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Review

AI-Driven Innovations in Earthquake Risk Mitigation: A Future-Focused Perspective

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Abstract: This study explores the transformative potential of artificial intelligence (AI) in revolutionizing earthquake risk mitigation across six key areas. Unlike traditional approaches, this paper examines how AI-driven innovations can uniquely enhance early warning systems, enabling real-time structural health monitoring, and providing dynamic, multi-hazard risk assessments that seamlessly integrate seismic data with other natural hazards such as tsunamis and landslides. It introduces groundbreaking applications of AI in earthquake-resilient design, where generative design algorithms and predictive analytics create structures that optimally balance safety, cost, and sustainability. The study also presents a novel discussion on the ethical implications of AI in this domain, stressing the critical need for transparency, accountability, and bias mitigation. Looking forward, the manuscript envisions the development of advanced AI platforms capable of delivering real-time, personalized risk assessments, immersive public training programs, and collaborative design tools that adapt to evolving seismic data. These innovations promise not only to significantly enhance current earthquake preparedness but also to pave the way toward a future where the societal impact of earthquakes is drastically reduced. This work underscores the potential of AI's role in shaping a safer, more resilient future, emphasizing the importance of continued innovation, ethical governance, and collaborative efforts.

Keywords: artificial intelligence (AI); earthquake risk mitigation; seismic hazard mapping; structural health monitoring; multi-hazard risk assessment; earthquake-resilient design; real-time data integration

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Citation: Plevris, V. AI-Driven Innovations in Earthquake Risk Mitigation: A Future-Focused Perspective. *Geosciences* **2024**, *14*, 244. https://doi.org/10.3390/geosciences14090244

Academic Editors: Riccardo Caputo, Chittenipattu P. Rajendran and Tejpal Singh

Received: 24 August 2024
Revised: 8 September 2024
Accepted: 14 September 2024
Published: 15 September 2024

1. Introduction

Earthquakes pose a significant threat to human life, infrastructure, and economies worldwide. Despite advancements in engineering and technology, the unpredictable nature of seismic events makes them particularly challenging to mitigate [1]. Recent catastrophic earthquakes have underscored the severe impact these events can have on communities around the globe. The 2023 Kahramanmaraş earthquakes in Türkiye [2,3] serve as a stark reminder of the devastation that can occur when large-scale seismic events strike populated areas. These earthquakes resulted in significant loss of life, widespread destruction of infrastructure, and economic turmoil, highlighting vulnerabilities in existing structural systems. Similar tragic outcomes have been observed in other major seismic events, such as the 2011 Tōhoku earthquake in Japan [4,5] and the 2010 Haiti earthquake [6]. These disasters emphasize the urgent need for innovative approaches to earthquake risk mitigation, particularly in improving the resilience of structures and enhancing early warning systems.

The core problem lies in the limitations of traditional earthquake risk assessment and management methods, which, while effective to some extent, often fail to keep up with the complex, dynamic factors that influence seismic activity. These conventional approaches rely heavily on historical data and static models, which are not capable of handling real-time data or predicting seismic events with high precision. As the frequency and severity of natural disasters appear to be increasing worldwide [7], it has become clear that more advanced and adaptable tools are needed to mitigate the impact of earthquakes.

This is where artificial intelligence (AI) offers transformative potential. AI can process vast amounts of data, recognize patterns, and generate dynamic, real-time predictions, addressing the limitations of traditional methods [8,9]. By incorporating lessons learned from past disasters and leveraging advances in AI, we have the potential to significantly enhance earthquake preparedness, prediction, and response strategies, reducing the devastating effects of future seismic events.

In this manuscript, we explore the critical role AI can play in transforming earthquake risk mitigation strategies. We have identified six key areas where AI technologies can make a significant impact, both now and in the future. Each of these areas is explored in detail in the following sections, demonstrating how AI-driven innovations are reshaping our approach to seismic risk management.

The first area of focus is **AI-Driven Earthquake Early Warning Systems** (Section 2), which hold the potential to provide crucial seconds or even minutes of warning before the most damaging waves of an earthquake arrive. These systems are essential for enabling timely protective actions that can save lives and reduce damage. Following this, we continue with **AI-Powered Structural Health Monitoring and Damage Assessment** (Section 3), which highlights how AI can be used to monitor the integrity of buildings and infrastructure in real time, predicting potential failures and assessing damage quickly before or after an event.

Next, we discuss **AI-Enhanced Seismic Hazard Mapping and Risk Assessment** (Section 4), where AI's ability to analyze vast datasets offers a new level of precision in understanding and predicting seismic hazards. This section is followed by **AI in Earthquake-Resilient Design** (Section 5), which explores how AI can assist engineers in creating structures that are not only safe but also cost-effective and sustainable. We then examine **AI and Community-Based Earthquake Preparedness** (Section 6), focusing on how AI can personalize and improve the effectiveness of public education and training. Finally, we cover the area of **AI and Seismic Data Integration for Multi-hazard Risk Assessment** (Section 7), where AI's role in synthesizing data from various natural hazards into a cohesive risk assessment framework is explored.

In addition to these six key areas, the manuscript also addresses the **Ethical Implications of AI in Earthquake Risk Mitigation** (Section 8). This section discusses the challenges associated with transparency, accountability, and potential biases in AI systems, emphasizing the need for ethical considerations in the development and deployment of AI technologies. The **Discussion and Conclusions** section (Section 9) then synthesizes the insights from the various areas, highlighting the interconnectedness of these AI applications and their collective potential to revolutionize earthquake risk management. The six areas covered and the section on ethical implications are presented schematically in Figure 1. The manuscript concludes with a reflection on the current state of AI in this field and offers an optimistic glimpse into the future, where AI may help us mitigate the risks of earthquakes to a degree that was previously unimaginable. Through continued innovation and thoughtful application of AI technologies, we can build safer, more resilient communities, better equipped to withstand the challenges posed by seismic events.

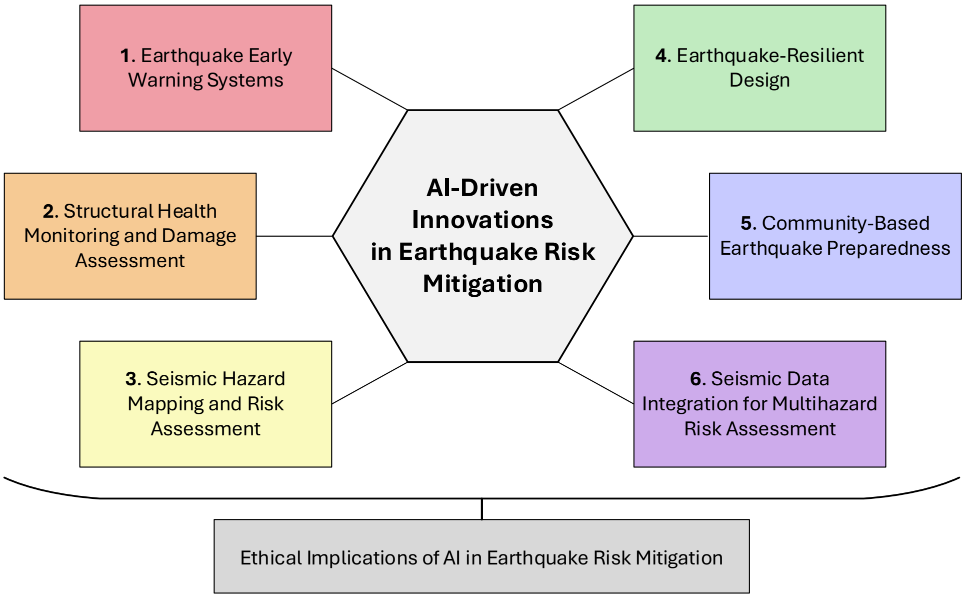

Figure 1. The six areas of AI-driven innovations in earthquake risk mitigation which are covered in the manuscript.

2. AI-Driven Earthquake Early Warning Systems (Area 1)

Earthquake early warning systems (EEW systems or EEWS) are critical tools designed to detect the initial seismic waves generated by an earthquake, known as P-waves, before the more destructive S-waves arrive. These systems aim to provide precious seconds to minutes of advance notice, allowing individuals, businesses, and emergency services to take protective actions, such as evacuating buildings, shutting down critical infrastructure, or halting transportation systems. By rapidly analyzing seismic data, EEWS can estimate the earthquake's magnitude, location, and the areas likely to be affected, thereby helping to mitigate the impact of the quake. The effectiveness of EEWS is particularly crucial in densely populated urban areas, where even a few seconds of warning can save lives and reduce damage.

Figure 2 shows schematically how an EEWS works, in particular the ShakeAlert® system managed by the U.S. Geological Survey (USGS) [10]. The system operates in California, Oregon, and Washington, serving over 50 million residents and visitors in these states. Cremen and Glasso [11] conducted a review of state-of-the-art approaches to EEW systems globally, with a focus on the various algorithms developed for the rapid calculation of seismic source parameters, ground shaking, and the potential consequences following an event.

The advent of AI is poised to revolutionize EEWS, enhancing both their accuracy and speed. Traditional EEWS rely on the rapid detection of seismic waves and the transmission of alerts before the most damaging waves arrive. While these systems have saved lives, their effectiveness is often limited by the complexity of seismic signals and the speed at which data can be processed and interpreted [12]. AI, with its ability to analyze vast amounts of data in real time and identify patterns that may elude human observation, offers a significant advancement in the capability of these systems [13].

One of the key areas where AI can improve EEWS is in the detection and differentiation of seismic signals. Seismic waves generated by earthquakes come in various forms, including P-waves and S-waves, each with different characteristics and levels of destructiveness. Traditional methods may struggle to distinguish between these waves quickly enough to issue timely warnings. AI algorithms, however, can be trained on large datasets of seismic activity to recognize these differences more effectively and make near-instantaneous decisions about the nature of the threat. Moreover, AI can filter out false alarms caused by non-seismic events, such as human activities or minor tremors, thereby improving the reliability of the warnings. A notable example of a successful AI-based EEW system is DeepShake, developed by researchers at Stanford University [14]. This system leverages deep spatiotemporal neural networks to enhance earthquake detection. During the 7.1 magnitude earthquake that struck Ridgecrest on 5 July 2019, DeepShake successfully delivered targeted alerts to all stations within its network 5 s before the arrival of MMI IV+ seismic waves.

