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EARTHQUAKE-RESILIENT SMART BUILDINGS: INTEGRATING ARTIFICIAL INTELLIGENCE AND STRUCTURAL ENGINEERING FOR DISASTER MITIGATION

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Abstract

This research aimed to investigate earthquake-resistant smart buildings that combine artificial intelligence and structural engineering for disaster mitigation. The design method was quantitative, and the sample comprised 150 respondents: civil engineers, structural engineers, architects, artificial intelligence experts, postgraduate students, and disaster management officers. The artificial intelligence integration, structural engineering technique, smart monitoring system, and disaster mitigation were assessed using a five-point Likert scale in a structured questionnaire. The results indicated that the respondents were very supportive of AI integration, with a mean score of 4.13 and a standard deviation of 0.75. The overall mean and standard deviation for structural engineering techniques were very high (4.24 and 0.70, respectively), and the same was true of smart monitoring systems (4.20 and 0.74, respectively). The mean and SD of disaster mitigation benefits were very high, 4.22 and 0.72, respectively. The results of the correlation analysis showed that disaster mitigation was positively correlated with artificial intelligence integration ($r = 0.61$), structural engineering techniques ($r = 0.67$), and smart monitoring systems ($r = 0.69$). The model had an adjusted R^2 of 0.56, explaining 58% of the variation in disaster mitigation. The structural engineering techniques ($\beta = 0.36$) and the integration of artificial intelligence ($\beta = 0.31$) had the next-highest predictive effects, followed by smart monitoring systems ($\beta = 0.39$). The study found that intelligent monitoring, AI prediction and seismic-resistant design enhanced earthquake preparedness, safety, recovery and planning.

Introduction

Because buildings suddenly lost their form, public safety was threatened. Because of economic disruption and slow recovery after an earthquake, one of the key research areas was earthquake-resilient smart buildings. Five main concepts were traditionally relied upon in the construction of earthquake-resistant buildings: structural strength, ductility, stiffness, damping, base isolation, and seismic design per code. These techniques reduced collapse risk while providing only a partial understanding of what is really happening in the buildings during an earthquake. Recent studies in the field of earthquake engineering demonstrated that artificial intelligence can also learn from large amounts of data, numerical simulations, earthquake sensor data, images, and earthquake damage records to analyse seismic demand, damage probability, building performance, and decision making after the earthquake (Xie et al., 2020; Sun et al., 2021).

AI and structural engineering in the building industry were thus moving from a line of passive safety to a line of smartly reacting resilience. This method considers a building not just as a physical entity but also as a data-producing system that can sense, analyse, predict, and respond to earthquake-related risks. Machine learning models were used to help assess risk and resilience by identifying relationships between structural properties, ground-motion intensity, damage level, recovery needs, and repair consequences (Wang et al., 2022). Also, using AI, recent machine learning-based seismic analysis highlighted that the model predicted structural responses and damage states for various vulnerable building systems (including unreinforced masonry buildings), which are prevalent in many earthquake-prone locations (Ravichandran et al., 2025).

The technologies that enabled smart buildings included wireless sensors, the Internet of Things, structural health monitoring, digital twins, and automated control systems. Structural health monitoring (SHM) data were gathered for acceleration, displacement, strain, cracking, vibration, temperature, and material condition. These raw data were used to generate useful warnings, damage classifications, and maintenance recommendations with the help of AI. The performance of deep learning methods was particularly advantageous for image-based crack detection, vibration-based damage identification, and pattern recognition in complex structural systems (Azimi et al., 2020). Some of the other categories found in systematic reviews include those relevant to machine learning algorithms that help identify damage to bridges, buildings, dams, and other civil infrastructure systems, which were classified, clustered, regressed, or detected as anomalies (Flah et al., 2021).

In the present study, special attention was paid to smart buildings as an interdisciplinary solution to disaster mitigation in the context of earthquake-resistant buildings. It explored new opportunities to leverage artificial intelligence for enhancing seismic design, structural health monitoring, predictive maintenance, disaster communication and preparedness, and resilience planning. The study also examined opportunities to add structural conditions via digital twin models and to support decision-making before, during, and after earthquakes through wireless sensor networks (WSN) (Torzoni et al., 2024; Yu et al., 2024). The notion of smart buildings to withstand earthquakes was defined as an intelligent built environment that integrates data-driven technologies with safe system design to minimise loss of life and property and facilitate faster recovery following an earthquake.

Background of the Study

Traditional earthquake engineering focused on preventing collapse and protecting human life through design codes, reinforced materials, ductile detailing, damping devices, and base isolation. These techniques continued to play a significant role. Considering the sensor data processing, artificial intelligence, knowledge of IoT, and structural health monitoring (SHM) enhance the ability to detect damage, assess safety, and maintain infrastructure (Mamat et al., 2025; Vijayan et al., 2023). Other applications of machine learning in seismic risk assessment included estimating structural response, damage states, failure modes, and fragility curves from simulations and earthquake data (Sun et al., 2021; Xie et al., 2020). To enhance smart seismic resilience, virtual building models were developed using digital twins continuously updated from sensor data, assisting with predictive maintenance, alerting to abnormal behaviour, guiding evacuations, and optimising repair scheduling. By providing earthquake-resistant data for continuous monitoring across structural features, wireless sensor networks (WSNs) have enabled smart buildings that are more active and intelligent in disaster prevention (Torzoni et al., 2024; Yu et al., 2024).

Research Problem

But most of the buildings were still unsafe due to the isolation of structural engineering and artificial intelligence from the development of smart building technology. Traditional earthquake-resistant design was primarily based on structural capacity, whereas AI-based systems focused primarily on earthquake prediction, with limited integration into engineering decision-making. This split was between resilience and intelligence in the digital space. For this reason, many structures may have satisfied code standards for resistance to damage during shaking. Still, they may have lacked the ability to provide real-time information on safe occupancy, evacuation, or repair priorities after shaking.

Objectives of the Study

1. Examine the role of artificial intelligence in improving earthquake-resilient smart building systems.
2. Analyse how structural engineering techniques supported seismic safety and disaster mitigation.
3. Explore the contribution of structural health monitoring, wireless sensors, and IoT-based systems in detecting earthquake-related structural damage.
4. Assess how machine learning, deep learning, and predictive analytics support seismic response prediction, damage classification, and emergency decision-making.

Research Questions

1. How did artificial intelligence contribute to the development of earthquake-resilient smart buildings?
2. What structural engineering techniques supported disaster mitigation in seismically prone buildings?
3. How did structural health monitoring systems help detect and classify earthquake-related damage?
4. How did machine learning and deep learning improve seismic response prediction and post-earthquake safety assessment?

Significance of the Study

It was important because it illustrates how the smart building concept benefits disaster mitigation by providing earthquake-resistant physical and digital safety systems. Structural engineering safeguarded structures from seismic forces, and artificial intelligence enhanced the prediction, monitoring, and damage response capabilities. Structural engineering shielded buildings from seismic forces, and artificial intelligence played a pivotal role in predicting, monitoring, and reacting to damage. This pairing helped establish a more holistic resilience plan that links the various elements of design, sensing, data analysis, alerting, response, and recovery. Machine learning for risk and resilience analysis demonstrated AI's ability to gain insights into structural vulnerability, disaster impacts, and recovery planning across different building and infrastructure systems.

