JOURNAL OF INNOVATION AND TECHNOLOGY
eISSN:2805-5179 Vol. 2025, Issue 2, No.05

Proposed an Intelligent Framework for Effective Disaster Management through the Integration of Artificial Intelligence

Surjandy[1*], Amril Mutoi Siregar[2], Albert Jofrandi Hutapea[2], Alphian Sucipto Lubis[2], Ferdinand Fassa[3]

[1]Digital Business, Institut Teknologi Sains Bandung, Kota Deltamas Lot-A1 CBD, Jl. Ganesha Boulevard No.1, Pasirranji, Kec. Cikarang Pusat, Kabupaten Bekasi, Jawa Barat, Indonesia
[2]Informatics, Institut Teknologi Sains Bandung, Kota Deltamas Lot-A1 CBD, Jl. Ganesha Boulevard No.1, Pasirranji, Kec. Cikarang Pusat, Kabupaten Bekasi, Jawa Barat, Indonesia
[3] Civil Engineering, Institut Teknologi Sains Bandung, Kota Deltamas Lot-A1 CBD, Jl. Ganesha Boulevard No.1, Pasirranji, Kec. Cikarang Pusat, Kabupaten Bekasi, Jawa Barat, Indonesia

***Email:** surjandy@itsb.ac.id

Abstract

Urbanization and climate change have contributed to disaster frequency and intensity, making disaster risk management essential. This study seeks to address these issues, including lack of future effect prediction, uncoordinated response, and early identification delays. AI can improve danger management, according to past studies. Practical approach issues like real data validation and system compatibility hinder deployment. This study uses case study analysis and literature evaluation based on the high-level Disaster Framework. The five pillars of this framework—Identify, Protect, Detect, Respond, and Recover—address threats throughout a crisis. After adding AI and Smart Identify, Smart Protect, Smart Detect, Smart Respond, and Smart Recover, the framework became the Disaster Smart Framework. The dataset includes Scopus-indexed journal papers, disaster records, and classic and cutting-edge machine learning model validation approaches. The Hazard Intelligence Framework is shaped by eight key AI elements identified in this study. The proposed work offers the groundwork for smarter, more efficient, and more adaptive catastrophe management systems and provides a framework for researching wider applications and ethical implications. Thus, AI catastrophe risk management technologies could save more lives and reduce socioeconomic impacts.

Keywords

Artificial Intelligence, Risk Management, Hazard Intelligence Framework, Internet of Things, Disaster Recovery.

Submission: 30 October 2025; **Acceptance:** 28 November 2025; **Available online:** December 2025

Introduction

Disaster risk management is an extremely critical building block for preserving life and property, as well as the ecosystem (Vicari & Komendatova, 2023a). Disasters caused by nature, such as earthquakes, floods, and forest fires, and those caused by human activities, such as chemical spills, explosions, and gas leaks, can cause huge losses if not handled properly. Climate change and rapid urbanization can increase both the frequency and severity of disasters, and the environmental pandemic of COVID-19 has demonstrated the importance of place-based risk management, yet the need for a more sophisticated mechanism to address hazards is vital if we are to prevent another pandemic like COVID-19. But current hazard management systems are severely limited. The major challenge is the challenge of early detection of hazards (Zheng et al., 2023a), such forecasts often come too late to make any mitigation measures, and existing technologies might not cover the entire section of the avalanche. Responding to disasters is also slow and poorly coordinated, leading to high human casualties as well as economic losses. One more challenge is the restricted capacity to foresee the long-term effects of a calamity and effective restoration planning (De Angeli et al., 2022; Moore et al., 2023; Nastos et al., 2021).

The study finds that artificial intelligence systems can empower hazard management processes across functions, hence helping to increase efficiency and accuracy at hazard identification, loss prevention, early detection, rapid reaction, and post-disaster recovery. While IoT-based solutions provide real-time detection and automated decision-making, machine learning methods use prior data to predict possible hazards (Hoffman, 2021; Zhang et al., 2025; Zhao, 2025). Despite identifying AI as a key factor, the reviewed studies lack the necessary detail regarding AI's practical application across the distinct phases of the hazard framework (Identify, Protect, Detect, Respond, and Recover). To address this deficit in granular process understanding, the present qualitative research is designed to explore these interactions in depth. This study will conduct an in-depth exploration utilizing bibliometric analysis, supported by the R application and by using the Scopus database. The research covers articles published up to 2025, totalling 271 items from 192 different publishers. The findings reveal eight fundamental factors necessary for the successful development of the hazard framework into an intelligent construct. These factors must be incorporated to ensure the framework possesses the sophisticated capabilities required for modern hazard identification and mitigation.