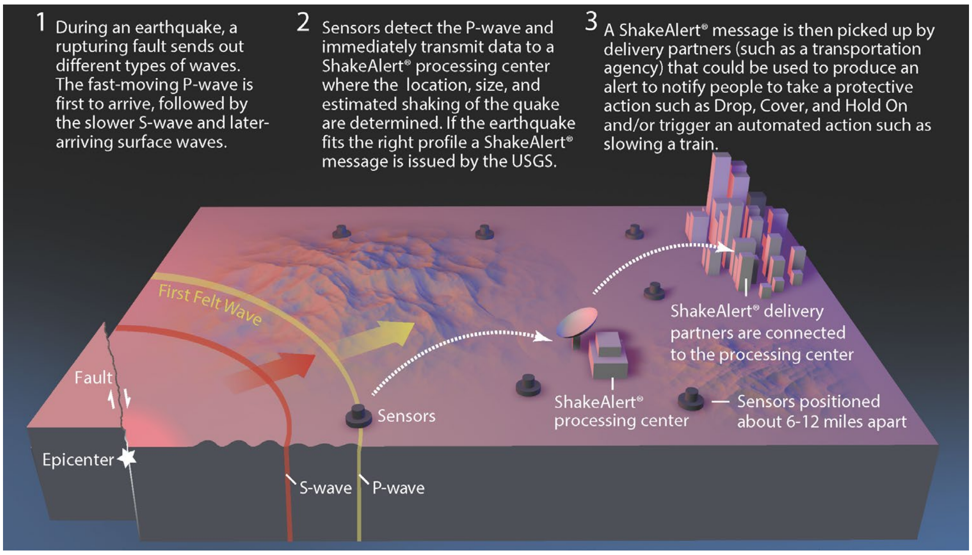

Figure 2. How the ShakeAlert® EEWS works [10].

The data used for training AI models in EEWS primarily come from seismic networks that capture earthquake events using seismometers and accelerometers. While these data sources are reliable for detecting seismic activity, a significant limitation is the underrepresentation of certain regions, particularly rural and less densely populated areas, where fewer sensors are deployed. Expanding sensor networks in these regions is crucial for improving the overall accuracy and timeliness of AI-driven warnings. However, scaling such networks presents challenges, including the high cost of infrastructure, maintenance difficulties, and limited accessibility in remote locations. Feasibility could be enhanced through innovative approaches like leveraging crowdsourced data, satellite information, and low-cost sensor technologies. These strategies could increase coverage without relying solely on traditional seismometer installations, making AI-based systems more inclusive and accurate across diverse regions.

Al Banna et al. [15] provided a comprehensive review of AI techniques applied to earthquake prediction, highlighting the challenges and potential of these methods. The study systematically examines 84 research papers, covering a range of AI approaches including rule-based methods, shallow machine learning (ML), and deep learning (DL) algorithms. The authors offer a comparative analysis of these techniques, focusing on their performance based on datasets and evaluation metrics. This analysis helps in identifying the most effective AI methods for predicting earthquake time, location, and magnitude, despite the inherent unpredictability of seismic events.

Several researchers have investigated the use of AI, ML, and the Internet of Things (IoT) for improving EEWS. Mousavi and Beroza [16] proposed an ML approach for earthquake magnitude estimation offering potential applications ranging from routine earthquake monitoring to EEWS. Prasanna et al. [17] examined the implementation of a low-cost EEWS using micro-electromechanical systems (MEMS)-based technologies and digital communication protocols. They propose a novel, decentralized EEWS architecture that leverages software-defined wide area network (SD-WAN) technology and MEMS-based accelerometers hosted by the public. Unlike traditional centralized systems, this approach uses node-level data processing to generate alerts, supported by a modified PLUM-based algorithm. Through simulations of hypothetical earthquakes, the study demonstrates that this decentralized architecture can outperform centralized systems, reducing latency and providing users with crucial extra seconds of warning. The findings contribute significantly to advancing cost-effective and efficient EEWS.

Abdalzaher et al. [18] explored the integration of ML and IoT technologies to enhance EEWS in smart cities. They present a comprehensive survey of the various components necessary for implementing such systems, emphasizing the critical role of IoT in observing and collecting data from different EEWS entities. They discuss how ML models, both linear and nonlinear, can be employed to analyze these observations, enabling more accurate and timely disaster management decisions. They further introduce a taxonomy of emerging efforts combining ML and IoT for EEWS, alongside a proposed generic architecture that leverages these technologies to optimize earthquake risk mitigation. Their work underscores the potential of ML in refining the observation and analysis of earthquake parameters, ultimately contributing to the development of more efficient and reliable EEWS in the context of smart cities. In another work [19], Abdalzaher et al. explored how IoT and cloud technologies can enhance EEWS. The study covers the fundamentals of seismic wave detection and the role of IoT networks in tracking EEWS activities, while cloud infrastructure facilitates data analysis and timely alerts. The authors discuss the integration of ML, distributed computing, and edge computing in EEWS, proposing a sustainable, efficient architecture. They also highlight the use of drones in disaster management and identify key research gaps. The work emphasizes that leveraging IoT and cloud infrastructure can significantly improve early earthquake detection, reducing both human casualties and economic impacts.

He et al. [20] assessed the effectiveness of EEW messages in China, focusing on the design aspects using affordance theory. They examine the functional, cognitive, sensory, and emotional affordances of the EEW message generated by the Institute of Care-Life (ICL). Using an immersive virtual reality experiment with 68 participants, the study finds that while the ICL message has strong emotional impact, it falls short in functional, cognitive, and sensory affordances. These findings suggest the need for improvements in EEW message design to enhance user interaction and response during earthquakes. The study also highlights the potential of virtual reality as a tool for evaluating and refining EEW communications.

In the work of Lara et al. [21], the authors introduce the Ensemble EEWS (E3WS), an ML framework designed to detect, locate, and estimate earthquake magnitudes using just 3 s of P-wave data from a single seismic station. E3WS employs six ensemble ML algorithms trained on datasets from various regions, including Peru, Chile, and Japan. The system operates in three stages: detection, P-phase picking, and source characterization, achieving a 99.9% success rate in distinguishing earthquakes from noise, with no false positives. The study demonstrates that E3WS provides highly accurate and virtually unbiased magnitude and location estimates, offering faster alerts than traditional multi-station systems, which could significantly enhance protective measures during seismic events.

Hou et al. [22] developed a DL approach for rapid and accurate earthquake magnitude estimation, incorporating three-component acceleration seismograms, differential P-arrivals, and seismometer locations. The model leverages a specific transformer architecture to account for distance information between seismometers and the earthquake hypocenter. The architecture significantly enhances magnitude estimation, making it robust for EEWS.

The Future of AI-Driven EEWS

Looking to the future, the integration of AI with the IoT and real-time data streams presents an exciting opportunity for creating even more responsive and adaptive EEWS [23]. This convergence of technologies has the potential to revolutionize how we monitor, predict, and respond to seismic events, offering unprecedented levels of precision and timeliness in alerts. IoT devices, such as seismic sensors embedded in the ground, drones equipped with real-time monitoring capabilities, and smart buildings outfitted with advanced sensor networks, can continuously feed vast amounts of data into AI systems. This continuous influx of data from diverse sources allows AI algorithms to operate with a much richer dataset, enhancing their ability to detect even the most subtle precursors to an earthquake.

As new data are collected, AI algorithms can continuously refine their models, learning from each event to improve both the accuracy of predictions and the speed at which alerts are generated. This iterative learning process is crucial for dealing with the complex and unpredictable nature of seismic activity, as it allows the system to adapt to new patterns or anomalies that may not have been present in historical data. For instance, if a particular region experiences a series of low-magnitude tremors that are atypical, the AI can adjust its parameters to better assess the likelihood of these being precursors to a larger event.

Moreover, the integration of AI and IoT in EEWS can facilitate the development of a more decentralized and resilient warning infrastructure. Instead of relying solely on centralized data processing centers, edge computing enabled by IoT devices can allow for quicker, localized decision-making, reducing the time it takes to issue alerts to the affected areas. This is particularly important in regions where seconds can make the difference between life and death. Drones, for example, could be deployed immediately following a seismic event to assess damage and feed real-time data back to AI systems, which could then predict the likelihood of aftershocks or secondary hazards such as landslides or tsunamis.

This dynamic, AI-driven system would not only react to seismic events as they happen but also evolve based on past experiences, becoming more effective with each occurrence. Over time, as the AI accumulates more data and refines its models, the system could achieve levels of predictive accuracy and responsiveness that are currently unattainable. This evolution would make the EEWS increasingly adept at not just detecting earthquakes but also providing actionable insights into how different regions and structures are likely to be affected, enabling more targeted and effective emergency responses. Ultimately, the fusion of AI, IoT, and real-time data streams holds the promise of a future where earthquake risks are significantly mitigated, saving lives and reducing the impact of these natural disasters on society.

While AI holds great potential for enhancing EEWS, there remain notable research gaps and challenges, particularly in applying AI to multi-hazard risk assessment. One of the primary challenges is the integration of AI-driven EEWS with other natural hazard monitoring systems, such as those for tsunamis, landslides, and floods. Often, these hazards occur concurrently or as secondary effects of an earthquake, yet current AI-based EEWS models are predominantly focused on seismic events alone. The capability to assess the combined risk of multiple hazards in real time is still at an early stage. Additionally, there is a need for more comprehensive datasets that capture these multi-hazard scenarios, allowing AI models to learn from past data and anticipate cascading events. Developing AI algorithms capable of handling the complexities and interactions between various hazards will be crucial for improving the accuracy and timeliness of risk assessments in real-world disaster situations. Another challenge involves cross-border coordination, where differences in technological infrastructure and data-sharing policies can hinder the rapid dissemination of AI-generated warnings across regions. For a more detailed discussion on AI's role in multi-hazard risk assessment, including its application in managing risks from multiple natural disasters, please refer to Section 7 (Area 6).