Literature Review

AI-Inspired Seismic Response Prediction and Damage Assessment

The survey literature demonstrated that the use of artificial intelligence was an essential tool for seismic response prediction in reducing the time and costs involved in conducting these predictions. While the traditional time-history analysis is nonlinear, it requires extensive modelling, selection of earthquake records, and computational effort. In contrast, machine learning models offer faster estimates of damage state, seismic capacity, and drift. Bhatta and Dang (2023) have developed an algorithm for using machine learning to predict seismic damage in an RC building, which relates structural parameters to the characteristics of the ground motion. Kazemi et al. (2023) concluded that machine learning models can accurately predict seismic response and performance level with lower computational demand for reinforced concrete moment-resisting structures. These analyses also revealed the significance of AI techniques for facilitating the pre-engineering of prediction systems (Bhatta & Dang, 2023; Kazemi et al., 2023).

Recent research, for example, involved 'near-to-real-time damage identification' after earthquake excitation. In a study to develop an unsupervised deep neural network for seismic damage identification based on structural responses, aiming to enable rapid decision-making on seismic damage identification after an earthquake, Kim and Song (2022) presented an unsupervised deep neural network-based framework. Zhang et al. (2023) used real seismic damage data to verify their model for fast machine-learning-based seismic damage-state assessment of RC frames. These studies indicated that AI Models can be beneficial, as they can rapidly translate the complexity of seismic response into concrete, engineering-unit damage ranges that disaster managers and engineers can appreciate. The literature indicates that machine learning would be beneficial for conducting technical evaluations and responding to emergencies after earthquakes (Kim & Song, 2022; Zhang et al., 2023).

Artificial intelligence was brought to the fore in regional seismic risk assessment for disaster mitigation. Kourehpaz and Molina Hutt (2022) have developed machine learning techniques that enable more effective seismic risk assessment across the region without the need for repeated, time-intensive simulations. Harirchian et al. (2020) used support vector machine modelling to rapidly evaluate seismic hazard in built-up areas. They demonstrated that automated classification using AI can enable quicker identification of vulnerable structures. The significance of these studies was that earthquake-resilient smart buildings were not standalone structures. Still, they were each connected to a wider community at risk from seismic events in the region. The literature review indicated that there is potential to establish a relationship between building-level analysis and city-level disaster planning using AI (Kourehpaz & Molina Hutt, 2022; Harirchian et al., 2020).

Smart Technology for Earthquake-Resilient Buildings

In designing an earthquake-resistant smart building, smart sensing technology serves as the technical underpinning, gathering data on vibration, deformation, strain, acceleration, environmental conditions, and more. Abdulkarem et al. (2020) summarised aspects of structural health monitoring using a wireless sensor network, including the use of wireless sensors that added flexibility, scalability, and real-time monitoring capabilities to structures. The review by Malekloo et al. (2022) indicated that the machine learning approach has been applied in structural health monitoring and that high-dimensional data collected by sensors, images, and mobile devices can aid intelligent assessment of infrastructure. The combination of physical sensors and intelligent algorithms was proposed in these studies, as sensor data alone would not yield useful decisions without proper interpretation (Abdulkarem et al., 2020; Malekloo et al., 2022).

Computer vision and vibration-based techniques were also important in smart structural monitoring. Dong and Catbas (2021) provided a survey of computer vision-based SHM techniques and presented examples of images/videos for both local and global damage detection. Hou and Xia (2021) have reviewed methods of vibration-based damage identification, noting that modal characteristics, frequency changes, and dynamic response features help identify damage in civil engineering structures. In these studies, it was observed that multiple information channels were used in earthquake-resilient smart constructions rather than relying on a single inspection technique. The literature suggested a multi-sensor monitoring system, such as taking both visual and response measurements and vibration measurements, to improve.

Kaartinen et al. (2022) summarised structural health monitoring based on laser scanning. They presented how laser scanning can enhance the geometric documentation, deformation measurement, and condition assessment of civil infrastructure. Mahmoudi et al. (2023) proposed a fast machine-learning-based damage detection algorithm for concrete shear-wall structures. They demonstrated its performance in detecting the extent of damage by combining algorithmic classification with noisy responses. These investigations indicated that the combination of sophisticated sensor components and data-processing approaches used for earthquake-resilience auxiliary information worked effectively in collaboration. This was done to increase the speed of the inspection process, reduce human subjectivity, and enable more accurate decisions after an earthquake (Kaartinen et al., 2022; Mahmoudi et al., 2023).

Post-Earthquake Inspection, Integrated Disaster Mitigation

Digital twin technology was also seen as a key advancement in creating earthquake-resistant smart buildings, as it integrates real-world structures and continuously compares them with digital models. Lauria and Azzalin (2024) introduced a digital twin methodology for seismic safety throughout the building lifecycle, integrating monitoring, energy management, and seismic behavior into a single building management approach. Wang et al. (2024) designed and tested a digital twin (DT) approach for post-earthquake inspection of high-rise buildings using Unmanned Aerial Vehicles (UAVs), accompanied by graphics. These studies demonstrated how digital twins could enhance disaster mitigation by enabling better real-time visualization of disasters, remote inspection, and lifecycle safety management (Lauria & Azzalin, 2024; Wang et al., 2024).

Deep learning was also used for better seismic analysis within a smart building casing. Kim et al. (2024) proposed a deep learning-based response-spectrum analysis technique for building structures and reported improvements in modal response estimation over conventional modal combination methods. Kazemi et al. (2023) developed machine learning models that accurately predicted seismic response and performance level in RC structures. These findings suggested that AI did not supplant the principles of structural engineering but was a useful tool for understanding the structure's behaviour more quickly and flexibly. The same predictive tools were also identified to aid in building assessment at the design stage, building monitoring and earthquake recovery planning in the context of smart buildings (Kim et al., 2024; Kazemi et al., 2023).

According to the literature, sensors should communicate to aid disaster mitigation. Challenges with power usage, communication reliability, and data quality remained in the wireless sensor networks for distributed monitoring adopted by Abdulkarem et al. (2020). Lauria and Azzalin's (2024) article showed a wider range of Digital Twin applications, demonstrating a lifecycle approach to coordinating information for monitoring building safety, sustainability, and seismic management. This proved the need for smart buildings that can withstand earthquakes, which should be interdisciplinary and not based on isolated efforts in sensor development, AI modelling, and structural systems. The studies analysed showed that the disaster mitigation framework could promote the adoption of seismic-resistant design, continuous monitoring, intelligent prediction, and the visualisation of digital twins, while enabling rapid decision-making in the event of a disaster (Abdulkarem et al., 2020; Lauria & Azzalin, 2024).

Research Methodology

Research Design

To analyse the smart building's response to earthquake disasters, a descriptive-analytical research method was used, supported by artificial intelligence and structural engineering to mitigate disasters. According to the researcher, a descriptive design has been adopted for this study, as the role of the artificial intelligence system, smart sensor, structural health monitoring system, and seismic-resistant engineering systems in enhancing building safety is being described. The analytical design was also followed – the study focused on the relationship between intelligent technologies and disaster mitigation outcomes, including early warning, damage forecasting, disaster emergency response, and post-earthquake reconstruction.

