammonds, P.; Fraser, S.; Raby, A.; Macabuag, J. Ground motion characteristics and shaking damage of the 11th March 2011 M_w9.0 Great East Japan earthquake. *Bull. Earthq. Eng.* **2013**, *11*, 141–170. [CrossRef]
37. Lizundia, B.; Davidson, R.A.; Hashash, Y.M.A.; Olshansky, R. Overview of the 2015 Gorkha, Nepal, Earthquake and the Earthquake Spectra special issue. *Earthq. Spectra* **2017**, *33*, S1–S20. [CrossRef]
38. Okamura, M.; Bhandary, N.P.; Mori, S.; Marasini, N.; Hazarika, H. Report on a reconnaissance survey of damage in Kathmandu caused by the 2015 Gorkha Nepal earthquake. *Soils Found.* **2015**, *55*, 1015–1029. [CrossRef]
39. Gokkaya, K. Geographic analysis of earthquake damage in Turkey between 1900 and 2012. *Geomat. Nat. Hazards Risk* **2016**, *7*, 1948–1961. [CrossRef]
40. Nichols, J.M.; Rodgers, S. Economic and societal challenges imposed by seismic risk on the built environment. *ASCE-ASME J. Risk Uncertain. Eng. Syst. Part A-Civ. Eng.* **2017**, *3*, 04017022. [CrossRef]
41. Booth, E. Dealing with earthquakes: The practice of seismic engineering 'as if people mattered'. *Bull. Earthq. Eng.* **2018**, *16*, 1661–1724. [CrossRef]
42. Aktas, Y.D.; So, E.; Johnson, C.; Cabuk, E.; Malcioglu, F.S.; Donmez, K.; Asinari, M.; Adamidis, O.; Milillo, P.; Tetik, T.; et al. Hybrid EEFIT Mission to February 2023 Kahramanmaraş Earthquake Sequence. In Proceedings of the SECED 2023 Conference Earthquake Engineering & Dynamics for a Sustainable Future, Society for Earthquake and Civil Engineering Dynamics (SECED), Cambridge, UK, 14–15 September 2023.
43. Sharma, K.; Apil, K.C.; Subedi, M.; Pokharel, B. Challenges for reconstruction after M(w)7.8 Gorkha earthquake: A study on a devastated area of Nepal. *Geomat. Nat. Hazards Risk* **2018**, *9*, 760–790. [CrossRef]
44. Moreno, J.; Shaw, D. Community resilience to power outages after disaster: A case study of the 2010 Chile earthquake and tsunami. *Int. J. Disaster Risk Reduct.* **2019**, *34*, 448–458. [CrossRef]
45. Imperiale, A.J.; Vanclay, F. Experiencing local community resilience in action: Learning from post-disaster communities. *J. Rural Stud.* **2016**, *47*, 204–219. [CrossRef]
46. Batabyal, A.A. On some aspects of ecological resilience and the conservation of species. *J. Environ. Manag.* **1998**, *52*, 373–378. [CrossRef]
47. International Strategy for Disaster Reduction. Hyogo framework for action 2005–2015: Building the resilience of nations and communities to disasters. In Proceedings of the World Conference on Disaster Reduction, Kobe, Japan, 18–22 January 2005.
48. Cutter, S.L. Building disaster resilience: Steps toward sustainability. *Chall. Sustain.* **2013**, *1*, 72–79. [CrossRef]
49. Iuchi, K.; Johnson, L.A.; Olshansky, R.B. Securing Tohoku's future: Planning for rebuilding in the first year following the Tohoku-Oki Earthquake and Tsunami. *Earthq. Spectra* **2013**, *29*, S479–S499. [CrossRef]
50. Sun, L. Modeling the Seismic Resilience of Electric Power Supply Systems. Ph.D. Thesis, Department of Civil, Environmental and Geomatic Engineering, Swiss Federal Institute of Technology Zurich (ETH Zurich), Zurich, Switzerland, 2017.
