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REVIEW

Artificial Intelligence in Earthquake Engineering: A Systematic Review from Machine Learning to Agentic AI

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ABSTRACT: Artificial intelligence (AI) is increasingly transforming earthquake engineering by supporting prediction, assessment, monitoring, and decision support. However, existing studies remain fragmented because machine learning (ML), deep learning (DL), physics-informed AI, hybrid models, large language models (LLMs), multimodal AI, digital twins, and agentic AI are often examined separately. This study presents a systematic literature review of AI applications in earthquake engineering, synthesizing 130 studies published between 2016 and 2026. The reviewed applications include seismic hazard assessment, earthquake prediction, earthquake early warning, ground-motion modeling, structural response prediction, damage detection, bridge and building assessment, structural health monitoring, geotechnical earthquake engineering, post-earthquake reconnaissance, and decision support. This study develops an integrated taxonomy and evaluates each AI paradigm in terms of strengths, limitations, maturity, interpretability, scalability, robustness, and deployment readiness. The findings show that ML is effective for structured regression and classification tasks, DL is suitable for waveform, image, sensor, and time-series data, and physics-informed and hybrid AI improve physical consistency. LLMs, multimodal AI, digital twins, and agentic AI extend AI toward knowledge interpretation, interaction, workflow automation, digital-twin-enabled integration, and human-supervised decision support. Key challenges include data limitations, weak generalization, uncertainty, explainability, cybersecurity, ethical–legal concerns, and deployment readiness. Overall, this review outlines pathways toward trustworthy, resilient, and deployment-ready earthquake-engineering AI systems.

KEYWORDS: Earthquake engineering; artificial intelligence; machine learning; deep learning; physics-informed AI; hybrid AI; large language models; multimodal AI; agentic AI; structural health monitoring; digital twins; explainable AI

1 Introduction

Earthquake engineering is essential for reducing seismic risk and improving the safety, functionality, and resilience of infrastructure exposed to earthquakes [1–4]. Traditionally, the field has relied on physics-based modeling, empirical attenuation relationships, experimental testing, structural dynamics, and probabilistic seismic hazard and risk assessment. Although these approaches remain fundamental, they can struggle with nonlinear structural behavior, uncertain ground motions, incomplete observations, heterogeneous infrastructure inventories, and rapidly changing post-earthquake conditions [5–9]. As seismic records, monitoring data, remote-sensing images, building inventories, and reconnaissance information become increasingly available, artificial intelligence (AI) offers powerful tools for pattern extraction, prediction, and decision support in earthquake engineering practice [10–14].

Machine learning (ML) and deep learning (DL) have been widely investigated for earthquake-related tasks such as seismic hazard assessment, earthquake prediction, earthquake early warning (EEW), ground-motion estimation, structural response prediction, damage detection, vulnerability assessment, and structural health monitoring (SHM) [15–19]. ML methods, including support vector machines, decision trees, and ensemble techniques, have proven effective for structured problems with limited complexity [20–22]. More recently, DL approaches—such as convolutional and recurrent neural networks—have enabled the analysis of high-dimensional, temporal, and multimodal data [23–25]. However, persistent challenges remain, including limited labeled datasets, issues with model generalization, and the lack of interpretability in many advanced models [26–28].

To address these limitations, new paradigms have emerged that aim to integrate domain knowledge with data-driven techniques. Physics-informed machine learning and hybrid modeling approaches incorporate fundamental principles of mechanics to improve model reliability and consistency [29]. At the same time, advances in foundation models, particularly large language models (LLMs), have introduced new possibilities for knowledge integration, reasoning, and support for engineering workflows [30]. Furthermore, the emergence of agentic AI—capable of autonomous decision-making and task execution—signals a shift toward intelligent systems that can assist in complex, multi-step engineering processes. However, their application in earthquake engineering remains in its early stages [31].

Several recent reviews have examined AI, ML, DL, SHM, EEW, and disaster-response technologies in earthquake-related fields. These studies summarize trends in model development and application but often focus on specific methods or domains, such as seismic performance assessment, damage detection, forecasting, or disaster management. Few reviews integrate ML, DL, physics-informed learning, hybrid models, LLMs, multimodal AI, digital twins, and agentic AI into a single earthquake-engineering framework and address uncertainty, explainability, reliability, deployment readiness, ethics, safety, and practical implementation.

To clarify the need for the present review, Table 1 compares the focus and limitations of existing review directions with the added value of this manuscript. The main contribution of this paper is not only to summarize AI applications but also to organize them by maturity, engineering function, practical readiness, and role in the broader seismic-resilience workflow.

Table 1: Comparison between existing review directions and the added value of this study.