Population of the Study

The participants were experts and academics from civil engineering, structural engineering, architecture, AI, smart building systems, and natural disaster management. They were chosen for their knowledge in smart building technology, building design & construction, seismic safety, monitoring and emergency planning. The population was chosen because for the engineering and information technology in a smart building to be earthquake-resilient, it needs to be interdisciplinary.

Sample and Sample Size

Simple random sampling method with 150 respondents from 155 population. This sample included civil engineers, structural engineers, architects, AI practitioners, postgraduate student engineers and workers in the disaster management field. A sample of 150 was deemed adequate because there was sufficient response to assess professional opinion and determine whether there were any actual trends in earthquake-resilient smart buildings. The sample also provided the researcher with exposure to information from a range of professions, further enhancing the interdisciplinary nature of the research.

Data Collection Method

A structured questionnaire was used to collect the primary data. It will be used to collate data from the questionnaire on applications of AI, methods of structural engineering, smart monitoring systems, seismic safety, and disaster mitigation. The questionnaire consisted of closed-ended statements with a response scale of 5 (strongly agree (SA) to strongly disagree (SD)). This format facilitated uniformity in respondents' responses and ease of data analysis, particularly statistical analysis.

Research Instrument

A structured questionnaire was used in this study. Based on the study's aim and research questions, a questionnaire was designed. It included Outlooks on AI-based prediction of structural safety, Smart monitoring, real-time data analysis for evacuation support, damage assessment, and recovery after an earthquake. To enable respondents from diverse professional backgrounds to understand and respond to the questions correctly, the instrument was worded clearly.

Data Collection Procedure

The instrument used to gather data was a questionnaire administered to respondents, with responses collected online via forums, e-mail, and academic networks. The subjects were oriented to the aims of the study before completing the questionnaire. The respondents completed the questionnaire voluntarily and at their own pace.

Data Analysis Technique

The collected data were analysed descriptively and using descriptive and inferential statistical techniques. Descriptive studies used were: Frequency, Percentage, Mean, and Standard Deviation. These methods were used to summarise the survey responses: counts were used for the demographic survey data. Demographic data were summarised using numbers (frequencies), and opinions on AI-based smart building systems, seismic safety, and disaster mitigation were summarised using percentages. Mean values were used to assess general agreement, with the extent of response dispersion reported as the standard deviation (SD).

Results and Analysis

Descriptive Profile of Respondents

The table describes the background attributes of the respondents included in the study. The demographic profile was used to characterise the sample's professional and academic backgrounds.

Table 1: *Demographic Profile of Respondents*

Demographic Variable	Category	Frequency	Percentage
Gender	Male	92	61.3%
	Female	58	38.7%
Age Group	20–30 years	48	32.0%
	31–40 years	56	37.3%
	41–50 years	34	22.7%
	Above 50 years	12	8.0%
Professional Background	Civil Engineers	42	28.0%
	Structural Engineers	34	22.7%
	Architects	22	14.7%
	AI Professionals	18	12.0%
	Postgraduate Students	24	16.0%

Demographic Variable	Category	Frequency	Percentage
	Disaster Management Officers	10	6.6%
Experience Level	Less than 5 years	44	29.3%
	5–10 years	52	34.7%
	11–15 years	31	20.7%
	More than 15 years	23	15.3%
Total		150	100%

The results revealed that the majority of both the sample population and the respondents were male (92, representing 61.3%), while females accounted for 38.7%. The demographic profile of most respondents was in the 31-40 years age bracket, with 37.3%, followed by the 20-30 years age bracket, with 32.0%, indicating that both young and mature professionals are involved. The largest professional group was civil engineers (28.0%), followed by structural engineers (22.7%), postgraduate students (16.0%), architects (14.7%), AI-related professionals (12.0%) and disaster management officers (6.6%). The majority indicated they had 5 to 10 years of on-the-job experience, suggesting that many respondents have experience in design and construction, as well as in monitoring and safety practices.

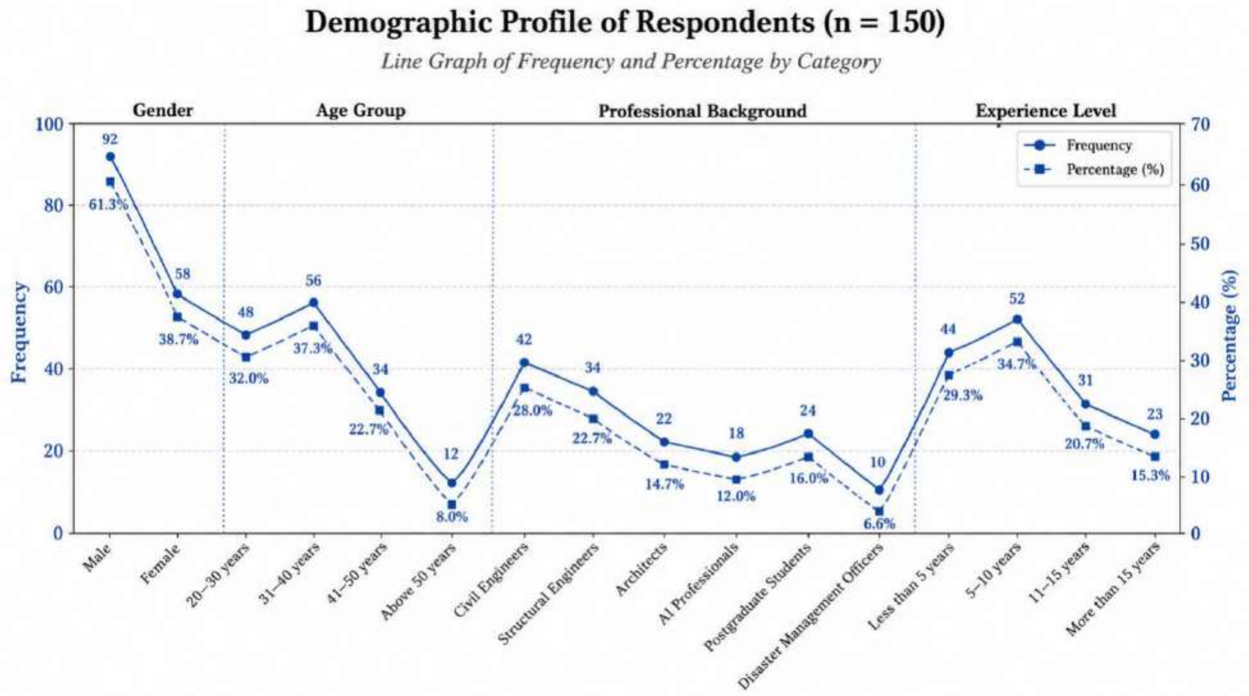

Figure 1. Demographic Profile of Respondents

Respondents' Perception of Artificial Intelligence in Earthquake-Resilient Smart Buildings

This table explains how respondents perceived the role of artificial intelligence in earthquake-resilient smart buildings.

