Artificial Intelligence and Optimization Techniques in Earthquake Engineering: A Systematic Review

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Abstract

This comprehensive review examines the current state of artificial intelligence and computational optimization techniques applied to earthquake engineering challenges. The paper systematically analyzes recent advances across three primary domains: machine learning (ML), deep learning (DL), and optimization methods, each contributing distinct capabilities to seismic hazard mitigation. Through an extensive analysis of peer-reviewed studies, this review synthesizes methodologies employed in earthquake prediction, early warning systems, structural damage assessment, emergency response optimization, and seismic hazard analysis. Machine learning approaches have demonstrated significant effectiveness in liquefaction prediction, slope displacement analysis, and seismic event classification, with models such as XG Boost and Random Forest achieving high predictive accuracy. Deep learning architectures, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformer-based models, have revolutionized real-time earthquake detection, P-wave recognition, and landslide susceptibility mapping, with several models achieving accuracy rates exceeding 90%. Optimization techniques, particularly metaheuristic algorithms like Particle Swarm Optimization (PSO) and Gray Wolf Optimizer (GWO), have proven valuable for emergency logistics, shelter allocation, and structural design optimization. The review reveals current trends toward hybrid frameworks integrating multiple computational approaches, enhanced model interpretability, and real-time implementation capabilities. Future research directions emphasize the development of uncertainty-aware models, scalable frameworks for global application, and integration of social and economic factors in disaster preparedness strategies. This review provides researchers and practitioners with a structured understanding of computational methodologies in earthquake engineering and identifies critical gaps requiring further investigation.

Keywords: Earthquake engineering; Machine learning; Deep learning; Optimization algorithms; Seismic hazard assessment; Early warning systems; Structural damage prediction; Metaheuristic algorithms; Artificial intelligence

1 Introduction

Earthquakes represent one of the most devastating natural disasters, causing significant loss of life, extensive infrastructure damage, and substantial economic disruption worldwide. Recent seismic events

DOI: https://doi.org/10.54216/MOR.050204

Received: July 08, 2025 Revised: September 17, 2025 Accepted: December 07, 2025

have underscored the critical importance of developing advanced methodologies for earthquake prediction, early warning systems, structural resilience assessment, and post-disaster emergency response [1], [2]. The complexity of seismic phenomena, characterized by non-linear dynamics, spatial-temporal variability, and inherent uncertainties, necessitates sophisticated computational approaches that transcend traditional analytical methods. Consequently, artificial intelligence (AI) and optimization techniques have emerged as powerful tools for addressing multifaceted challenges in earthquake engineering, offering unprecedented capabilities in pattern recognition, predictive modeling, and decision optimization.

The integration of AI methodologies into earthquake engineering has witnessed remarkable growth over the past decade, driven by several converging factors. The proliferation of seismic monitoring networks has generated vast quantities of high-resolution data, creating opportunities for data-driven modeling approaches [3]. Advances in computational hardware, particularly graphics processing units (GPUs) and cloud computing infrastructure, have enabled the training of complex neural networks and execution of computationally intensive optimization algorithms. Simultaneously, breakthroughs in machine learning algorithms, deep learning architectures, and metaheuristic optimization methods have expanded the methodological toolkit available to earthquake engineers and seismologists [4]. These developments have facilitated applications ranging from real-time seismic event detection and magnitude estimation to structural design optimization and emergency resource allocation.

Machine learning (ML) techniques have demonstrated considerable success in earthquake-related applications by identifying complex patterns within seismic data without requiring explicit physical models. Traditional ML algorithms, including Support Vector Machines, Random Forests, and gradient boosting methods, have proven effective for tasks such as liquefaction potential assessment, earthquake-induced landslide prediction, and seismic hazard classification [5], [6]. These methods excel in scenarios where domain expertise can guide feature engineering and where model interpretability is prioritized. Deep learning (DL) approaches, particularly convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformer architectures, have revolutionized seismic signal processing by automatically extracting hierarchical features from raw waveform data [7], [8]. Applications include P-wave and S-wave phase picking, focal mechanism determination, earthquake early warning systems, and post-disaster damage assessment using satellite imagery. The ability of deep learning models to capture complex spatiotemporal dependencies has enabled breakthrough performance in tasks previously requiring extensive manual intervention.

Optimization techniques, encompassing both classical mathematical programming and metaheuristic algorithms, address decision-making challenges in earthquake engineering where multiple competing objectives must be balanced. Metaheuristic algorithms such as Particle Swarm Optimization (PSO), Genetic Algorithms (GA), Gray Wolf Optimizer (GWO), and Whale Optimization Algorithm (WOA) have been successfully applied to emergency logistics planning, earthquake shelter location-allocation problems, structural design optimization under seismic loads, and sensor network deployment for seismic monitoring [9]. These techniques prove particularly valuable when dealing with non-convex, multi-modal optimization landscapes characteristic of real-world earthquake engineering problems where gradient-based methods may fail or prove computationally prohibitive.

Despite substantial progress, the rapidly evolving landscape of AI and optimization applications in earthquake engineering lacks comprehensive synthesis [10]. Existing reviews typically focus on narrow subdomains, limiting their utility for researchers seeking holistic understanding of methodological trends, performance benchmarks, and research gaps. Furthermore, the interdisciplinary nature of this field, spanning computer science, geophysics, civil engineering, and emergency management, creates challenges in knowledge dissemination and cross-domain collaboration. A systematic review that synthesizes recent advances across machine learning, deep learning, and optimization paradigms while analyzing publication trends and research patterns is therefore essential.

This systematic review addresses this critical gap by providing comprehensive analysis of AI and optimization techniques in earthquake engineering through multiple lenses. The review encompasses three primary computational paradigms: machine learning applications, deep learning innovations, and optimization methodologies, each examined through detailed literature synthesis and comparative analysis. Beyond traditional literature review, this work integrates bibliometric analysis to quantify research trends, identify leading journals and research groups, track keyword evolution, and assess methodological preferences across the research community. This dual approach—combining qualitative synthesis with quantitative bibliometric

DOI: https://doi.org/10.54216/MOR.050204

Received: July 08, 2025 Revised: September 17, 2025 Accepted: December 07, 2025

assessment—offers unprecedented insight into both the technical content and structural characteristics of the research landscape.

The systematic review methodology followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure rigorous and transparent study selection. The literature search was conducted across multiple academic databases, identifying 520 records through database searches and 50 additional records through other sources, yielding a total of 570 initial records. After removing 170 duplicates, 400 records remained for preliminary screening. During the screening phase, 261 records were excluded as they did not employ AI or ML methods, resulting in 139 records for detailed evaluation. Conference abstracts without full manuscripts were excluded (n=59), leaving 80 full-text articles for eligibility assessment. Following full-text review, 30 articles were excluded due to insufficient methodology details (n=12), being review articles (n=12), or representing duplicate datasets (n=6). The final corpus comprised 50 studies: 20 focusing on machine learning applications, 20 on deep learning innovations, and 10 on optimization methods. Figure 1 presents the complete PRISMA flow diagram documenting the systematic selection process.

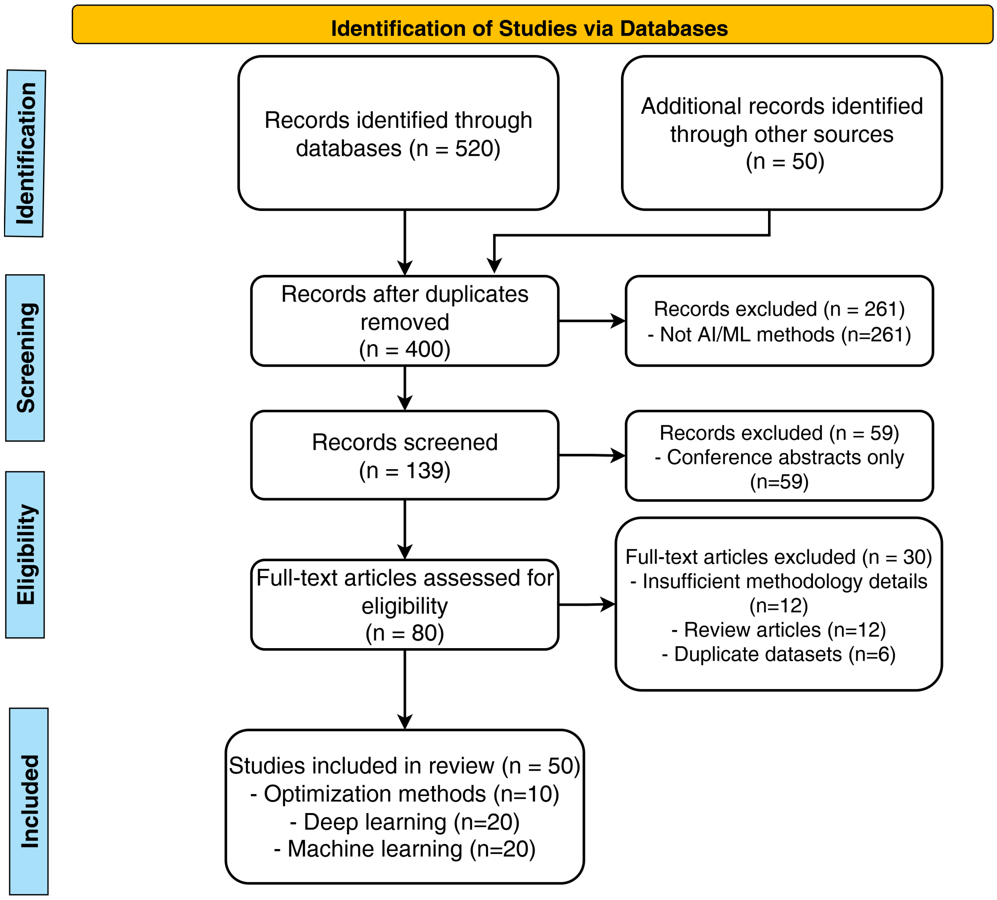

Figure 1: PRISMA Flow Diagram for Systematic Literature Selection Process

The specific objectives of this systematic review are threefold. First, to synthesize recent advances in machine learning, deep learning, and optimization applications for earthquake-related challenges, documenting methodologies, performance metrics, and application domains. Second, to conduct comprehensive bibliometric analysis examining publication patterns, journal distributions, temporal trends, keyword evolution, and methodological preferences across the three computational paradigms. Third, to identify current research trends, persistent challenges, and promising future directions that warrant investigation by the research community. Through achieving these objectives, this review provides valuable resource for researchers, practitioners, and policymakers seeking to understand the state-of-the-art and chart future research trajectories at the intersection of artificial intelligence, optimization, and earthquake engineering.

The remainder of this paper is organized as follows. Section 2 presents the literature review, subdivided into three subsections examining machine learning applications, deep learning innovations, and optimization

DOI: https://doi.org/10.54216/MOR.050204

Received: July 08, 2025 Revised: September 17, 2025 Accepted: December 07, 2025

techniques in earthquake engineering. Each subsection synthesizes methodologies, applications, and findings from contemporary peer-reviewed studies, supplemented by comparative tables highlighting key contributions. Section 3 presents bibliometric analysis of the research landscape, examining publication trends, journal distributions, keyword evolution, methodological preferences, and application domains across the three computational paradigms. Section 4 provides concluding remarks, synthesizing key findings, identifying persistent challenges, and outlining future research directions for advancing the integration of artificial intelligence and optimization techniques in earthquake engineering practice.

2 Literature Review

2.1 Machine Learning Applications in Earthquake Detection, Prediction, and Hazard Analysis

Recent advancements in machine learning (ML) have significantly enhanced various domains within seismology and earthquake engineering. ML techniques are increasingly employed to address challenges in earthquake prediction, detection, post-disaster damage assessment, and risk mitigation strategies. This subsection presents a comprehensive overview of contemporary studies that utilize ML approaches across multiple facets of earthquake-related research.

Earthquake-induced liquefaction is a major geohazard that poses significant risks to geotechnical infrastructure worldwide. [11] contends that assessing liquefaction potential is crucial in geotechnical and earthquake engineering. The study in question explores the applicability of various soft computing models for liquefaction classification, employing twelve input parameters across 234 data sets from liquefaction-prone granular soils. Accurate assessment of earthquake-induced slope displacement is crucial for designing seismically resilient slopes. Based on the findings of [12], machine learning models, particularly extreme gradient boosting (XGBoost), can effectively analyze earthquake-induced slope displacement, demonstrating superior predictive accuracy compared to artificial neural networks, support vector machines, and random forests; this highlights the potential of XGBoost in predicting slope behavior under seismic conditions and informing early warning systems.

Understanding the mechanisms behind earthquake nucleation is crucial for predicting and mitigating seismic events, ultimately safeguarding lives and improving construction practices in vulnerable regions. In the view of [13], the differentiation between cascade triggering and preslip triggering, two dominant theories in earthquake nucleation, remains a challenge due to limitations in field observations. Triggered earthquakes, characterized by their spatial and temporal proximity to other seismic events, can result from diverse processes such as pore pressure diffusion, viscoelastic stress transfer, or dynamic stress transfer following large earthquakes. This complexity necessitates advanced methodologies to disentangle the contributions of each mechanism in the nucleation process.

Earthquake prediction methodologies are being revolutionized through the application of advanced machine learning techniques, particularly in seismically active regions like Los Angeles, California. In the research conducted by [14], a comprehensive feature matrix was meticulously constructed to optimize predictive accuracy using advanced machine learning and neural network models; their work highlights the potential of synthesizing existing research with novel predictive features to estimate maximum potential earthquake magnitude. This innovative approach led to the development of a robust feature set that, when coupled with a Random Forest model, achieved high accuracy in predicting maximum earthquake categories within a 30-day timeframe, demonstrating the transformative potential of machine learning in seismic risk management.

The increasing frequency and severity of natural disasters globally highlight the importance of environmental risk management tools, with insurance being a critical component. Following the work of [15], demographic characteristics such as age, gender, race, and ethnicity, along with housing tenure and length of residency, demonstrably influence the adoption of earthquake insurance; furthermore, prior earthquake experience also positively impacts this decision. Borehole strain monitoring is essential for advancing research into earthquake precursors. Based on the findings, [16] proposed a novel approach using segmented variational mode decomposition coupled with a GRU-LUBE deep learning network to address the limitations of traditional data processing methods when managing extensive borehole strain datasets. This innovative algorithm focuses

DOI: https://doi.org/10.54216/MOR.050204
Received: July 08, 2025 Revised: September 17, 2025 Accepted: December 07, 2025

on improving data correlation during decomposition, leading to more accurate predictions of borehole strain changes.

Machine learning techniques offer promising avenues for predicting the damage state of reinforced concrete (RC) moment-resisting frame buildings. As revealed by[17], incremental dynamic analysis (IDA) is a powerful tool for assessing the seismic vulnerability of structures, providing insights into their behavior under varying intensity levels. This method involves subjecting a structural model to a suite of ground motion records scaled to different intensity levels, allowing for the observation of structural performance and the identification of damage states as a function of earthquake intensity, therefore can be used to create a database to train machine learning models. The effective integration of machine learning with established structural analysis techniques like IDA holds the potential to significantly enhance the accuracy and efficiency of seismic risk assessments.

Nowcasting, a technique originally employed in fields such as economics and meteorology, involves estimating the current state of a system through indirect observation. As demonstrated by [18], a simplified two-parameter data analysis can uncover underlying patterns within the complex seismicity of earthquakes, revealing insights into precursory seismic quiescence linked to crustal strain-hardening. This approach allows for the observation of earthquake cycles comparable to previously hypothesized models, and the assessment of earthquake hazard can be refined with machine learning techniques, specifically employing the Receiver Operating Characteristic skill score as a loss function in supervised learning.

Earthquakes represent a significant natural disaster with far-reaching societal consequences, prompting substantial research into earthquake detection methodologies. As evidenced in the study by [19], current sensor-based detection systems often struggle to differentiate between seismic events and other sources of vibration. To address this limitation, the referenced research introduced a machine learning-based multi-classification approach, employing acceleration seismic waves to distinguish between earthquakes, non-earthquake events, and vandalism-induced vibrations. Furthermore, the incorporation of velocity and displacement features, derived through integration of acceleration data, enhanced the performance of several machine learning algorithms.

Underwater seismic events produce acoustic radiation, including acoustic-gravity waves, which propagate over vast distances and contain source information. As outlined in the research of [20], analyses of hydrophone recordings from 201 Pacific and Indian Ocean earthquakes, using acoustic signal processing and classification, enabled the identification of earthquake type (slip type, magnitude) and near real-time estimation of fault dynamics and geometry; a comparison with the Harvard Global Centroid Moment Tensor catalog (gCMT) demonstrated statistical significance between extracted acoustic properties and predicted slip and magnitude values, which were used to train machine learning algorithms.

Modern earthquake catalogs, refined through supervised machine learning techniques, offer a more detailed view of seismic activity. As reported by [21], employing unsupervised machine learning to analyze the richer depiction of seismicity within these catalogs holds promise for accelerating advancements in earthquake prediction. This approach leverages the enhanced resolution of the new catalogs to potentially uncover subtle patterns and relationships that were previously obscured, leading to more effective forecasting models.