Existing Review Focus	Limitations of Existing Reviews	Added Value of this Study
AI/ML applications in earthquake engineering	Often focus mainly on conventional ML and DL models, with limited discussion of emerging LLMs, digital twins, and agentic workflows.	Provides an integrated review spanning ML and DL, physics-informed AI, hybrid AI, LLMs, and agentic AI.
Structural health monitoring and damage detection	Often emphasize sensor-based monitoring or image-based damage classification, but do not fully connect SHM to hazard and emergency decision-making and intelligent systems.	Places SHM and damage assessment within a broader earthquake-engineering lifecycle, including hazard, structural response, post-earthquake evaluation, and decision support.

(Continued)

Table 1 (continued)

Existing Review Focus	Limitations of Existing Reviews	Added Value of this Study
Earthquake early warning and seismic signal processing	Usually focus on detection, phase picking, magnitude estimation, or warning performance, with limited treatment of infrastructure decisions.	Connects EEW and seismic signal analysis to structural response prediction, damage assessment, uncertainty quantification, and deployment challenges.
Reviews of LLMs, foundation models, and AI agents	Often, they remain general and are not tailored to earthquake engineering constraints, such as safety, interpretability, and validation.	Critically discusses LLMs and agentic AI in terms of validated applications, early-stage prototypes, hallucination risk, human-in-the-loop control, and deployment readiness.
Bibliometric or trend-based AI reviews	May identify publication growth but provide a limited critical comparison of model maturity and engineering applicability.	Combines literature trends with a taxonomy and comparative synthesis of AI paradigms in terms of interpretability, robustness, scalability, and practical readiness.

To the best of the authors' knowledge, no previous review has simultaneously synthesized ML, DL, physics-informed AI, hybrid AI, LLMs, multimodal AI, digital twins, and agentic AI within a unified earthquake-engineering framework. Therefore, this review addresses this gap by connecting these paradigms to earthquake-engineering applications, practical readiness, and challenges for future deployment.

This review focuses on AI applications that directly support earthquake engineering, earthquake-induced infrastructure, and geotechnical earthquake problems. Covered domains include seismic hazard assessment, earthquake prediction, EEW, ground-motion modeling, structural response estimation, structural and bridge damage assessment, SHM, geotechnical earthquake engineering, earthquake-induced landslide and liquefaction assessment, post-earthquake reconnaissance, and resilient-infrastructure decision support. Broader disaster management, remote sensing, tunneling, road cracking, and social media studies are included only when explicitly linked to earthquake-induced damage, seismic risk, emergency response, or infrastructure resilience, thereby maintaining a focused earthquake-engineering perspective.

This review provides a systematic synthesis of recent advances in artificial intelligence for earthquake engineering, covering the progression from ML and DL to physics-informed and hybrid models, LLMs, and agentic AI. It examines studies published from 2016 to 2026 (Fig. 1) across key domains, including seismic hazard assessment, earthquake prediction, early warning, structural response estimation, earthquake damage detection, structural health monitoring, rapid response, and decision support. The review highlights the transition from isolated predictive models toward integrated, multimodal, and intelligent systems for more reliable earthquake-engineering applications.

Publications from 2026 refer to online-first, early-access, accepted, or indexed articles available at the time of the literature search and were not treated as projected full-year counts. The reviewed studies are grouped into five AI paradigms: ML, DL, physics-informed and hybrid AI, LLMs and multimodal AI, and agentic AI. These paradigms are assessed beyond reported performance by considering interpretability, scalability, uncertainty handling, robustness, and deployment readiness. Because performance metrics differ across datasets, seismic conditions, protocols, and benchmarks, accuracy values are interpreted within each study's task and engineering context.

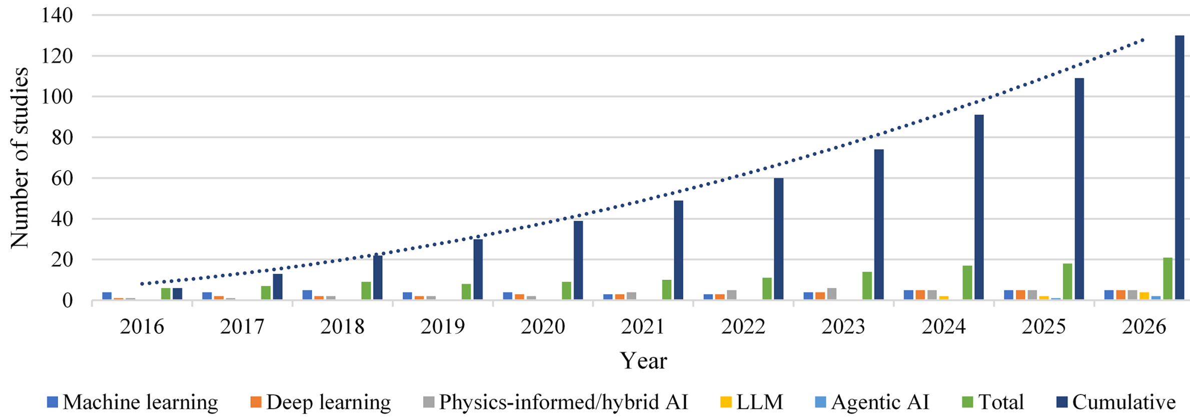

Figure 1: Publication trends in AI-based earthquake engineering studies from 2016 to 2026.