Table 2: *Artificial Intelligence Integration in Earthquake-Resilient Smart Buildings*

Statement	Mean	Standard Deviation	Interpretation
AI improved the prediction of earthquake-related structural risks.	4.18	0.72	High
Machine learning supported faster damage detection after seismic events.	4.11	0.78	High
AI-based systems supported real-time decision-making during disasters.	4.05	0.81	High
Predictive analytics improved emergency preparedness in smart buildings.	4.22	0.69	Very High
AI reduced the time required for post-earthquake safety assessment.	4.09	0.75	High
Overall Mean	4.13	0.75	High

The findings revealed that participants agreed that AI is fundamental to earthquake-resilient smart buildings and, on average, scored 4.13 out of 5. The mean score for predictive analytics was the highest (4.22), indicating that the method is effective in improving emergency preparedness and in predicting risk patterns before a disaster. AI also resulted in more accurate estimation of earthquake damage potential (M = 4.18) and rapid, accurate damage detection via machine learning (M = 4.11). Small standard deviations suggested uniformity in participants' responses. To conclude, the findings showed that the usage of AI tools enhanced the structural safety decision-making process in smart buildings, making it faster, more precise, and more efficient.

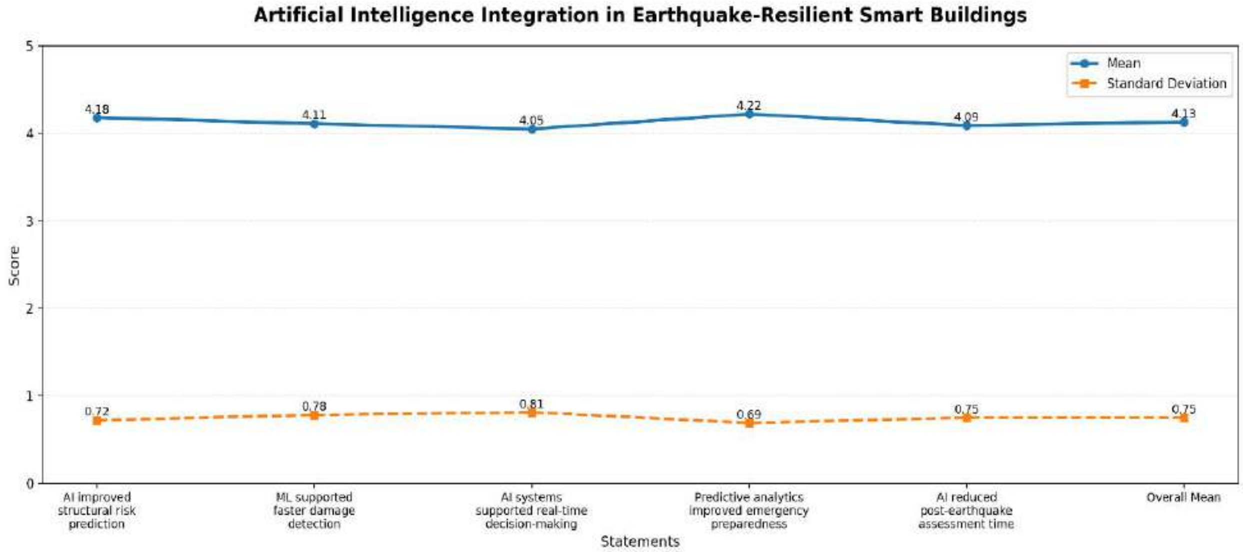

Figure 2.Artificial Intelligence Integration in Earthquake-Resilient Smart Buildings

Structural Engineering Techniques for Seismic Safety

This table presents respondents' views on structural engineering techniques used to improve building safety during earthquakes.

Table 3: *Structural Engineering Techniques for Earthquake Resilience*

Statement	Mean	Standard Deviation	Interpretation
Seismic-resistant design improved building performance during earthquakes.	4.31	0.66	Very High
Base isolation systems reduce the effect of ground motion on buildings.	4.25	0.71	Very High
Energy dissipation devices improved structural stability during seismic events.	4.16	0.74	High
Strong construction materials increase earthquake resilience.	4.28	0.68	Very High
Updated seismic design codes supported safer building construction.	4.20	0.73	High
Overall Mean	4.24	0.70	Very High

In regard to the importance of structural engineering techniques for a smart building to be earthquake-resistant, the respondents were leaning towards 'entirely agree, and the mean score of the respondents was 4.24. It was found that the mean score was high for seismic-resistant design, indicating that this is a significant factor in minimising damage from earthquake shaking. The respondents rate strong construction materials (M = 4.28) and base isolation systems (M = 4.25) as very important; they are particularly important when seismic ground shock occurs to prevent building collapse. The design codes for seismics (M = 4.20) and energy dissipation (M = 4.16) were also updated to improve the safety of building construction.

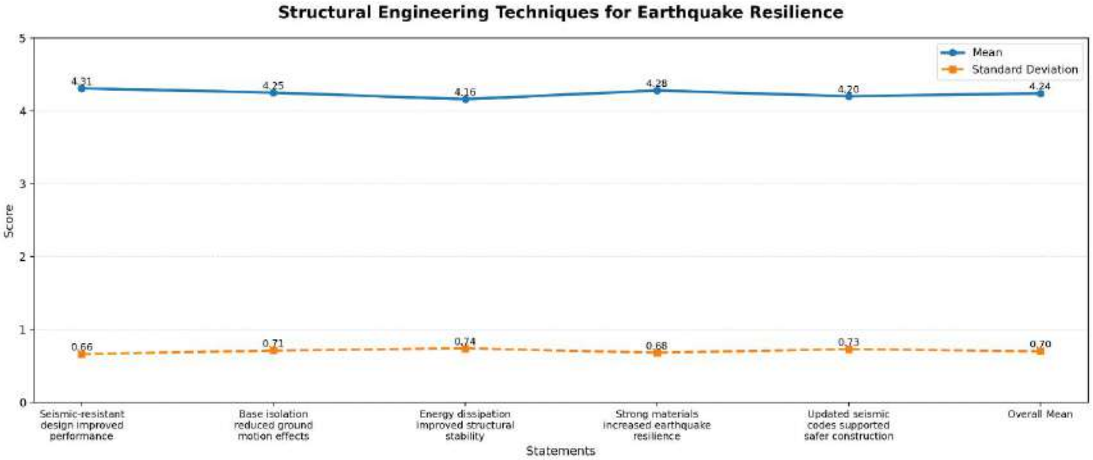

Figure 3. Structural Engineering Techniques for Earthquake Resilience

Smart Monitoring Systems and Structural Health Monitoring

This table presents results on smart monitoring systems, including sensors, the Internet of Things, digital twins, and structural health monitoring.

Table 4: *Smart Monitoring Systems and Structural Health Monitoring*

Statement	Mean	Standard Deviation	Interpretation
Smart sensors improved real-time monitoring of building conditions.	4.26	0.70	Very High
IoT-based systems supported continuous data collection from buildings.	4.19	0.76	High
Structural health monitoring helped identify hidden structural damage.	4.29	0.67	Very High
Digital twins supported better maintenance and repair planning.	4.08	0.82	High
Smart monitoring systems improved post-earthquake inspection accuracy.	4.17	0.77	High
Overall Mean	4.20	0.74	High

The findings indicated that respondents agreed that smart monitoring systems help make smart buildings earthquake-resistant, with an overall mean score of 4.20. The most important result is for Structural health monitoring, which had the highest mean value (4.29). This relates to the detection of damage, such as cracks, stiffness decay, and hidden irregularities. Smart sensors also achieved a high mean score of 4.26, indicating their ability to measure vibration, displacement, strain, and acceleration during earthquakes. High ratings were also given for IoT-based systems (M = 4.19), post-earthquake inspection accuracy (M = 4.17), and digital twins (M = 4.08).