Finally, implementation of AI for management of hazards of disasters not only can save more lives but also greatly reduce social and economic impacts. This research significantly contributes to the enhancement of scientific knowledge, especially in risk or hazard management systems, and its subsequent implementation in the industrial sector.

Literature Review

Several significant challenges prevent AI from being used in natural disaster hazard management. Due to forecasts utilizing only historical data, accuracy is limited. This technique struggles to depict catastrophic trends, especially those related to urbanization and climate change. However, AI-Bayesian approaches can improve risk assessments and mitigations by analyzing complex data (Zheng et al. 2023).

Furthermore, straightforward device-based early detection models—such as those utilized for seismographs or precipitation measuring instruments—require manual analysis, hence impeding response times. Delays during emergencies may intensify the repercussions of disasters. Recent research reveals that AI can process data 30% more rapidly than before (Mansell et al., 1995 The use of Internet of Things (IoT)-based sensors facilitates near real-time data readouts. Thus, AI-driven early warning systems are more proficient at managing high-velocity crisis scenarios.

Conventional information systems are unable to manage large-scale emergencies due to their manual data processing and coordination which requires many human resources. Automation, labor reduction, and operational efficiency can be achieved with AI. AI Makes Complex Disaster Management More Flexible through Adaptability and Novel Data Acquisition AI-driven simulations can also improve post-disaster recovery and design for future disasters. AI solves the problems of past technologies, making it more relevant today.

This qualitative study uses Bibliometrics to analyze 42 Scopus papers from 1954 to 2025 from 42 publishers. Results show a rising research trend in AI-based hazard management frameworks. The report identifies eight important requirements for incorporating AI technology into hazard management frameworks to create a Hazard Intelligence Framework. This study's findings are significant for future research, notably in threat management framework theory. This research will illuminate industry hazard intelligence framework implementation.

Methodology

The methodology employed in this study is Bibliometric (Aria & Cuccurullo, 2017). This approach comprises five main stages, each designed to systematically analyze and interpret bibliometric data. These stages provide a structured framework for extracting valuable insights and ensuring the research is both comprehensive and robust in its findings.

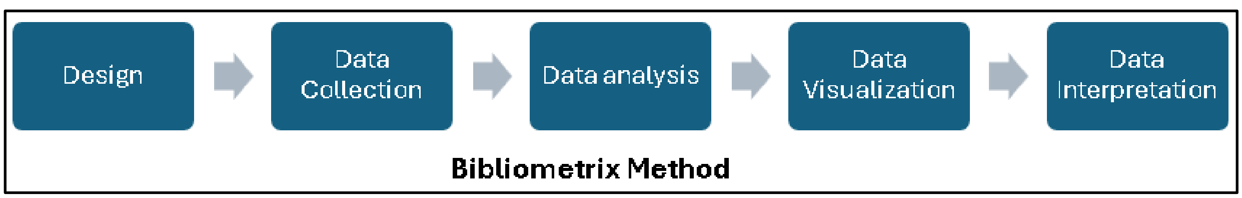

Figure 1. Bibliometric Method

In order to direct this investigation, a research definition is developed during the design phase see Figure 1. and expressed as research questions. The purpose of this study is to expand on literature analysis to investigate the difficulties encountered in hazard risk framework research utilizing artificial intelligence. The methods used to collect the data for this study are described in the Data Gathering section. By using keywords such as "Artificial Intelligence," "Hazard Management," "Disaster Response," and "Risk Assessment," the Scopus database was searched for relevant publications. To ensure that the data used was up to date, the search was limited to articles released between 2015 and 2025.

The data analysis step describes the procedures and techniques used to examine the information gathered. For the data to be successfully understood and represented in later phases, it is essential. To extract valuable insights and build a solid foundation for the visualization process, a thorough analysis is essential. This will enable the research findings to be presented in a way that is both effective and understandable. The data visualization stage entails turning unprocessed data into visual representations like charts, graphs, diagrams, and other images. Because it enables the data to be presented in a more effective and accessible manner, the procedure is crucial for improving understanding and communication of findings. This step helps improve interpretation and aids the efficient dissemination of insights to the audience by transforming data into visual components.