The main contributions of this review are fivefold. First, it synthesizes AI applications across the earthquake-engineering lifecycle, from seismic hazard and prediction to structural response, damage assessment, SHM, and decision support. Second, it develops a taxonomy linking ML, DL, physics-informed learning, hybrid AI, LLMs, multimodal systems, and agentic AI. Third, it compares these paradigms by strengths, limitations, maturity, and deployment readiness, rather than accuracy alone. Fourth, it highlights uncertainty, explainable artificial intelligence (XAI), trustworthy AI, generalization, and operational reliability. Fifth, it identifies priorities for interpretable, reliable, and deployable AI systems in earthquake engineering.

The remainder of this paper is organized as follows. Section 2 presents the review methodology, including the search strategy, eligibility criteria, screening process, study classification, and literature counting procedures. Section 3 introduces the taxonomy of AI paradigms in earthquake engineering. Sections 4 and 5 review ML and DL applications, respectively, while Section 6 discusses physics-informed and hybrid AI models. Section 7 examines LLM and multimodal AI applications, and Section 8 discusses agentic AI and digital-twin workflows. Section 9 provides a critical discussion of cross-paradigm trends, data quality, generalization, benchmarking, uncertainty quantification, explainability, deployment readiness, ethics, and human supervision. Section 10 concludes the paper and outlines future research priorities.

2 Review Methodology

2.1 Search Strategy and Data Sources

Table 2 summarizes the review framework and literature selection criteria used to ensure a structured, state-of-the-art survey. The review strategy was adapted from previous systematic and domain-specific review studies in earthquake engineering, disaster research, construction AI, and machine learning applications [32–36]. This approach focused on AI applications supporting earthquake engineering, earthquake-induced infrastructure challenges, and geotechnical earthquake engineering problems.

Table 2: Review framework and the literature selection criteria used in this study.

Issue	Criterion
Sector	Civil and construction engineering.
General topic	Artificial intelligence in earthquake engineering.
Discipline	Seismic hazard assessment, earthquake prediction, early warning, structural response prediction, damage detection, structural health monitoring, rapid response, and decision support.
Particular topic	Machine learning, deep learning, physics-informed and hybrid AI, large language models (LLMs), and agentic AI for earthquake engineering.
Main search keywords	Artificial intelligence in earthquake engineering; machine learning in earthquake engineering; deep learning in earthquake engineering; physics-informed AI in earthquake engineering; hybrid AI in earthquake engineering; large language models in earthquake engineering; agentic AI in earthquake engineering.
Model-specific keywords	LR, DT, RF, SVM, SVR, KNN, NB, ANN, MLP, CNN, RNN, LSTM, GRU, Transformer, GAN, physics-informed neural network, hybrid deep learning, multimodal learning, LLM, chatbot, agentic AI, multi-agent system.
Application-specific keywords	Seismic hazard assessment, earthquake prediction, early warning, structural response prediction, damage detection, structural health monitoring, rapid response, and decision support.
Time span	January 2016 to March 2026.
Search date	March 2026.
Language	English only.
Availability	Full-text publications are available online.
Source platforms	Engineering Village; ScienceDirect; Springer Nature; Wiley Online Library; Taylor & Francis; Sage; Tech Science Press; MDPI; Frontiers; and arXiv.
Publication type	Research articles, review papers, conference papers, books, book chapters, and preprints are considered when directly relevant to emerging AI paradigms.

The search was conducted using Engineering Village and major academic platforms, including ScienceDirect, Springer Nature, Wiley Online Library, Taylor & Francis, Sage, Tech Science Press, MDPI, Frontiers, and arXiv. These sources were selected because they cover engineering, geotechnical, structural, computational, and AI-related studies relevant to earthquake engineering. In addition, the reference lists of relevant review papers and highly cited articles were checked to identify additional studies that met the review scope.

The search strings combined AI-related terms with earthquake-engineering application terms. The main search expression was structured as follows: (“artificial intelligence” OR “machine learning” OR “deep learning” OR “physics-informed” OR “physics-informed neural network” OR “hybrid AI” OR “large language model" OR "LLM" OR "multimodal AI" OR "agentic AI" OR "multi-agent system" OR "digital twin") AND ("earthquake engineering" OR "seismic hazard" OR "earthquake prediction" OR "earthquake early warning" OR "ground motion" OR "structural response" OR "seismic response" OR "damage detection" OR "structural health monitoring" OR "post-earthquake" OR "bridge damage" OR "liquefaction" OR "earthquake-induced landslide" OR "geotechnical earthquake engineering" OR "decision support").

The core Boolean expression was adapted to each platform according to its search syntax; no platform-specific restrictions were applied beyond title, abstract, keyword, or full-text availability where supported.