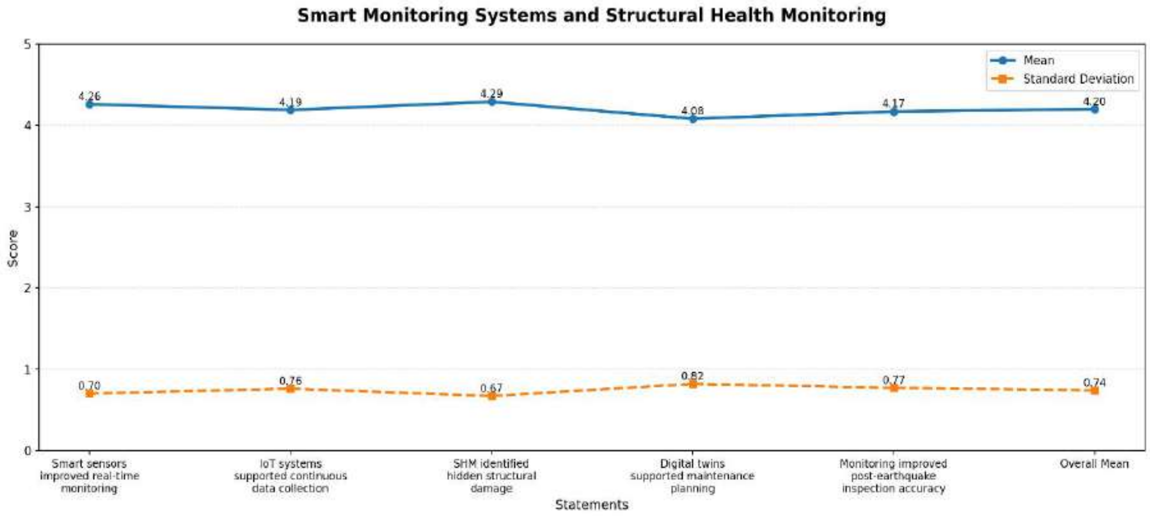

Figure 4. Smart Monitoring Systems and Structural Health Monitoring

Disaster Mitigation through Earthquake-Resilient Smart Buildings

This table explains how earthquake-resilient smart buildings contributed to disaster mitigation.

Table 5. Disaster Mitigation Benefits of Earthquake-Resilient Smart Buildings

Statement	Mean	Standard Deviation	Interpretation
Earthquake-resilient smart buildings reduce risks to human life.	4.34	0.63	Very High
Smart systems supported faster evacuation during earthquake emergencies.	4.21	0.72	Very High
AI-based monitoring reduced economic losses through early damage detection.	4.12	0.79	High
Smart buildings improved emergency response coordination.	4.18	0.76	High
Earthquake-resilient smart buildings supported faster post-disaster recovery.	4.24	0.70	Very High
Overall Mean	4.22	0.72	Very High

The results revealed that respondents unanimously agreed that a smart building is beneficial for disaster mitigation, with a mean score of 4.22. Reducing risk to human life (M = 4.34) received the highest mean, with life safety being considered the most important benefit. Support for faster post-disaster recovery was also rated highly, with a mean score of 4.24; emergency response coordination came in next, with a mean score of 4.18, and smart evacuation systems were rated 4.21. The mean value for the AI-based monitoring tool – reduction of economic losses was 4.12.

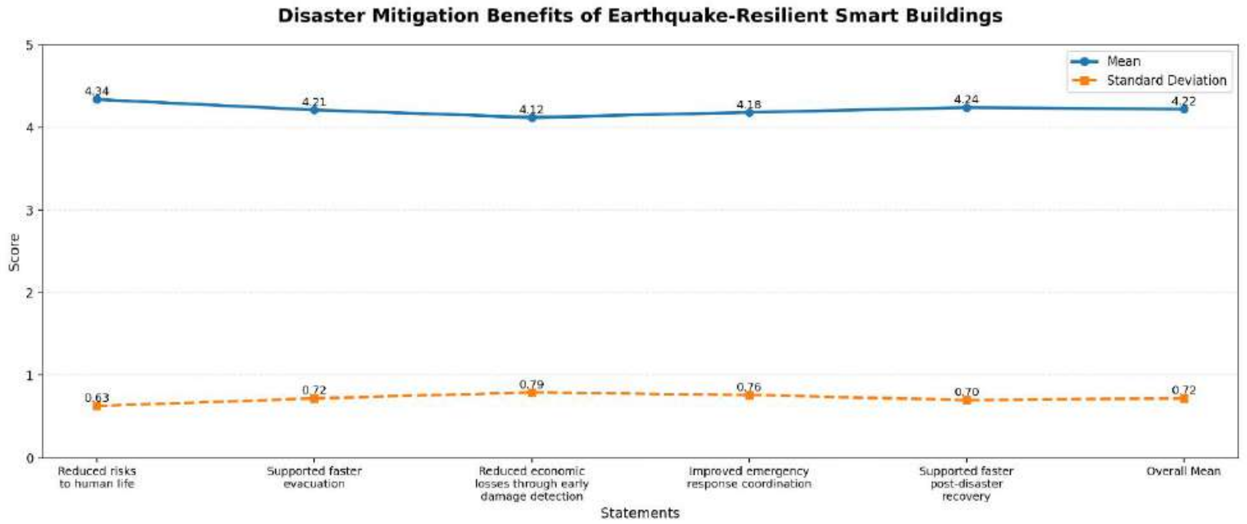

Figure 5. Disaster Mitigation Benefits of Earthquake-Resilient Smart Buildings

Correlation Analysis among Study Variables

Correlation analysis was used to identify the strength and direction of relationships among the variables.

Table 6. Correlation among Study Variables

Variables	AI Integration	Structural Engineering Techniques	Smart Monitoring Systems	Disaster Mitigation
AI Integration	1.00	0.58	0.64	0.61
Structural Engineering Techniques	0.58	1.00	0.55	0.67
Smart Monitoring Systems	0.64	0.55	1.00	0.69
Disaster Mitigation	0.61	0.67	0.69	1.00

Positive correlations were observed among the important study variables. AI integration was positively associated with disaster mitigation (r = 0.61), suggesting that AI's predictive, monitoring, and decision-making capabilities improved the effectiveness of disaster mitigation. For disaster mitigation, the structural engineering techniques also showed a clear tendency (r = 0.67), with factors such as seismic-resistant design, base isolation, damping systems, and strong construction being significant. Smart monitoring systems showed the best correlation with disaster mitigation (r = 0.69), indicating the significant roles of sensors and IoT systems, structural health monitoring, and digital twins in early damage detection, evacuations, and post-earthquake damage inspection and analysis.