Stage of Interpretation: The Bibliometric process culminates with the interpretation stage. At this point, the data is examined and interpreted to make sure it can be used effectively in further studies and comprehended. This stage is essential for drawing insightful conclusions from the data and laying the groundwork for further research. In academic pursuits, the interpretation stage helps to bridge the gap between raw facts and their practical application by promoting greater knowledge.

Results and Discussion

Results

This paragraph highlights the research's findings from data use to interpretation. The data was meticulously examined and translated into meaningful insights. This section links data utilization and analysis to emphasize the results' importance and relevance to the study goals.

Figure 2. Statistical Overview of Data

Figure 2: The dataset includes 42 articles from 1954 to 2025 with 131 authors and 3.14 co-authors. The 14.29 percent international collaboration rate shows minimal cross-border participation. Low international collaboration in our fields can hinder innovation, scientific progress, and research's worldwide impact. To overcome this, worldwide collaboration networks and joint research funding must be expanded. Documents average 11.4 years old and grow 0% annually. The average of 4,071 citations per manuscript proved science's efficacy despite the few papers. The lack of references makes assessing the data set's legitimacy difficult.

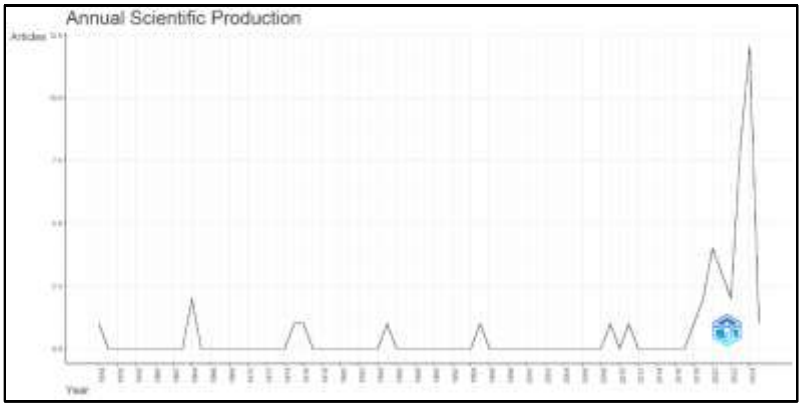

Figure 3. Research Trend Development

Illustration 3. The graph, spanning the years 1954 to 2025, illustrates the annual distribution of scientific publications. Article production was minimal and inconsistent from 2007 to 2010. Subsequently, there was a significant surge in publications, culminating in 2024 with the highest number of articles exceeding twelve. A more comprehensive data analysis is necessary to attain a deeper understanding of the correlation between industrial and technological advancements and peak publishing years. By addressing the inquiries and conducting further analysis, we may identify the variables contributing to the increase in publications in 2024 and formulate implications for future research.

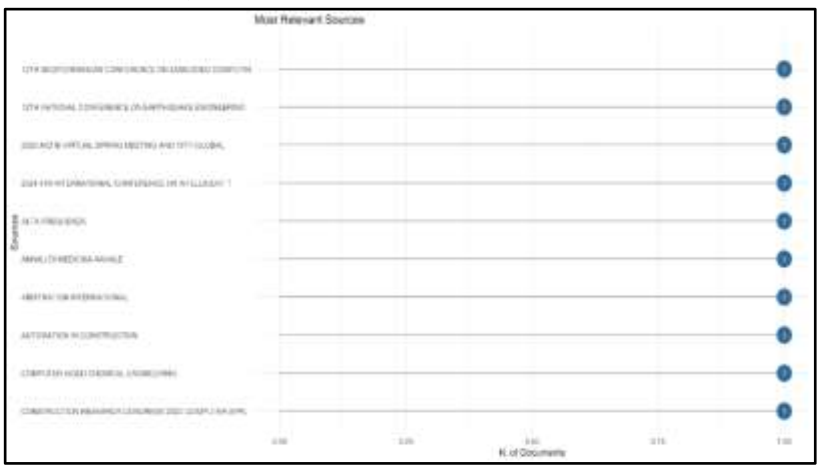

Figure 4. The most Sources

Each of the ten most often cited sources—the 12th Mediterranean Conference on Embedded Computing, the 12th National Conference on Earthquake Engineering, the 2020 AIChE Virtual Spring Meeting, the 2024 4th International Conference on Intelligent Systems, Alta Frequenza, Annali di Medicina Navale, Arbitration International, Automation in Construction, Computer Aided Chemical Engineering, and the Construction Research Congress 2020: Computer Applications—contains one pertinent study pertaining to hazards, as shown in Figure 4.