Additional targeted searches were performed for specific AI paradigms and application domains, including "machine learning earthquake engineering," "deep learning seismic response prediction," "physics-informed neural network seismic response," "hybrid AI earthquake early warning," "large language model structural damage assessment," "multimodal AI post-earthquake damage," "agentic AI earthquake engineering," and "digital twin seismic monitoring." Abbreviated model names such as LR, DT, RF, SVM, SVR, KNN, NB, ANN, MLP, CNN, RNN, LSTM, GRU, Transformer, GAN, and PINN were also used when searching for model-specific studies.

2.2 Inclusion, Exclusion, and Screening Criteria

Studies were included when they satisfied the following criteria: (1) the study applied or reviewed AI methods in a context directly related to earthquake engineering or earthquake-induced infrastructure and geotechnical problems; (2) the study addressed at least one relevant application domain, such as seismic hazard assessment, earthquake prediction, earthquake early warning, ground-motion modeling, structural response prediction, damage detection, structural health monitoring, geotechnical earthquake engineering, earthquake-induced landslide or liquefaction assessment, post-earthquake reconnaissance, or decision support; (3) the study involved one or more AI paradigms, including ML, DL, physics-informed or hybrid AI, LLMs, multimodal AI, digital twins, or agentic AI; (4) the publication was written in English and available in full text; and (5) the study was published between January 2016 and March 2026.

Studies were excluded when they were outside the scope of earthquake engineering, did not include an AI-based method or AI-related review component, were not available in full text, were not written in English, or focused only on general disaster management without a clear connection to earthquake-induced damage, seismic risk, infrastructure assessment, emergency response, or resilience. Studies related to remote sensing, tunneling, road cracks, landslides, social media, or emergency management were retained only when their connection to earthquake engineering or earthquake-induced effects was explicit. Editorial notes, news articles, nontechnical commentaries, and duplicate records were excluded.

Different publication types were treated according to their evidential role. Peer-reviewed journal articles were prioritized for technical findings, model performance, and engineering conclusions. Review papers were used primarily to identify research trends, summarize established knowledge, and support comparison with existing review directions. Conference papers, books, and book chapters were included when they provided relevant technical or methodological contributions. Preprints, including arXiv records, were considered only for rapidly emerging topics such as LLMs, multimodal AI, and agentic AI, and were interpreted cautiously when discussing engineering maturity and deployment readiness.

2.3 Study Classification, Counting Method, and PRISMA-Style Review Process

The screening process followed a PRISMA-style workflow, as illustrated in Fig. 2. PRISMA checklists are available in the supplementary materials. At the identification stage, 842 records were retrieved from the database and platform searches, and 46 additional records were identified through reference checking and targeted searches. After removing 213 duplicate records, 675 records remained for title and abstract screening. During this stage, 439 records were excluded because they were outside the earthquake-engineering scope, did not involve AI methods, or were not available as English full-text publications. A total of 236 full-text records were then assessed for eligibility. After full-text assessment, 106 records were excluded for insufficient relevance to earthquake engineering, limited technical detail, duplicate content, or a weak connection to the AI paradigms considered in this review. Finally, 130 studies were included in the qualitative synthesis. A small number of earlier foundational or background studies were cited to support historical context and conceptual explanation, but they were not included in the PRISMA-style review framework.