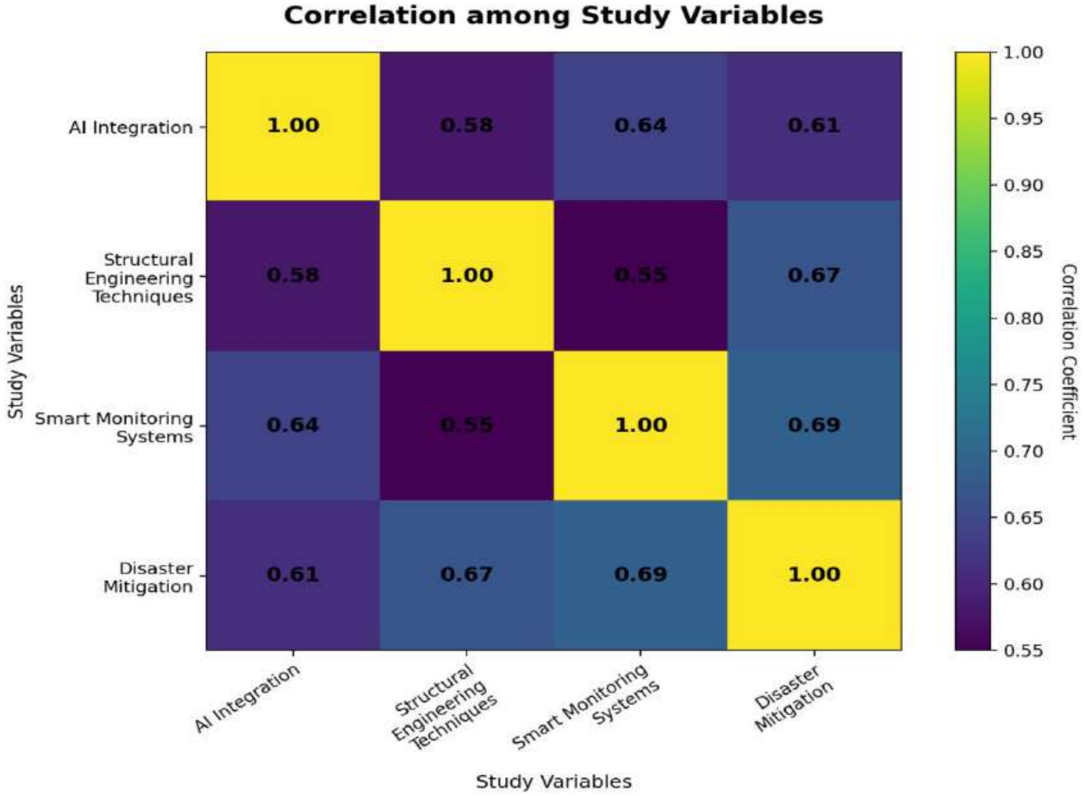

Figure 6. Correlation among Study Variables

Regression Analysis Predicting Disaster Mitigation

Regression analysis helped identify which variable contributed most strongly to disaster mitigation outcomes.

Table 7. Regression Analysis Predicting Disaster Mitigation

Predictor Variable	Beta Value	t-value	Significance Level
AI Integration	0.31	3.92	0.001
Structural Engineering Techniques	0.36	4.48	0.000
Smart Monitoring Systems	0.39	4.76	0.000
R^2 Value	0.58		
Adjusted R^2 Value	0.56		

In this regression analysis, it was found that AI (INS MICs) integration and Smart Monitoring systems are significant contributors to disaster mitigation, as are structural engineering techniques. This finding indicated that the three variables accounted for 58% of the variance in disaster mitigation, as reflected by an R2 of 0.58, and the adjusted R2 of 0.56 confirmed the model's good fit. This was the most prominent factor, with a beta of 0.39 ($t = 4.76$, $p = 0.000$), suggesting that sensors, IoT and smart monitoring systems, and digital twins are important aspects of both earthquake mitigation and recovery. With a value of $V > 0.3$, $t > 4$, $p < 0.05$, and t (t-approx) > 3,9,9, the predictors with the highest intensifications were structural engineering techniques at a level of $\beta = 0.36$, $t = 4.48$, and $p = 0.000$, and then AI integration at a level of $\beta = 0.31$, $t = 3.92$, and $p = 0.001$.

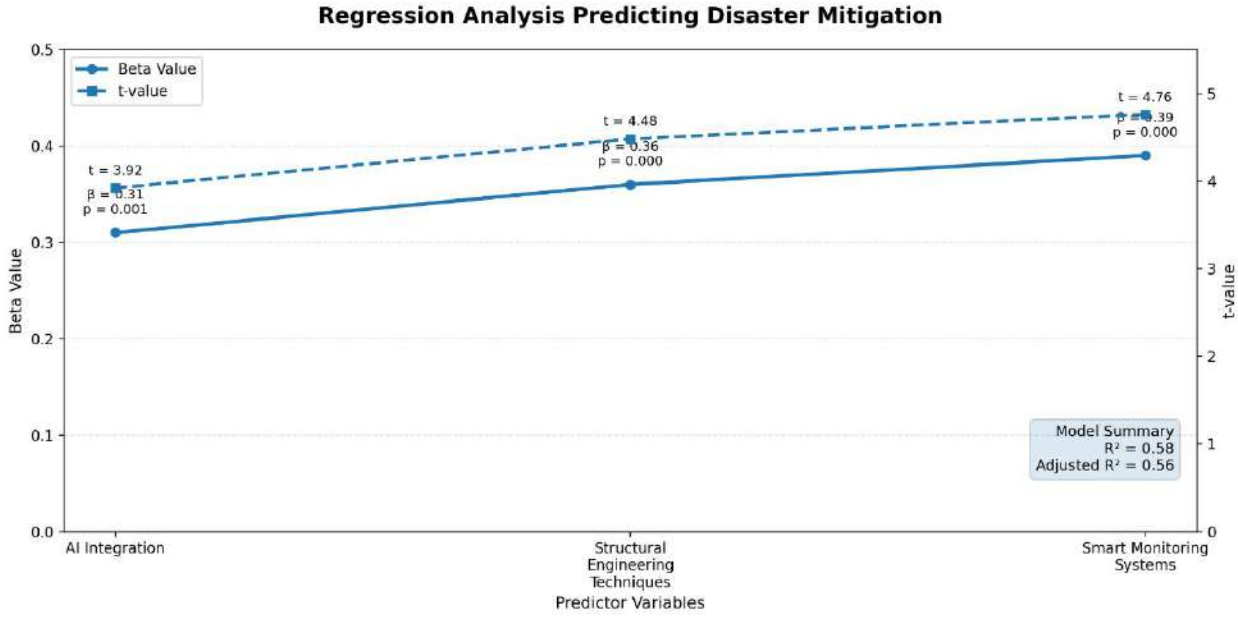

Figure 7. Regression Analysis Predicting Disaster Mitigation

Discussion

The results revealed the potential positive role of AI in enhancing the seismic resilience of smart buildings for seismic risk prediction, seismic damage detection, and post-earthquake building safety assessment. They enjoyed AI as a useful tool that works alongside them, since using it doesn't require the time-consuming, slow, nonlinear comparisons. The work done during recent years also confirmed this finding, as AI models have been developed for the classification of earthquake damage, prediction, and verification of the pattern of building vulnerabilities in a faster and more accurate manner (Yuan et al., 2023; Rajapaksha et al., 2024; Demir et al., 2024; Imam et al., 2024).