Table 1. The 10 most Relevant Affiliation

NO	AFFILIATION	ARTICLES	(%)
1	EXCEL ENGINEERING COLLEGE	2	4.76
2	INDIAN INSTITUTE OF TECHNOLOGY KHARAGPUR	2	4.76

3	SEJONG UNIVERSITY	2	4.76
4	UNIVERSITY OF SHARJAH	2	4.76
5	AIT AUSTRIAN INSTITUTE OF TECHNOLOGY GMBH	1	2.38
6	BEIJING NORMAL UNIVERSITY	1	2.38
7	BENCHMARK LABS	1	2.38
8	CENTRO INTERUNIVERSITARIO PER LO STUDIO DELLE FRANE E DELLA EROSIONE	1	2.38
9	CHINA TRANSPORT TELECOMMUNICATIONS INFORMATION CENTER	1	2.38
10	CHINA UNIVERSITY OF MINING AND TECHNOLOGY	1	2.38

Table 1 presents the institutions that contributed to the published articles. The scholarly contributions from global institutions are reflected in two articles (4.76%) from Excel Engineering College, Indian Institute of Technology Kharagpur, Sejong University, and University of Sharjah, alongside one article (2.38%) from six additional institutions, including AIT Austrian Institute of Technology GmbH, Beijing Normal University, and Benchmark Labs.

Table 2. Essential Factors

NO	ESSENSIAL FAKTORs	REFERENCES
1.	**Immediate Response**	(Charalampidou et al., 2024; Espinoza et al., 2024; Vahid Razavi-Termeh et al., 2025)
2.	**Verify**	(Charalampidou et al., 2024; Espinoza et al., 2024; Vahid Razavi-Termeh et al., 2025)
3.	**Real-Time**	(Bai et al., 2019; Lee & Yu, 2023; Schaefer & Revheim, 2024; Williams et al., 2023)
4.	**Optimal**	(Patil et al., 2024; Vahid Razavi-Termeh et al., 2025; Zheng et al., 2023a)
5.	**Efficient**	(Chen et al., 2023; Lee & Yu, 2023; Schwing, 2020; Velmurugan et al., 2023)
6.	**Scalable**	(Cummings, 2024; Schaefer & Revheim, 2024; Velmurugan et al., 2023; Zheng et al., 2023b)
7.	**Resilience**	(Bai et al., 2019; Vicari & Komendatova, 2023b; Zheng et al., 2023b)
8.	**Comply**	(Chen et al., 2023; Panagiotou et al., 2023)

Table 1 reveals eight critical AI-related aspects that influence the Hazard Framework both directly and indirectly, derived from a comprehensive examination of scholarly articles. The integration of AI technology enhances the operational efficiency of the hazard framework by facilitating a swift response to activities within it. All these components collaborate to improve the framework's precision, responsiveness, and adaptability in risk management.

Discussion

In a hazard framework, quick response and real-time capabilities affect the speed and accuracy of hazards identification. An immediate response ensures prompt action when a hazard is discovered, eliminating delays that could escalate hazards. Real-time functionality allows ongoing monitoring and data upgrades, eliminating delays in spotting unexpected or rapidly changing threats. The verify component ensures the validity and correctness of hazard signals and prevents misidentification that could lead to unnecessary or inefficient responses.

Conversely, the scalable, efficient, and optimal elements help to guarantee that the identification process maximizes results while working efficiently with constrained resources. While efficiency reduces waste of time and money, optimization guarantees the selection of the best identification techniques. Whether on a local or large scale, scalability enables the identification system to adjust to changing demands. By strengthening the system's resistance to disturbances, the resilience factor guarantees ongoing identification even in the event of partial failures. Lastly, compliance reduces legal risks and enhances system reliability by ensuring that the entire identification process complies with safety norms and laws. By combining these elements, a reliable, quick, and strong framework for hazard identification is created.