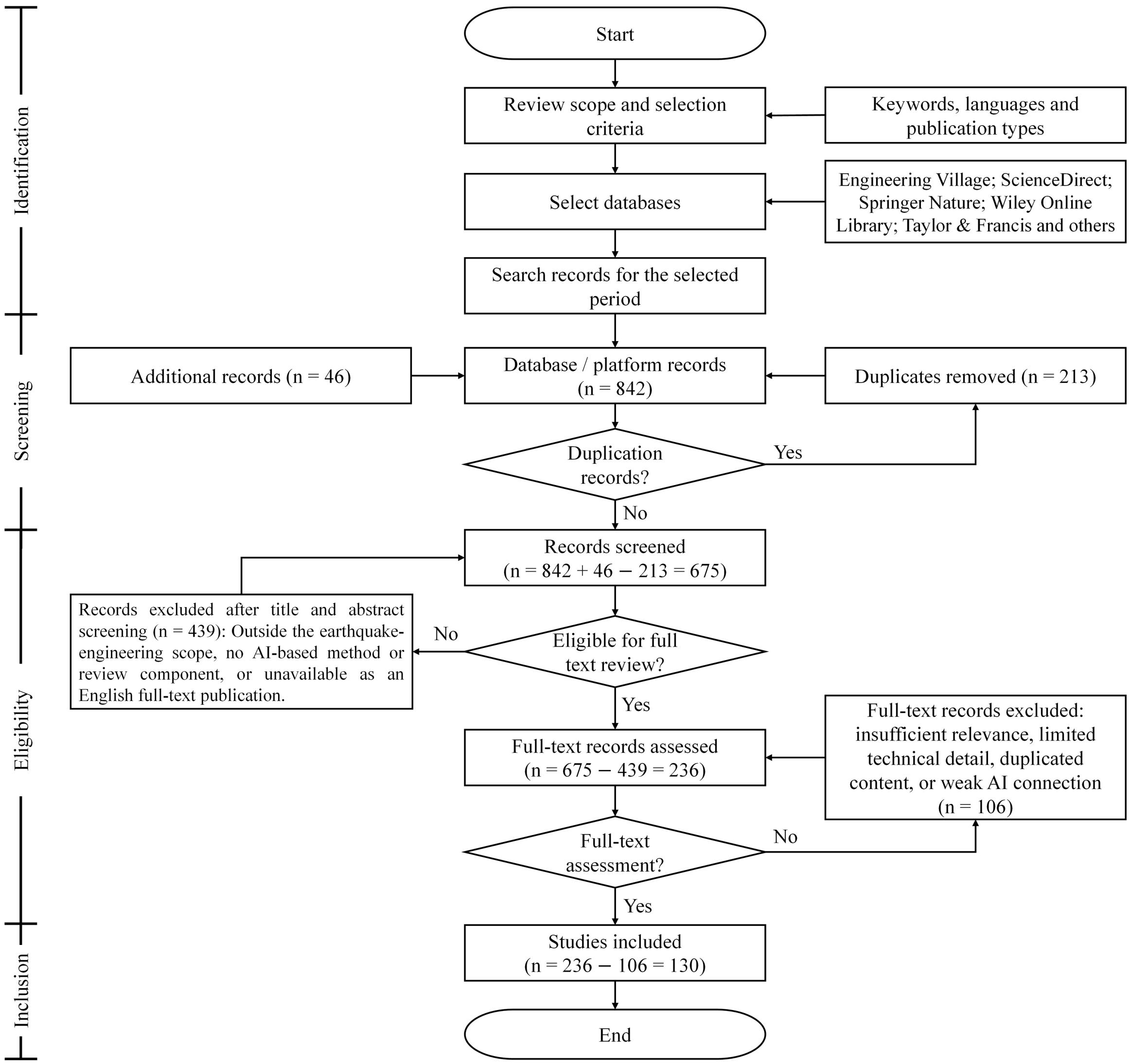

Figure 2: PRISMA-style literature screening process used in this review.

Each included study was classified according to three dimensions: AI paradigm, earthquake-engineering application domain, and review function. The AI paradigm categories were ML, DL, physics-informed and hybrid AI, LLMs and multimodal AI, and agentic AI. The application domains included seismic hazard assessment, earthquake prediction, EEW, ground-motion modeling, structural response estimation, structural and bridge damage assessment, SHM, geotechnical earthquake engineering, earthquake-induced landslide and liquefaction assessment, post-earthquake reconnaissance, and decision support. The review function described whether the study mainly contributed to prediction, classification, optimization, monitoring, assessment, interpretation, decision support, or conceptual framework development.

This review has several limitations related to its search scope and selection criteria. The literature search was restricted to English-language publications available online and primarily focused on studies published between 2016 and 2026. Although this time frame was selected to capture recent developments in ML, DL, physics-informed AI, LLMs, multimodal AI, digital twins, and agentic AI, some relevant earlier or non-English studies may not have been included. In addition, the search was conducted through selected academic platforms, including Engineering Village and major platforms such as ScienceDirect, Springer Nature, Wiley Online Library, Taylor & Francis, Sage, Tech Science Press, MDPI, Frontiers, and arXiv. Therefore, studies published outside these databases, unavailable in full text, or indexed under different terminology may have been missed. These limitations should be considered when interpreting the scope, coverage, and conclusions of this review, although reference checking was used to improve literature coverage.

3 Taxonomy of Artificial Intelligence in Earthquake Engineering

The rapid evolution of AI has produced a diverse range of methods for earthquake engineering, making a clear taxonomy necessary to organize current research and identify the maturity of different approaches [37–40]. In this review, AI methods are classified into five main paradigms: ML, DL, physics-informed and hybrid AI models, LLMs and multimodal AI, and agentic AI systems. These paradigms differ in terms of data requirements, feature representation, interpretability, computational complexity, physical consistency, and deployment readiness. Fig. 3 illustrates the progression from conventional ML models to more integrated and autonomous AI systems, with digital twins serving as an enabling framework that connects these AI paradigms within engineering workflows.