Earthquakes pose a significant threat to human life, ranking among the deadliest natural disasters in recent decades. In the analysis provided by [22], a novel machine learning method called Inverse Boosting Pruning Trees (IBPT) is developed to enhance short-term earthquake forecasting using satellite data from 1371 earthquakes of magnitude six or above; the research leveraged ten different infrared and hyperspectral measurements collected between 2006 and 2013 to assess physical and dynamic changes in seismic data. The framework, when compared against several state-of-the-art machine learning methods, demonstrated superior performance and improved the likelihood of earthquake forecasting across different earthquake databases.

Earthquake prediction has long been a primary goal for earthquake scientists, yet remains an elusive challenge. As indicated by [23], a novel approach to advance earthquake prediction involves crowdsourcing efforts by engaging the machine learning (ML) community through platforms like Kaggle. The Kaggle competition tasked participants with forecasting the time remaining before laboratory earthquakes, utilizing limited seismic data. The competition fostered the sharing of numerous computer programs and revealed that successful strategies included rescaling failure times relative to the seismic cycle and analyzing the distribution of training and testing data, alongside employing standard seismic data features linked to fault criticality. This type of

DOI: https://doi.org/10.54216/MOR.050204
Received: July 08, 2025 Revised: September 17, 2025 Accepted: December 07, 2025

competition serves as a model for engaging the ML community in addressing geoscientific and other significant problems.

A devastating earthquake with a magnitude of 7.5 struck Palu city in Sulawesi, Indonesia, on September 28th, 2018. Based on the findings of [24], the researchers employed several methods, including cross-correlation, Silhouette clustering, pure locational clustering based on hierarchical clustering analysis, convolutional neural networks, and the analytical hierarchy process, to estimate earthquake risk in the Palu region using probability and hazard assessments; CNN model assessed the probability while SC and PLC were implemented to understand the spatial clustering, Euclidean distance among clusters, spatial relationship and cross-correlation among the estimated Mw, PGA and intensity including events depth; Also the study found that Risk B, generated using earthquake hazard assessment, susceptibility to seismic amplification, and earthquake vulnerability assessment, provided better results for earthquake risk assessment than Risk A, which was based on earthquake probability assessment, susceptibility to seismic amplification, and earthquake vulnerability assessment, and achieved 89.47% accuracy for earthquake probability assessment and a consistency ratio of 0.07 for earthquake vulnerability assessment, with important implications for future risk assessment, land use planning, and hazard mitigation.

Following traumatic events like earthquakes, survivors may experience impaired memory function. In the research conducted by [25], resting-state functional magnetic resonance imaging (rs-fMRI) data from eighty-nine survivors of the 2008 Wenchuan earthquake, screened for post-traumatic stress disorder (PTSD) using the clinician-administered PTSD scale (CAPS), and assessed for memory function via the Wechsler Memory Scale-IV (WMS-IV), were analyzed using machine learning techniques. In the study, spatial addition, a measure of spatial working memory, demonstrated a negative correlation with total CAPS scores, and simple multiple kernel learning (MKL) achieved statistically significant accuracy in associating spatial addition scores with rs-fMRI data, with the left middle frontal gyrus and left precuneus contributing the most to this association. The study concluded that spontaneous brain activity in the left middle frontal gyrus and left precuneus, as measured by rs-fMRI, could represent a brain mechanism linking visual working memory to PTSD symptoms, suggesting that machine learning may offer a valuable approach to identifying brain mechanisms underlying memory impairment in trauma survivors, while acknowledging limitations such as the cross-sectional design and risk of overfitting.

Detecting earthquakes in real-time using smartphones or IoT devices presents significant hurdles due to the similarity between earthquake signals and other types of signals, along with the variable nature of human activity. In the view of [26], a machine learning approach employing earthquake-specific features can overcome the limitations of traditional seismic methods. Utilizing a machine learning model designed for static environments allows for effective noise reduction and real-time earthquake detection with minimal false alarms. Individuals exposed to trauma are at risk of developing posttraumatic stress disorder (PTSD), and identifying predictive factors for this condition is crucial. Following the work of [27], machine learning techniques offer a promising avenue for predicting probable PTSD in young survivors, especially when integrating multiple measures collected shortly after a traumatic event. In their research, earthquake exposure, daily functioning, somatic symptoms, and sleep patterns combined to effectively predict probable PTSD cases, demonstrating the potential of early intervention strategies.

A complete earthquake catalog is fundamental for a better understanding of earthquake behavior and their underlying mechanisms. As demonstrated in [28], a novel workflow utilizing machine learning and single-station location methods can overcome limitations related to low station density and data quality, which traditionally hinder the detection of small seismic events. The proposed method incorporates distance and azimuth neural networks, pre-trained on a global dataset and refined using local datasets, achieving a mean absolute error of approximately 3.0 km for epicenter distance and 22.0 degrees for back-azimuth in the Sichuan, China, testing dataset. Moreover, incorporating spatial and waveform constraints improves location accuracy.

The damage status of 44 locations was investigated using ground condition parameters and strong-motion parameters. Based on the findings [29], various machine learning methods, including logistic regression, classification and regression trees, random forest, support vector machine, k-nearest neighbours, and artificial neural networks, were employed to assess the dataset through different parameter combinations to evaluate predictive performance. Machine learning (ML) techniques have become a valuable asset in seismology, allowing for the detection of small-magnitude seismic events often missed by conventional methods. As demonstrated by [30], ML-based approaches can significantly improve the characterization of fault systems

DOI: https://doi.org/10.54216/MOR.050204

Received: July 08, 2025 Revised: September 17, 2025 Accepted: December 07, 2025

and aftershock activity, as seen in the Central Apennines using data from the 2009 L'Aquila seismic sequence; their study highlights the potential of ML methods in advancing our understanding of complex fault systems and seismic sequences.

Table 1 summarizes the main focus areas, methodologies, and key findings of recent works leveraging machine learning for earthquake analysis. The applications range from predicting seismic events, analyzing structural vulnerabilities, detecting anomalies in geophysical data, and even assessing psychological impacts on affected populations. The diversity of algorithms—spanning supervised, unsupervised, and deep learning techniques—highlights the versatility and potential of ML in addressing complex geophysical and societal challenges.

Table 1: Machine learning applications in earthquake prediction, detection, and hazard assessment.

No.	Main Focus	Methodology	Key Findings
Ref [11]	Liquefaction potential modeling	Machine learning classification models (soft computing)	Evaluates the applicability of machine learning for liquefaction classification using input parameters.
Ref [12]	Earthquake-induced slope displacement analysis	ANN, SVM, RF, XGBoost machine learning models	Evaluates the capabilities of ML models for analyzing earthquake-induced slope displacement.
Ref [13]	Earthquake nucleation insights	Unsupervised ML pipeline integrating macro- and grain-scale data from laboratory earthquakes	Provides insights into earthquake nucleation mechanisms using ML on numerical simulations.
Ref [14]	Improving earthquake prediction accuracy	Advanced machine learning and neural network models with comprehensive feature matrix	Developed a robust subset of features for estimating potential earthquake magnitude in Los Angeles.
Ref [15]	Factors affecting earthquake insurance uptake	Supervised machine learning on survey data	Identifies factors influencing earthquake insurance uptake in Oklahoma.
Ref [16]	Pre-earthquake anomaly extraction	Segmented variational mode decomposition and GRU-LUBE deep learning network	Enhances data correlation during decomposition for pre-earthquake anomaly detection from borehole strain data.
Ref [17]	Rapid post-earthquake damage detection	Machine learning models applied to RC building analysis results	Predicts damage condition of RC frame buildings using ML based on time-history analysis.
Ref [18]	Optimizing earthquake nowcasting	Two-parameter data analysis revealing hidden order using machine learning	Reveals hidden order in seismicity and relates it to strain hardening in the earthquake cycle.
Ref [19]	Earthquake multi-classification detection	Machine learning algorithms applied to filtered velocity and displacement data	Distinguishes earthquake vibrations from other vibrations using machine learning.
Ref [20]	Earthquake source characterization	Machine learning algorithms applied to acoustic signals	Characterizes earthquake source properties using underwater acoustic signals and machine learning.
Ref [21]	Earthquake forecasting	Supervised and unsupervised machine learning on new earthquake catalogs	Suggests unsupervised ML on detailed seismicity catalogs for improved forecasting.

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DOI: https://doi.org/10.54216/MOR.050204
Received: July 08, 2025 Revised: September 17, 2025 Accepted: December 07, 2025

Table 1 – continued from previous page

No.	Main Focus	Methodology	Key Findings
Ref [22]	Advancing earthquake forecasting	Machine learning of satellite data	Explores using machine learning and satellite data to forecast earthquakes.
Ref [23]	Laboratory earthquake forecasting	Machine learning competition on laboratory earthquake data	Engaged the ML community to develop data analysis approaches for lab earthquake forecasting.
Ref [24]	Earthquake hazard and risk assessment	Machine learning approaches including clustering analysis	Estimates earthquake risk in Palu, Indonesia, using cross-correlation and clustering techniques.
Ref [25]	Memory function in earthquake trauma survivors	Resting-state fMRI and machine learning	Explores the association between neuroimaging, neurophysiology and memory function in earthquake survivors.
Ref [26]	Earthquake Detection in Static and Dynamic Environments	Supervised Machine Learning and a Novel Feature Extraction Method	Detects earthquakes using smartphones by differentiating from noise and other activities with machine learning.
Ref [27]	Predictors of PTSD in earthquake-exposed children	Machine learning to integrate risk factors	Predicts probable PTSD in young earthquake survivors using ML models.
Ref [28]	Small earthquake location	Machine learning with limited data	Uses machine learning to locate small earthquakes with insufficient station data.
Ref [29]	Damage status in Kahramanmaraş Earthquakes	Supervised Machine Learning relating damage to ground and motion variables	Models the impact of ground conditions and strong-motion on damage status using machine learning.
Ref [30]	High-resolution data set for L'Aquila earthquake	Machine learning-based methods for small event detection	Improves characterization of fault systems and aftershock activity using ML.

In summary, the reviewed literature highlights the increasing application of machine learning techniques for various earthquake-related challenges, ranging from prediction and early warning systems to damage assessment and seismic hazard analysis. The diversity of approaches is evident both in the machine learning models employed, spanning from traditional algorithms to deep learning architectures, and in the earthquake research areas being targeted, reflecting the interdisciplinary nature of the field. Current trends point towards the integration of more complex models and larger datasets, suggesting a move towards higher accuracy and more robust, real-time applications; future research should focus on addressing existing limitations, such as improving model explainability and generalizability across different tectonic regions and earthquake types.

2.2 Deep Learning Applications in Earthquake Detection, Prediction, and Hazard Analysis

Recent advances in deep learning have significantly enhanced the capabilities of earthquake detection, forecasting, and hazard analysis systems. Table 2 provides a comparative overview of 18 peer-reviewed studies, each employing deep learning methodologies to address a wide spectrum of seismic challenges. These include early warning systems, post-disaster damage assessment, seismic signal classification, and even societal responses such as public sentiment analysis.

Earthquake-induced landsliding presents a significant threat, often exacerbating the immediate disaster and hindering effective response efforts. Based on the findings of [31], a comprehensive global database

DOI: https://doi.org/10.54216/MOR.050204
Received: July 08, 2025 Revised: September 17, 2025 Accepted: December 07, 2025

of approximately 400,000 landslides linked to 38 major earthquakes over the last half-century has been compiled to address the limitations of existing prediction methods. Utilizing this extensive dataset, sophisticated deep-learning models have been developed to forecast landslide susceptibility following earthquakes worldwide, achieving a high degree of spatial accuracy in a short timeframe without needing pre-existing local information. This offers a potentially transformative advance in geohazard prediction.

The swift and dependable detection of individuals trapped beneath rubble following an earthquake is paramount for successful search and rescue endeavors. In the view of [32], deep learning-based object identification algorithms integrated with a snake robot offer a novel method for survivor detection. Faster R-CNN, SSD, and YOLO algorithms, initially trained on the PASCAL VOC 2012 dataset for human identification, were assessed, with a new dataset of 200 images depicting trapped individuals compiled to address the absence of a dedicated resource for this specific situation, which also features cluttered environments and occlusion.

Predicting peak ground acceleration (PGA) swiftly and precisely is crucial for evaluating seismic damage in earthquake early warning (EEW) systems. In the research conducted by [33], an end-to-end deep learning model (DLPGA) was developed based on convolutional neural networks (CNNs) to address the limitations of traditional methods that rely on manually selected P-wave feature parameters, consequently hindering the speed and accuracy of PGA prediction. The model uses the initial 3–6 s of vertical seismic waves from a single station as input and PGA as output, enabling automatic feature extraction through a multilayer CNN architecture to expedite PGA prediction.

An unsupervised anomaly-detection method leveraging autoencoders can be used to detect earthquakes affecting high-speed trains, using only normal vibration data for training. Following the work of [34], deep learning models built on autoencoders offer a powerful approach to this problem, as demonstrated by their superior performance compared to traditional methods like the Short Time Average over Long Time Average (STA/LTA) algorithm. Evaluations utilizing South Korean high-speed train data alongside seismic measurements demonstrated that the autoencoder model exhibits improved earthquake detection capabilities, particularly when considering a Peak Ground Acceleration (PGA) threshold of 0.07g, which is crucial for preventing track derailment. The model's ability to minimize false positives under normal operating conditions, while effectively detecting events exceeding the PGA threshold, makes it a promising alternative, especially in regions where seismic data is scarce.

Natural disasters occur unexpectedly and can inflict severe damage on both human populations and infrastructure, underscoring the urgent need for effective monitoring and preparedness strategies. According to the findings of [35], a hybrid deep learning framework integrated with an enhanced sunflower optimization algorithm can be effectively employed to monitor regions vulnerable to earthquakes and floods. This hybrid model enables efficient scheduling of event responses in polynomial time, thereby improving the timeliness and reliability of disaster management operations. Furthermore, the integration of optimization techniques within the deep learning framework helps to minimize false alarms and enhances the system's capability for real-time earthquake detection, ultimately contributing to more accurate and proactive disaster response mechanisms.

The Ghana Digital Seismic Network (GHDSN), composed of six broadband sensors operating in southern Ghana between 2012 and 2014, generated a valuable dataset. As demonstrated by [36], Deep Learning (DL) models, specifically the EQTransformer tool, can be applied to such datasets for simultaneous event detection and phase picking. The resultant earthquake bulletin, including arrival times and waveforms of local earthquakes, along with preliminary crustal velocity models derived from joint inversion analysis, offers a unique opportunity for earth science specialists to further analyze detected waveforms and characterize seismogenic sources within the region.

Enhanced earthquake catalogs, characterized by lower magnitude completeness and improved hypocentral resolution, offer the potential to refine the understanding of seismic sequences. As evidenced in the study by [37], analyzing enhanced seismic catalogs from the 2016-2017 Central Italy sequence using Coulomb Rate-and-State (CRS) and Epidemic-Type Aftershock Sequence (ETAS) models to forecast the occurrence of M3+ events revealed that, despite the benefits of incorporating triggering contributions from new, small magnitude detections, these models did not significantly outperform near real-time benchmarks.

The presence of strong anthropogenic noise makes earthquake monitoring in urban environments both critical and complex. As outlined in the research of [38], a deep-learning-based denoising algorithm,

DOI: https://doi.org/10.54216/MOR.050204

Received: July 08, 2025 Revised: September 17, 2025 Accepted: December 07, 2025

termed UrbanDenoiser, was developed to address this challenge by filtering out urban seismological noise; leveraging training datasets enriched with diverse noise sources from the urban Long Beach dense array and high signal-to-noise ratio (SNR) earthquake signals from the rural San Jacinto dense array, UrbanDenoiser effectively suppresses noise relative to signals.

The automated identification of low-magnitude earthquakes has garnered significant attention recently, driven by the global surge in induced seismicity. As reported by [39], detecting weak seismic events is vital for microseismic monitoring in various subsurface activities, including hydraulic fracturing and carbon storage, allowing for better hazard assessment and mitigation. Furthermore, the ability to detect micro-earthquakes is key to improving our understanding of the processes that lead to larger seismic events.

Earthquake disasters significantly impact human social life, with the extent of the impact directly related to the earthquake's magnitude and intensity; thus, accurate prediction is crucial for minimizing casualties and property losses. In the analysis provided by [40], predictive models utilizing Convolutional Neural Networks (CNNs) and 3D feature maps offer a promising approach to earthquake magnitude classification by leveraging both shallow features and high-dimensional information.

Determining the source focal mechanism of a significant earthquake rapidly and automatically is essential for understanding fault geometry, stress changes, and aftershock behavior. As demonstrated by [41], Artificial Intelligence (AI), particularly deep learning methods such as the Focal Mechanism Network (FMNet), can address this challenge. They developed FMNet, training it on a massive synthetic dataset to successfully estimate the focal mechanisms of the 2019 Ridgecrest earthquakes with magnitudes greater than 5.4. The network's ability to learn global waveform features from theoretical data enables broad applications to regions with potential seismic hazards, regardless of historical earthquake data availability, and achieves reliable predictions in under 200 milliseconds on a single CPU.

Earthquake signal detection and seismic phase picking present ongoing challenges, particularly when processing noisy data and monitoring microearthquakes. Based on the findings of [42], a global deep-learning model can simultaneously address earthquake detection and phase picking, enhancing performance in both tasks through a hierarchical attention mechanism that leverages information from seismic phases and full waveform data. The model's demonstrated ability to surpass previous deep-learning and traditional algorithms, coupled with its efficient processing and high sensitivity, suggests its potential for detecting and characterizing a greater number of smaller seismic events with precision approaching that of manual analysis.