The efficacy of preventative and mitigating measures is determined by immediate response and real-time capabilities, which are crucial components of the protection process within hazard frameworks. An instant reaction lowers the possibility of impact escalation by guaranteeing the prompt application of protective measures upon hazard detection. At the same time, dynamic monitoring and immediate protective measure adjustment in response to changing danger conditions are made possible by real-time functionality, which guarantees that reactions stay contextually appropriate. In order to avoid mistakes that can result in misallocated resources or increased hazards, the verify factor is essential for confirming the accuracy of hazard data before preventive action is taken. Furthermore, the long-term viability of protective systems is determined by the combination of optimal, efficient, and scalable variables. While efficiency provides minimal time, money, and effort expenditure without sacrificing effectiveness, optimization guarantees the selection of protective approaches that deliver optimum efficacy within resource restrictions. Protection systems may adjust to different hazard scopes and complexities, whether local or worldwide, thanks to scalability. By strengthening the system's resistance to operational disturbances, the resilience factor guarantees protection even in the event of partial failures or harsh circumstances. Lastly, regulatory compliance strengthens the validity and dependability of the overall protection framework in addition to reducing legal risks. When these elements work together harmoniously, a protective system that is resilient, flexible, and sustainable is produced.

Immediate response, real-time monitoring, verification, optimization, efficiency, scalability, resilience, and compliance are some of the crucial elements that greatly impact a hazard response framework's efficacy. While real-time data processing improves situational awareness and decision-making accuracy, an immediate response guarantees prompt action to neutralize hazards. In order to confirm the accuracy of information and keep false information from jeopardizing response efforts, verification procedures are crucial. Impact is increased, and delays are reduced through effective operational workflows and optimal resource utilization. Additionally, resilience guarantees continuity in the face of disturbances, while scalability enables the framework to adjust to different threat magnitudes. Finally, conformity with operational and regulatory standards ensures that response measures meet moral and legal obligations, which promotes cooperation and confidence among stakeholders. When combined, these elements produce a strong and flexible hazard response system that can successfully handle changing threats. The recovery phase of a hazard framework depends significantly on prompt response and real-time capabilities to facilitate rapid and informed responses. A prompt response mitigates extended interruptions by commencing recovery initiatives upon danger detection, while real-time data acquisition and analysis provide adaptive modifications to recovery techniques. The absence of these elements may intensify damage and extend system downtime due to delays in decision-making. Moreover, verification is essential for ensuring that recovery measures are founded on precise and validated information, so averting resource misallocation or unforeseen repercussions.

Efficiency and optimization are essential in enhancing recovery operations, guaranteeing that resources—be they human, financial, or technological—are employed efficiently. An effective recovery procedure minimizes waste and hastens the return to normalcy, while an optimal approach guarantees that tactics are customized to the particular requirements of the impacted system. Scalability improves recovery by enabling the framework to adapt to different levels of hazards, ranging from isolated events to extensive disasters. A scalable system guarantees that recovery mechanisms operate well irrespective of the magnitude of the disruption, preserving consistency in performance and results.

Ultimately, resilience and adherence dictate the enduring viability and legitimacy of recovery initiatives. Resilience guarantees that systems not only recuperate but also adjust to avert future weaknesses, integrating acquired insights into enhanced frameworks. Compliance with regulatory standards and best practices ensures that recovery procedures adhere to legal, ethical, and operational criteria, hence enhancing stakeholder confidence and coordination. Collectively, these elements establish a resilient recovery framework that is both reactive and proactive, guaranteeing systemic stability and ongoing enhancement in hazard management.

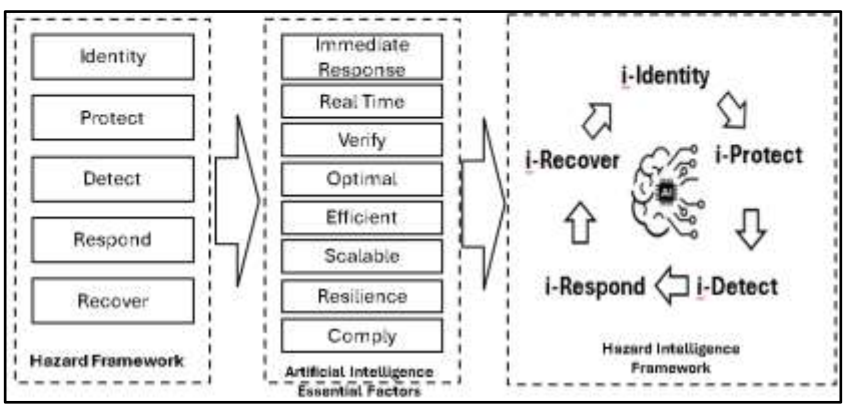

Figure 5. Hazard Intelligence Framework

This study concludes that AI technology is essential in transforming the Hazard Framework into a Hazard Intelligence Framework. The incorporation of AI produces significant advantages, facilitating the alleviation—or complete eradication—of current obstacles. Figure 5 depicts the transition from a traditional hazard framework to an AI-enhanced hazard intelligence framework, highlighting the essential incorporation of intelligent systems for increased risk management.