3. AI-Powered Structural Health Monitoring and Damage Assessment (Area 2)

Structural health monitoring (SHM) is a critical process for ensuring the safety, reliability, and longevity of infrastructure such as buildings, bridges, and other essential structures [24]. By continuously or periodically assessing the condition of these structures, SHM aims to detect early signs of wear, damage, or deterioration, allowing for timely maintenance and repairs. This proactive approach helps prevent catastrophic failures and ensures the safety of both the structures and the people who rely on them. The tragic collapse of the Morandi Bridge in Genoa, Italy, on 14 August 2018 [25], which resulted in

43 fatalities [26], serves as a stark reminder of the importance of SHM. The disaster was linked to undetected structural deterioration, highlighting the urgent need for more effective monitoring systems to prevent such tragedies in the future. With aging infrastructure, particularly in Europe and the U.S., where many bridges and structures have surpassed their expected lifespans, there is an increasing need for robust SHM systems to ensure their continued safety.

Historically, SHM methods have relied heavily on visual inspections and manual assessments, which, while effective, can be time-consuming, labor-intensive, and sometimes dangerous. To address these challenges, more modern SHM methods have incorporated sensor technologies, such as accelerometers, strain gauges, and temperature monitors, which provide real-time data on a structure's performance [27]. These sensors allow for more efficient monitoring, enabling early detection of potential issues and reducing the reliance on manual inspections. A typical contemporary SHM system based on sensors is illustrated in Figure 3.

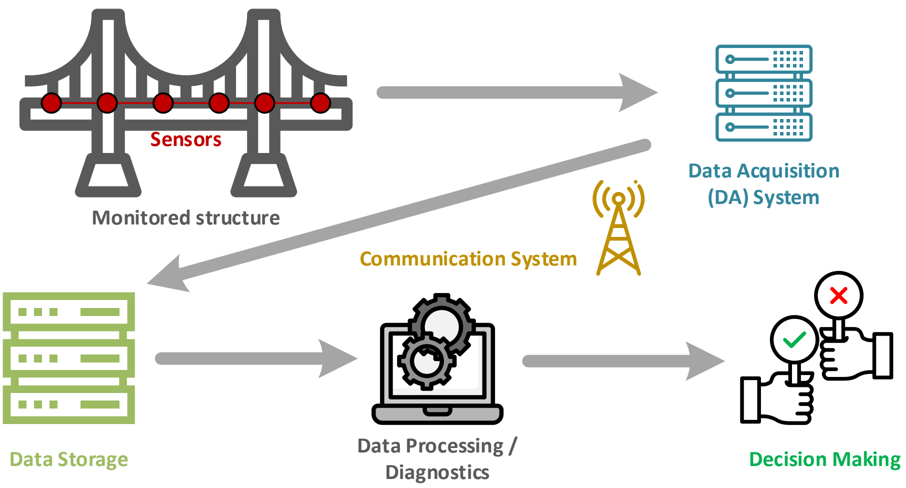

Figure 3. Visual schematic of a typical SHM system based on sensors.

AI is transforming the field of SHM and damage assessment, offering unprecedented capabilities for real-time evaluation of buildings and infrastructure following an earthquake [28]. AI, combined with advanced sensor technologies, enables a shift from these reactive approaches to proactive, continuous monitoring that can identify potential failures before they occur and assess damage in real time. Central to AI-powered SHM is the use of ML algorithms to analyze data collected from sensors embedded in structures [29]. These sensors generate vast amounts of data on the physical state of a building or infrastructure. AI algorithms are capable of processing these data to detect subtle changes in structural behavior that may indicate damage or deterioration [30]. For example, a sudden change in vibration patterns or an increase in strain readings could signal the onset of structural weakness. By identifying these anomalies early, AI systems can predict potential failures and alert engineers to take preventative action, thereby reducing the risk of catastrophic collapse. Moving forward, SHM must become a priority, integrating advanced technologies and AI-driven approaches to better protect against future infrastructure failures [31].

ML algorithms excel in pattern recognition and anomaly detection [32], making them particularly well-suited for analyzing the complex data generated by SHM systems [33,34]. Over time, these algorithms can be trained on historical data from previous earthquakes and structural performance records to improve their predictive accuracy. In the event of an earthquake, the AI system can quickly assess the extent of damage by comparing real-time data with established models, providing a rapid and accurate assessment of which parts of the structure are compromised. This real-time insight is crucial for prioritizing repair efforts and ensuring the safety of occupants.

In an interesting review paper, Sun et al. [35] offered meaningful perspectives and suggestions for employing big data and AI techniques in the field of SHM, focusing on bridges. Avci et al. [36] provided an overview of traditional SHM methods and offered a comprehensive review of recent applications of ML and DL algorithms for vibration-based structural damage detection in civil structures, effectively bridging the gap between these two approaches.

Malekloo et al. [37] reviewed the integration of ML with SHM, focusing on how ML enhances the capabilities of SHM systems in the context of smart cities, IoT, and big data analytics. The paper analyzes ML pipelines, highlighting in-demand methods and algorithms that address past inefficiencies in damage detection and decision-making. Emerging technologies such as mobile devices, unmanned aerial vehicles, virtual/augmented reality, and digital twins are discussed as pivotal to the next generation of SHM systems. The authors also examine current and future challenges, emphasizing that while ML-driven SHM is still developing, it holds significant potential for advancing civil infrastructure monitoring and integrity assessment.

In the work of Zinno et al. [38], the authors explored the integration of AI and emerging technologies in the SHM of bridges. The study examines how AI, alongside technologies like drones and 3D printing, can enhance SHM systems by improving the efficiency, accuracy, and longevity of bridge maintenance. The authors discuss the benefits and challenges of these advancements, proposing conceptual frameworks for future SHM systems in smart cities. Additionally, they highlight new research opportunities, emphasizing the role of AI and innovative technologies in optimizing the management and upkeep of urban infrastructure, ultimately contributing to the development of smarter, more resilient cities.

In the work of Payawal et al. [39], the authors conducted a systematic review of image-based SHM methodologies. The study analyzes 109 selected sources to identify key purposes and applications of image-based SHM, including damage identification, monitoring, automation, efficiency improvements, and the creation of 3D models. The review also addresses the roles and significance of various components and parameters necessary for implementing these systems, highlighting both the potential benefits and existing challenges. By consolidating current findings, the study provides valuable insights for future research and innovation in image-based SHM, offering guidance for enhancing safety monitoring and structural integrity assessment of civil infrastructures.

Shibu et al. [40] explored the use of AI and ML to enhance SHM by analyzing multimodal sensor data. The study focuses on the impact of climatic changes, such as temperature and humidity variations, on the structural integrity of buildings and bridges. By applying AI–ML algorithms, the authors aim to improve the correlation between climate factors and structural responses, enabling more accurate monitoring and prediction of structural health. The study specifically analyzes sensor data related to crack development, using linear regression to predict potential failures. The findings emphasize the importance of proactive risk management and timely intervention to prevent structural damage during natural disasters.

Cha et al. [41] conducted a comprehensive review of DL applications in SHM. The study covers a range of DL-based approaches, including non-destructive methods, computer vision, digital twins, and unmanned aerial vehicles (UAVs), as well as their integration with DL. Vibration-based strategies, sensor fault detection, and data recovery methods are also discussed. The review highlights the connections between traditional ML and DL, along with local-to-global approaches, presenting state-of-the-art methods, their advantages, and limitations. Despite rapid advancements, the authors note that DL-based SHM is still in its early stages, with significant potential for future developments to enhance its practical use, performance reliability, and automation in SHM.

It has to be noted that the data used in AI-powered SHM systems are predominantly gathered from sensors such as accelerometers, strain gauges, and temperature monitors embedded in the structures. These sensors provide high-resolution, real-time data on structural integrity. While these data are valuable for identifying issues early, a limitation is that sensor networks can be expensive to install and maintain, particularly in older structures. Additionally, the accuracy of AI models is influenced by the quality and density of sensor placements, which may vary across different infrastructures. More comprehensive datasets combining sensor data with historical structural performance records could improve predictive accuracy.

Kim et al. [42] reviewed the advancements and challenges of image-processing-based technologies for SHM of civil infrastructures. The study highlights various imaging techniques, including satellite imagery, LiDAR, and optical cameras, used for damage detection, crack identification, and deformation monitoring. The review also explores the integration of AI and ML with image processing to enhance automation and accuracy in SHM. By consolidating these developments, the authors demonstrate the potential of image-based approaches to improve the monitoring and maintenance of civil infrastructures.

Figure 4 illustrates a visual schematic of a modern SHM system that incorporates optical cameras, digital imaging, LiDAR scanning, and AI. This system primarily relies on image and point cloud data to assess the condition of structures. However, it can also be integrated with sensor-based SHM systems, creating a comprehensive multi-dimensional dataset. This combination can provide a more detailed understanding and evaluation of the current state of structures and infrastructure, enhancing the accuracy and effectiveness of the monitoring process.

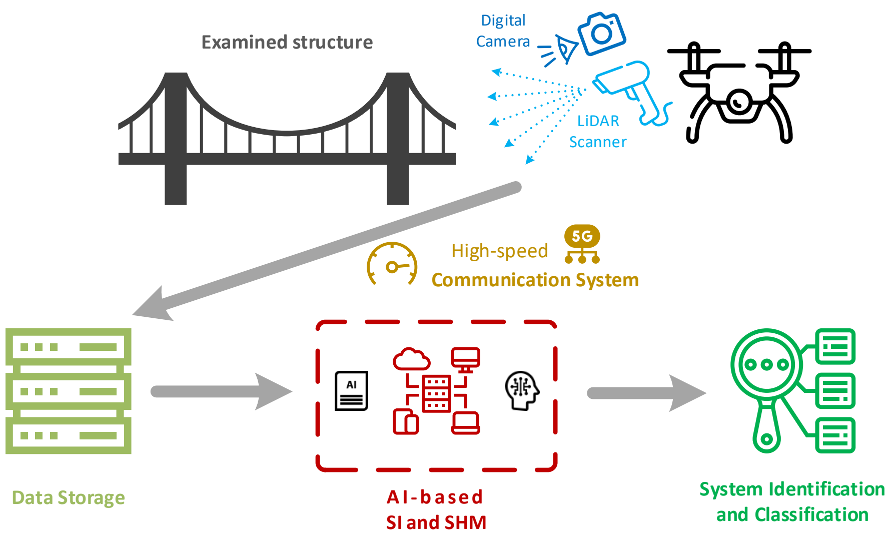

Figure 4. Visual schematic of a modern SHM system based on optical cameras, digital imaging, LiDAR scanning, and AI.