51. Cimellaro, G.P.; Reinhorn, A.M.; Bruneau, M. Performance-based metamodel for healthcare facilities. *Earthq. Eng. Struct. Dyn.* **2011**, *40*, 1197–1217. [CrossRef]
52. Ameri, M.R.; van de Lindt, J.W. Seismic performance and recovery modeling of natural gas networks at the community level using building demand. *J. Perform. Constr. Facil.* **2019**, *33*, 04019043. [CrossRef]
53. Liu, W.; Song, Z.; Ouyang, M.; Li, J. Recovery-based seismic resilience enhancement strategies of water distribution networks. *Reliab. Eng. Syst. Saf.* **2020**, *203*, 107088. [CrossRef]
54. Shinozuka, M.; Dong, X.; Chen, T.C.; Jin, X. Seismic performance of electric transmission network under component failures. *Earthq. Eng. Struct. Dyn.* **2007**, *36*, 227–244. [CrossRef]
55. Dueñas-Osorio, L.; Vemuru, S.M. Cascading failures in complex infrastructure systems. *Struct. Saf.* **2009**, *31*, 157–167. [CrossRef]
56. Casari, M.; Wilkie, S.J. Sequencing lifeline repairs after an earthquake: An economic approach. *J. Regul. Econ.* **2005**, *27*, 47–65. [CrossRef]
57. Sun, L.; Stojadinovic, B.; Sansavini, G. Agent-based recovery model for seismic resilience evaluation of electrified communities. *Risk Anal.* **2019**, *7*, 1597–1614. [CrossRef]
58. Batty, M. *Cities and Complexity: Understanding Cities with Cellular Automata, Agent-Based Models, and Fractals*; MIT Press: Cambridge, MA, USA, 2007.
59. Mackie, K.R.; Wong, J.M.; Stojadinovic, B. Post-earthquake bridge repair cost and repair time estimation methodology. *Earthq. Eng. Struct. Dyn.* **2010**, *39*, 281–301. [CrossRef]
60. Decò, A.; Bocchini, P.; Frangopol, D.M. A probabilistic approach for the prediction of seismic resilience of bridges. *Earthq. Eng. Struct. Dyn.* **2013**, *42*, 1469–1487. [CrossRef]
61. Hu, F.; Yeung, C.H.; Yang, S.; Wang, W.; Zeng, A. Recovery of infrastructure networks after localised attacks. *Sci. Rep.* **2016**, *6*, 24522. [CrossRef]

62. Wu, Y.; Hou, G.; Chen, S. Post-earthquake resilience assessment and long-term restoration prioritization of transportation network. *Reliab. Eng. Syst. Saf.* **2021**, *211*, 107612. [CrossRef]
63. Albert, R.; Albert, I.; Nakarado, G.L. Structural vulnerability of the North American power grid. *Phys. Rev. E* **2004**, *69*, 025103. [CrossRef] [PubMed]
64. Berizzi, A. The Italian 2003 blackout. In Proceedings of the IEEE Power Engineering Society General Meeting, Denver, CO, USA, 6–10 June 2004.
65. Corsi, S.; Sabelli, C. General blackout in Italy Sunday September 28, 2003, h. 03:28:00. In Proceedings of the IEEE Power Engineering Society General Meeting, Denver, CO, USA, 6–10 June 2004.
66. Andersson, G.; Donalek, P.; Farmer, R.; Hatziargyriou, N.; Kamwa, I.; Kundur, P.; Martins, N.; Paserba, J.; Pourbeik, P.; Sanchez-Gasca, J.; et al. Causes of the 2003 major grid blackouts in North America and Europe, and recommended means to improve system dynamic performance. *IEEE Trans. Power Syst.* **2005**, *20*, 1922–1928. [CrossRef]
67. Krishnamurthy, V.; Kwasinski, A.; Duenas-Osorio, L. Comparison of power and telecommunications dependencies and interdependencies in the 2011 Tohoku and 2010 Maule Earthquakes. *J. Infrastruct. Syst.* **2016**, *22*, 04016013. [CrossRef]
68. Aydin, N.Y.; Duzgun, H.S.; Heinimann, H.R.; Wenzel, F.; Gnyawali, K.R. Framework for improving the resilience and recovery of transportation networks under geohazard risks. *Int. J. Disaster Risk Reduct.* **2018**, *31*, 832–843. [CrossRef]
69. Zhang, L.L.; Liu, X.; Li, Y.P.; Liu, Y.; Liu, Z.P.; Lin, J.C.; Shen, J.; Tang, X.F.; Zhang, Y.; Liang, W.N. Emergency medical rescue efforts after a major earthquake: Lessons from the 2008 Wenchuan earthquake. *Lancet* **2012**, *379*, 853–861. [CrossRef]