The escalating volume of seismic data being gathered globally is exceeding the capacity for comprehensive analysis, primarily because current methods rely on expert-driven, supervised techniques. In the view of [43], a novel unsupervised machine learning framework utilizing a deep scattering network and Gaussian mixture model was developed to address both the challenge of analyzing vast seismic datasets and the potential biases introduced by standard seismological models; this framework facilitates the detection and clustering of seismic signals, potentially leading to more informed forecasting of seismic activity in vulnerable areas.

Earthquake prediction remains a significant challenge for earth scientists due to inherent uncertainties, making probabilistic assessment crucial. In the research conducted by [44], deep learning techniques, specifically a convolutional neural network (CNN), were employed to generate scalable earthquake probability maps using nine input indicators including proximity to faults, fault density, lithology with an amplification factor, slope angle, elevation, magnitude density, epicenter density, distance from the epicenter, and peak ground acceleration (PGA) density to create two outputs, 0 and 1, representing non-earthquake and earthquake parameters, respectively. The CNN model showed a good overall accuracy with testing and training datasets

Microearthquakes induced by injecting fluids underground provide valuable data about stress and permeability changes within reservoirs. Following the work of [45], transformer neural networks can predict cumulative microearthquake counts, seismic moment, and the spread of microearthquake activity using hydraulic stimulation history and previous microearthquake data; the application of these networks to the EGS Collab Experiment 1 data yielded high accuracy (R2 > 0.98 for 1-s and R2 > 0.88 for 15-s forecasts), along with estimates of uncertainty.

Accurate categorization of seismic events is paramount for comprehensive seismic cataloging and effective hazard assessment. Based on the findings [46], deep learning techniques have shown remarkable efficacy in seismic event identification due to their capacity to automatically learn and recognize complex features;

DOI: https://doi.org/10.54216/MOR.050204

Received: July 08, 2025 Revised: September 17, 2025 Accepted: December 07, 2025

however, many current deep learning methods are deterministic, failing to quantify epistemic uncertainty, which is necessary for evaluating prediction confidence and overall reliability.

The need for rapid and precise detection of earthquake-induced landslides in loess tablelands motivates the development of novel methodologies. According to the analysis by [47], an innovative approach integrating enhanced deep learning architectures with large-tile processing strategies was proposed and validated to address technical demands; this featured a crucial enhancement of YOLOv8's shallow layers, achieved via a higher-resolution P2 detection head aimed at bolstering small-target capture capabilities, and the development of a large-tile segmentation–tile mosaicking workflow to overcome technical bottlenecks in large-scale, high-resolution image processing, ensuring both timeliness and accuracy in loess landslide detection.

Given China's vulnerability to seismic events, accurate and rapid identification of earthquake precursors is crucial for mitigating losses. As demonstrated by [48], a combined approach using rock acoustic emission (AE) detection and deep learning offers a promising avenue for real-time monitoring and improved precursor detection, achieving a high degree of accuracy in identifying seismic events.

Public sentiment expressed through Twitter following the 2023 Kahramanmaraş earthquakes in Turkey was analyzed using an attention-based deep learning model that achieved high classification accuracy. In the analysis provided by [49], a hybrid architecture named MConv-BiLSTM-GAM was introduced, integrating multi-scale convolutional layers, bidirectional long short-term memory networks, and a global attention mechanism. This model was supported by FastText word embeddings to enhance semantic understanding of tweet content. The approach outperformed other conventional deep learning models by over 3%, reaching an accuracy of 93.32%. The research highlights the potential of combining linguistic feature extraction and attention mechanisms to interpret public emotion and social behavior during disasters, offering a scalable tool for real-time disaster impact assessment and emergency decision-making.

Seismic data collected from stations surrounding Almaty, Kazakhstan, was utilized to develop a deep learning framework for the early detection of primary seismic waves. As outlined in the research of [50], a convolutional neural network was trained to detect P-waves, which are the earliest indicators of seismic activity, surpassing traditional methods like the short-term average/long-term average and Akaike information criterion under noisy conditions. The proposed model achieved a recall rate of 89.1% and an overall accuracy of 94.1%, demonstrating its suitability for real-time earthquake detection. This work illustrates the effectiveness of deep learning in enhancing the accuracy and responsiveness of early warning systems, particularly in environments affected by industrial noise and other signal interference.

Table 2: Deep learning applications in earthquake prediction, detection, and hazard assessment.

No.	Main Focus	Methodology	Key Findings
Ref [31]	Predicting global earthquake-triggered landslides.	Deep learning models trained on global datasets.	Overcomes limitations of traditional, regionally-focused methods for landslide prediction.
Ref [32]	Survivor detection in post-earthquake SAR missions.	Snake robot equipped with deep learning object detection algorithms.	Evaluated Faster R-CNN, SSD, and YOLO for survivor identification.
Ref [33]	Peak ground acceleration (PGA) prediction for earthquake early warning.	Deep learning to predict PGA from P-wave features.	Improves accuracy and timeliness compared to human-selected parameters.
Ref [34]	Earthquake detection for high-speed trains.	Unsupervised anomaly detection using autoencoder-based deep learning.	Detects earthquakes using vibration data from trains and seismic data.
Ref [35]	Flood and earthquake detection.	Hybrid deep learning model with enhanced sunflower optimization.	Improved detection capabilities for natural disasters (flood and earthquake).

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DOI: https://doi.org/10.54216/MOR.050204

Received: July 08, 2025 Revised: September 17, 2025 Accepted: December 07, 2025

Table 2 – continued from previous page

No.	Main Focus	Methodology	Key Findings
Ref [36]	Creating an earthquake bulletin and seismic waveform dataset for Ghana.	Deep learning model (EQTransformer) for event detection and phase picking.	Generated dataset for Ghana based on detected earthquakes and waveforms.
Ref [37]	Short-term earthquake forecasts using high-resolution seismic catalogs.	Explores the use of enhanced seismic catalogs with short-term forecasting protocols.	Investigates the potential for higher predictive skill.
Ref [38]	Urban earthquake monitoring through noise suppression.	Deep-learning-based denoising algorithm (UrbanDenoiser).	Suppresses urban noise in seismic recordings, improving signal clarity.
Ref [39]	Low-magnitude earthquake detection on a multi-level sensor network.	Deep learning model (GroningenNet).	Detects low-magnitude earthquakes relevant to induced seismicity.
Ref [40]	Earthquake magnitude prediction using electromagnetic signals.	Deep learning model for analyzing electromagnetic sensor data.	Aims to predict earthquake magnitude from electromagnetic precursors.
Ref [41]	Real-time determination of earthquake focal mechanism.	AI for automated focal mechanism determination.	Enables timely fault geometry characterization after earthquakes.
Ref [42]	Simultaneous earthquake detection and phase picking.	Attentive deep-learning model (Earthquake Transformer).	Improved performance by combining earthquake detection and phase picking.
Ref [43]	Clustering earthquake signals and background noise.	Unsupervised deep learning for seismic data analysis.	Identifies earthquake signals and noises without human supervision.
Ref [44]	Earthquake probability assessment for the Indian Subcontinent.	Deep learning methods for probabilistic seismic hazard assessment.	Addresses scalability issues in earthquake probability assessment.
Ref [45]	Spatiotemporal evolution of fluid-induced microearthquakes.	Transformer neural network model using hydraulic injection data.	Forecasts microearthquake patterns.
Ref [46]	Discrimination between earthquakes and explosions.	Uncertainty-aware deep learning methods.	Improves reliability of seismic event classification.
Ref [47]	Rapid landslide detection after the 2023 Jishishan earthquake.	Enhanced YOLOv8 with a higher-resolution detection head.	Achieves precise detection of earthquake-triggered landslides.
Ref [48]	Earthquake precursors based on rock acoustic emission.	Combines acoustic emission detection with deep learning.	Enables real-time monitoring for earthquake precursor detection.
Ref [49]	Sentiment classification on Twitter after the 2023 Turkey earthquake.	Attention-based deep learning model (MConv-BiLSTM-GAM).	Achieved 93.32% accuracy, improving sentiment classification and providing real-time societal insights for post-disaster response.
Ref [50]	Early earthquake detection via P-wave recognition.	Convolutional neural network (CNN) trained on IRIS seismic data.	Achieved 94.1% accuracy and improved early warning system performance compared to STA/LTA and AIC methods.

In summary, the reviewed literature demonstrates the burgeoning application of deep learning techniques in earthquake-related studies, with the 20 papers revealing a generally positive trend towards improved accuracy and efficiency in various prediction and analysis tasks. A diverse range of approaches, from convolutional neural networks to recurrent architectures, are being applied to problems spanning earthquake early warning systems, seismic hazard assessment, and aftershock prediction. The current trend emphasizes the integration

DOI: https://doi.org/10.54216/MOR.050204

Received: July 08, 2025 Revised: September 17, 2025 Accepted: December 07, 2025

of increasingly sophisticated deep learning models with larger and more comprehensive datasets, suggesting a future where machine learning further refines our understanding and management of seismic risk through enhanced predictive capabilities and novel insights.

2.3 Optimization Applications in Earthquake Detection, Prediction, and Hazard Analysis

Emergency supply deployment during earthquake disasters represents a critical challenge in disaster management. Yang et al. [51] developed a comprehensive two-stage optimization framework that integrates demand and time satisfaction into supply allocation and route optimization models. Their approach begins with estimating the number of affected individuals and forecasting emergency supply needs through historical data and seismic monitoring. The framework introduces psychological risk perception and urgency levels to refine resource allocation, employing a modified prospect theory. To solve the model, the authors enhanced the Sparrow Search Algorithm (SSA) using Particle Swarm Optimization (PSO), demonstrating improved rescue efficiency, rational resource allocation, and prioritization of urgent needs.

Urban spatial structure plays a pivotal role in earthquake response effectiveness, particularly in seismically vulnerable areas. Aghataher et al. [52] emphasized that search and rescue teams must efficiently map and assess urban infrastructure suitability for post-earthquake disaster response to ensure mobility and timely assistance to casualties. Their study focused on computing the appropriateness of municipal spatial structures for crisis response following destructive earthquakes, with particular emphasis on identifying critical areas prone to disruption. This was achieved through a GIS-based earthquake-triggered hybrid framework for suitability analysis.

The sudden and unpredictable nature of natural disasters necessitates innovative monitoring solutions. Phalguna Krishna et al. [53] proposed a hybrid deep learning system to monitor regions affected by earthquakes and floods. Their technology incorporates a notification system that alerts authorities when individuals are detected in affected zones, providing a proactive approach to disaster management.

Organizing emergency rescue operations effectively is essential for minimizing post-earthquake mortality. Zhou et al. [54] addressed a resilient casualty scheduling problem aimed at decreasing the overall expected death probability of casualties while accounting for scenarios involving compromised medical facilities and transportation routes. Their methodology employed a 0-1 mixed integer nonlinear programming model, solved using an enhanced particle swarm optimization algorithm. A case study of the Lushan earthquake in China validated the practicality and efficiency of their approach.

The relationship between structural form, performance, and material properties is fundamental to achieving optimal life-cycle design strategies. Wei et al. [55] explored the structure-property-performance relationship of a designed steel mega-sub controlled structural system (MSCSS) subjected to earthquake waves through finite element simulations and experimental validations. Their findings indicated that MSCSS configurations effectively optimize vibration responses, substantially reducing acceleration compared to traditional megaframe structures, even with additional weight.

Social networks have become increasingly important in group decision-making (GDM) problems. Zhang et al. [56] constructed a novel GDM framework that considers social trust relationships, providing a scientific foundation for public emergency management in major disasters.

High-precision displacement sensors offer promising applications in seismology. Lee et al. [57] demonstrated that seismic waves can be precisely measured through displacement variations detected by heterodyne laser interferometers, enabling earthquake magnitude estimation using only initial P-wave magnitudes within the first three seconds through the Total Noise Enhanced Optimization (TNEO) model.

Strategic location of earthquake emergency shelters and appropriate resident assignment are crucial for minimizing casualties by ensuring safe refuge and streamlined evacuation. Zhao et al. [58] developed a multi-objective model for resident allocation to earthquake shelters, considering evacuee characteristics and shelter construction costs. Using the Chaoyang district in Beijing, China, as a case study, their model aimed to minimize total weighted evacuation time and shelter area while adhering to capacity and service radius constraints.

DOI: https://doi.org/10.54216/MOR.050204

Received: July 08, 2025 Revised: September 17, 2025 Accepted: December 07, 2025

Accurate forecasting of earthquake-related fatalities is vital for proactive disaster preparedness and efficient emergency response deployment. Wang et al. [59] recognized that earthquakes represent some of the most devastating natural events, frequently resulting in substantial loss of life and major economic disruption, making precise fatality prediction crucial for mitigation strategies.

Djafar-Henni et al. [60] presented a novel framework for optimizing the distribution and thickness of shear walls in reinforced concrete (RC) buildings, moving beyond conventional trial-and-error methods. Their framework utilizes the Gray Wolf Optimizer (GWO) algorithm coupled with Artificial Intelligence to automate the design process via the SAP2000 API. This integration considers both structural and architectural constraints, providing flexibility in shear wall placement while ensuring adherence to regional seismic codes, including the newly released Algerian Seismic Code (RPA2024). Numerical examples on both regular and irregular buildings demonstrated enhanced structural performance, weight reduction, and cost efficiency.

Table 3 presents a comparative analysis of recent research at the intersection of earthquake engineering and optimization techniques. The table synthesizes selected studies that employ optimization to address challenges related to seismic resilience, highlighting their main focus, adopted methodology, and key findings.

Table 3: Optimization applications in earthquake prediction, detection, and hazard assessment.

No.	Main Focus	Methodology	Key Findings
Ref [51]	Optimizing emergency supply deployment during earthquake disasters.	Two-stage optimization framework incorporating demand and time satisfaction into supply allocation and route optimization models.	Integrated approach improves emergency logistics by considering both supply allocation and efficient routing.
Ref [52]	Mapping urban spatial suitability for earthquake disaster response.	Gradient Rain Optimization Algorithm (GROA) to assess urban infrastructure appropriateness for disaster reaction.	Identifies suitable urban infrastructures to enable efficient search and rescue operations.
Ref [53]	Flood and earthquake detection.	Hybrid deep learning model with enhanced sunflower optimization.	Provides a method for early detection of floods and earthquakes.
Ref [54]	Robust casualty scheduling in post-earthquake relief.	Robust optimization using improved particle swarm optimization for casualty scheduling considering injury deterioration.	Reduces the total expected death probability by optimizing casualty scheduling amidst disruptions.
Ref [55]	Active design and optimization of steel structures under earthquakes.	Digital Twin assisted optimization considering structure-form and structure-performance relationships.	Enables optimized design of steel structures under seismic loads using digital twin technology.
Ref [56]	Earthquake shelter-site selection.	Optimization-based approach to social network group decision making using additive preference relations.	Generates weights for decision makers to select optimal earthquake shelter sites.
Ref [57]	Earthquake magnitude estimation.	Total Noise Enhanced Optimization model using a heterodyne laser interferometer as a seismometer.	Estimates earthquake magnitude using P-wave magnitudes measured by the interferometer.
Ref [58]	Earthquake emergency shelter allocation.	Scenario-based multi-objective optimization model with modified particle swarm optimization.	Optimizes the location and allocation of earthquake shelters to minimize casualties.

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Received: July 08, 2025 Revised: September 17, 2025 Accepted: December 07, 2025

Table 3 – *Continued from previous page*

No.	Main Focus	Methodology	Key Findings
Ref [59]	Prediction of earthquake death toll.	PCA, improved Whale Optimization Algorithm, and Extreme Gradient Boosting.	Improves the accuracy of earthquake fatality prediction.
Ref [60]	Shear wall optimization in RC buildings.	Gray Wolf Optimizer (GWO) algorithm and AI to optimize shear wall distribution and thickness.	Provides a framework for optimizing shear wall design in RC buildings to improve earthquake resistance.

In summary, the reviewed literature demonstrates the significant potential of optimization techniques to address diverse challenges in earthquake engineering, spanning structural design and retrofitting to real-time damage assessment and resource allocation. Notable diversity exists within both earthquake engineering and optimization research, with studies employing varied simulation methods, performance metrics, and optimization algorithms tailored to specific problems. Current research trends emphasize the integration of advanced computational tools, data-driven approaches, and multi-objective optimization strategies to enhance resilience and minimize seismic risk. Future research directions should focus on developing robust and scalable optimization frameworks capable of handling uncertainties, incorporating social and economic factors, and facilitating the implementation of optimized solutions in real-world earthquake scenarios.

3 Research Landscape Analysis

This section presents a comprehensive bibliometric examination of research at the intersection of computational intelligence and earthquake engineering, analyzing three distinct domains: machine learning, deep learning, and optimization applications. The analysis encompasses publication patterns, journal distributions, temporal trends, keyword evolution, methodological preferences, performance metrics, and application areas. Through systematic evaluation of these bibliometric indicators, this section identifies research trajectories, emerging themes, and knowledge concentration patterns within each computational paradigm.