Such AI applications have also extended into the realm of rapid visual safety evaluations, where AI-powered systems can quickly assess the condition of buildings and infrastructure post-earthquake. Using computer vision and ML techniques, these systems can analyze images or video footage of structures to detect visible damage, such as cracks or deformations, within minutes. This approach significantly reduces the time required for manual inspections, providing emergency responders with crucial information for prioritizing interventions. Recent studies have demonstrated the effectiveness of these systems in rapidly assessing the safety of structures, particularly in densely populated areas prone to frequent seismic activity [43,44].

The Future of AI-Powered SHM and Damage Assessment

Looking to the future, advancements in AI have the potential to revolutionize SHM and damage assessment by introducing autonomous drones and robots capable of operating in hazardous environments. These AI-driven machines could be deployed immediately after an earthquake to inspect areas that are too dangerous for human inspectors, such as collapsed buildings, unstable structures, or areas with potential for further seismic activity. Equipped with high-resolution cameras, LiDAR, thermal imaging, and other advanced sensing technologies, these drones or robots would be able to capture detailed images and data from multiple angles, providing a comprehensive view of the damage. The use of such technologies would enable rapid, thorough assessments of structural integrity, significantly enhancing the speed and safety of post-earthquake evaluations.

In addition to their ability to access dangerous areas, these autonomous systems would be equipped with AI algorithms capable of analyzing the collected data in real time. These algorithms could detect and identify signs of structural damage that might be difficult or impossible to discern with the naked eye, such as internal cracks, stress points, or material fatigue. By processing vast amounts of data quickly, the AI could generate detailed reports on the condition of buildings and infrastructure, allowing emergency responders and engineers to prioritize their efforts and focus on the most critical areas. This real-time analysis would not only accelerate the overall assessment process but also ensure that resources are allocated more effectively, potentially saving lives by enabling quicker responses to the most severe damage.

As AI-driven systems continue to evolve, their role in autonomous decision-making within hazardous environments is expected to expand. For instance, AI-powered drones and robots could be deployed immediately after an earthquake to assess secondary risks, such as landslides. In such scenarios, these autonomous systems could gather critical real-time data, enabling rapid mapping of unstable slopes and identifying areas at high risk of landslides. AI models could analyze the collected data on the spot, helping to prioritize mitigation efforts or determine whether evacuation is necessary. These drones could also assist in detailed structural assessments of damaged buildings, offering critical insights for engineers planning repair strategies. By working alongside human experts, these AI-driven systems would significantly enhance the speed and accuracy of post-earthquake assessments, leading to more effective and efficient recovery efforts.

The integration of AI with autonomous systems represents a major advancement in the field of earthquake response, offering a level of efficiency and safety that was previously unattainable. By combining real-time monitoring with rapid, automated damage assessment, AI can help engineers and emergency responders make informed decisions more quickly, ultimately saving lives and minimizing the economic impact of earthquakes. Moreover, the data collected by these systems could be used to improve future building designs, incorporating lessons learned from each disaster to create structures that are better able to withstand seismic forces.

Despite the advancements in AI-powered SHM, there remain significant challenges in applying AI to multi-hazard risk assessment. One key gap is the lack of comprehensive models that can evaluate the impact of multiple hazards on a structure simultaneously. For example, while AI algorithms are effective at assessing seismic damage, they are less adept at accounting for the combined effects of earthquakes and other hazards, such as post-seismic landslides, flooding, or fire. Developing SHM systems that can integrate multi-hazard risk data into their assessments will require more advanced AI models capable of learning from diverse and interconnected datasets. Additionally, current SHM models struggle to scale across different types of infrastructure, such as bridges, tunnels, and high-rise buildings, which may exhibit varying vulnerabilities to multiple hazards. Another challenge is the integration of AI with IoT devices in areas with limited connectivity, as real-time data processing can be hindered by infrastructure deficiencies, particularly in rural or less-developed regions. Addressing these gaps in the future will be key to improving the resilience of infrastructures in the face of increasingly complex and interconnected hazard scenarios. Multi-hazard risk assessment and the role of AI are covered in more detail in Section 7.

As AI technology continues to evolve, we can expect to see even more sophisticated systems that not only monitor and assess structural health but also collaborate with human engineers in designing and implementing effective repair strategies. The future of AI-powered SHM and damage assessment is one of increased automation, enhanced precision, and greater safety for both responders and the public. By harnessing the full potential of AI, we can develop more resilient infrastructures, be better prepared to face the challenges of natural disasters, and ultimately, create safer communities worldwide.

4. AI-Enhanced Seismic Hazard Mapping and Risk Assessment (Area 3)

Seismic hazard mapping and risk assessment are essential processes for identifying and understanding the potential risks posed by earthquakes in specific geographic regions. These maps play a crucial role in informing infrastructure design, land-use planning, and disaster preparedness strategies by highlighting areas that are most vulnerable to seismic events. Traditionally, seismic hazard maps are developed using historical earthquake records, geological surveys, and seismic activity models, which provide insights into the likelihood and potential intensity of future earthquakes. However, the creation of accurate seismic hazard maps is a complex task due to the unpredictable nature of seismic activity and the numerous factors that influence ground motion, including geological conditions and local site effects.

While traditional methods have provided valuable insights, they often rely heavily on historical data and models that may not fully account for the complexities of future seismic events or the influence of local geological variations. To address these limitations, the U.S. Geological Survey (USGS) periodically updates the National Seismic Hazard Model (NSHM) using the latest data and advanced forecasting techniques. Figure 5 shows the 2023 Long-term National Seismic Hazard Map for the USA [45], depicting peak ground accelerations with a 2% probability of being exceeded within 50 years at a firm rock site. This map is revised every few years, with the previous version released in 2018. It is essential to recognize that local seismic hazards may be higher than represented, as site-specific conditions like soil composition and topography can amplify ground motions and elevate seismic risks.

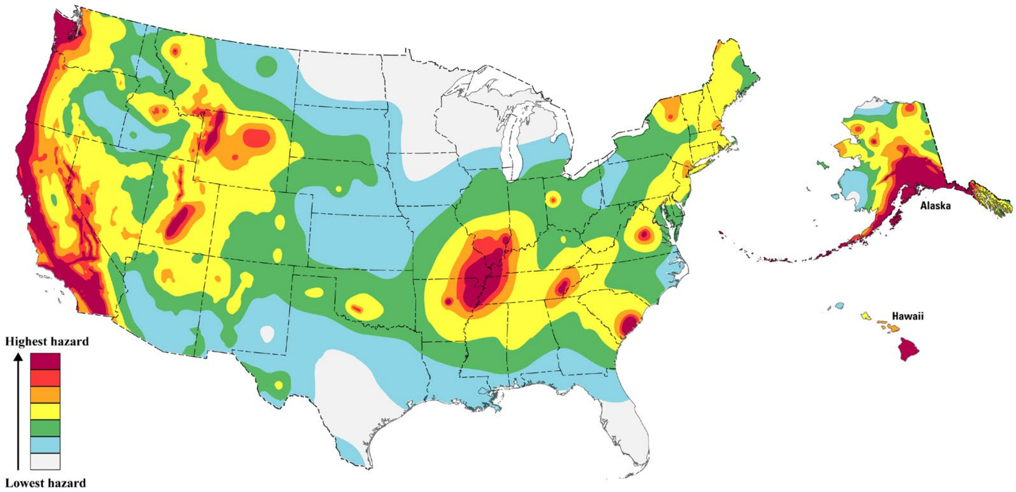

Figure 5. 2023 Long-term National Seismic Hazard Map for the USA [45].

AI offers a transformative approach to seismic hazard mapping and risk assessment, enabling more precise and dynamic analyses by leveraging its capacity to process and learn from massive datasets. AI's potential in seismic hazard mapping lies in its ability to analyze vast and diverse data sources, including historical earthquake records, geological surveys, and satellite imagery. ML algorithms can be trained to recognize patterns in these data that might be overlooked by conventional methods. For instance, AI can identify correlations between seismic activity and underlying geological features that are not immediately apparent. By analyzing these complex interactions, AI can refine seismic hazard models, leading to more accurate predictions of where and when earthquakes might occur [46]. This enhanced precision is crucial for improving the reliability of seismic hazard maps, which are used by engineers, urban planners, and policymakers to design safer buildings and develop effective disaster preparedness strategies.

One of the most significant advantages of AI in this context is its ability to continuously learn and adapt. Traditional seismic hazard maps are often static, based on data that might be years or even decades old. In contrast, AI-driven systems can be designed to update hazard maps in real time as new data become available. This dynamic approach allows for the incorporation of the latest seismic activity, geological changes, and even human-induced factors such as fracking or construction activities. As a result, the maps become living documents that evolve with the landscape they describe, providing up-to-date risk assessments that can guide immediate and long-term decision-making.

Jena et al. [47] assessed earthquake hazard and risk in Palu, Indonesia, using advanced ML approaches. The study employs convolutional neural networks (CNN) for probability estimation, along with silhouette clustering and pure locational clustering for spatial analysis. The research develops two risk calculation methods, Risk A and Risk B, comparing their effectiveness. The findings indicate that Risk B provides more accurate earthquake risk assessments. The study, achieving 89.47% accuracy in earthquake probability assessment, offers valuable insights for land-use planning, large-scale risk assessment, and hazard mitigation efforts in earthquake-prone regions.

In a similar work [48], Jena et al. estimated earthquake spatial probability and hazard in the Arabian Peninsula using ML and explainable AI (XAI) models. The study evaluates twelve seismological and geophysical factors using light gradient boosting machine and deep recurrent neural networks (RNN), achieving 89% and 87% accuracy, respectively. Three XAI approaches—smart predictor, smart explainer, and LIME—are compared, with smart predictor providing superior spatial outputs. Key factors identified include magnitude variation, earthquake frequency, depth variation, and seismic gap. The research highlights several high-risk areas in the region, offering valuable insights for planners and decision-makers in emergency planning, infrastructure development, and reconstruction projects.