Conclusions

This study concludes that Artificial Intelligence (AI) technology will enhance the Hazard Framework process, resulting in a Hazard Intelligence Framework that includes intelligence identity, protection, detection, response, and recovery processes. The implementation of AI technology would mitigate adverse effects and reduce casualties, hence enhancing the safety of disaster victims. The eight essential factors (Immediate Response, Real-time, Verify, Optimal, Efficient, Scalable, Resilience, and Comply) intrinsic to AI technology will augment the efficiency and efficacy of the Hazard Framework process. The constraints of this study need a comprehensive elucidation of each process within the Hazard Intelligence Framework to serve as a foundation for subsequent research that will augment this study. This study is crucial for theoretical advancement and practical application in industry.

Acknowledgements

Surjandy thanks colleague's lecturers Amril Mutoi Siregar and Ferdinand Fassa for reviewing and giving feedback. All research students (Albert Jofrandi Hutapea, Alphian Sucipto Lubis). The help is valuable. An AI application assisted with writing this English article.

References

Aria, M., & Cuccurullo, C. (2017). *bibliometrix:* An R-tool for comprehensive science mapping analysis. *Journal of Informetrics*, *11*(4), 959–975. https://doi.org/10.1016/j.joi.2017.08.007

Bai, X., Sang, L., Khan, J., Kang, H., & Liu, Z. (2019). Initial Thoughts and Application of AI in Geo-hazards Monitoring and Early Warning of Highroad in Beijing. *2019 5th International Conference on Transportation Information and Safety (ICTIS)*, 1358–1363. https://doi.org/10.1109/ICTIS.2019.8883743

Charalampidou, S., Zeleskidis, A., & Dokas, I. M. (2024). Hazard analysis in the era of AI: Assessing the usefulness of ChatGPT4 in STPA hazard analysis. *Safety Science*, *178*, 106608. https://doi.org/10.1016/j.ssci.2024.106608

Chen, C., Chen, Z., Luo, W., Xu, Y., Yang, S., Yang, G., Chen, X., Chi, X., Xie, N., & Zeng, Z. (2023). Ethical perspective on AI hazards to humans: A review. *Medicine*, *102*(48), e36163. https://doi.org/10.1097/MD.0000000000036163

Cummings, M. L. (2024). A Taxonomy for AI Hazard Analysis. *Journal of Cognitive Engineering and Decision Making*, *18*(4), 327–332. https://doi.org/10.1177/15553434231224096

De Angeli, S., Malamud, B. D., Rossi, L., Taylor, F. E., Trasforini, E., & Rudari, R. (2022). A multi-hazard framework for spatial-temporal impact analysis. *International Journal of Disaster Risk Reduction*, *73*, 102829. https://doi.org/10.1016/j.ijdrr.2022.102829

Espinoza, D., Ali, G., & Tarawneh, C. (2024, May 13). AI-Based Hazard Detection for Railway Crossings. *2024 Joint Rail Conference*. https://doi.org/10.1115/JRC2024-124640

Hoffman, S. (2021). The Emerging Hazard of AI-Related Health Care Discrimination. *Hastings Center Report*, *51*(1), 8–9. https://doi.org/10.1002/hast.1203

Lee, S.-K., & Yu, J.-H. (2023). Ontological inference process using AI-based object recognition for hazard awareness in construction sites. *Automation in Construction*, *153*, 104961. https://doi.org/10.1016/j.autcon.2023.104961

Moore, D. W., Ruffle, B., McQueen, A., Thakali, S., & Edwards, D. (2023). Frameworks for screening and risk management of chemicals and advanced materials: A critical review. *Integrated Environmental Assessment and Management*, *19*(5), 1192–1206. https://doi.org/10.1002/ieam.4590