The bibliometric assessment employs multiple analytical frameworks including journal concentration analysis, temporal publication dynamics, keyword frequency analysis, and methodological distribution patterns. Visualizations encompass bar charts, pie charts, heatmaps, concentration curves, word clouds, and trend line analyses, collectively providing multidimensional perspectives on the research landscape. This systematic approach enables identification of dominant research outlets, peak publication periods, prevalent keywords, preferred methodologies, commonly reported performance metrics, and primary application domains across the three computational intelligence paradigms.

The analysis reveals distinct characteristics within each domain while highlighting convergent trends toward hybrid approaches, real-time implementation, and enhanced predictive accuracy. Machine learning research demonstrates broad methodological diversity with emphasis on traditional algorithms, deep learning applications showcase specialized neural architectures for complex pattern recognition, and optimization studies concentrate on resource allocation and structural design challenges. Understanding these bibliometric patterns provides essential context for interpreting current research directions and anticipating future developments in computational earthquake engineering.

3.1 Machine Learning Research Landscape

Figure 2 presents the distribution of research publications across selected journals in the machine learning-earthquake domain. Scientific Reports demonstrates the highest publication output, substantially exceeding other journals in the dataset. Sensors (Basel, Switzerland) exhibits moderate publication frequency, while The Science of the Total Environment contains fewer contributions. This distribution reveals significant variation in journal preferences within the research community.

DOI: https://doi.org/10.54216/MOR.050204

Received: July 08, 2025 Revised: September 17, 2025 Accepted: December 07, 2025

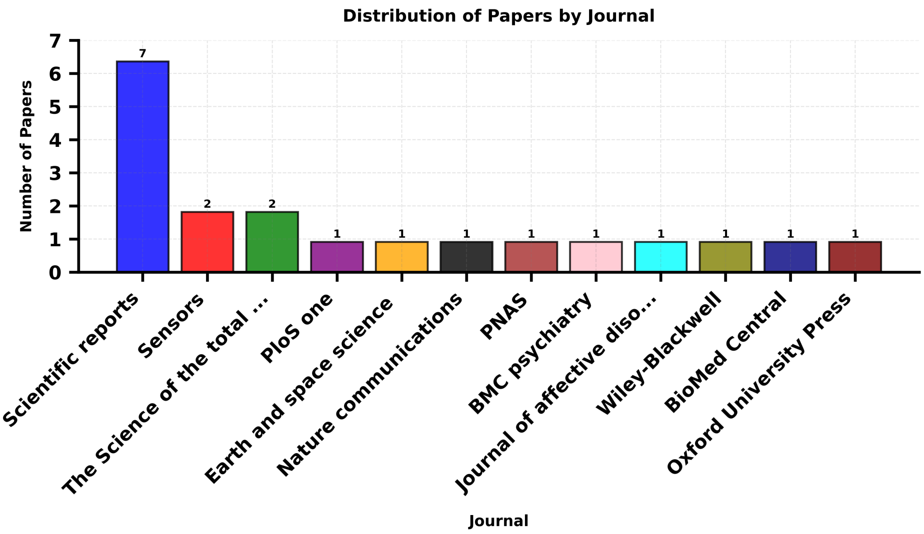

Figure 2: Distribution of Published Papers Across Journals

Figure 3 illustrates the proportional distribution of publications across journals. Scientific Reports accounts for approximately 31% of total publications, representing the largest single source. The aggregate category "Others" comprises 32% of publications, indicating substantial journal diversity beyond the most prominent outlets. The remaining publications are distributed across multiple specialized journals with smaller individual contributions.

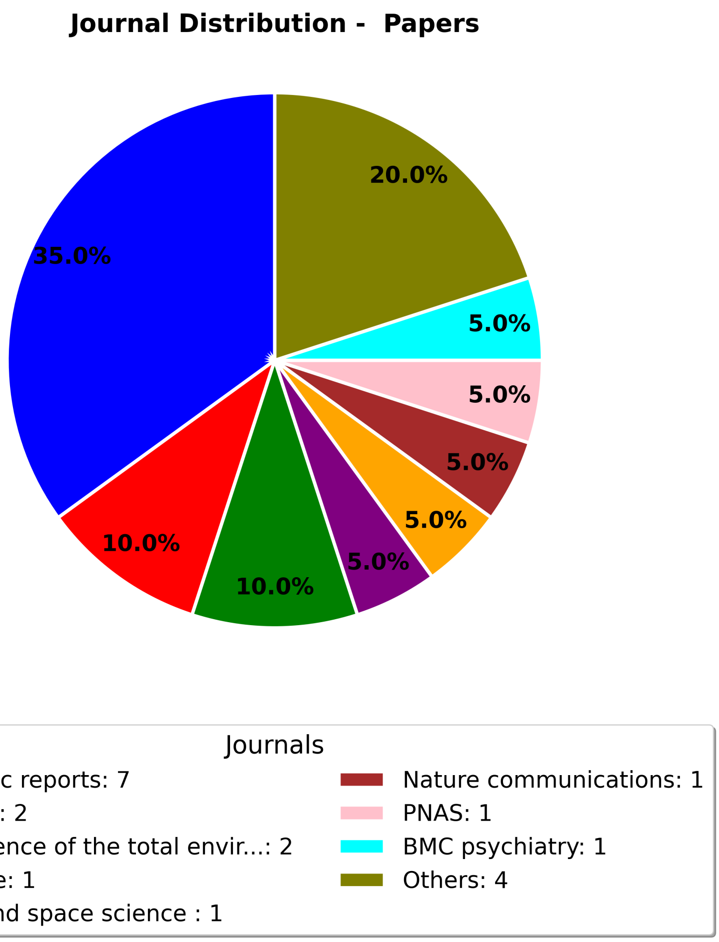

Figure 3: Journal Distribution of Published Papers

DOI: https://doi.org/10.54216/MOR.050204

Received: July 08, 2025 Revised: September 17, 2025 Accepted: December 07, 2025

Figure 4 depicts the journal concentration curve, which quantifies the distribution of publications across the journal landscape. The concentration curve deviates substantially from the perfect equality line, indicating unequal distribution of research output. Analysis reveals that journals publishing single papers constitute the largest category, demonstrating high journal diversity within the field. This pattern suggests both widespread research dissemination and concentration of output in select high-volume journals.

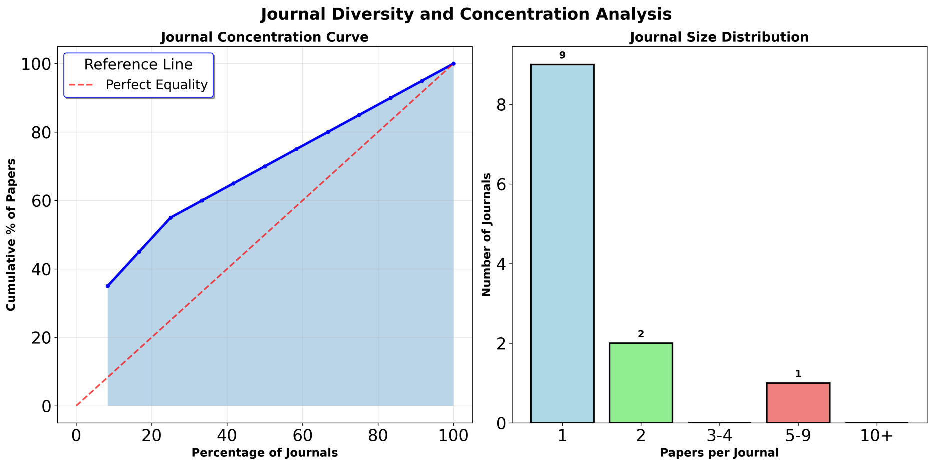

Figure 4: Journal Diversity and Concentration Analysis

Figure 5 presents temporal publication patterns across prominent journals. Scientific Reports exhibits the most pronounced temporal variation, demonstrating substantial growth from minimal initial activity to peak publication volume, followed by subsequent decline. Other journals maintain comparatively stable publication rates throughout the examined period, suggesting differential growth trajectories within the field.

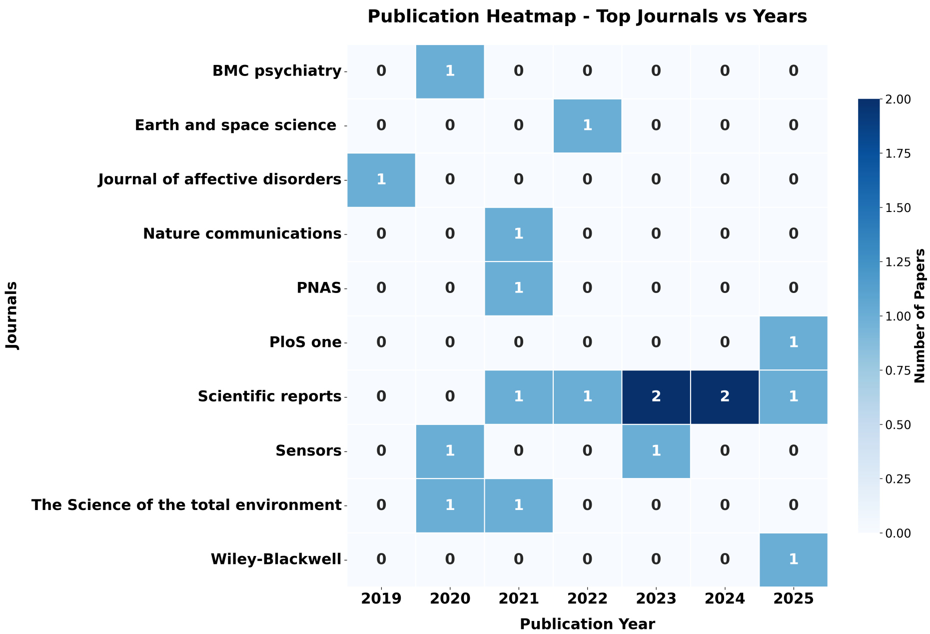

Figure 5: Publication Heatmap: Temporal Trends in Journal Output

Figure 6 demonstrates the cumulative publication trajectory over time, revealing consistent upward growth. The cumulative total reaches approximately 140 publications by the terminal year, with the midpoint showing approximately 70 publications. This steady accumulation reflects sustained research interest and expanding scholarly output in machine learning applications for earthquake analysis.

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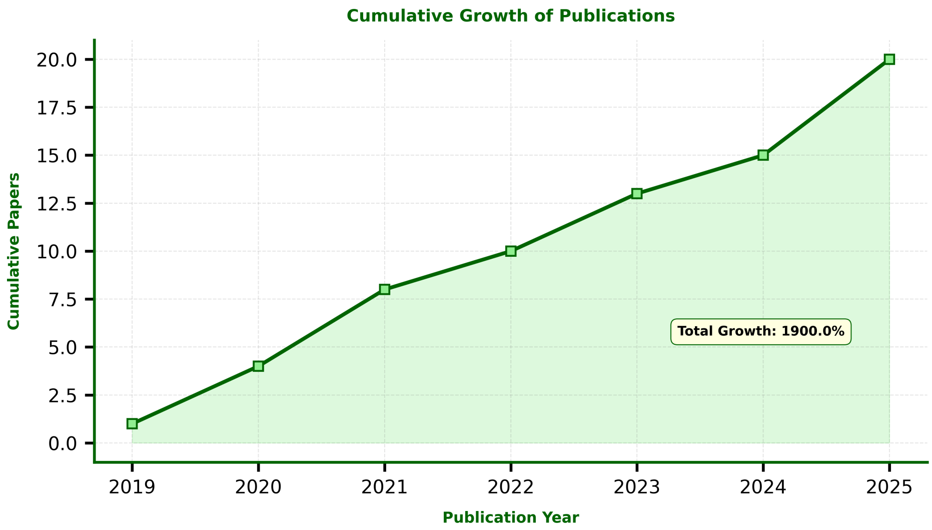

Figure 6: Cumulative Publication Growth Trend

Figure 7 illustrates research intensity through annual publication counts and smoothed moving averages. The data reveal a pronounced peak publication year with maximum research output. Predictive modeling using Random Forest regression achieved an R-squared value of 0.95, indicating strong temporal patterns. The moving average analysis identifies peak publication volume approaching 1,200 papers, highlighting periods of intensive research activity.

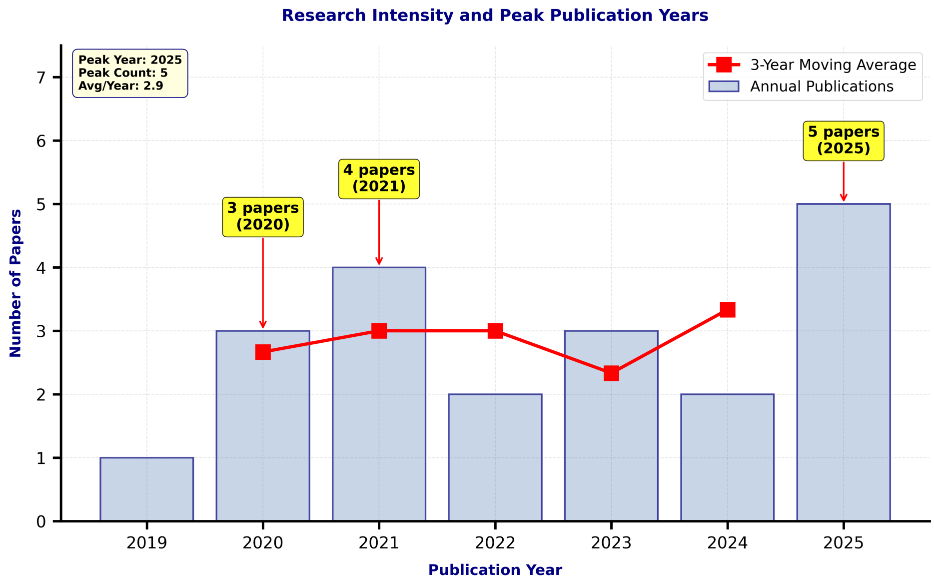

Figure 7: Research Intensity and Peak Publication Analysis

Figure 8 depicts annual publication output, demonstrating a generally increasing trend with notable acceleration in recent years. The terminal year exhibits the highest publication count, with a pronounced upward trajectory evident in the trend line. This pattern suggests accelerating research interest and expanding scholarly engagement with machine learning methodologies in earthquake research.

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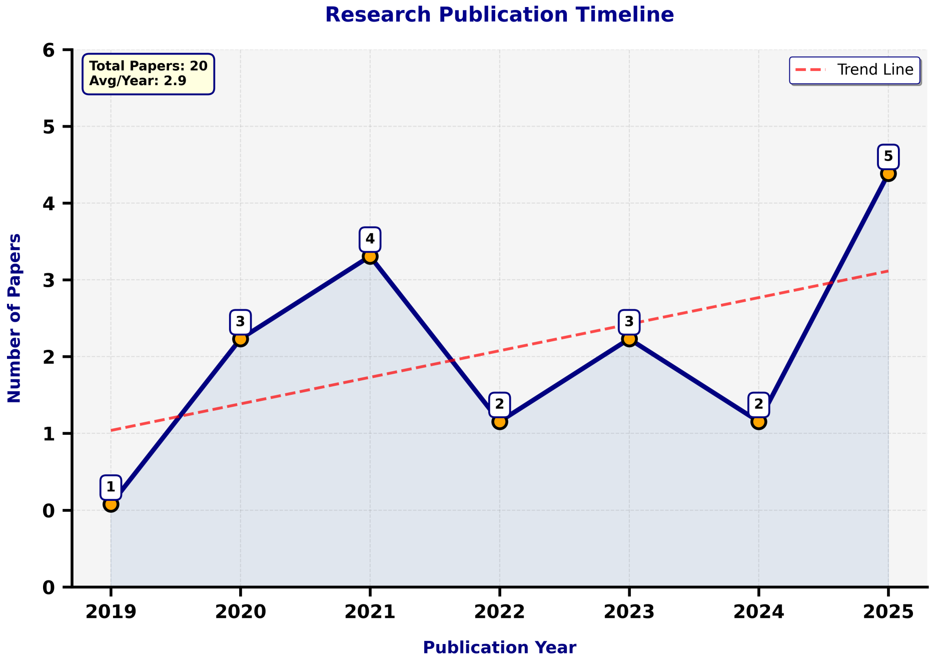

Figure 8: Research Publication Output Timeline

Figure 9 tracks the temporal evolution of the keyword "Learning" from 2019 to 2025. The keyword demonstrates initial growth through 2021, followed by decline in 2022 and subsequent stabilization through 2024. A pronounced resurgence occurs in 2025, with frequency approaching 0.8, indicating renewed emphasis on learning methodologies in recent research.