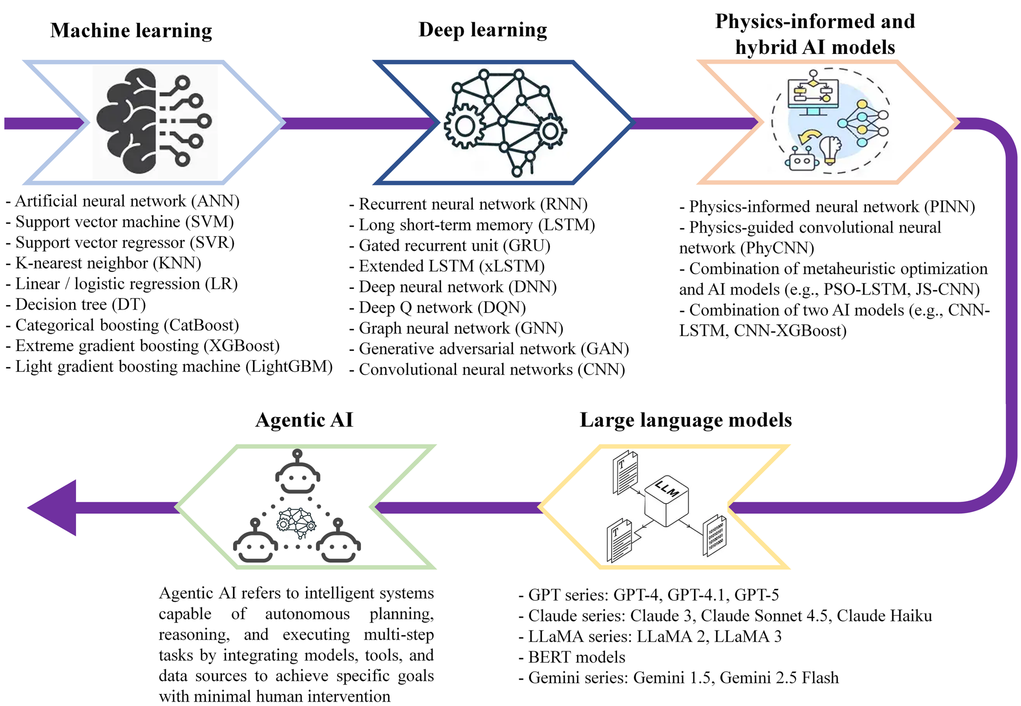

Figure 3: Evolution of AI paradigms from machine learning to agentic AI.

ML methods represent the earliest and most widely adopted stage of AI in earthquake engineering [41]. These methods generally rely on structured datasets, handcrafted features, and statistical learning algorithms, such as regression models, support vector machines, decision trees, random forests, gradient boosting models, and artificial neural networks [20,42–44]. They have been applied to seismic hazard assessment, ground-motion prediction, earthquake detection, liquefaction assessment, structural vulnerability evaluation, and damage classification. Their main strengths are computational efficiency, ease of implementation, and greater interpretability than more complex DL models. However, their performance depends strongly on feature selection, data quality, and the representativeness of the training dataset [45,46].

DL methods extend conventional ML by automatically learning hierarchical features from high-dimensional data, including seismic waveforms, structural response time histories, images, remote-sensing data, and multimodal inputs [25,47–49]. Convolutional neural networks, recurrent neural networks, long short-term memory networks, graph neural networks, and transformer-based models have expanded the applications of AI in seismic signal processing, earthquake early warning, structural response prediction, and post-earthquake damage assessment. These models are particularly useful when nonlinear, temporal, or spatial patterns are difficult to capture through manually designed features [48,49]. Nevertheless, DL models often require large labeled datasets, greater computational resources, and careful validation to avoid overfitting and weak generalization across different seismic regions and structural systems [50,51].

Physics-informed and hybrid AI models have emerged to address some limitations of purely data-driven ML and DL methods. These approaches incorporate physical laws, engineering constraints, numerical simulations, optimization algorithms, or domain-specific knowledge into the learning process [52]. In earthquake engineering, this paradigm is especially important because model predictions must remain consistent with structural dynamics, soil behavior, ground-motion characteristics, and seismic performance principles. Physics-informed and hybrid models can improve robustness, reduce data dependency, and enhance trust in safety-critical applications [53]. However, challenges remain in selecting appropriate physical constraints, balancing data-driven flexibility with physical consistency, and scaling these methods to complex real-world infrastructure systems.

LLMs and multimodal AI represent a more recent paradigm that shifts AI applications from only numerical prediction toward knowledge integration, reasoning support, and human–AI interaction [54,55]. In earthquake engineering, these models can support literature synthesis, technical reporting, code interpretation, visual question answering, structural damage description, and interactive decision support. Multimodal extensions are relevant because earthquake engineering combines text, images, sensor signals, maps, and numerical simulation results. However, LLM-based applications remain in their early stages, and outputs may suffer from hallucinations, data bias, limited grounding, or insufficient validation. Therefore, they should support expert-supervised workflows rather than replace engineering judgment in safety-critical decision-making and assessment.

Agentic AI represents an emerging frontier in which AI systems can plan, coordinate, and execute multi-step tasks by integrating LLMs, external tools, simulation software, databases, sensor streams, and domain-specific models [56]. In earthquake engineering, agentic AI may support automated workflows for seismic risk assessment, structural analysis, post-earthquake inspection planning, digital twin updating, and emergency decision support. Unlike single-task prediction models, agentic systems aim to coordinate multiple components toward broader engineering objectives. However, their use in earthquake engineering remains largely conceptual or in its early stages. Reliability, explainability, accountability, validation, cybersecurity, and human-in-the-loop control remain essential before these systems can be considered suitable for real-world safety-critical deployment.