AI-Enhanced Seismic Hazard Mapping and Risk Assessment in the Future

Looking to the future, we can anticipate the development of AI systems that not only update seismic hazard maps in real time but also offer dynamic risk assessments tailored to specific regions or infrastructure. These systems could integrate data from a variety of sources, including IoT-enabled sensors, satellite monitoring, and even crowd-sourced reports of seismic activity. AI algorithms would analyze these data continuously, generating real-time risk assessments that account for the latest information. For example, in the aftermath of a significant earthquake, the AI system could rapidly update hazard maps to reflect new fault lines or shifts in seismic activity, providing critical information to emergency responders and engineers tasked with rebuilding.

The future of seismic hazard mapping with AI also includes the potential for more personalized risk assessments. By combining AI with detailed data on building structures, population density, and local geological conditions, it is possible to create highly specific hazard maps that provide tailored risk assessments for individual neighborhoods, buildings, or even critical infrastructure. These personalized maps could inform targeted mitigation strategies, such as retrofitting vulnerable buildings or adjusting land-use plans to reduce exposure to seismic hazards.

AI has the potential to revolutionize seismic hazard mapping and risk assessment by enhancing the precision of hazard maps through advanced pattern recognition and continuous data integration. As AI technology evolves, it promises to create dynamic, real-time hazard maps that reflect the latest seismic data, offering more accurate and personalized risk assessments. These AI-driven hazard maps will significantly impact urban planning and infrastructure development, as they provide city planners, architects, and engineers with precise, up-to-date information about seismic risks in specific regions. By incorporating AI-enhanced seismic hazard maps into urban planning, decision-makers can identify high-risk areas, optimize land-use strategies, and prioritize the design and construction of earthquake-resilient infrastructure. This will enable more informed zoning laws, strategic placement of critical infrastructure, and retrofitting of vulnerable buildings. Ultimately, these advancements will play a crucial role in improving earthquake preparedness and resilience, ensuring safer communities and more robust infrastructure that can withstand seismic events.

5. AI in Earthquake-Resilient Design (Area 4)

Earthquake-resilient design is a critical aspect of structural engineering that focuses on developing buildings and infrastructure capable of withstanding the forces generated by seismic events. The goal of earthquake-resilient design is to minimize damage, protect lives, and ensure that structures remain functional even after an earthquake. Traditionally, this process has relied on well-established principles of seismic engineering, including the use of flexible materials, strategic structural forms, and construction techniques that can absorb or dissipate seismic energy. By understanding the behavior of structures during earthquakes and incorporating features like base isolators, shock absorbers, and reinforced materials, engineers have been able to design buildings that reduce the risk of collapse and damage during seismic events.

However, as the complexity of modern structures and the variability of seismic conditions continue to grow, traditional methods are often limited in their ability to optimize designs that address multiple factors such as safety, cost-efficiency, and sustainability. This is where AI is starting to make a significant impact [49]. The application of AI in earthquake-resilient design is revolutionizing the field by providing engineers with advanced tools to process vast amounts of data and optimize complex systems more efficiently than ever before [50]. AI can analyze a wide range of variables, such as material properties, seismic data, and environmental factors, to generate innovative design solutions that not only improve structural safety but also strike a balance between cost and sustainability [51].

One of the most promising applications of AI in this domain is the optimization of materials and structural forms [52,53], which has demonstrated significant improvements in both theoretical and practical settings. AI algorithms can analyze a multitude of variables, including material properties, load distributions, and seismic wave patterns, to identify the optimal combination that maximizes a structure's earthquake resistance [54]. For instance, in a case study comparing AI-driven structural design with traditional methods [55], AI algorithms achieved an 18–26% reduction in material cost for the design of doubly reinforced concrete beams, utilizing a large dataset of 100,000 records. AI can assist in selecting materials that offer the best compromise between strength, flexibility, and weight, ensuring that buildings can withstand seismic forces without compromising other critical factors such as cost and environmental impact.

AI-driven simulations of various structural forms have shown significant improvements in energy dissipation across different seismic scenarios, offering engineers innovative design concepts that are more effective at minimizing structural damage [56,57]. A specific case study demonstrating this is the work of Kazemi et al. [58], who developed an ML-based risk-assessment tool for retrofitting and designing RC buildings. This tool integrates prediction results with seismic hazard curves, providing enhanced risk assessments that lead to more targeted retrofitting strategies, ultimately minimizing structural damage. Additionally, Gharagoz et al. [59] applied an ML-based design procedure to a new seismic retrofit system, which was tested on case study structures and proved effective in meeting multiple performance levels, significantly reducing damage. These examples underscore the practical advantages of AI in optimizing both materials and structural designs, leading to more resilient, cost-effective buildings that minimize damage during earthquakes [60].

Sun et al. [61] conducted a comprehensive review on the application of ML in building structural design and performance assessment, discussing the challenges and opportunities associated with implementing ML in practical scenarios. A state-of-the-art review using bibliometric maps on the application of computational intelligence methods in simulation and modeling of structures can be found in [62]. In the work of Falcone et al. [63], the authors propose the use of ANNs to streamline the seismic retrofitting process for existing reinforced concrete (RC) structures. Traditional seismic analysis and optimization for selecting the best retrofitting solutions often require extensive computational resources, making them time-consuming even for modern systems. To address this, an ANN is trained to substitute finite element analysis (FEA), enabling rapid and accurate assessment of various structural configurations. The results demonstrate that the ANN can effectively approximate the outcomes of FEA, significantly speeding up the identification of viable RC strengthening configurations. This approach offers a more efficient method for seismic retrofitting, allowing for quicker decision-making and subsequent refinement using detailed FEA.

In [57], Wang et al. introduced an innovative AI-assisted simulation-driven framework for earthquake-resistant structural design. Traditional methods often overlook the extensive plasticity that occurs during earthquakes, leading to suboptimal design parameters. To address this, the proposed framework integrates nonlinear numerical simulation with AI tools, enabling the automatic generation of optimal design parameters that account for a wide range of input factors and nonlinear structural responses. The framework involves creating a database through nonlinear response history analyses and training ANN models, to output the best design parameters. The study demonstrates the framework's effectiveness, with the ANN model achieving highly accurate results, marking a significant advancement in earthquake-resistant design practices.

AI's potential to optimize structural designs goes beyond traditional methods by using advanced algorithms to predict, analyze, and adjust structural responses to seismic events. For instance, recent research has proposed combining fuzzy control strategies with long short-term memory (LSTM) neural networks to predict structural responses and improve seismic mitigation performance through adaptive variable-stiffness intelligent structures [64]. These techniques enable structures to adjust in real time to earthquake excitations, significantly enhancing resilience and safety.

5.1. Generative Design

Generative design algorithms represent another exciting development in AI-driven earthquake-resilient design. Generative design differs from shape optimization in that its goal is not to find a single optimal solution, but rather to generate a wide range of design options that meet the specified constraints set by the designer. By automating this process, generative design offers a diverse array of potential designs, serving as a source of inspiration and providing a starting point for further refinement by the designer. Generative adversarial networks (GANs) offer an innovative solution for generating synthetic seismic data that closely mirror real-world samples, addressing the challenges of acquiring large, high-quality datasets in seismology, geology, and structural engineering.

Generative AI leverages existing data to create innovative design solutions by learning from past experiences, analyzing complex structural drawings, integrating requirement texts, and combining mechanical and empirical knowledge [65]. These algorithms use AI to generate a wide range of design alternatives based on predefined criteria, such as safety, cost, and sustainability. Engineers can input specific requirements, and the AI will produce numerous design options that meet those criteria, often revealing innovative solutions that might not have been considered through traditional design processes. Generative design can lead to the creation of unconventional structural forms or hybrid materials that optimize seismic performance while reducing material usage and construction costs. This approach not only enhances the safety of buildings but also supports the growing demand for sustainable construction practices. A systematic review on generative systems in the architecture, engineering, and construction (AEC) industry can be found in [66], focusing on studies published between 2009 and 2019.

Kallioras and Lagaros [67] introduced the DzAIℕ methodology for generative design, which integrates topology optimization using the solid isotropic material with penalization

(SIMP) method with DL techniques, specifically deep belief networks. DzAIℕ significantly reduces response time in generating a variety of design shapes, as it requires only a small number of SIMP iterations, while the application of multiple DBNs contributes negligibly to the overall processing time. In a later work, the same authors proposed the MLGen generative design framework based on ML and topology optimization [68]

In the work of Luo and Paal [69], the authors introduce an AI-enhanced method for predicting the seismic response of reinforced concrete (RC) frames, addressing the limitations of existing physics-based models. Traditional high-fidelity models offer accuracy but are computationally intensive, while simplified models usually sacrifice accuracy for efficiency. The proposed approach combines an AI technique with a shear building model, utilizing real-world experimental data from RC columns to determine lateral stiffness. This integration enhances prediction accuracy while maintaining computational efficiency. Results show that the AI-enhanced method outperforms fiber-based models, offering a promising tool for accurate and efficient seismic response prediction in structural engineering.

In [70], Noureldin et al. present an ML-based procedure for seismic design and qualitative assessment of structures, focusing on safety and serviceability. The method integrates ANN, fuzzy inference systems, and ensemble bagged tree classification algorithms to evaluate structures based on key characteristics like natural period and strength ratio. The model is trained and validated using over 60,000 nonlinear time history analyses (NLTHA). Results demonstrate strong agreement with traditional NLTHA, offering reliable and accurate assessments with significantly reduced computational effort. The procedure is applied to case studies, showcasing its effectiveness in seismic retrofitting, collapse capacity estimation, and fragility analysis. Regenwetter et al. [71] provided a review of deep generative models in engineering design with focus on mechanical engineering applications, covering recent advances, focusing on algorithms, datasets, representation methods, and key applications.