Nastos, P. T., Dalezios, N. R., Faraslis, I. N., Mitrakopoulos, K., Blanta, A., Spiliotopoulos, M., Sakellariou, S., Sidiropoulos, P., & Tarquis, A. M. (2021). Review article: Risk management framework of environmental hazards and extremes in Mediterranean ecosystems. *Natural Hazards and Earth System Sciences*, *21*(6), 1935–1954. https://doi.org/10.5194/nhess-21-1935-2021

Panagiotou, C., Fraile, L. P., & Koulamas, C. (2023). Detecting Health & Safety Hazards through AI and Edge Computing on Mobile Devices. *2023 12th Mediterranean Conference on Embedded Computing (MECO)*, 1–4. https://doi.org/10.1109/MECO58584.2023.10155077

Patil, S. S., Shaam, N., Kodipalli, A., & Rao, T. (2024). Asteroid Hazard Assessment: Optimizing ExtraTrees with RandomizedSearch CV and SHAP Explainable AI. *2023 4th International Conference on Intelligent Technologies (CONIT)*, 1–5. https://doi.org/10.1109/CONIT61985.2024.10627604

Schaefer, S., & Revheim, O. (2024, April 17). Building Trust in AI/ML Solutions: Key Factors for Successful Adoption in Drilling Optimization and Hazard Prevention. *Day 1 Wed, April 17, 2024*. https://doi.org/10.2118/218455-MS

Schwing, M. A. (2020). Don’t rage against the machine: Why AI may be the cure for the ‘moral hazard’ of party appointments. *Arbitration International*, *36*(4), 491–507. https://doi.org/10.1093/arbint/aiaa033

Vahid Razavi-Termeh, S., Sadeghi-Niaraki, A., Ali, F., Ali Naqvi, R., & Choi, S.-M. (2025). Cutting-Edge strategies for absence data identification in natural hazards: Leveraging Voronoi-Entropy in flood susceptibility mapping with advanced AI techniques. *Journal of Hydrology*, *648*, 132337. https://doi.org/10.1016/j.jhydrol.2024.132337

Velmurugan, G., Arun, S. R., K., V., & R., V. (2023). Minimizing Risks in Close Proximity ARC Welding with Autonomous AI-Powered Welding System: Risk Assessment and Hazard Prevention. *2023 3rd International Conference on Pervasive Computing and Social Networking (ICPCSN)*, 1750–1755. https://doi.org/10.1109/ICPCSN58827.2023.00293

Vicari, R., & Komendatova, N. (2023a). Systematic meta-analysis of research on AI tools to deal with misinformation on social media during natural and anthropogenic hazards and disasters. *Humanities and Social Sciences Communications*, *10*(1), 332. https://doi.org/10.1057/s41599-023-01838-0

Vicari, R., & Komendatova, N. (2023b). Systematic meta-analysis of research on AI tools to deal with misinformation on social media during natural and anthropogenic hazards and disasters. *Humanities and Social Sciences Communications*, *10*(1), 332. https://doi.org/10.1057/s41599-023-01838-0

Williams, B., Suryasentana, S., Perry, M., & Donaldson, K. (2023, September 12). Artificial Intelligence (AI) Driven 3D Point Scanner for Monitoring Soil Plug Hazards During the Installation of Suction Caisson Foundations. *9th International SUT Offshore Site*

Investigation Geotechnics Conference Proceedings "Innovative Geotechnologies for Energy Transition." https://doi.org/10.3723/THIQ6200

Zhang, N., Qiu, H., Cai, H., Li, Z., Li, Y., Li, Z., Qi, L., Du, H., Pan, Y., Jing, H., Ning, J., Xian, B., & Gao, S. (2025). HazChemNet: A Deep Learning Model for Hazardous Chemical Prediction. *International Journal of Molecular Sciences*, *26*(19), 9288. https://doi.org/10.3390/ijms26199288

Zhao, L. (2025). Geologic Disaster Prediction Method Based on Remote Sensing Images and Artificial Intelligence. *Proceedings of the 2024 8th International Conference on Electronic Information Technology and Computer Engineering*, 305–309. https://doi.org/10.1145/3711129.3711183

Zheng, X.-W., Li, H.-N., & Shi, Z.-Q. (2023a). Hybrid AI-Bayesian-based demand models and fragility estimates for tall buildings against multi-hazard of earthquakes and winds. *Thin-Walled Structures*, *187*, 110749. https://doi.org/10.1016/j.tws.2023.110749