It was further established that structural engineering concepts remained vital for achieving earthquake resilience, confirming the findings. Seismic-resistant design, base isolation, energy dissipation devices, strong materials, and updated design codes were strongly agreed to have increased building safety. This demonstrated the effectiveness of AI in predicting and decision-making, but the safety of the buildings remained reliant on their physical strength and seismic performance. In other studies, the same was found to be true for AI-backed seismic assessment, which relies on engineering demand parameters (Junda et al., 2023), material behaviour, drift demands, and structural features (Kostinakis et al., 2023).

The most prominent relationship between AI and structural engineering was with smart monitoring systems. The real-time data fed into this enabled sensors, IoT systems, structural health monitoring, and digital twins to detect and assess damage and to plan maintenance. Further, the correlation and regression results revealed a strong relationship between smart monitoring systems and disaster mitigation, making smart monitoring the strongest predictor of disaster mitigation. The finding indicated the need for real-time monitoring for evacuation, emergency response, repair planning, and post-disaster recovery (To et al., 2024; Xu et al., 2024; Sun et al., 2025; Mahmoodian et al., 2022).

In short, the disaster was mitigated effectively when AI integration, structural engineering techniques, and smart monitoring systems were integrated. Smart buildings not only achieved collapse-free performance during earthquakes but also contributed to shorter evacuation times, reduced human casualties and economic damage, easier emergency management, and faster reconstruction. Thus, future buildings aiming to withstand earthquakes should be designed with strong seismic resistance, incorporate the AI methodology and capabilities of sensor networks, digital twins, interpretable AI, automatic warning systems, and post-earthquake decision-support platforms, as introduced by Habib et al. (2025), Afshar et al. (2024), Demertzis et al. (2023), Wei et al. (2025), and Xiong et al. (2024.

Conclusion

The researchers found that the earthquake-resistant smart building is an effective solution for disaster mitigation, as it is centred on the structure's strength and on artificial intelligence's analytical capabilities. The results indicated the benefits of artificial intelligence for seismic risk prediction, damage detection, emergency response, and post-earthquake safety assessment. The findings further illustrated that structural engineering techniques, including earthquake-resistant design, base isolation, energy dissipation systems, the use of strong construction materials, and updated design codes, contributed significantly to minimising earthquake damage. However, the resilience of an earthquake would not have been possible without digital technologies and a robust and safe structural design.

Recommendations

The Director-General of the Engineering Institute of Tito's recommends that the field of earthquake-resilient building design and monitoring incorporate artificial intelligence, urging engineers, architects, and construction industry professionals to take the initiative in advancing this area. The potential of using AI-based tools for seismic risk prediction, damage classification, structural response analysis, and emergency decision support.The potential for using AI-based tools for seismic risk prediction, damage classification, structural response analysis, and emergency decision support. A set of these tools may facilitate quicker and/or more accurate decision-making before, during, and after earthquakes. AI systems should complement, rather than supplant, the use of engineering judgement. Rather, they should assist engineers by providing data-driven insights and alerts.

Future Direction

Further research is suggested in future parts on the development of more reliable, low-cost, and practical algorithms based on artificial intelligence for earthquake-resilient smart buildings. AI models successfully functioned in simulated environments and on well-structured datasets; real buildings and the complexities of environmental conditions, material differences, sensor noise, and variations in earthquake response were not accounted for. The effects of these AIs need to be confirmed in real buildings and real seismic environments in future studies. This would help boost confidence in the AI systems used for prediction and damage.

References

Abdulkarem, M., Samsudin, K., Rokhani, F. Z., & Rasid, M. F. A. (2020). Wireless sensor network for structural health monitoring: A contemporary review of technologies, challenges, and future directions. *Structural Health Monitoring, 19*(3), 693–735. https://doi.org/10.1177/1475921719854528

Afshar, A., Nouri, G., Ghazvineh, S., & Hosseini Lavassani, S. H. (2024). Machine-learning applications in structural response prediction: A review. *Practice Periodical on Structural Design and Construction, 29*(3), 04024020. https://doi.org/10.1061/PPSCFX.SCENG-1292

Azimi, M., Eslamlou, A. D., & Pekcan, G. (2020). Data-driven structural health monitoring and damage detection through deep learning: State-of-the-art review. *Sensors, 20*(10), 2778. https://doi.org/10.3390/s20102778

Bhatta, S., & Dang, J. (2023). Seismic damage prediction of RC buildings using machine learning. *Earthquake Engineering & Structural Dynamics, 52*(11), 3504–3527. https://doi.org/10.1002/eqe.3907

Demertzis, K., Kostinakis, K. G., Morfidis, K. E., & Iliadis, L. S. (2023). An interpretable machine learning method for the prediction of R/C buildings' seismic response. *Journal of Building Engineering, 63*, 105493. https://doi.org/10.1016/j.jobe.2022.105493

Demir, A., Sahin, E. K., & Demir, S. (2024). Advanced tree-based machine learning methods for predicting the seismic response of regular and irregular RC frames. *Structures, 64*, 106524. https://doi.org/10.1016/j.istruc.2024.106524

Dong, C.-Z., & Catbas, F. N. (2021). A review of computer vision–based structural health monitoring at local and global levels. *Structural Health Monitoring, 20*(2), 692–743. https://doi.org/10.1177/1475921720935585

Flah, M., Nunez, I., Ben Chaabene, W., & Nehdi, M. L. (2021). Machine learning algorithms in civil structural health monitoring: A systematic review. *Archives of Computational Methods in Engineering, 28*(4), 2621–2643. https://doi.org/10.1007/s11831-020-09471-9

Habib, A., Alnaemi, A., & Habib, M. (2025). Developing a framework for integrating blockchain technology into earthquake risk mitigation and disaster management strategies of smart cities. *Smart and Sustainable Built Environment, 14*(5), 1513–1537. https://doi.org/10.1108/SASBE-12-2023-0376

Harirchian, E., Lahmer, T., Kumari, V., & Jadhav, K. (2020). Application of support vector machine modeling for the rapid seismic hazard safety evaluation of existing buildings. *Energies, 13*(13), 3340. https://doi.org/10.3390/en13133340

Hou, R., & Xia, Y. (2021). Review on the new development of vibration-based damage identification for civil engineering structures: 2010–2019. *Journal of Sound and Vibration, 491*, 115741. https://doi.org/10.1016/j.jsv.2020.115741

Imam, M. H., Mohiuddin, M., Shuman, N. M., Oyshi, T. I., Debnath, B., & Liham, M. I. M. H. (2024). Prediction of seismic performance of steel frame structures: A machine learning approach. *Structures, 69*, 107547. https://doi.org/10.1016/j.istruc.2024.107547

Junda, E., Málaga-Chuquitaype, C., & Chawgien, K. (2023). Interpretable machine learning models for the estimation of seismic drifts in CLT buildings. *Journal of Building Engineering, 70*, 106365. https://doi.org/10.1016/j.jobe.2023.106365

Kaartinen, E., Dunphy, K., & Sadhu, A. (2022). LiDAR-based structural health monitoring: Applications in civil infrastructure systems. *Sensors, 22*(12), 4610. https://doi.org/10.3390/s22124610

Kazemi, F., Asgarkhani, N., & Jankowski, R. (2023). Machine learning-based seismic response and performance assessment of reinforced concrete buildings. *Archives of Civil and Mechanical Engineering, 23*, 94. https://doi.org/10.1007/s43452-023-00631-9