In [72], the application of GANs in earthquake-related engineering fields was reviewed, emphasizing their role in data augmentation. The study highlights how GANs have revolutionized the generation of synthetic seismic signals, providing valuable tools for seismic detection, ground motion simulation, and the assessment of building and infrastructure responses to earthquakes. The review also critically examines the strengths and limitations of current GAN applications in these fields, offering insights to guide future research and advancements in AI-driven seismic studies. Chai et al. [73] conducted a comprehensive review of GANs and their applications in the construction industry, identifying four key domains where GANs are predominantly applied. These domains showcase the potential of GANs to advance construction processes, though the study also highlights several existing limitations.

Liao et al. [74] explored the application of generative AI in building structural design. The review highlights significant advancements in using generative AI for building design, while also identifying ongoing challenges and future prospects, ultimately aiming to guide the shift toward more intelligent and efficient design processes.

Hadid et al. [75] explored the transformative potential of generative artificial intelligence (GAI) and large language models in the field of geoscience. They highlight how recent advancements in ML and DL have expanded the utility of generative models for a variety of geoscience applications, such as prediction, simulation, and multi-criteria decision-making. The study discusses the use of models like GANs, physics-informed neural networks (PINNs), and GPT-based structures in tasks such as data generation, super-resolution, and land surface change detection. Despite the promising applications, the authors also address challenges related to physical interpretation, ethical concerns, and trustworthiness, emphasizing the need for continued research to fully realize GAI's potential in geoscience.

5.2. The Future of AI in Earthquake-Resilient Design

Looking ahead, the future of AI in earthquake-resilient design promises to revolutionize how we approach the construction and maintenance of structures in seismically active regions. One of the most exciting developments on the horizon is the creation of AI-driven analysis and design tools that work in close collaboration with human engineers. These tools will not only assist in the initial design phases but will also be capable of continually learning and adapting as new data on seismic activity, material properties, and construction techniques emerge. By integrating real-time data from seismic events and advances in material science, AI systems will refine their recommendations, ensuring that the design solutions they propose are always at the forefront of safety, efficiency, and innovation.

As AI systems become more sophisticated, they will be able to offer highly customized design solutions tailored to the specific seismic challenges of each project. Whether it is a high-rise building in a densely populated urban area, where the stakes of structural failure are incredibly high, or a critical infrastructure project in a remote, earthquake-prone region, AI-driven tools will provide engineers with the insights needed to address the unique demands of each environment. These tailored solutions will consider a multitude of factors, including local geological conditions, historical seismic activity, and even the socioeconomic context, to create designs that are both robust and contextually appropriate.

In addition to customizing designs for immediate seismic risks, AI-driven tools will increasingly incorporate predictive analytics to evaluate the long-term performance of structures under varying seismic conditions. This capability will be particularly important in the context of climate change and urbanization, which are expected to alter the frequency and intensity of seismic events in some regions. By simulating the potential impacts of future earthquakes, AI can help engineers design buildings that not only comply with current safety standards but are also resilient to the evolving risks of the future. This forward-looking approach is essential for ensuring that our built environment remains durable and safe, even as the external conditions affecting it continue to change.

Moreover, the integration of AI into earthquake-resilient design is set to play a pivotal role in optimizing the use of materials, structural forms, and construction methods. AI can analyze vast datasets to identify the most effective combinations of materials and structural designs that maximize strength and flexibility while minimizing costs and environmental impact. Through the use of generative design algorithms, AI can explore a wide range of design possibilities, presenting engineers with innovative solutions that might not have been considered through traditional methods. This collaborative process between AI and human expertise will lead to the development of structures that are better equipped to withstand seismic forces and also designed with sustainability in mind.

As AI technology continues to evolve, its role in earthquake-resilient design will expand, leading to a new era in construction where buildings and infrastructure are not just static entities but dynamic systems capable of adapting to changing risks. Future AI-driven design tools could incorporate real-time monitoring systems that continuously assess the health of a structure and suggest modifications or reinforcements as needed. This ongoing interaction between AI systems and the physical structures will create an environment where buildings are constantly optimized for safety and performance, significantly reducing the risks associated with seismic events. In this way, AI will not only enhance the initial design process but will also play a critical role in the ongoing maintenance and resilience of our built environment, ultimately contributing to the development of safer, more sustainable communities worldwide.

6. AI and Community-Based Earthquake Preparedness (Area 5)

Community-based earthquake preparedness plays a vital role in building resilience at the local level, ensuring that communities are better equipped to withstand and recover from seismic events. In earthquake-prone areas, preparedness at the community level involves educating residents, businesses, and organizations about the specific risks they face and the steps they can take to mitigate those risks. By fostering awareness and encouraging proactive participation, communities can develop stronger connections, trust, and collective responsibility, all of which are essential during and after an earthquake. This approach empowers individuals and groups to contribute to the safety and well-being of their neighborhoods, creating a culture of preparedness that extends beyond individual households.

Effective community-based earthquake preparedness involves a combination of public education on seismic risks, the development of emergency plans tailored to local needs, regular disaster drills, and ensuring that buildings and infrastructure are either designed or retrofitted to withstand seismic forces. By taking a proactive stance, communities can improve their ability to respond quickly and efficiently when an earthquake occurs, reducing the potential for casualties and property damage [76]. Prepared communities are also better positioned to recover and rebuild, which highlights the importance of incorporating such efforts into broader disaster management strategies. Conversely, a lack of preparedness can lead to confusion, delayed response times, and increased vulnerability during seismic events, ultimately putting more lives and property at risk [77].

Figure 6 provides a visual representation of the Disaster Management Cycle, which encapsulates the comprehensive approach to managing and responding to disasters. The cycle is divided into four key phases: preparedness, response, recovery, and mitigation (prevention).

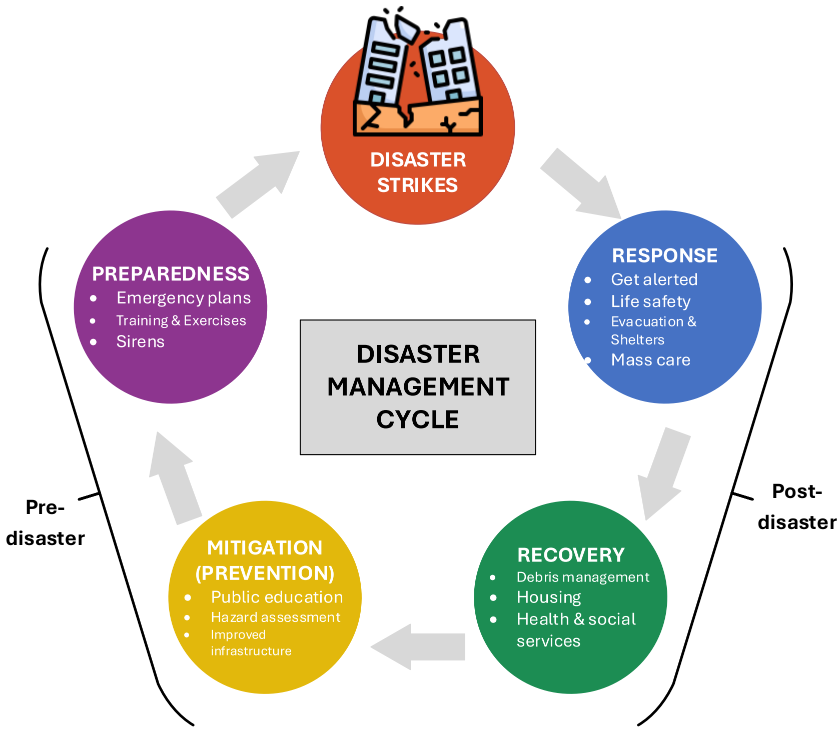

Figure 6. Four phases of emergency management.

This cyclical model underscores the interconnectedness of these phases, demonstrating how each stage informs and supports the others in creating a resilient and responsive disaster management system. Each phase plays a critical role in minimizing the impact of disasters and enhancing community resilience:

- **Preparedness** involves proactive measures such as developing emergency plans, conducting training and exercises, and setting up alert systems like sirens to ensure readiness before a disaster strikes.
- **Response** focuses on immediate actions taken during and immediately after a disaster to safeguard lives, including alerting the population, conducting evacuations, providing shelter, and delivering mass care.

- **Recovery** emphasizes the longer-term efforts needed to restore normalcy, such as debris management, rebuilding housing, and providing health and social services.
- **Mitigation (Prevention)** aims to reduce the long-term risk of future disasters through public education, hazard assessment, and improvements to infrastructure.

Historically, research has concentrated on finding the most effective ways to communicate risk and encourage preparedness through public hazard education campaigns and risk communication programs. Today, web- and mobile-based technologies offer new, expansive ways to inform communities about how to prepare for or respond to extreme events, greatly enhancing community preparedness [78]. AI has the potential to further elevate these efforts by providing predictive analytics and personalized risk assessments tailored to specific regions, neighborhoods, and even individual buildings. Traditional earthquake preparedness strategies often rely on generalized guidelines and emergency plans that may not consider the unique risks different communities face [79]. AI can bridge this gap by analyzing extensive data, including local seismic history, geological conditions, and building characteristics, to create precise risk profiles. These profiles can then inform community members of their specific vulnerabilities and offer targeted advice on mitigating those risks.

One of the most impactful applications of AI in earthquake preparedness is in public education. AI-driven platforms can provide personalized recommendations to residents based on their location, the type of building they live in, and other relevant factors. For example, an AI system could analyze the structural integrity of a person's home and suggest specific retrofitting measures to improve its earthquake resilience. Similarly, it could provide tailored emergency plans that take into account the local infrastructure and available resources, ensuring that residents have clear, actionable steps to follow in the event of an earthquake. By offering customized advice, AI can empower individuals and communities to take proactive measures that are more effective than generic preparedness strategies.

AI can also enhance public education by offering interactive simulations that demonstrate the potential impact of an earthquake on specific locations. These simulations can be based on real-time data and predictive models, allowing residents to visualize how their neighborhood or building might respond to different seismic scenarios. By seeing the potential consequences of an earthquake firsthand, individuals are more likely to understand the importance of preparedness and take the necessary steps to protect themselves and their property. Furthermore, AI can use these simulations to identify areas where public awareness is lacking and direct educational campaigns accordingly, ensuring that no community is left behind in earthquake preparedness efforts.