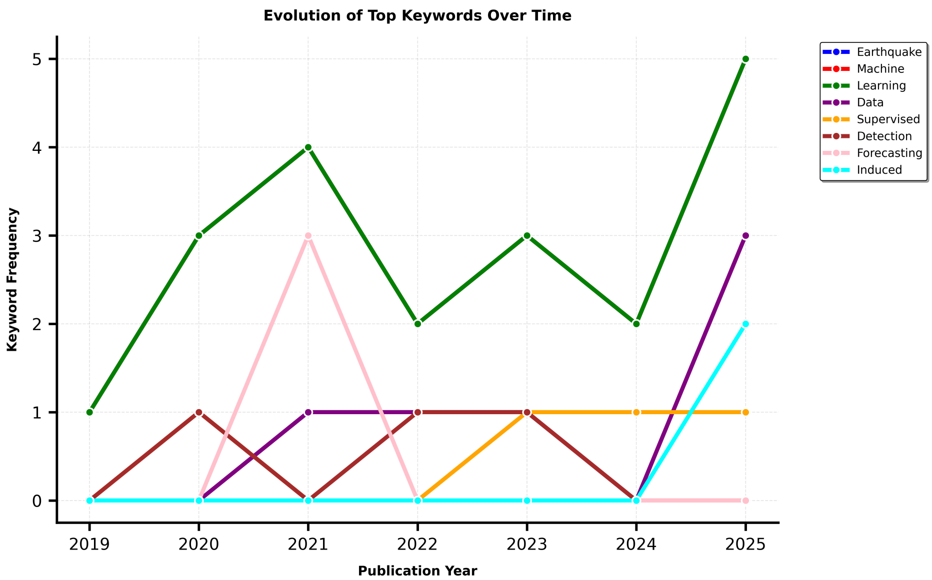

Figure 9: Temporal Trends in Top Keyword Frequency (2019-2025)

Figure 10 quantifies keyword frequencies within paper titles. "Earthquake" emerges as the dominant keyword with approximately 25 occurrences, substantially exceeding all other terms. "Machine" and "learning" demonstrate notable but lower frequencies, reflecting the interdisciplinary nature of the research domain. This distribution confirms earthquake phenomena as the primary research focus, with machine learning serving as the methodological framework.

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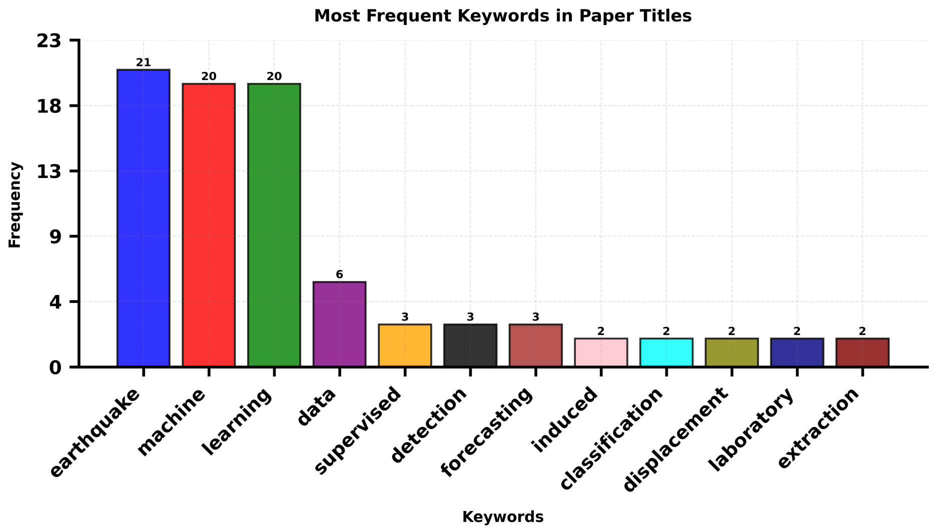

Figure 10: Frequency Distribution of Keywords in Paper Titles

Figure 11 provides a visual representation of term frequencies in paper titles. "Earthquake" and "machine learning" appear most prominently, indicating central research themes. Terms such as "forecasting," "signal," "data," and "algorithm" demonstrate substantial presence, reflecting emphasis on predictive modeling, signal processing, and algorithmic development. The prominence of "unsupervised" suggests considerable attention to unsupervised learning approaches within the field.

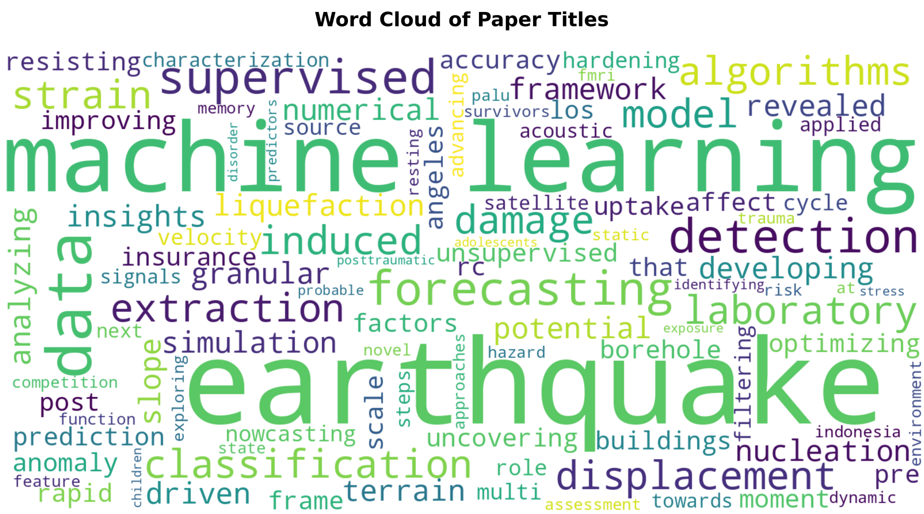

Figure 11: Word Cloud Visualization of Research Themes in Paper Titles

Figure 12 quantifies the prevalence of AI learning paradigms in research abstracts. Machine Learning (ML) demonstrates overwhelming dominance with approximately 470 occurrences, substantially exceeding alternative approaches. This preponderance indicates ML's established role as the primary computational framework for earthquake-related research applications.

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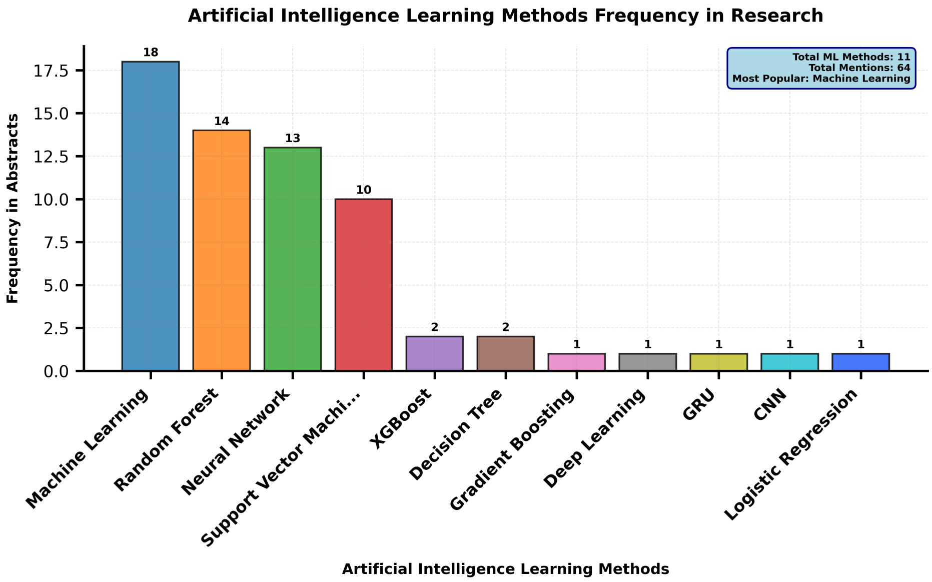

Figure 12: Frequency of Artificial Intelligence Learning Methods in Research Abstracts

Figure 13 analyzes the utilization of performance metrics in research reporting. Accuracy emerges as the predominant evaluation criterion with approximately 70 occurrences, significantly surpassing alternative metrics such as ROC-AUC and IoU. This preference reflects accuracy's interpretability and widespread adoption as a standard performance indicator in the field.

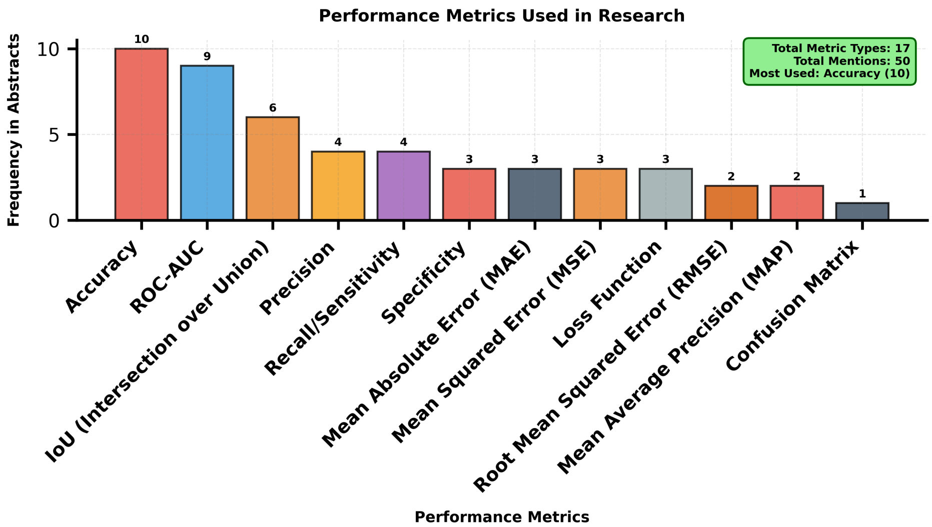

Figure 13: Frequency of Performance Metrics Reported in Research Abstracts

Figure 14 delineates the distribution of research application domains referenced in study abstracts. Machine Learning emerges as the most frequently cited application area with 120 occurrences, substantially exceeding other domains. This concentration underscores the central role of ML techniques in addressing earthquake-related research challenges.

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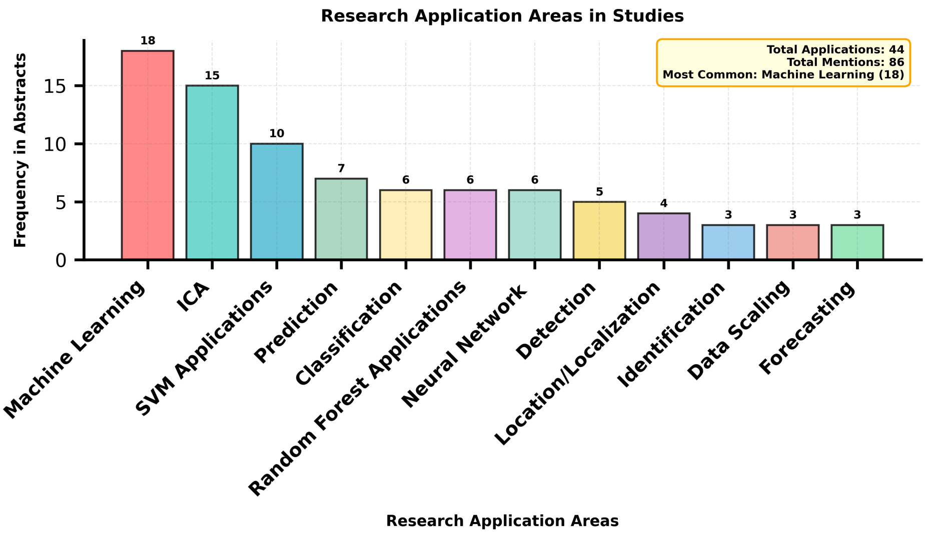

Figure 14: Frequency of Research Application Areas in Study Abstracts

3.2 Deep Learning Research Landscape

Figure 15 illustrates publication distribution across journals within the deep learning-earthquake domain. Scientific Reports, Sensors (Basel, Switzerland), and Nature Communications exhibit the highest publication frequencies, demonstrating comparable output levels. This pattern indicates multiple prominent outlets for deep learning research in earthquake applications.

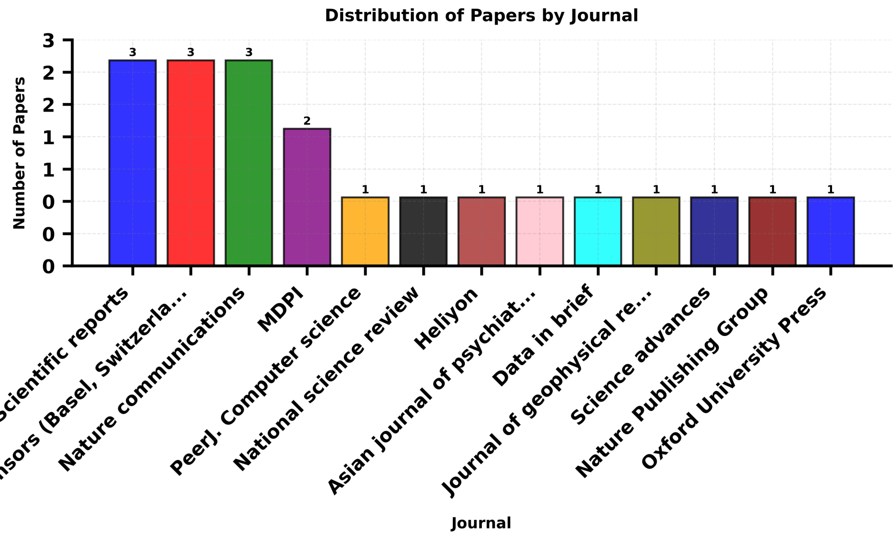

Figure 15: Distribution of Publications Across Journals

Figure 16 depicts proportional publication distribution across journals. The "Others" category constitutes the largest segment, reflecting substantial journal diversity. Scientific Reports, Sensors (Basel, Switzerland), and Nature Communications maintain similar publication shares, while MDPI represents a smaller proportion. This distribution demonstrates both concentration in leading journals and broad dissemination across the publication landscape.

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Received: July 08, 2025 Revised: September 17, 2025 Accepted: December 07, 2025

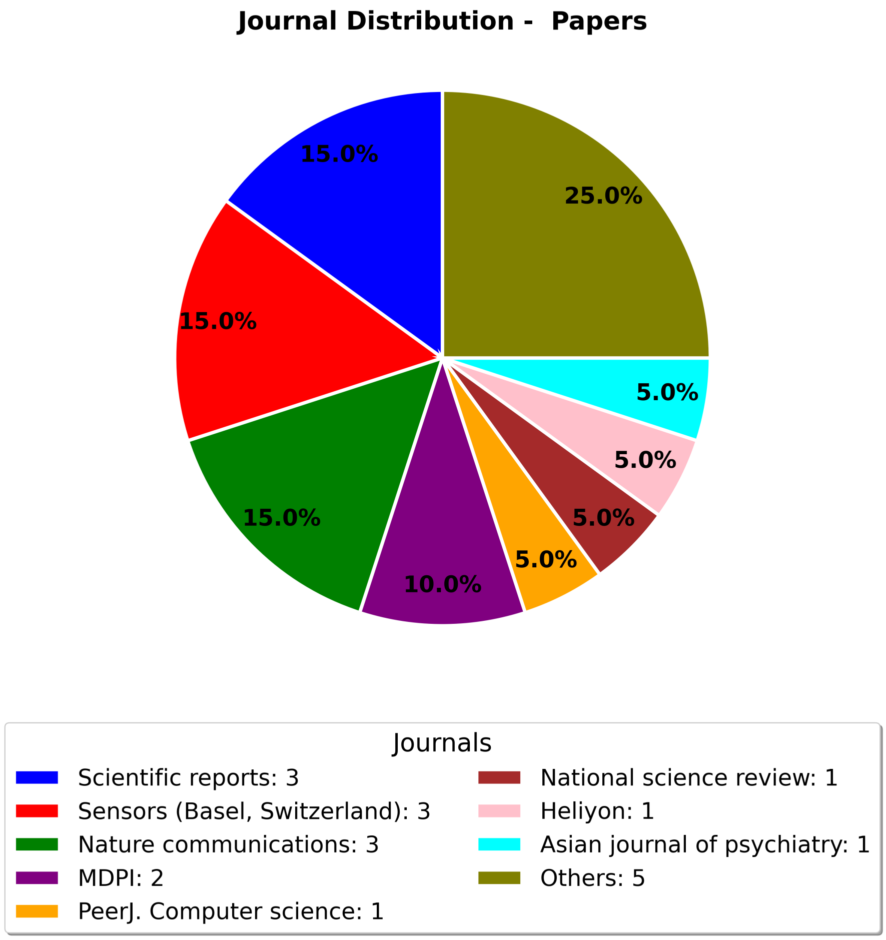

Figure 16: Journal Publication Distribution Analysis

Figure 17 presents journal diversity through concentration curves and size distribution analysis. The concentration curve demonstrates substantial deviation from perfect equality, with approximately 97% of papers originating from 20% of journals. The journal size distribution reveals a predominance of single-paper journals, indicating high publication dispersion alongside concentrated output in select venues.