Overall, this taxonomy shows a progression from task-specific, data-driven models toward more integrated AI systems that combine data, physics, reasoning, and tool-based execution. ML remains useful for structured problems requiring efficiency and interpretability; DL is powerful for complex signals, images, and temporal data; physics-informed and hybrid AI improves consistency with engineering principles; LLMs and multimodal AI enhance knowledge interaction and interpretation; and agentic AI offers a potential pathway toward coordinated engineering workflows. Understanding the strengths, limitations, and maturity of each paradigm is essential for selecting appropriate methods and for guiding future research toward reliable, interpretable, and deployment-ready AI systems in earthquake engineering.

4 Machine Learning in Earthquake Engineering

Machine learning (ML) is among the earliest and most widely used approaches in artificial intelligence for earthquake engineering. It relies on structured datasets, engineered features, and statistical learning algorithms to model seismic and structural problems [57]. Common methods include support vector machines, decision trees, random forests, gradient boosting, k-nearest neighbors, Naïve Bayes, logistic regression, and artificial neural networks. These models depend on domain knowledge to define inputs such as intensity measures, ground-motion parameters, structural properties, site conditions, and damage indicators [58]. ML remains valuable because it is efficient, easy to implement, and often more interpretable than deep learning [59,60]. Table 3 summarizes representative ML applications in earthquake engineering, including their methods, application domains, key findings, and limitations.

Table 3: Summary of machine learning applications in earthquake engineering.

Ref.	Machine Learning Method	Application Domain	Key Findings	Limitations
[61]	Seasonal Autoregressive Integrated Moving Average (SARIMA) with statistical anomaly analysis	Total electron content-based earthquake precursor assessment (Regression)	SARIMA-based forecasting identified anomalous variations in GPS-derived Total Electron Content associated with seismic activity in Northeast India.	Total Electron Content anomalies may be influenced by solar, geomagnetic, atmospheric, and regional effects, requiring broader validation.
[62]	Support Vector Machine (SVM)	Seismic detection for early-warning applications (Classification)	SVM achieved 94.4% accuracy, showing potential for rapid seismic event detection.	Robustness must be improved to reduce false alarms and missed detections.
[63]	Support Vector Machine (SVM)	Seismic detection from waveform signals (Classification)	SVM performed comparably to STA/LTA detection logic for seismic monitoring.	Manual signal-feature design limits flexibility for complex waveform analysis.
[64]	Multilayer Perceptron (MLP)	Earthquake detection in static and dynamic environments (Classification)	MLP achieved 98.96% accuracy with strong precision, recall, and F1-score values.	The model may remain noise-sensitive for large waveform datasets.
[65]	Decision Tree (DT), Random Forest (RF), Logistic Regression (LR), Extreme Gradient Boosting (XGBoost)	Earthquake damage prediction (Classification)	XGBoost achieved the best performance for earthquake-induced building collapse prediction.	Hyperparameter optimization and automatic feature selection were not fully explored.

(Continued)

Table 3 (continued)

Ref.	Machine Learning Method	Application Domain	Key Findings	Limitations
[66]	Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbors (KNN), Multilayer Perceptron (MLP)	Post-earthquake building damage assessment (Classification)	SVM achieved the highest accuracy for post-earthquake building damage-level assessment.	Deep learning and hyperparameter tuning may further improve performance.
[67]	Support Vector Machine (SVM)	Earthquake-induced landslide-prone region assessment (Classification)	SVM achieved an AUROC of 0.9878 for landslide-prone region assessment.	Deep learning may better capture complex landslide-related spatial patterns.
[68]	Random Forest (RF), Extreme Gradient Boosting (XGBoost), Active Learning (AL)	Rapid seismic damage state assessment (Classification)	Active learning achieved 84% accuracy and outperformed XGBoost using fewer samples.	Nonstructural damage and broader loss estimation require further investigation.
[69]	Artificial Neural Network (ANN), Gradient Boosting (GB), Random Forest (RF)	Earthquake early warning (Regression)	Gradient Boosting achieved the lowest MSE and showed stable residual behavior.	Predictions remain sensitive to data distribution and magnitude-range coverage.
[70]	Multilayer Perceptron (MLP), Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbors (KNN), Categorical Boosting (CatBoost)	Earthquake-induced bridge damage prediction (Classification)	MLP achieved the best accuracy and supported fast bridge damage-state prediction.	Heterogeneous datasets may introduce feature inconsistency and reduce reliability.
[71]	Artificial Neural Network (ANN), Random Forest (RF), Support Vector Machine (SVM)	Seismic zone prediction (Classification)	ANN achieved the highest accuracy and F1-score for seismic zone prediction.	Possible overfitting requires broader comparison with other ML variants.
[72]	Random Forest (RF), K-Nearest Neighbors (KNN), Logistic Regression (LR), Decision Tree (DT), Support Vector Machine (SVM), Stochastic Gradient Descent (SGD), Multilayer Perceptron (MLP)	Seismic vulnerability prediction (Classification)	RF achieved 0.90 test accuracy and strong F1 scores across damage classes.	Several evaluated models showed overfitting under training-data-specific conditions.
[73]	K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), Artificial Neural Network (ANN), Adaptive Boosting (AdaBoost), Naïve Bayes (NB)	Post-earthquake building usability prediction (Classification)	RF performed best using building, site, and seismic-intensity features.	Complex input attributes may limit the performance of conventional ML models.