70. Smith, K. *Environmental Hazards: Assessing Risk and Reducing Disaster*, 6th ed.; Routledge: Abingdon, UK, 2013.
71. Lindell, M.K.; Perry, R.W. Hazardous materials releases in the Northridge Earthquake: Implications for seismic risk assessment. *Risk Anal.* **1997**, *17*, 147–156. [CrossRef]
72. Young, S.; Balluz, L.; Malilay, J. Natural and technologic hazardous material releases during and after natural disasters: A review. *Sci. Total Environ.* **2004**, *322*, 3–20. [CrossRef] [PubMed]
73. Funabashi, Y.; Kitazawa, K. Fukushima in review: A complex disaster, a disastrous response. *Bull. At. Sci.* **2012**, *68*, 9–21. [CrossRef]
74. Reasenberg, P.A.; Jones, L.M. Earthquake hazard after a mainshock in California. *Science* **1989**, *243*, 1173–1176. [CrossRef]
75. Pollitz, F.F.; Stein, R.S.; Sevilgen, V.; Burgmann, R. The 11 April 2012 east Indian Ocean earthquake triggered large aftershocks worldwide. *Nature* **2012**, *490*, 250–253. [CrossRef]
76. Sun, L.; D'Ayala, D.; Fayjaloun, R.; Gehl, P. Agent-based model on resilience-oriented emergency responses of road networks under seismic hazard. *Reliab. Eng. Syst. Saf.* **2021**, *216*, 108030. [CrossRef]
77. Gehl, P.; Fayjaloun, R.; Sun, L.; Tubaldi, E.; Negulescu, C.; Ozer, E.; D'Ayala, D. Rapid earthquake loss updating of spatially distributed systems via sampling-based Bayesian inference. *Bull. Earthq. Eng.* **2022**, *20*, 3995–4023. [CrossRef]
78. Imperiale, A.J.; Vanclay, F. Command-and-control, emergency powers, and the failure to observe United Nations disaster management principles following the 2009 L'Aquila earthquake. *Int. J. Disaster Risk Reduct.* **2019**, *36*, 101099. [CrossRef]
79. Gehl, P.; Auclair, S.; Fayjaloun, R.; Meresse, P. Decision support for emergency road traffic management in post-earthquake conditions. *Int. J. Disaster Risk Reduct.* **2022**, *77*, 103098. [CrossRef]
80. Mavroulis, S.; Ilgac, M.; Tunca, M.; Lekkas, E.; Püskülcü, S.; Kourou, A.; Sextos, A.; Mavrouli, M.; Can, G.; Thoma, T.; et al. Emergency response, intervention, and societal recovery in Greece and Turkey after the 30th October 2020, M-W=7.0, Samos (Aegean Sea) earthquake. *Bull. Earthq. Eng.* **2022**, *20*, 7933–7955. [CrossRef]
81. Ausiello, G.; Marchetti-Spaccamela, A.; Crescenzi, P.; Gambosi, G.; Protasi, M.; Kann, V. *Complexity and Approximation (Corrected Ed.)*; Springer: Berlin/Heidelberg, Germany, 2003.
82. Powell, W.B. A unified framework for stochastic optimization. *Eur. J. Oper. Res.* **2019**, *275*, 795–821. [CrossRef]
83. Morita, N.; Miura, M.; Yoshida, M.; Kumagai, A.; Ohtsuru, A.; Usa, T.; Kudo, T.; Takamura, N.; Yamashita, S.; Matsuda, N. Spatiotemporal characteristics of internal radiation exposure in evacuees and first responders after the radiological accident in Fukushima. *Radiat. Res.* **2013**, *180*, 299–306. [CrossRef]
84. LeCun, Y.; Bengio, Y.; Hinton, G. Deep learning. *Nature* **2015**, *521*, 436–444. [CrossRef]
85. Mnih, V.; Kavukcuoglu, K.; Silver, D.; Rusu, A.A.; Veness, J.; Bellemare, M.G.; Graves, A.; Riedmiller, M.; Fidjeland, A.K.; Ostrovski, G.; et al. Human-level control through deep reinforcement learning. *Nature* **2015**, *518*, 529–533. [CrossRef]