The AI models used to enhance community-based earthquake preparedness often draw from a variety of data sources, including seismic activity records, population density data, and building vulnerability assessments. A strength of this approach is that it allows for localized, real-time risk assessments tailored to specific communities. However, these models are limited by the availability and accuracy of socioeconomic data, which can vary widely between regions. To address these limitations, incorporating data from satellite imagery, social media, and local hazard maps can provide a more holistic and accurate understanding of a community's risk profile.

In the work of Shafik [80], the integration of AI with community engagement is explored as a transformative approach to disaster management and preparedness. The study emphasizes the critical role of local communities in strengthening disaster response through active participation and AI-enhanced activities. Shafik investigates how AI can improve early warning systems, optimize resource allocation, and support decision-making processes in disaster scenarios. The research highlights real-world examples where AI and community involvement have effectively combined to enhance disaster response, offering practical insights and recommendations. Additionally, the study addresses the ethical, social, and technical challenges of adopting this approach, ultimately proposing a holistic framework for future disaster management that leverages both AI capabilities and community-driven efforts.

The Future of AI and Community-Based Earthquake Preparedness

In the future, AI-driven virtual reality (VR) platforms could revolutionize public training programs by providing immersive simulations of earthquake scenarios. Unlike traditional drills, which often involve basic, low-fidelity exercises, VR platforms can create highly realistic environments that simulate the experience of an earthquake in real time. Participants could navigate through virtual spaces that mirror their own homes or neighborhoods, learning how to respond to different situations as they unfold. For example, a VR simulation could teach residents how to evacuate a building safely, locate emergency supplies, or provide first aid to injured individuals. By engaging multiple senses and offering a more realistic experience, these AI-driven VR platforms can enhance the effectiveness of preparedness training, making it more memorable and impactful.

In addition to training, AI-driven VR platforms could also serve as powerful tools for community planning and risk communication. Local governments and emergency management agencies could use VR simulations to test and refine their disaster response plans, ensuring that they are well-prepared for a range of earthquake scenarios. These simulations could also be used to engage the public in discussions about earthquake preparedness, helping to build a culture of resilience within the community. By making the potential risks and necessary responses more tangible, AI and VR can foster a greater sense of urgency and collective responsibility, ultimately leading to better-prepared communities.

AI offers transformative potential for enhancing community-based earthquake preparedness through predictive analytics, personalized risk assessments, and tailored public education. By leveraging AI to provide customized advice and simulations, communities can better understand their specific risks and take proactive measures to mitigate them. Looking ahead, the integration of AI-driven virtual reality platforms into public training programs promises to create more immersive and effective preparedness experiences, empowering individuals and communities to respond more effectively to earthquake threats and build a more resilient future.

7. AI and Seismic Data Integration for Multi-Hazard Risk Assessment (Area 6)

Multi-hazard risk assessment is a critical process that involves evaluating the potential impacts of multiple natural hazards, such as earthquakes, floods, landslides, and tsunamis, on a given area. This comprehensive approach is essential for understanding the complex interactions between different hazards and how they can exacerbate each other's effects, leading to more severe outcomes [81]. By considering multiple hazards simultaneously, rather than in isolation, multi-hazard risk assessment provides a more accurate and holistic view of the risks faced by communities and infrastructure. This enables decision-makers to develop more effective disaster preparedness, mitigation, and response strategies, ultimately reducing the vulnerability of populations and minimizing the overall impact of natural disasters. This approach is especially crucial for safeguarding critical infrastructures, such as nuclear power plants, where the consequences of a disaster can be particularly severe [82].

The integration of seismic data with other natural hazard information, such as tsunamis, landslides, and floods, is essential for developing comprehensive risk assessments that can inform more effective disaster preparedness and response strategies [83]. However, the complexity and variability of data from different natural hazards present significant challenges [84]. Each type of hazard is influenced by distinct environmental factors and requires different monitoring techniques, resulting in data that vary in format, resolution, and frequency. AI offers a promising solution to these challenges by providing advanced tools for integrating and analyzing diverse datasets, leading to a more holistic understanding of the risks faced by communities.

One of the primary challenges in multi-hazard risk assessment is the need to combine data from various sources, each with its own characteristics and limitations. Seismic data, for instance, are typically captured by ground-based sensors that measure vibrations and ground movement, while tsunami data might come from ocean buoys or satellite observations, and landslide data could be derived from topographical surveys and remote sensing. These datasets differ not only in the type of information they provide but also in how they are collected, processed, and stored. AI can address these challenges by using ML algorithms to harmonize and integrate these disparate data streams, identifying correlations and patterns that might not be apparent when analyzing each dataset in isolation.

AI's ability to process and analyze large volumes of data from multiple sources allows it to create more accurate and comprehensive risk models. For example, an AI system could integrate seismic data with topographical and hydrological data to assess the likelihood of secondary hazards, such as landslides or tsunamis, following an earthquake. By understanding how different hazards are interconnected, AI can help predict cascading events and their potential impact on infrastructure and communities. This integrated approach not only improves the accuracy of risk assessments but also enables more targeted mitigation strategies, such as identifying areas that are particularly vulnerable to multiple hazards and prioritizing them for protective measures.

Several researchers have worked on the integration of AI and multi-hazard risk assessment. Yousefi et al. [85] developed an ML framework for modeling and mapping multi-hazard risks in a mountainous region of southwestern Iran. The study focuses on predicting the likelihood of snow avalanches, landslides, wildfires, land subsidence, and floods using models such as support vector machines (SVM), boosted regression trees (BRT), and generalized linear models (GLM). The models incorporate various climatic, topographic, geological, social, and morphological factors as inputs. The results indicate that SVM is the most accurate for predicting landslides, land subsidence, and floods, while GLM excels in wildfire mapping, and FDA (functional discriminant analysis) is most effective for snow avalanche prediction. With AUC values exceeding 0.8, the models provide robust predictive maps, offering essential tools for hazard management and disaster mitigation in the region.

Javidan et al. [86] developed and evaluated a multi-hazard map for the Gorganrood Watershed in Iran using the maximum entropy (MaxEnt) ML technique. The study synthesizes susceptibility maps for floods, landslides, and gully erosion, incorporating 17 geo-environmental factors as predictors. The MaxEnt model demonstrated excellent predictive performance, with key factors identified for each hazard type, such as river density, elevation, and lithological units. The resulting integrated multi-hazard map revealed that 60% of the area is susceptible to natural hazards, with landslides affecting 21.2% of the region. This multi-hazard map serves as a valuable tool for local administrators and policymakers, aiding in hazard management and land-use planning at large scales.

Rocchi et al. [87] developed an ML framework for multi-hazard risk assessment, focusing on regions prone to both earthquakes and floods. The methodology integrates large datasets encompassing various risk components, using ML to cluster and rank municipalities by their combined seismic and hydraulic risk. Applied to the Emilia Romagna region, the framework categorizes municipalities into four clusters based on relative risk levels. This approach provides a robust tool for governments and stakeholders, aiding in decision-making and prioritizing interventions for disaster mitigation. The study emphasizes the importance of multi-hazard modeling at the regional scale, offering valuable insights for effective hazard management and risk reduction strategies.

Zhang et al. [88] presented an ML-enabled approach to regional multi-hazard risk assessment that incorporates social vulnerability. The study addresses the complexities of evaluating risks associated with multiple hazards, such as flooding, wildfires, and seismic events, while also considering the social vulnerability of affected populations. Utilizing five ML models, including random forest, K-nearest neighbors, and logistic regression, the methodology integrates hazard mapping, social vulnerability assessment, and the spatial interaction between these factors. The RF model outperformed others, identifying that 34.12% of the studied cities face significant multi-hazard risks, with 15.88% of these also being highly socially vulnerable. The resulting risk map highlights the critical need for targeted policies to mitigate natural hazard risks in vulnerable areas.

Youssef et al. [89] developed a multi-hazard susceptibility map for the Hasher-Fayfa Basin in southwestern Saudi Arabia, focusing on landslides, floods, and gully erosion. They employ several ML algorithms, incorporating topographic, geologic, meteorological, hydrologic, and human activity factors. The resulting multi-hazard map reveals that 66.5% of the area is vulnerable to at least one hazard, highlighting the utility of ML in hazard management and mitigation.

Nguyen et al. [90] developed a multi-hazard susceptibility mapping framework for the north central region of Vietnam, focusing on flooding and landslides. They employ ML models, including support vector machines, random forest, and AdaBoost, using data from 4591 flood points, 1315 landslide points, and 13 conditioning factors. The models demonstrated high predictive accuracy, with AUC values exceeding 0.95 for all hazards. The study revealed that approximately 60% of the area is prone to landslides, 30% to floods, and 8% to both hazards. The resulting multi-hazard maps provide critical insights for decision-makers, aiding in sustainable land-use planning and infrastructure development to mitigate the impacts of these natural hazards in the region.

AI and Seismic Data Integration for Multi-Hazard Risk Assessment: A Glimpse into the Future

Looking to the future, AI-driven platforms could offer real-time, multi-hazard risk assessments that dynamically update as new data become available. These platforms would continuously collect and analyze data from a wide range of sources, including seismic sensors, weather stations, satellite imagery, and IoT devices, to provide a real-time picture of the evolving risk landscape. Urban planners and emergency response teams could use these platforms to guide decision-making, ensuring that resources are allocated where they are needed most and that evacuation plans are adjusted based on the latest information. For instance, in the aftermath of a major earthquake, an AI platform could quickly assess the potential for related hazards, such as tsunamis or landslides, and provide real-time alerts to at-risk areas, allowing for quicker and more effective responses.

In addition to guiding immediate response efforts, AI-driven multi-hazard risk assessment platforms could also play a crucial role in long-term urban planning and resilience building. By integrating historical data with predictive models, these platforms could identify areas that are most likely to be affected by multiple hazards over time, informing decisions about where to build new infrastructure or how to retrofit existing structures. They could also help planners design cities that are more resilient to a range of natural hazards, incorporating features such as green spaces that absorb floodwaters, building codes that account for seismic activity, and early warning systems that consider multiple types of threats.