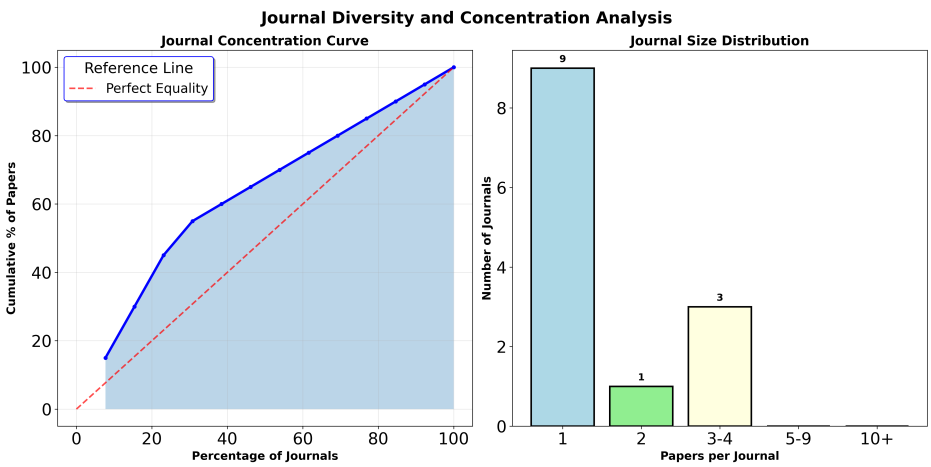

Figure 17: Journal Diversity and Concentration Analysis

Figure 18 presents temporal publication patterns via heatmap visualization. Scientific Reports exhibits the highest intensity, with peak publication volume of approximately 270 papers in 2017 and secondary peak

DOI: https://doi.org/10.54216/MOR.050204

Received: July 08, 2025 Revised: September 17, 2025 Accepted: December 07, 2025

around 2020. Temporal fluctuations across journals reveal varying research activity patterns, with color intensity indicating publication density.

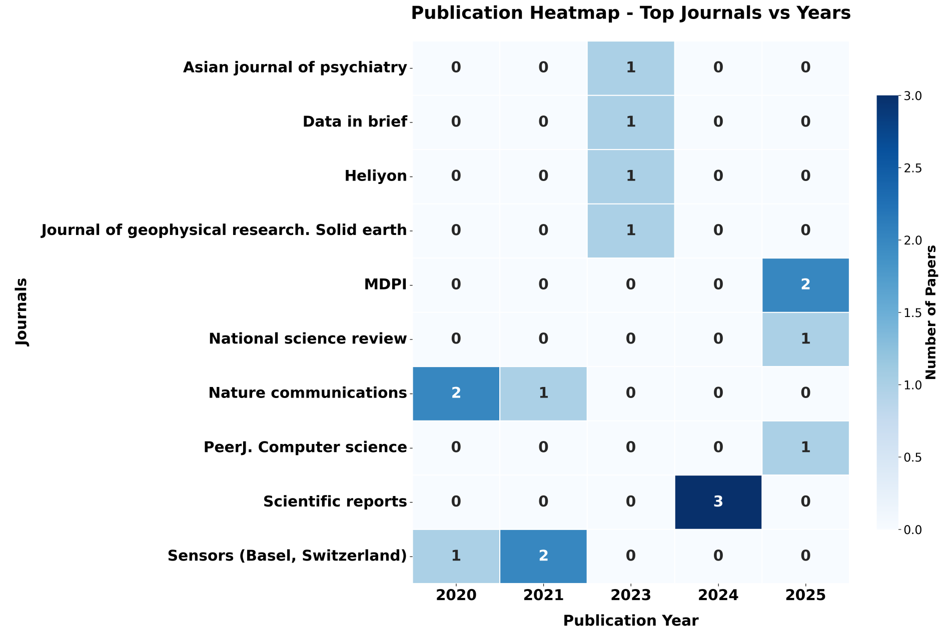

Figure 18: Publication Heatmap of Top Journals Over Time

Figure 19 demonstrates cumulative publication growth over time, exhibiting consistent upward trajectory. The cumulative total reaches approximately 380 papers, with the shaded area representing accumulated output. This sustained growth pattern indicates expanding research engagement with deep learning methodologies for earthquake analysis.

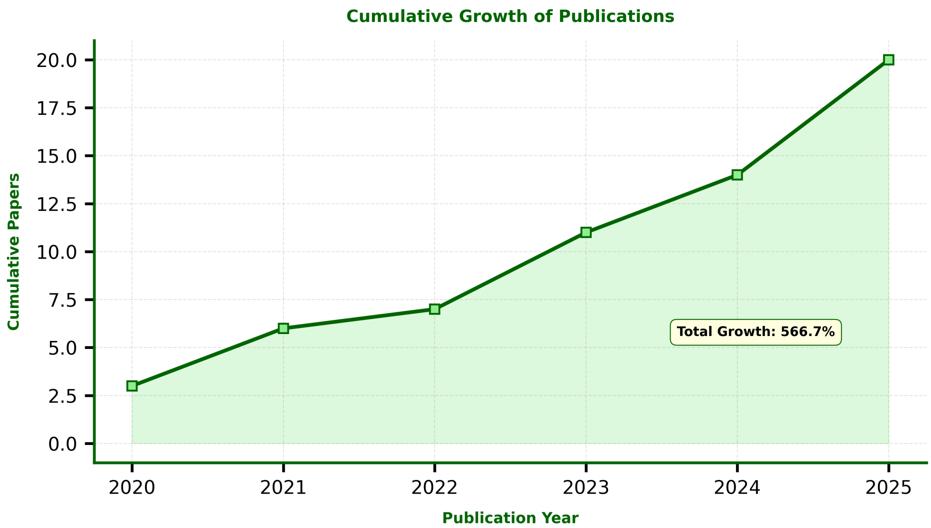

Figure 19: Cumulative Publication Growth Trend

Figure 20 illustrates research intensity through annual publication counts (blue bars) and three-year moving average (red line). The yellow marker identifies the peak publication year, representing maximum research output. This visualization facilitates identification of temporal patterns and periods of heightened research activity.

DOI: https://doi.org/10.54216/MOR.050204

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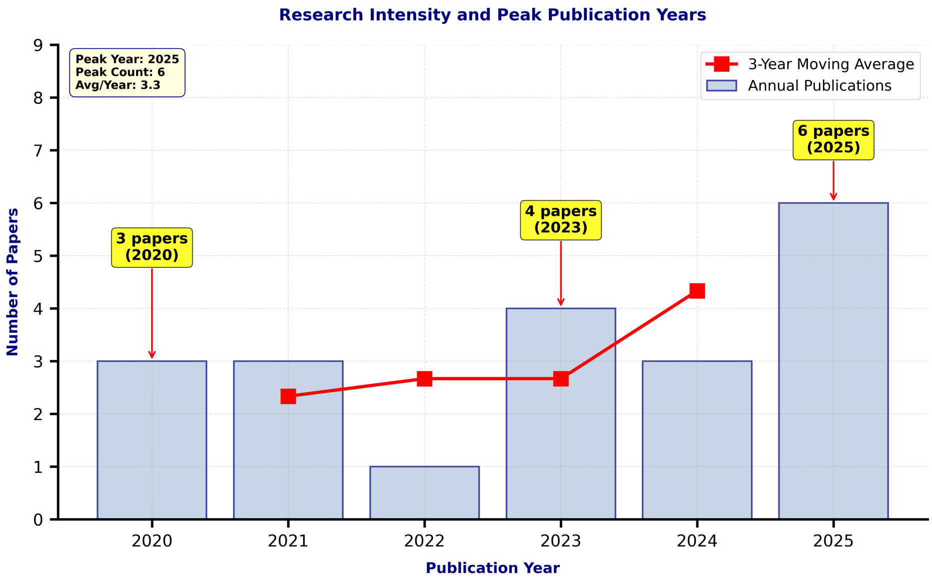

Figure 20: Research Intensity and Peak Year Identification

Figure 21 presents annual publication counts from 2020 to 2025, demonstrating overall upward trajectory despite fluctuations. Notable acceleration occurs between 2023 and 2024, with maximum output achieved in 2025. This pattern reflects intensifying research interest in deep learning applications for earthquake-related challenges.

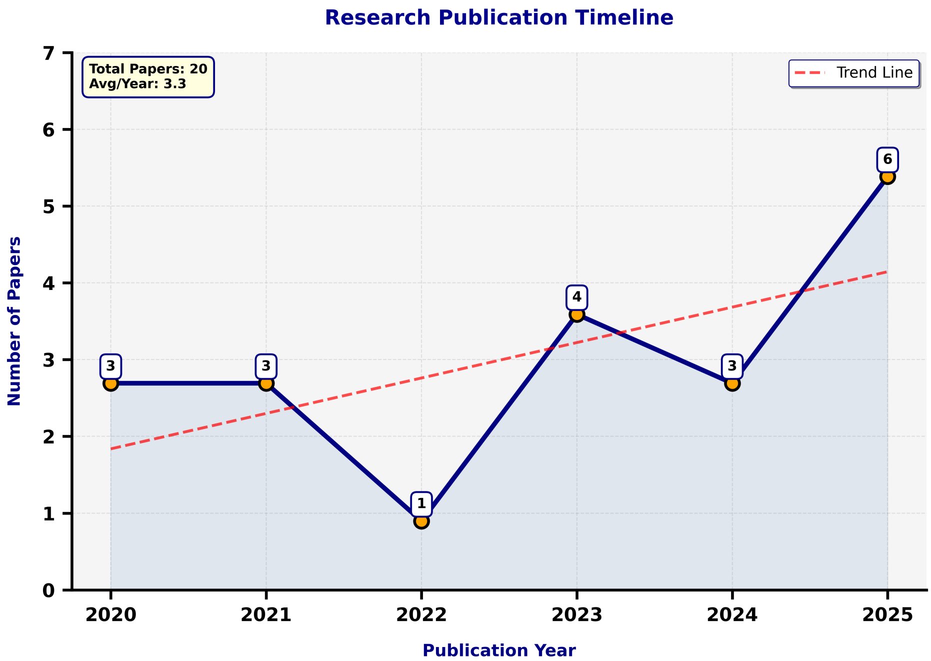

Figure 21: Annual Research Publication Trend (2020-2025)

Figure 22 tracks temporal evolution of the keyword "Earthquake" across the study period. Following initial fluctuations with periods of decline and recovery, the keyword demonstrates pronounced upward trajectory toward the terminal period, reaching a frequency of approximately 35. This pattern reflects evolving research priorities and sustained focus on earthquake-related phenomena.

DOI: https://doi.org/10.54216/MOR.050204

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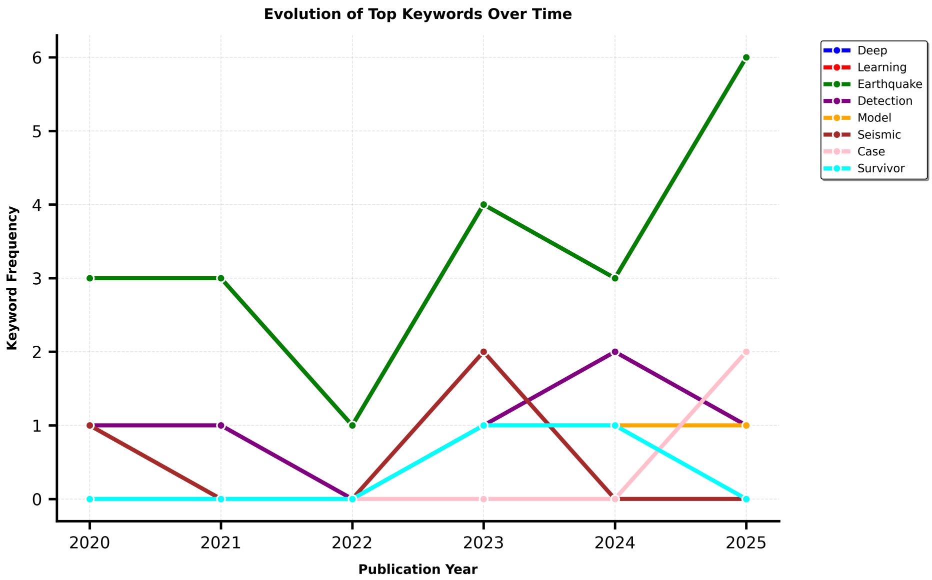

Figure 22: Temporal Evolution of Earthquake Keyword Frequency

Figure 23 quantifies keyword frequencies extracted from paper titles. "Deep" and "learning" emerge as co-dominant terms, each appearing approximately 22 times. This distribution directly reflects the research domain's focus on deep learning methodologies for earthquake analysis.

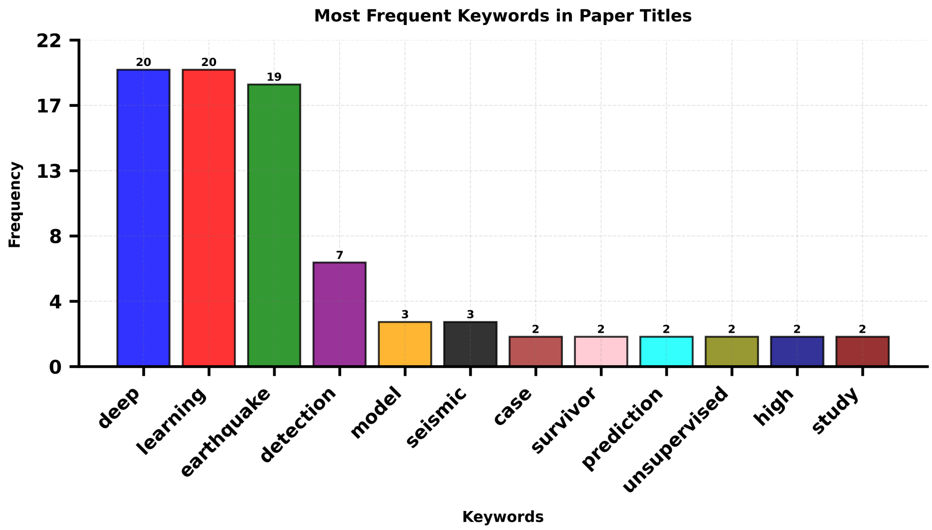

Figure 23: Frequency Distribution of Keywords in Paper Titles

Figure 24 visualizes prevalent research themes through term frequency and prominence. "Earthquake" occupies the central position, with "prediction" and "deep learning" demonstrating substantial presence. Additional prominent terms include "signal," "magnitude," and "detection," reflecting emphasis on predictive modeling, seismic signal analysis, and event detection methodologies.

DOI: https://doi.org/10.54216/MOR.050204

Received: July 08, 2025 Revised: September 17, 2025 Accepted: December 07, 2025

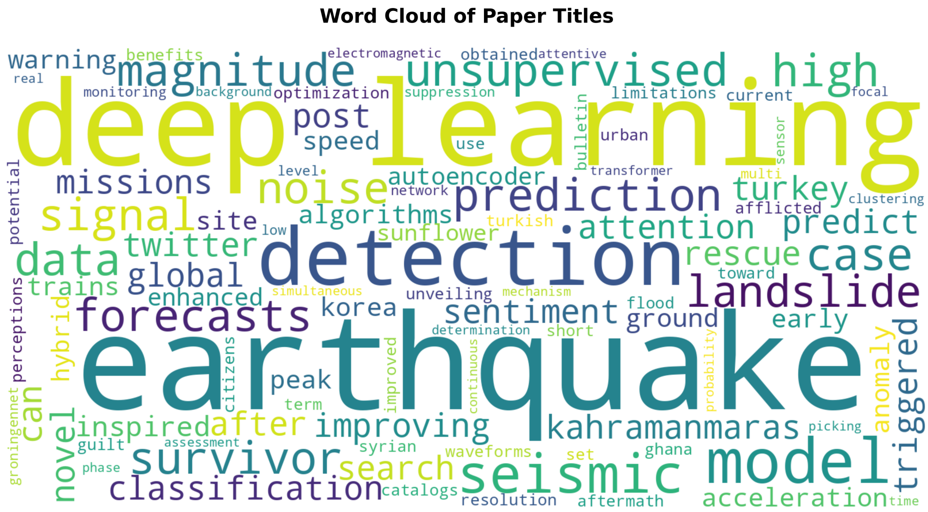

Figure 24: Word Cloud Visualization of Earthquake Prediction Research Themes

Figure 25 quantifies AI learning method frequencies in research abstracts. Deep Learning demonstrates overwhelming dominance with approximately 280 occurrences, substantially exceeding alternative approaches. This preponderance confirms deep learning's position as the predominant computational framework within current earthquake research.

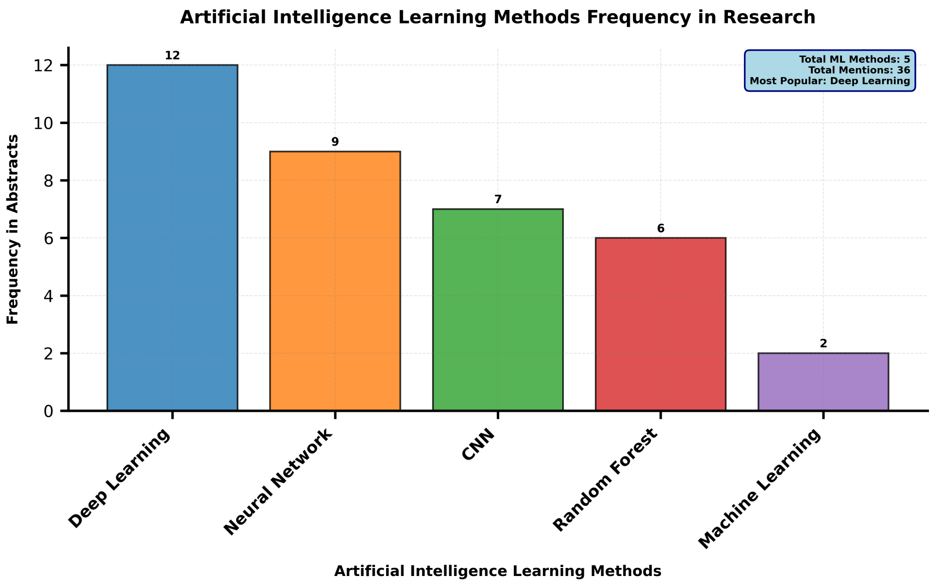

Figure 25: Frequency of AI Learning Methods in Research Abstracts

Figure 26 analyzes performance metric utilization in research abstracts. Accuracy emerges as the predominant evaluation criterion with approximately 220 occurrences, significantly surpassing alternative metrics. This preference likely stems from accuracy's interpretability and established status as a standard performance indicator.