Kim, M., & Song, J. (2022). Near-real-time identification of seismic damage using unsupervised deep neural network. *Journal of Engineering Mechanics, 148*(3), 04022006. https://doi.org/10.1061/(ASCE)EM.1943-7889.0002066

Kim, T., Kwon, O.-S., & Song, J. (2024). Deep learning-based response spectrum analysis method for building structures. *Earthquake Engineering & Structural Dynamics, 53*(4), 1638–1655. https://doi.org/10.1002/eqe.4086

Kostinakis, K., Morfidis, K., Demertzis, K., & Iliadis, L. (2023). Classification of buildings' potential for seismic damage using a machine learning model with auto hyperparameter tuning. *Engineering Structures, 290*, 116359. https://doi.org/10.1016/j.engstruct.2023.116359

Kourehpaz, P., & Molina Hutt, C. (2022). Machine learning for enhanced regional seismic risk assessments. *Journal of Structural Engineering, 148*(9), 04022126. https://doi.org/10.1061/(ASCE)ST.1943-541X.0003421

Lauria, M., & Azzalin, M. (2024). Digital transformation in the construction sector: A digital twin for seismic safety in the lifecycle of buildings. *Sustainability, 16*(18), 8245. https://doi.org/10.3390/su16188245

Mahmoodian, M., Shahrivar, F., Setunge, S., & Mazaheri, S. (2022). Development of digital twin for intelligent maintenance of civil infrastructure. *Sustainability, 14*(14), 8664. https://doi.org/10.3390/su14148664

Mahmoudi, H., Bitaraf, M., Salkhordeh, M., & Soroushian, S. (2023). A rapid machine learning-based damage detection algorithm for identifying the extent of damage in concrete shear-wall buildings. *Structures, 47*, 482–499. https://doi.org/10.1016/j.istruc.2022.11.041

Malekloo, A., Ozer, E., AlHamaydeh, M., & Girolami, M. (2022). Machine learning and structural health monitoring overview with emerging technology and high-dimensional data source highlights. *Structural Health Monitoring, 21*(4), 1906–1955. https://doi.org/10.1177/14759217211036880

Mamat, N., Abdulghafor, R., Turaev, S., & Yakub, F. (2025). Comparative review of intelligent structural safety in building seismic risk mitigation utilizing an integrated artificial intelligence controller. *Discover Applied Sciences, 7*, 393. https://doi.org/10.1007/s42452-025-06914-5

Rajapaksha, D., Siriwardana, C., Ruparathna, R., Maqsood, T., Setunge, S., Rajapakse, L., & De Silva, S. (2024). Systematic mapping of global research on disaster damage estimation for buildings: A machine learning-aided study. *Buildings, 14*(6), 1864. https://doi.org/10.3390/buildings14061864

Ravichandran, N., Bidorn, B., Mercan, O., & Paneerselvam, B. (2025). Data-driven machine-learning-based seismic response prediction and damage classification for an unreinforced masonry building. *Applied Sciences, 15*(4), 1686. https://doi.org/10.3390/app15041686

Sun, H., Burton, H. V., & Huang, H. (2021). Machine learning applications for building structural design and performance assessment: State-of-the-art review. *Journal of Building Engineering, 33*, 101816. https://doi.org/10.1016/j.jobe.2020.101816

Sun, Z., Jayasinghe, S., Sidiq, A., Shahrivar, F., Mahmoodian, M., & Setunge, S. (2025). Approach towards the development of digital twin for structural health monitoring of civil infrastructure: A comprehensive review. *Sensors, 25*(1), 59. https://doi.org/10.3390/s25010059

To, Q. B., Lee, K., Cuong, N. H., & Shin, J. (2024). Development of machine learning based seismic retrofit scheme for AFRP retrofitted RC column. *Structures, 69*, 107279. https://doi.org/10.1016/j.istruc.2024.107279

Torzoni, M., Tezzele, M., Mariani, S., Manzoni, A., & Willcox, K. E. (2024). A digital twin framework for civil engineering structures. *Computer Methods in Applied Mechanics and Engineering, 418*, 116584. https://doi.org/10.1016/j.cma.2023.116584

Vijayan, D. S., Sivasuriyan, A., Devarajan, P., Krejsa, M., Chalecki, M., Żółtowski, M., Kozarzewska, A., & Koda, E. (2023). Development of intelligent technologies in SHM on the innovative diagnosis in civil engineering—A comprehensive review. *Buildings, 13*(8), 1903. https://doi.org/10.3390/buildings13081903

Wang, J., Wu, Y., Wang, S., Narazaki, Y., Liu, H., & Spencer, B. F. (2024). Development and validation of graphics-based digital twin framework for UAV-aided post-earthquake inspection of high-rise buildings. *The Structural Design of Tall and Special Buildings, 33*(13), e2127. https://doi.org/10.1002/tal.2127

Wang, X., Mazumder, R. K., Salarieh, B., Salman, A. M., Shafieezadeh, A., & Li, Y. (2022). Machine learning for risk and resilience assessment in structural engineering: Progress and future trends. *Journal of Structural Engineering, 148*(8), 03122003. https://doi.org/10.1061/(ASCE)ST.1943-541X.0003392

Wei, Z., Wang, X., Fan, B., & Shahzad, M. M. (2025). A stacking ensemble-based multi-channel CNN strategy for high-accuracy damage assessment in mega-sub controlled structures. *Buildings, 15*(11), 1775. https://doi.org/10.3390/buildings15111775

Xie, Y., Ebad Sichani, M., Padgett, J. E., & DesRoches, R. (2020). The promise of implementing machine learning in earthquake engineering: A state-of-the-art review. *Earthquake Spectra, 36*(4), 1769–1801. https://doi.org/10.1177/8755293020919419

Xiong, Q., Kong, Q., Yuan, C., Li, Y., Ji, K., & Xiong, H. (2024). Fusing physics-based and machine learning models for rapid ground-motion-adaptative probabilistic seismic fragility assessment. *Journal of Building Engineering, 87*, 108938. https://doi.org/10.1016/j.jobe.2024.108938

Xu, W., Zhao, Y., Yang, W., Yu, D., & Zhao, Y. (2024). Seismic fragility analysis of RC frame structures based on IDA analysis and machine learning. *Structures, 65*, 106774. https://doi.org/10.1016/j.istruc.2024.106774

Yu, X., Fu, Y., Li, J., Mao, J., Hoang, T., & Wang, H. (2024). Recent advances in wireless sensor networks for structural health monitoring of civil infrastructure. *Journal of Infrastructure Intelligence and Resilience, 3*, 100066. https://doi.org/10.1016/j.iintel.2023.100066

Yuan, X., Li, L., Zhang, H., Zhu, Y., Chen, G., & Dagli, C. (2023). Machine learning-based seismic damage assessment of residential buildings considering multiple earthquake and structure uncertainties. *Natural Hazards Review, 24*(3), 04023024. https://doi.org/10.1061/NHREFO.NHENG-1681

Zhang, H., Cheng, X., Li, Y., He, D., & Du, X. (2023). Rapid seismic damage state assessment of RC frames using machine learning methods. *Journal of Building Engineering, 65*, 105797. https://doi.org/10.1016/j.jobe.2022.105797