AI offers significant potential for integrating seismic data with other natural hazard information to provide comprehensive, multi-hazard risk assessments. By overcoming the challenges of combining diverse datasets, AI can create more accurate and dynamic risk models that inform both immediate disaster response and long-term urban planning. As AI technology continues to advance, we can expect to see the development of real-time, AI-driven platforms that provide continuous, multi-hazard risk assessments, ultimately leading to safer, more resilient communities.

8. The Ethical Implications of AI in Earthquake Risk Mitigation

The integration of AI into earthquake forecasting and mitigation holds immense potential for improving public safety and reducing the impact of seismic events. However, the use of AI in this critical domain also raises several ethical considerations that must be carefully addressed to ensure that these technologies are used responsibly and equitably. Key ethical issues include the transparency of AI algorithms, accountability for decisions made by AI systems, and the potential for these technologies to perpetuate or even exacerbate existing biases in risk assessment and resource allocation [91].

Transparency is a major ethical concern when it comes to AI, also in the field of earthquake risk mitigation. AI algorithms, particularly those that rely on ML, often operate as "black boxes", making decisions based on complex data processing that can be difficult for humans to understand or interpret [92]. This lack of transparency can be problematic, especially in high-stakes situations where the accuracy and reliability of AI predictions are crucial. If an AI system fails to accurately predict an earthquake or misjudges the level of risk, it is essential that stakeholders understand how and why the system made its decisions. To address this, future AI development should prioritize explainability, ensuring that the processes and reasoning behind AI-generated forecasts and risk assessments are clear and comprehensible to users, including engineers, policymakers, and the general public. Markus et al. [93] emphasize the importance of explainability in building trustworthy AI systems. While their study primarily focuses on the healthcare sector, the findings have broader implications. They suggest that explainable modeling can enhance trust in AI, but stress that the practical benefits of explainability must be demonstrated, and additional measures may be necessary to fully establish trust in AI systems.

Accountability is another critical ethical issue. As AI systems become more integrated into earthquake forecasting and mitigation, determining who is responsible for the outcomes—whether positive or negative—becomes increasingly complex [94]. If an AI system incorrectly predicts an earthquake or fails to issue a timely warning, who should be held accountable: the developers of the AI, the engineers who implemented it, or the decision-makers who relied on it? Establishing clear lines of accountability is essential to ensure that AI systems are developed and deployed with the utmost care. This may involve creating specific roles or bodies responsible for overseeing the ethical use of AI in this field, as well as developing protocols for addressing failures or errors in AI predictions.

A particularly concerning ethical challenge is the potential for AI systems to exacerbate social inequalities and existing biases [95], particularly in the context of earthquake preparedness. AI algorithms are often trained on historical data that can reflect existing social and economic inequalities. This can lead to skewed outcomes in earthquake risk mitigation. For example, data collected from wealthier, urban areas—where more seismic sensors and monitoring technologies are concentrated—may result in more accurate predictions for those regions. Conversely, poorer, rural areas, which are often underrepresented in data collection efforts, may receive less accurate or incomplete predictions, leading to uneven allocation of resources. This disparity can result in wealthier regions benefiting from more robust earthquake preparedness, while vulnerable, lower-income communities may be left with inadequate protection.

To **mitigate these inequalities**, several solutions can be proposed. First, AI developers should critically assess the datasets used to train AI systems, ensuring that they are inclusive and representative of all at-risk populations. This could involve actively seeking data from underrepresented regions, such as rural and lower-income areas, and incorporating them into the models. Governments and international organizations should support these efforts by funding data collection in underserved regions, ensuring that AI systems have access to comprehensive and diverse datasets.

Moreover, AI systems must be designed with the flexibility to **prioritize resources** for regions most in need, rather than those that are simply better represented in the data. For example, policies should be developed to ensure that earthquake preparedness efforts target communities that are both socioeconomically vulnerable and geologically at risk, rather than focusing solely on high-risk urban areas. This will require collaboration between AI developers, policymakers, and local governments to create equitable frameworks for resource distribution and disaster preparedness based on AI-generated insights.

Additionally, **regular auditing of AI systems** for bias is crucial. Independent bodies or oversight committees should periodically evaluate the performance of AI systems in different socioeconomic regions, identifying any disparities in predictions or resource allocation. Corrective measures should be implemented as needed to ensure that these systems provide equitable protection to all communities, regardless of socioeconomic status. This could include adjusting algorithms to account for underrepresented regions or integrating supplementary data to improve prediction accuracy for vulnerable areas.

The ethical use of AI in earthquake forecasting and mitigation will also require the development of **robust regulatory frameworks**. These frameworks should establish clear standards for the transparency, accountability, and fairness of AI systems, ensuring that they are designed and used in ways that prioritize public safety and equity. Governments, international organizations, and industry stakeholders should collaborate to create regulations that govern the deployment of AI in this field, including guidelines for data privacy, the ethical use of predictive analytics, and the equitable distribution of resources based on AI-generated risk assessments. Moreover, these frameworks should be flexible enough to adapt to the rapid pace of technological advancement, ensuring that new developments in AI are integrated responsibly.

In terms of current challenges, a significant regulatory gap exists, as there are no widely adopted global frameworks specifically addressing the use of AI in disaster mitigation. While some regions have general AI guidelines, such as the EU's General Data Protection Regulation (GDPR) for AI and data privacy, these frameworks do not yet adequately cover the specific ethical, legal, and operational challenges posed by AI in earthquake risk mitigation. Moreover, cross-border coordination is critical in developing unified regulations due to the nature of earthquakes, which can affect multiple regions simultaneously. The variability in data privacy laws, infrastructure capabilities, and ethical standards between countries complicates the integration of AI-driven early warning systems on a global scale.

To address these challenges, international collaboration is required, with organizations like the United Nations Office for Disaster Risk Reduction (UNDRR) potentially playing a central role in shaping guidelines for the responsible use of AI in disaster risk reduction. Furthermore, specific regulations that outline liability and accountability in cases where AI systems fail or deliver inaccurate predictions are needed to complement existing legal frameworks, which often do not cover the complexities of AI-driven disaster response systems.

By addressing these issues of transparency, accountability, and bias, and by establishing clear regulatory frameworks, we can ensure that AI tools are used responsibly and equitably. As AI continues to evolve, it is essential that these ethical considerations remain at the forefront of development and deployment efforts, ultimately leading to more just and effective earthquake risk mitigation strategies. Furthermore, by mitigating the potential for AI to exacerbate social inequalities, we can ensure that all communities—regardless of socioeconomic status—benefit from the advancements AI has to offer in protecting against seismic risks.

9. Discussion and Conclusions

The integration of AI into earthquake risk mitigation represents a significant advancement in our ability to protect lives, structures, and communities from the devastating effects of seismic events. This study has highlighted several key areas where AI-driven innovations are making a substantial impact. AI is enhancing early warning systems by providing faster and more accurate predictions of seismic events, allowing for timely protective actions. In structural health monitoring (SHM), AI enables real-time analysis of data from sensors embedded in infrastructure, facilitating quicker and more precise damage assessments. Furthermore, AI-powered multi-hazard risk assessments are improving our ability to predict and respond to complex scenarios involving multiple natural hazards, such as earthquakes, tsunamis, and landslides. AI's role in earthquake-resilient design is also transformative, as generative design algorithms and predictive analytics help create structures that balance safety, cost, and sustainability.

An important aspect of AI's effectiveness in these applications is its accuracy. In EEWS, for instance, AI models have demonstrated high accuracy in differentiating between seismic waves and non-seismic signals, significantly reducing false alarms. Accuracy rates in magnitude estimation have also improved with the integration of ML models, with some AI systems achieving very low prediction errors for magnitude estimates within seconds of P-wave detection. In structural health monitoring, AI algorithms have proven to be highly effective in anomaly detection, identifying even minor deviations in sensor data that indicate potential damage. However, it is essential to note that the accuracy of these systems relies heavily on the quality and diversity of the data used for training the models. Ensuring that AI models are trained on comprehensive and representative datasets is crucial for maintaining high accuracy across different regions and infrastructure types.

In any case, the deployment of AI in this field is not without its challenges. Ethical considerations, such as transparency, accountability, and the potential for bias, must be carefully managed to ensure that AI tools are used responsibly and equitably. This study underscores the importance of establishing robust regulatory frameworks and guidelines that govern the use of AI in earthquake risk mitigation. By doing so, we can maximize the benefits of AI while minimizing the risks, ultimately leading to more effective and fair strategies for disaster preparedness and response.

Looking ahead, the future of AI in earthquake risk mitigation is filled with promise. Advances in ML, data integration, and predictive analytics are paving the way for even more sophisticated tools that can anticipate and respond to seismic events with unprecedented precision. The continued development of AI-driven systems will enable the design of structures that are not only more resilient but also adaptive to the changing landscape of seismic risks. Additionally, AI's potential to enhance community-based preparedness through personalized education and immersive training programs will help build a culture of resilience that extends beyond individual structures to entire communities.

To maximize the impact of these innovations, future research and policy should focus on several actionable recommendations. First, comprehensive datasets incorporating seismic, geological, and environmental factors need to be developed and shared across institutions to improve the accuracy and applicability of AI models. Policies promoting open data standards could accelerate these efforts. Second, real-time data collection and analysis capabilities should be integrated with emerging technologies such as the Internet of Things (IoT) and 5G networks, which would enhance the responsiveness of early warning systems and structural health monitoring. Governments and institutions should consider incentivizing infrastructure investments that enable such integrations.

Additionally, future research should prioritize the development of AI-driven tools that can simulate long-term seismic impacts in the context of climate change, providing more adaptive and resilient design solutions. Policymakers can encourage the adoption of these technologies by incorporating AI-based tools into building codes and disaster risk management plans. Finally, interdisciplinary collaborations among AI experts, seismologists, engineers, and policymakers are critical for addressing the ethical and regulatory challenges associated with AI deployment. Regulatory frameworks must be established to ensure transparency, accountability, and bias mitigation in AI-driven solutions. A concerted effort between industry, academia, and government is essential to ensure that these technologies are implemented safely, ethically, and equitably.

By following these recommendations, future research and policy can help harness the full potential of AI to revolutionize earthquake risk mitigation, ultimately leading to a future where the devastating impacts of earthquakes are minimized.

Funding: This research received no external funding.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Conflicts of Interest: The author declares no conflicts of interest.

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