86. Schmidt, M.; Lipson, H. Distilling free-form natural laws from experimental data. *Science* **2009**, *324*, 81–85. [CrossRef]
87. Silver, D.; Huang, A.; Maddison, C.J.; Guez, A.; Sifre, L.; van den Driessche, G.; Schrittwieser, J.; Antonoglou, I.; Panneershelvam, V.; Lanctot, M.; et al. Mastering the game of *Go* with deep neural networks and tree search. *Nature* **2016**, *529*, 484–489. [CrossRef]
88. Silver, D.; Schrittwieser, J.; Simonyan, K.; Antonoglou, I.; Huang, A.; Guez, A.; Hubert, T.; Baker, L.; Lai, M.; Bolton, A.; et al. Mastering the game of *Go* without human knowledge. *Nature* **2017**, *550*, 354–359. [CrossRef] [PubMed]
89. Kwiatkowski, R.; Lipson, H. Task-agnostic self-modeling machines. *Sci. Robot.* **2019**, *4*, eaau9354. [CrossRef] [PubMed]
90. Schrittwieser, J.; Antonoglou, I.; Hubert, T.; Simonyan, K.; Sifre, L.; Schmitt, S.; Guez, A.; Lockhart, E.; Hassabis, D.; Graepel, T.; et al. Mastering Atari, Go, chess and shogi by planning with a learned model. *Nature* **2020**, *588*, 604–609. [CrossRef] [PubMed]
91. Jumper, J.; Evans, R.; Pritzel, A.; Green, T.; Figurnov, M.; Ronneberger, O.; Tunyasuvunakool, K.; Bates, R.; Žídek, A.; Potapenko, A.; et al. Highly accurate protein structure prediction with AlphaFold. *Nature* **2021**, *596*, 583–589. [CrossRef] [PubMed]
92. Zhang, L.X.; Shen, J.K.; Zhu, B.J. A review of the research and application of deep learning-based computer vision in structural damage detection. *Earthq. Eng. Eng. Vib.* **2022**, *21*, 1–21.

93. Krizhevsky, A.; Sutskever, I.; Hinton, G.E. ImageNet classification with deep convolutional neural networks. *Commun. ACM* **2017**, *60*, 84–90. [CrossRef]
94. Rawat, W.; Wang, Z.H. Deep convolutional neural networks for image classification: A comprehensive review. *Neural Comput.* **2017**, *29*, 2352–2449. [CrossRef] [PubMed]
95. Zhao, Z.Q.; Zheng, P.; Xu, S.T.; Wu, X.D. Object detection with deep learning: A review. *IEEE Trans. Neural Netw. Learn. Syst.* **2019**, *30*, 3212–3232. [CrossRef] [PubMed]
96. Liu, L.; Ouyang, W.L.; Wang, X.G.; Fieguth, P.; Chen, J.; Liu, X.W.; Pietikainen, M. Deep learning for generic object detection: A survey. *Int. J. Comput. Vis.* **2020**, *128*, 261–318. [CrossRef]
97. Ghosh, S.; Das, N.; Das, I.; and Maulik, U. Understanding deep learning techniques for image segmentation. *ACM Comput. Surv.* **2019**, *52*, 73. [CrossRef]
98. Lateef, F.; Ruichek, Y. Survey on semantic segmentation using deep learning techniques. *Neurocomputing* **2019**, *338*, 321–348. [CrossRef]
99. Liu, X.L.; Deng, Z.D.; Yang, Y.H. Recent progress in semantic image segmentation. *Artif. Intell. Rev.* **2019**, *52*, 1089–1106. [CrossRef]
100. Sony, S.; Dunphy, K.; Sadhu, A.; Capretz, M. A systematic review of convolutional neural network-based structural condition assessment techniques. *Eng. Struct.* **2021**, *226*, 111347. [CrossRef]
101. Mondal, T.G.; Jahanshahi, M.R.; Wu, R.T.; Wu, Z.Y. Deep learning-based multi-class damage detection for autonomous post-disaster reconnaissance. *Struct. Control Health Monit.* **2020**, *27*, e2507.