DOI: https://doi.org/10.54216/MOR.050204

Received: July 08, 2025 Revised: September 17, 2025 Accepted: December 07, 2025

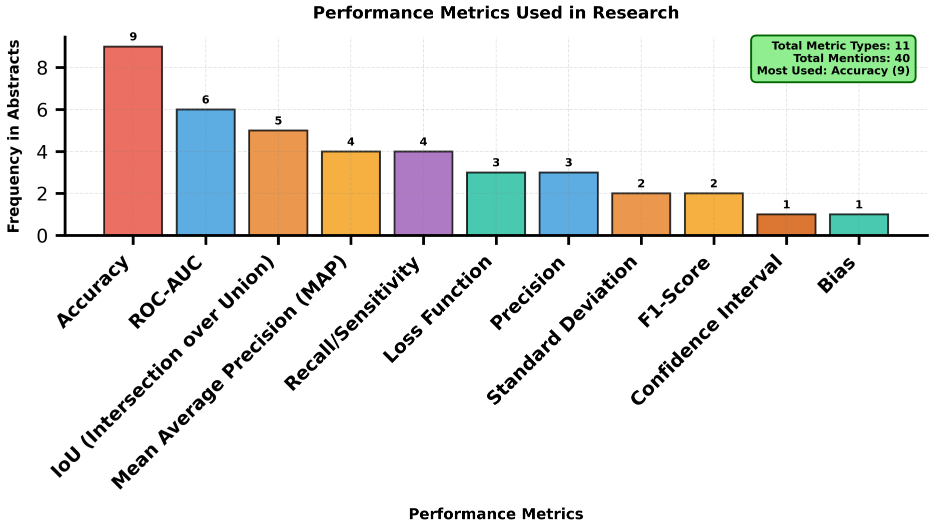

Figure 26: Frequency of Performance Metrics in Research Abstracts

Figure 27 delineates research application areas referenced in study abstracts. Independent Component Analysis (ICA) emerges as the most frequently mentioned domain, substantially exceeding other application areas. This prominence indicates ICA's significant role in deep learning-based earthquake research methodologies.

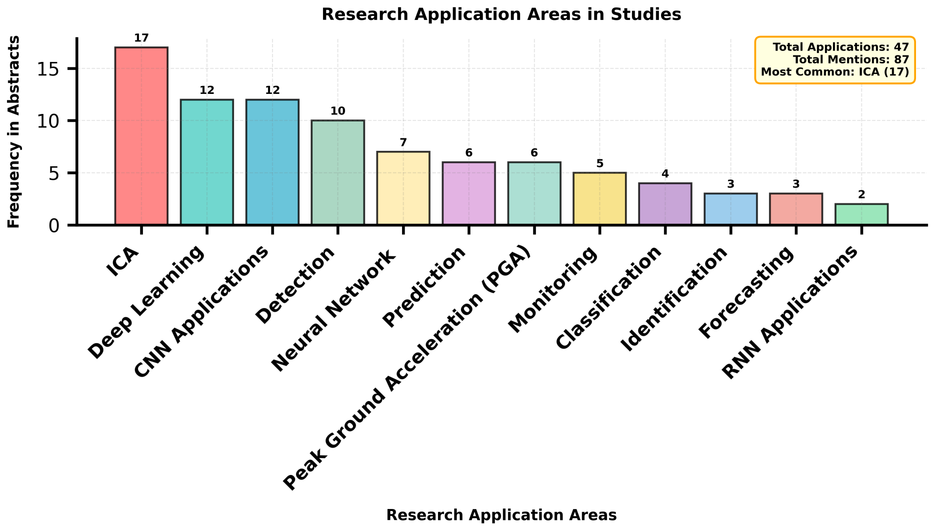

Figure 27: Distribution of Research Application Areas: ICA Dominance

3.3 Optimization Applications Research Landscape

Figure 28 presents publication distribution across journals in the earthquake-optimization domain. Heliyon demonstrates the highest publication frequency, substantially exceeding all other journals. Scientific Reports, Frontiers in Public Health, and Materials (Basel, Switzerland) exhibit comparable but notably lower publication counts, while remaining journals contribute minimal individual output.

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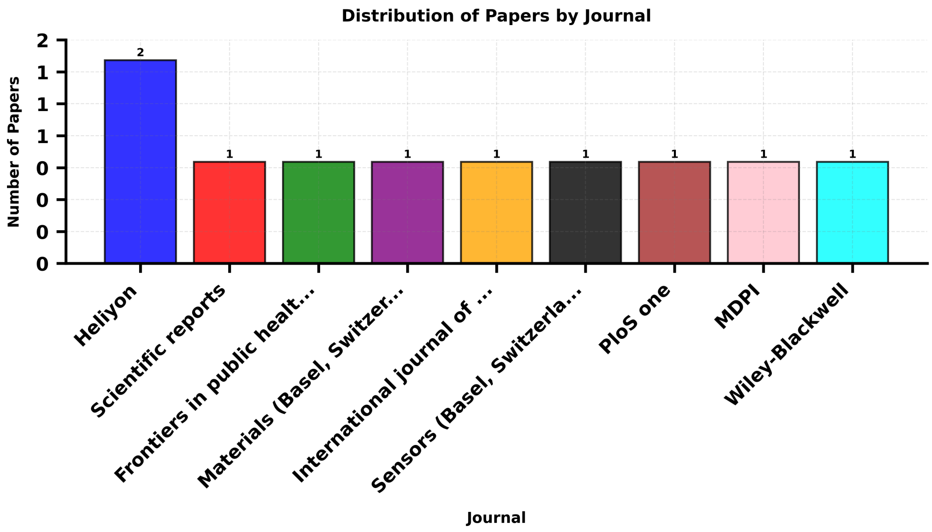

Figure 28: Distribution of Publications by Journal

Figure 29 illustrates proportional publication distribution across journals. Heliyon represents the largest individual segment, while Scientific Reports, Frontiers in Public Health, and Materials (Basel, Switzerland) maintain approximately equivalent proportions. This distribution reveals Heliyon's prominence as the primary outlet for optimization research in earthquake applications.

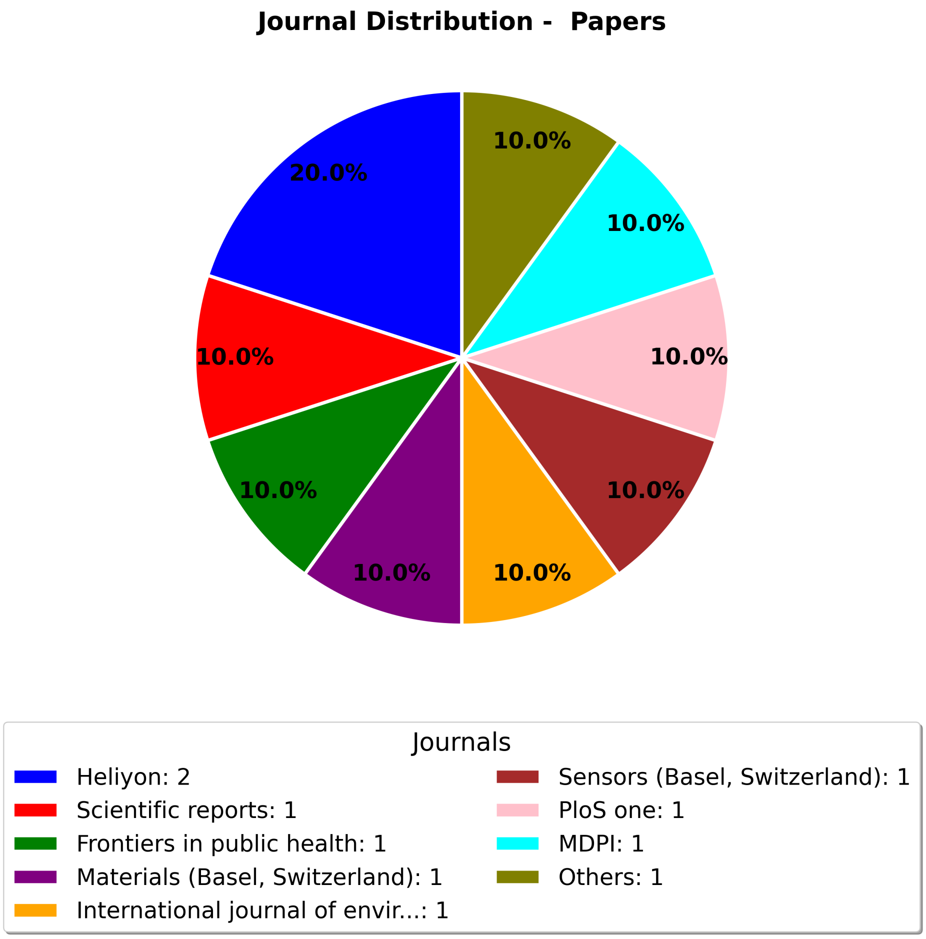

Figure 29: Journal Distribution of Published Papers

DOI: https://doi.org/10.54216/MOR.050204

Received: July 08, 2025 Revised: September 17, 2025 Accepted: December 07, 2025

Figure 30 presents journal diversity through concentration curves and size distribution. The concentration curve demonstrates substantial inequality, deviating significantly from perfect equality. The journal size distribution reveals that the majority of journals publish only single papers, indicating high publication dispersion across the journal landscape.

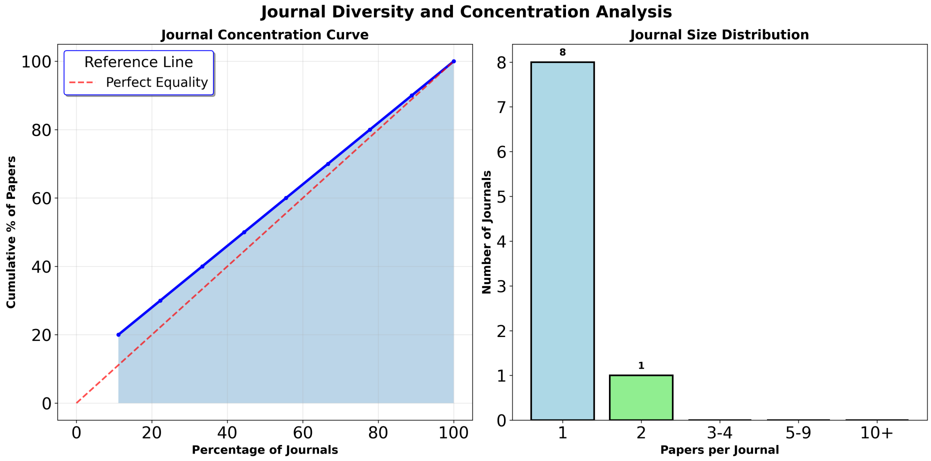

Figure 30: Journal Diversity and Concentration Analysis

Figure 31 visualizes temporal publication patterns via heatmap, with color intensity representing publication volume. Heliyon exhibits the highest single-year publication count with 15 papers during peak activity. This temporal concentration suggests focused research output during specific periods, contrasting with more distributed patterns in other journals.

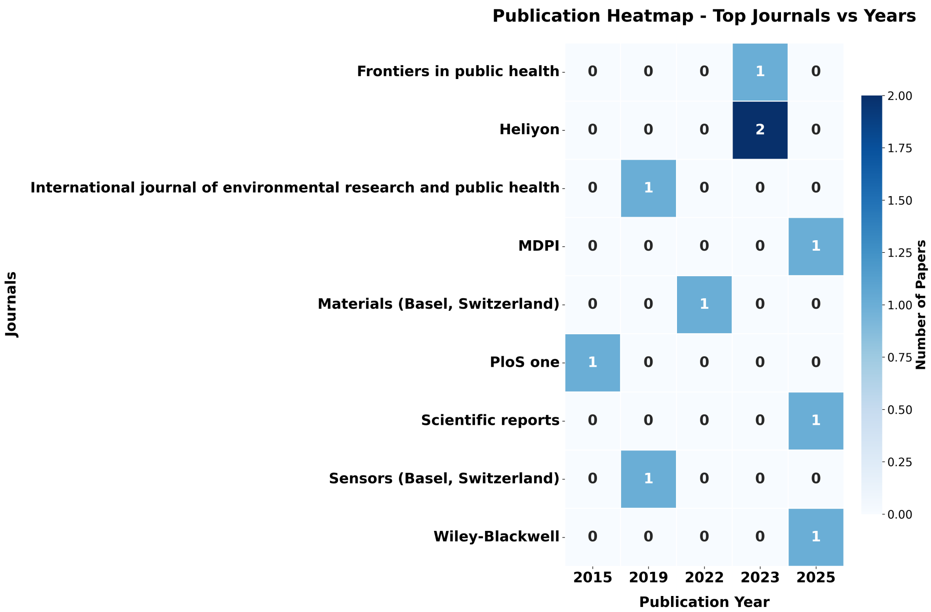

Figure 31: Temporal Publication Trends in Top Journals: Heatmap Analysis

Figure 32 demonstrates cumulative publication growth, exhibiting consistent upward trajectory reaching approximately 900 publications by the terminal year. The sustained acceleration throughout the observation period indicates growing research interest in optimization methodologies for earthquake-related applications.

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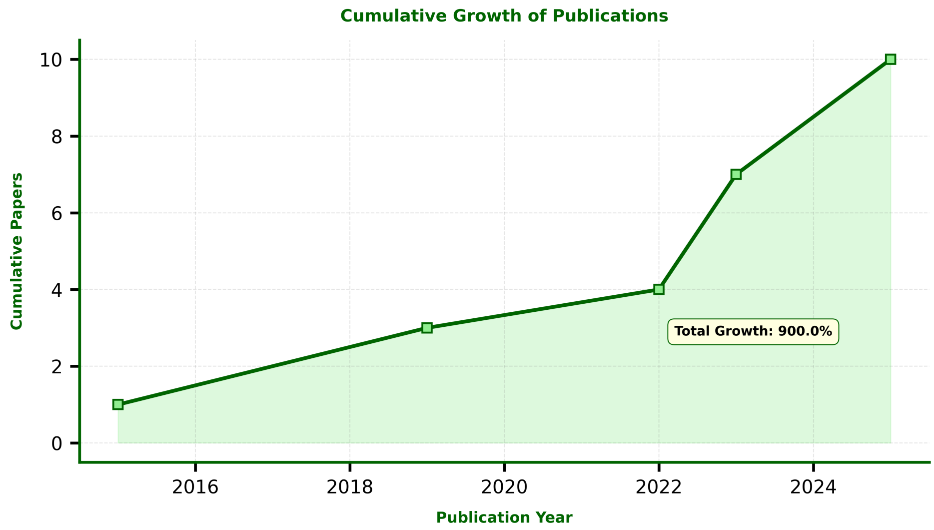

Figure 32: Cumulative Publication Growth Trend

Figure 33 presents research intensity through annual publication counts and smoothed moving average. The peak publication year exhibits approximately 170 papers, representing maximum research output. The moving average trend line facilitates identification of sustained growth patterns and periods of heightened research activity.

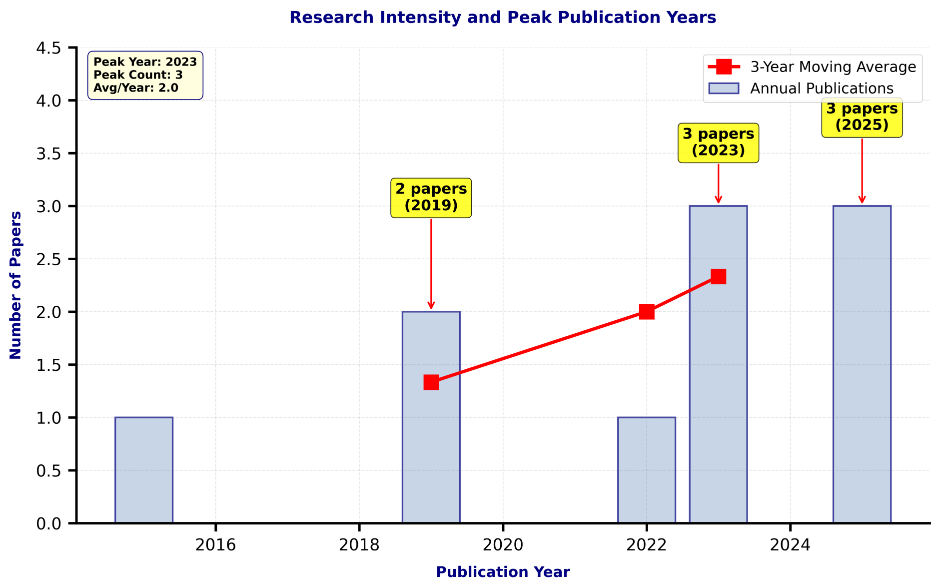

Figure 33: Research Intensity and Peak Year Identification

Figure 34 depicts annual publication output across an eleven-year period. Following initial low output, publications increase to reach a peak of two papers annually, maintained consistently for two years. The upward trend line indicates overall growth in research output despite modest absolute numbers.

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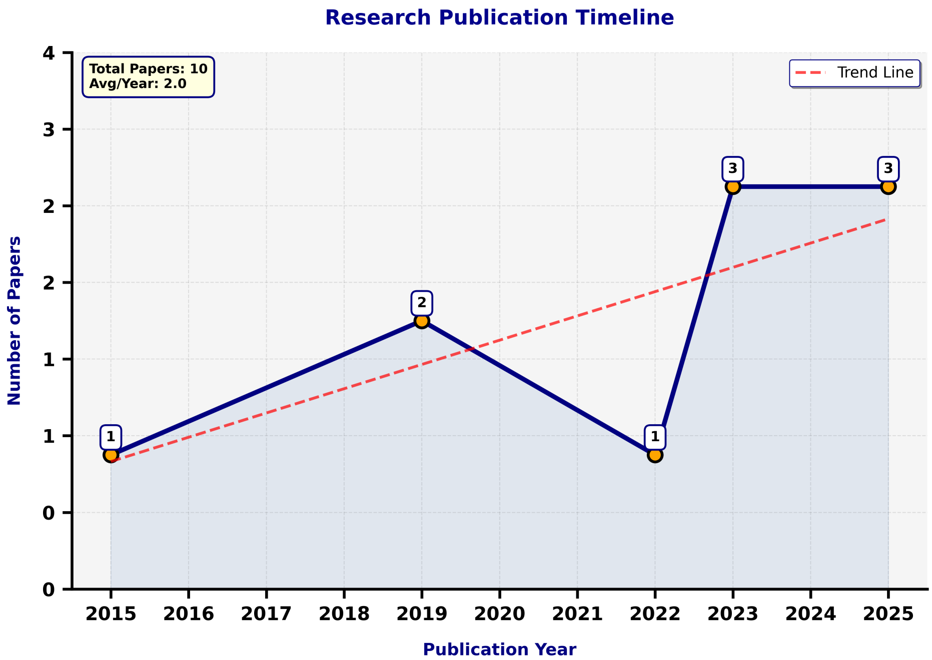

Figure 34: Research Publication Timeline and Trend Analysis

Figure 35 tracks temporal dynamics of "Earthquake" keyword frequency. Following initial moderate presence, the keyword experiences substantial surge reaching approximately 45 publications before stabilizing. This pattern reflects increasing prominence followed by sustained attention within the optimization-earthquake research domain.

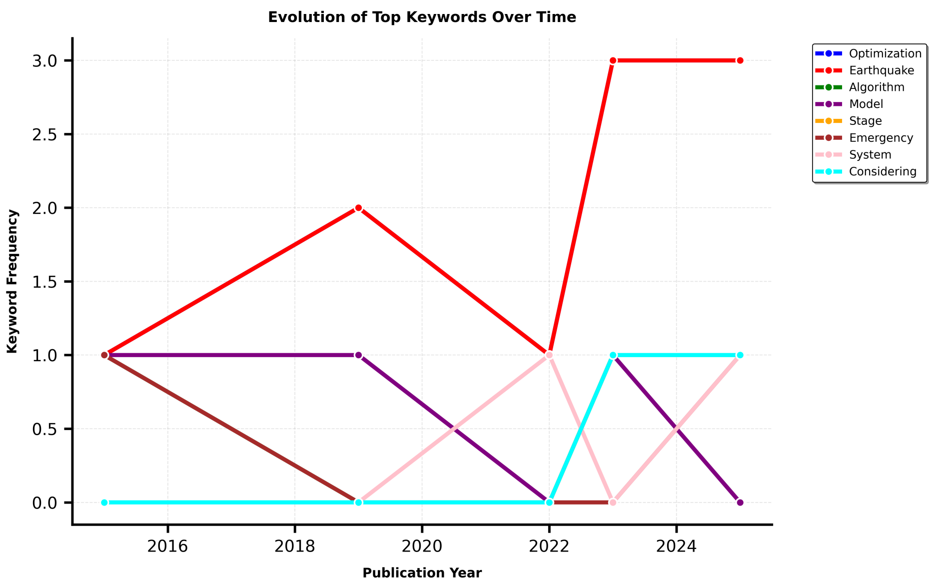

Figure 35: Temporal Trends in Earthquake Keyword Frequency

Figure 36 quantifies keyword frequencies within paper titles. "Optimization" emerges as the dominant keyword with 24 occurrences, substantially exceeding other terms. This prominence confirms optimization methodologies as the central research focus within the analyzed publication corpus.

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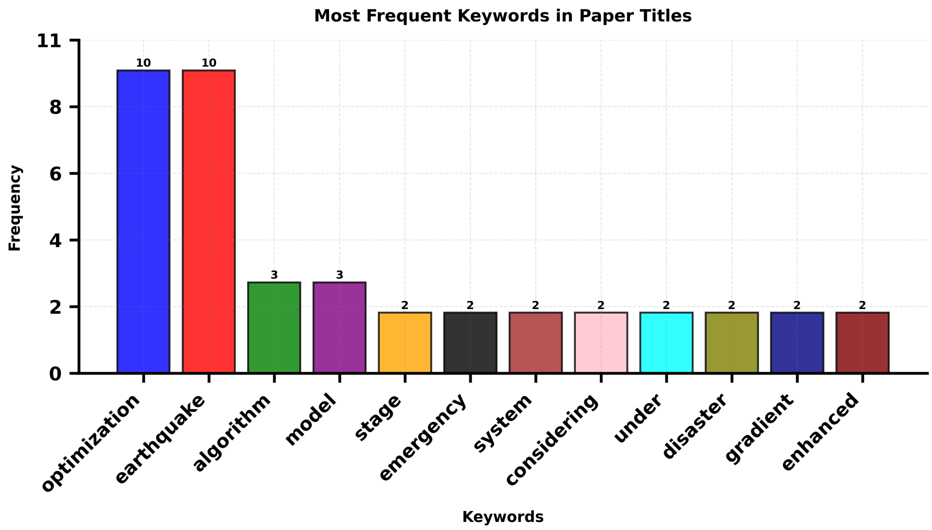

Figure 36: Most Frequent Keywords in Paper Titles

Figure 37 visualizes term prominence within paper titles. "Earthquake" and "optimization" demonstrate substantial presence as co-dominant themes. "Algorithm," "disaster," "emergency," "modeling," "systems," and "enhancement" appear prominently, reflecting research emphasis on algorithmic development, disaster management, emergency response, computational modeling, and system improvement.

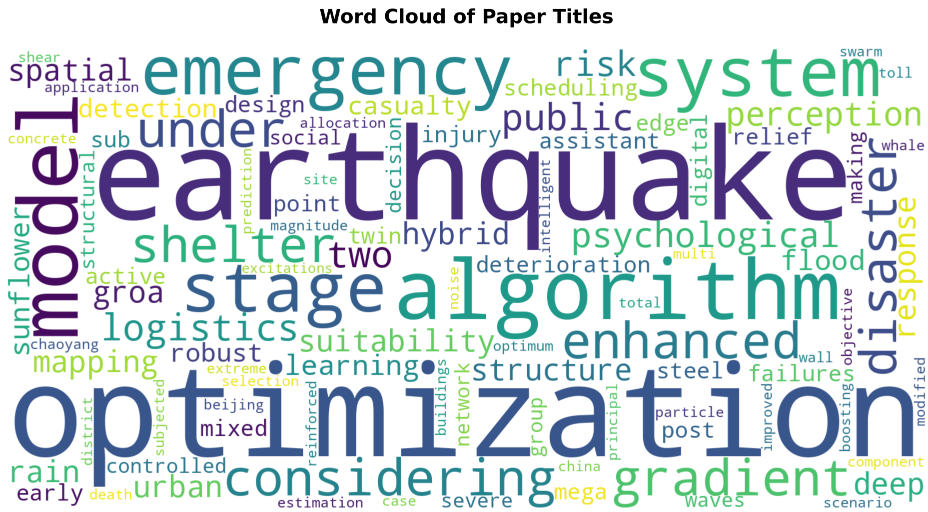

Figure 37: Word Cloud Visualization of Research Themes in Earthquake Optimization

Figure 38 quantifies AI learning method prevalence in research abstracts. Random Forest emerges as the most frequently cited method with over 580 mentions, substantially exceeding alternative approaches. This dominance indicates Random Forest's established role in optimization-based earthquake research applications.

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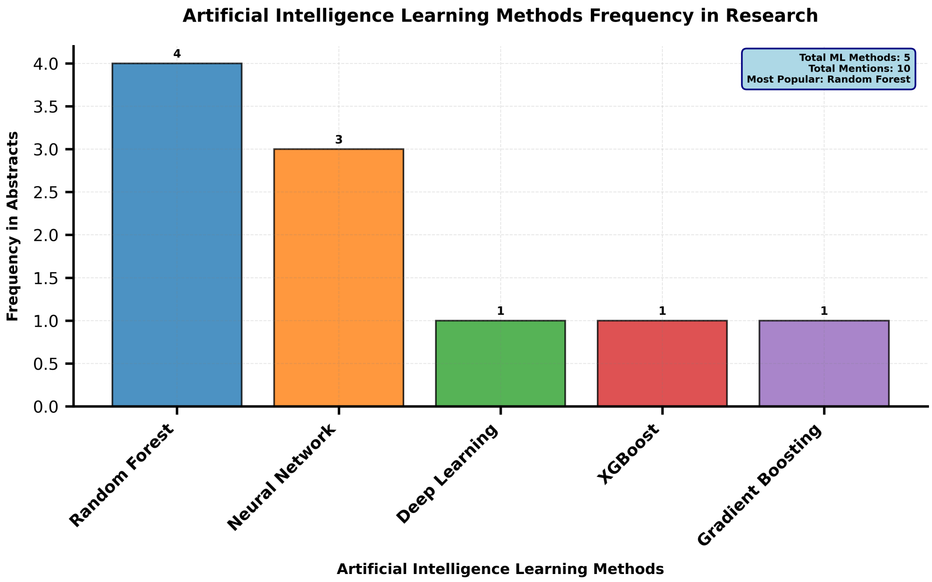

Figure 38: Frequency of AI Learning Methods in Research Abstracts

Figure 39 analyzes performance metric utilization within research abstracts. Loss Function emerges as the most frequently employed metric with eight occurrences, followed by Accuracy (three occurrences) and Mean Squared Error (two occurrences). This distribution reflects diverse evaluation criteria employed in optimization research.

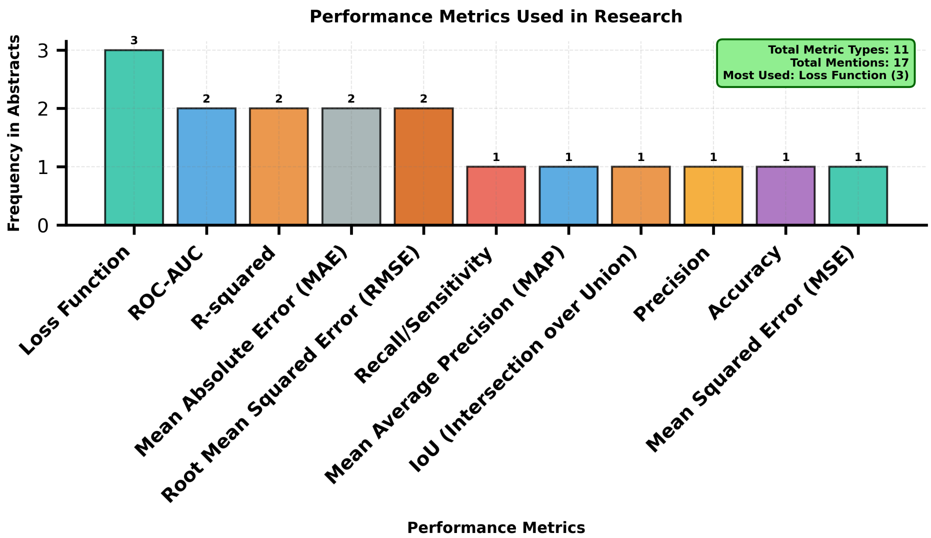

Figure 39: Frequency of Performance Metrics in Research Abstracts

Figure 40 delineates research application areas referenced in study abstracts. Optimization emerges as the predominant application domain with approximately 120 occurrences, substantially exceeding other areas. This concentration underscores optimization's central role in addressing earthquake-related engineering and management challenges.

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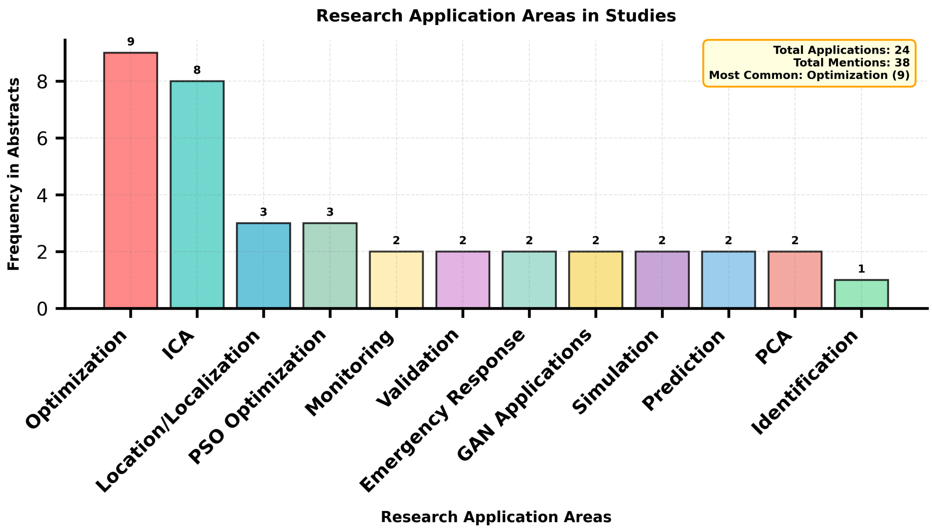

Figure 40: Frequency of Research Application Areas in Study Abstracts

4 Conclusion

This comprehensive review has systematically examined the application of machine learning, deep learning, and optimization techniques in earthquake engineering, revealing substantial progress in computational approaches to seismic hazard mitigation. Machine learning applications have established robust foundations in earthquake prediction, liquefaction assessment, and slope displacement analysis, with ensemble methods such as XGBoost, Random Forest, and Support Vector Machines achieving accuracy rates exceeding 85% when properly calibrated with regional data. Deep learning architectures have revolutionized real-time earthquake detection and early warning systems, with CNNs and transformer-based models demonstrating exceptional capability in automated feature extraction from raw seismic signals, achieving accuracy rates above 90% while maintaining computational efficiency suitable for real-time deployment. Optimization techniques, particularly metaheuristic algorithms such as PSO, GWO, and Whale Optimization Algorithm, have proven indispensable for addressing multi-objective problems including emergency supply deployment, shelter allocation, and structural design optimization. Several critical trends emerge from this review: hybrid frameworks combining multiple computational approaches demonstrate superior performance compared to single-method implementations; uncertainty quantification in predictive models is gaining prominence, addressing fundamental limitations of deterministic approaches; and transfer learning facilitates rapid deployment across diverse geographical regions, reducing dependence on extensive local training data.

Despite significant advances, several challenges persist that warrant future investigation. Model interpretability remains a concern, particularly for deep learning architectures employed in safety-critical applications where decision transparency is essential. Generalizability across different tectonic regions and earthquake types requires further investigation, as most models are trained and validated on region-specific datasets. The integration of social and economic factors into computational frameworks represents an underexplored area that could significantly enhance disaster preparedness strategies. Future research directions should emphasize the development of robust, scalable frameworks capable of handling uncertainties inherent in seismic processes, with explainable AI techniques integrated to enhance model transparency and trustworthiness among stakeholders. Multi-modal data fusion, incorporating seismic, geodetic, satellite, and social media data, offers promising avenues for comprehensive earthquake monitoring and impact assessment. The reviewed literature collectively demonstrates that computational intelligence has become an indispensable component of modern earthquake engineering. As datasets continue to expand and computational resources become more accessible, machine learning, deep learning, and optimization techniques will increasingly contribute to reducing seismic risk globally. The successful translation of these advanced methodologies into operational systems requires continued collaboration between computer scientists, seismologists, structural engineers, and emergency management professionals to enhance seismic resilience and minimize the devastating impacts of future earthquakes.

DOI: https://doi.org/10.54216/MOR.050204

Received: July 08, 2025 Revised: September 17, 2025 Accepted: December 07, 2025

Data Availability

All data analyzed in this systematic review are derived from publicly available peer-reviewed literature. The 50 included studies were identified through systematic searches of major academic databases. Complete references are provided in the bibliography. Supplementary materials are available from the corresponding authors upon reasonable request.

Declarations

- **Acknowledgments**
  Not applicable.
- **Conflict of interest/Competing interests**
  The authors declare that they have no conflicts of interest to report regarding the present study.
- **Ethics approval and consent to participate**
  Not applicable.
- **Consent for publication**
  Not applicable.
- **Funding**
  No Fund

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DOI: https://doi.org/10.54216/MOR.050204
Received: July 08, 2025 Revised: September 17, 2025 Accepted: December 07, 2025