102. Pan, X.; Yang, T.Y. Postdisaster imaged-based damage detection and repair cost estimation of reinforced concrete buildings using dual convolutional neural networks. *Comput.-Aided Civ. Infrastruct. Eng.* **2020**, *35*, 495–510. [CrossRef]
103. Liang, X. Image-based post-disaster inspection of reinforced concrete bridge systems using deep learning with Bayesian optimization. *Comput.-Aided Civ. Infrastruct. Eng.* **2019**, *34*, 415–430. [CrossRef]
104. Chachra, G.; Kong, Q.K.; Huang, J.; Korlakunta, S.; Grannen, J.; Robson, A.; Allen, R.M. Detecting damaged buildings using real-time crowdsourced images and transfer learning. *Sci. Rep.* **2022**, *12*, 8968. [CrossRef]
105. Braik, A.M.; Koliou, M. Automated building damage assessment and large-scale mapping by integrating satellite imagery, GIS, and deep learning. *Comput.-Aided Civ. Infrastruct. Eng.* **2024**, *39*, 2389–2404. [CrossRef]
106. Shamsabadi, E.A.; Xu, C.; Rao, A.S.; Nguyen, T.; Ngo, T.; Dias-da-Costa, D. Vision transformer-based autonomous crack detection on asphalt and concrete surfaces. *Autom. Constr.* **2022**, *140*, 104316. [CrossRef]
107. Sutton, R.S.; Barto, A.G. *Reinforcement Learning: An Introduction*, 2nd ed.; MIT Press: Cambridge, MA, USA, 2018.
108. Bellman, R. A Markovian decision process. *J. Math. Mech.* **1957**, *6*, 679–684. [CrossRef]
109. Schwarting, W.; Pierson, A.; Alonso-Mora, J.; Karaman, S.; Rus, D. Social behavior for autonomous vehicles. *Proc. Natl. Acad. Sci. USA* **2019**, *116*, 24972–24978. [CrossRef] [PubMed]
110. Silver, D.; Hubert, T.; Schrittwieser, J.; Antonoglou, I.; Lai, M.; Guez, A.; Lanctot, M.; Sifre, L.; Kumaran, D.; Graepel, T.; et al. A general reinforcement learning algorithm that masters chess, shogi, and Go through self-play. *Science* **2018**, *362*, 1140–1144. [CrossRef] [PubMed]
111. Nozhati, S.; Sarkale, Y.; Ellingwood, B.; Chong, E.K.P.; Mahmoud, H. Near-optimal planning using approximate dynamic programming to enhance post-hazard community resilience management. *Reliab. Eng. Syst. Saf.* **2019**, *181*, 116–126. [CrossRef]
112. Tao, W.; Wang, N. Determination of optimum post-earthquake restoration strategies for highway bridges by Markov Decision Process. In Proceedings of the 13th International Conference on Applications of Statistics and Probability in Civil Engineering (ICASP13), Seoul, Republic of Korea, 26–30 May 2019.
113. Sun, L.; Shawe-Taylor, J.; D'Ayala, D. Artificial intelligence-informed planning for the emergency response of hazard-impacted road networks. *Sci. Rep.* **2022**, *12*, 16286.
114. Inanlouganji, A.; Pedrielli, G.; Reddy, T.A.; Aponte, F.T. A computational approach for real-time stochastic recovery of electric power networks during a disaster. *Transp. Res. Part E Logist. Transp. Rev.* **2022**, *163*, 102752. [CrossRef]
115. Zhang, N.; Alipour, A. A stochastic programming approach to enhance the resilience of infrastructure under weather-related risk. *Comput.-Aided Civ. Infrastruct. Eng.* **2023**, *38*, 411–432. [CrossRef]
116. Liang, H.; Xie, Q. Resilience-Based Sequential Recovery Planning for Substations Subjected to Earthquakes. *IEEE Trans. Power Deliv.* **2023**, *38*, 353–362. [CrossRef]
117. Xu, M.; Ouyang, M.; Hong, L.; Mao, Z.J.; Xu, X.L. Resilience-driven repair sequencing decision under uncertainty for critical infrastructure systems. *Reliab. Eng. Syst. Saf.* **2022**, *221*, 108378. [CrossRef]
118. Xu, M.; Li, G.Y.; Chen, A. Resilience-driven post-disaster restoration of interdependent infrastructure systems under different decision-making environments. *Reliab. Eng. Syst. Saf.* **2024**, *241*, 109599. [CrossRef]
119. Nozhati, S. A resilience-based framework for decision making based on simulation-optimization approach. *Struct. Saf.* **2021**, *89*, 102032. [CrossRef]
120. Balakrishnan, S.; Zhang, Z. Criticality and Susceptibility Indexes for Resilience-Based Ranking and Prioritization of Components in Interdependent Infrastructure Networks. *J. Manag. Eng.* **2020**, *36*, 04020022. [CrossRef]
121. Valcamonico, D.; Sansavini, g.; Zio, E. Cooperative co-evolutionary approach to optimize recovery for improving resilience in multi-communities. *Reliab. Eng. Syst. Saf.* **2020**, *197*, 106800. [CrossRef]

122. Yoon, S.; Suh, W.; Lee, Y.J. Optimal decision making in post-hazard bridge recovery strategies for transportation networks after seismic events. *Geomat. Nat. Hazards Risk* **2021**, *12*, 2629–2653. [CrossRef]
123. Fang, Y.P.; Zio, E. An adaptive robust framework for the optimization of the resilience of interdependent infrastructures under natural hazards. *Eur. J. Oper. Res.* **2019**, *276*, 1119–1136. [CrossRef]
124. Ghannad, P.; Lee, Y.C.; Friedland, C.J.; Choi, J.O.; Yang, E. Multiobjective Optimization of Postdisaster Reconstruction Processes for Ensuring Long-Term Socioeconomic Benefits. *J. Manag. Eng.* **2020**, *36*, 04020038. [CrossRef]
125. Fan, X.; Zhang, X.; Yu, X.B. A graph convolution network-deep reinforcement learning model for resilient water distribution network repair decisions. *Comput. Aided Civ. Infrastruct.* **2022**, *37*, 1547–1565. [CrossRef]
126. Yang, S.; Zhang, Y.; Lu, X.Z.; Guo, W.; Miao, H.Q. Multi-agent deep reinforcement learning based decision support model for resilient community post-hazard recovery. *Reliab. Eng. Syst. Saf.* **2024**, *242*, 109754. [CrossRef]
127. Nozhati, S.; Sarkale, Y.; Chong, E.K.P.; Ellingwood, B.R. Optimal stochastic dynamic scheduling for managing community recovery from natural hazards. *Reliab. Eng. Syst. Saf.* **2020**, *193*, 106627. [CrossRef]
128. Werfel, J.; Petersen, K.; Nagpal, R. Designing collective behavior in a termite-inspired robot construction team. *Science* **2014**, *343*, 754–758. [CrossRef] [PubMed]
129. Petersen, K.H.; Napp, N.; Stuart-Smith, R.; Rus, D.; Kovac, M. A review of collective robotic construction. *Sci. Robot.* **2019**, *4*, eaau8479. [CrossRef]
130. Fagnant, D.J.; Kockelman, K. Preparing a nation for autonomous vehicles: Opportunities, barriers and policy recommendations. *Transp. Res. Part A Policy Pract.* **2015**, *77*, 167–181. [CrossRef]
131. Lipson, H.; Kurman, M. *Driverless at Last: Cars, Artificial Intelligence, and You*; MIT Press: Cambridge, MA, USA, 2022.
132. Ma, Q.C.; Kobayashi, E.; Suenaga, H.; Hara, K.; Wang, J.C.; Nakagawa, K.; Sakuma, I.; Masamune, K. Autonomous surgical robot with camera-based markerless navigation for oral and maxillofacial surgery. *IEEE/ASME Trans. Mechatron.* **2020**, *25*, 1084–1094. [CrossRef]
133. Murphy, R.R. Trial by fire-Activities of the rescue robots at the World Trade Center from 11–21 September 2001. *IEEE Robot. Autom. Mag.* **2004**, *11*, 50–61. [CrossRef]
134. Holley, P. Firefighters had a secret weapon when Notre Dame caught fire: A robot named 'Colossus'. *The Washington Post*, 17 April 2019. Available online: https://www.washingtonpost.com/technology/2019/04/17/firefighters-had-secret-weapon-when-notre-dame-caught-fire-robot-named-colossus/ (accessed on 17 April 2019).
135. Murphy, R.R.; Kravitz, J.; Stover, S.L.; Shoureshi, R. Novel application of robotics mobile robots in mine rescue and recovery. *IEEE Robot. Autom. Mag.* **2009**, *16*, 91–103. [CrossRef]
136. Murphy, R.R. *Disaster Robotics*; MIT Press: Cambridge, MA, USA, 2014.
137. Tominaga, T.; Hachiya, M.; Tatsuzaki, H.; Akashi, M. The accident at the Fukushima Daiichi Nuclear Power Plant in 2011. *Health Phys.* **2014**, *106*, 630–637. [CrossRef] [PubMed]
138. Huang, X.W.; Kroening, D.; Ruan, W.J.; Sharp, J.; Sun, Y.C.; Thamo, E.; Wu, M.; Yi, X.P. A survey of safety and trustworthiness of deep neural networks: Verification, testing, adversarial attack and defence, and interpretability? *Comput. Sci. Rev.* **2020**, *37*, 100270. [CrossRef]
139. Abdar, M.; Pourpanah, F.; Hussain, S.; Rezazadegan, D.; Liu, L.; Ghavamzadeh, M.; Fieguth, P.; Cao, X.; Khosravi, A.; Acharya, U.R.; et al. A review of uncertainty quantification in deep learning: Techniques, applications and challenges. *Inf. Fusion* **2021**, *76*, 243–297. [CrossRef]
140. Rudin, C. Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. *Nat. Mach. Intell.* **2019**, *1*, 206–215. [CrossRef]
141. Turchetta, M.; Berkenkamp, F.; Krause, A. Safe exploration in finite Markov Decision Processes with Gaussian Processes. In Proceedings of the 29th Conference on Neural Information Processing Systems (NIPS 2016), Barcelona, Spain, 5–10 December 2016.
142. Wachi, A.; Sui, Y.; Yue, Y.; Ono, M. Safe exploration and optimization of constrained MDPs using Gaussian Processes. *Proc. AAAI Conf. Artif. Intell.* **2018**, *32*, 6548–6555. [CrossRef]
143. Bonnefon, J.F.; Shariff, A.; Rahwan, I. The social dilemma of autonomous vehicles. *Science* **2016**, *352*, 1573–1576. [CrossRef] [PubMed]
144. Awad, E.; Dsouza, S.; Kim, R.; Schulz, J.; Henrich, J.; Shariff, A.; Bonnefon, J.F.; Rahwan, I. The moral machine experiment. *Nature* **2018**, *563*, 59–64. [CrossRef] [PubMed]
145. Rahwan, I.; Cebrian, M.; Obradovich, N.; Bongard, J.; Bonnefon, J.F.; Breazeal, C.; Crandall, J.W.; Christakis, N.A.; Couzin, I.D.; Jackson, M.O.; et al. Machine behaviour. *Nature* **2019**, *568*, 477–486. [CrossRef] [PubMed]
146. Velazquez, O.; Pescaroli, G.; Cremen, G.; Galasso, C. A Review of the technical and socio-organizational components of earthquake early warning systems. *Front. Earth Sci.* **2020**, *8*, 533498. [CrossRef]
147. Cremen, G.; Galasso, C. A decision-making methodology for risk-informed earthquake early warning. *Computer-Aided Civ. Infrastruct. Eng.* **2021**, *36*, 747–761. [CrossRef]
148. Cremen, G.; Galasso, C.; McCloskey, J.; Barcena, A.; Creed, M.; Filippi, M.E.; Gentile, R.; Jenkins, L.T.; Kalaycioglu, M.; Mentese, E.Y.; et al. A state-of-the-art decision-support environment for risk-sensitive and pro-poor urban planning and design in Tomorrow's cities. *Int. J. Disaster Risk Reduct.* **2023**, *85*, 103400. [CrossRef]

149. Galasso, C.; McCloskey, J.; Pelling, M.; Hope, M.; Bean, C.J.; Cremen, G.; Guragain, R.; Hancilar, U.; Menoscal, J.; Mwang'a, K.; et al. Editorial. Risk-based, pro-poor urban design and planning for Tomorrow's Cities. *Int. J. Disaster Risk Reduct.* **2021**, *58*, 102158. [CrossRef]
150. Mesta, C.; Cremen, G.; Galasso, C. Urban growth modelling and social vulnerability assessment for a hazardous Kathmandu Valley. *Sci. Rep.* **2022**, *12*, 6152. [CrossRef]
151. Soden, R.; Lallemant, D.; Kalirai, M.; Liu, C.; Wagenaar, D.; Jit, S. The importance of accounting for equity in disaster risk models. *Commun. Earth Environ.* **2023**, *4*, 386. [CrossRef]
152. Caldarelli, G.; Arcaute, E.; Barthelemy, M.; Batty, M.; Gershenson, C.; Helbing, D.; Mancuso, S.; Moreno, Y.; Ramasco, J.J.; Rozenblat, C.; et al. The role of complexity for digital twins of cities. *Nat. Comput. Sci.* **2023**, *3*, 374–381. [CrossRef]