(Continued)

Table 3 (continued)

Ref.	Machine Learning Method	Application Domain	Key Findings	Limitations
[20]	Decision Tree (DT), Support Vector Machine (SVM)	Earthquake magnitude detection (Regression)	DT achieved the highest R^2 value with low computational time.	The model did not fully capture the complexity of the magnitude distribution.
[46]	K-Nearest Neighbors (KNN), Random Forest (RF), Artificial Neural Network (ANN), Extreme Gradient Boosting (XGBoost)	Earthquake magnitude detection (Classification)	ANN achieved the highest accuracy and F1-score over a 7-day window.	Accuracy decreased as the prediction window became longer.
[74]	Maximum Likelihood Estimation (MLE), Random Forest (RF), Support Vector Machine (SVM)	Earthquake probability and land-use assessment (Classification)	SVM achieved the highest accuracy for both evaluated datasets.	Class imbalance requires stronger preprocessing or data augmentation strategies.
[75]	Multilayer Perceptron (MLP), Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Gradient Boosting Classifier (GBC), Gradient Bagging	Earthquake damage assessment (Classification)	RF and GBC showed strong performance across the evaluated damage datasets.	Broader damage datasets are needed to improve model generalization.
[76]	Gradient Boosting (GB), Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Adaptive Boosting (AdaBoost)	Earthquake magnitude detection (Classification)	Gradient Boosting achieved the best accuracy and F1-score among the evaluated models.	Conventional ML may not fully capture nonlinear seismic patterns.
[45]	Artificial Neural Network (ANN), Support Vector Regressor (SVR), Random Forest (RF)	Post-earthquake failure probability assessment (Regression)	ANN achieved the highest R^2 and the lowest error values.	Input features were manually selected using correlation analysis.
[77]	Random Forest (RF), Artificial Neural Network (ANN), Extreme Gradient Boosting (XGBoost), and Support Vector Machine (SVM)	Post-earthquake bridge-network functionality and resilience prediction (Regression)	The stacking ensemble efficiently predicted bridge-network functionality and resilience, with less than 1% error and repair-decision support.	Validation was limited to the Sioux Falls bridge network; broader real-world bridge networks require further testing.
[78]	Decision Tree (DT), Logistic Regression (LR), Random Forest (RF), XGBoost, and K-Nearest Neighbors (KNN)	Earthquake-induced bridge damage prediction (Classification)	ML models supported bridge damage prediction using earthquake-related factors such as magnitude, epicenter, and soil conditions.	Broader validation with larger bridge inventories and diverse seismic regions is needed to improve generalizability.

(Continued)

Table 3 (continued)

Ref.	Machine Learning Method	Application Domain	Key Findings	Limitations
[79]	Lasso Regression, Artificial Neural Network (ANN), Support Vector Machine (SVM), Random Forest (RF), Extreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM)	High-speed railway bridge seismic response prediction and fragility assessment (Regression)	XGBoost reliably predicted bridge seismic responses and supported rapid fragility assessment with reduced nonlinear analysis cost.	Validation focused on a typical high-speed railway continuous bridge; broader bridge types and ground-motion conditions require further testing.
[80]	Decision Tree (DT), Naïve Bayes (NB), Light Gradient Boosting Machine (LightGBM), Support Vector Machine (SVM), Extreme Gradient Boosting (XGBoost)	Seismic damage prediction (Classification)	SVM outperformed the evaluated models for seismic damage prediction.	Better preprocessing and DL-based feature learning may improve performance.
[81]	Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Least-Squares Boosting (LSBoost)	Ground-motion acceleration and velocity prediction (Regression)	LSBoost achieved the highest R^2 and lowest RMSE for ground-motion prediction.	More high-magnitude records are needed for stronger validation.
[82]	Twenty-two ML models, including traditional and ensemble models	Cyclic resistance ratio prediction for liquefaction analysis (Regression)	Extra Trees achieved the best CRR prediction performance, with R^2 = 0.89.	Standardized datasets from diverse seismic regions remain limited.
[83]	Extreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), K-Nearest Neighbors (KNN)	Seismic resilience prediction (Classification)	LightGBM achieved the highest accuracy and supported the derivation of fragility curves.	Automation and user-friendly tools are still needed for practical use.

Note: References [62,63] are earlier foundational studies cited for historical context and were not included in the PRISMA-style review framework or publication-trend counts.

As shown in Table 3, ML has been widely applied to regression and classification tasks in earthquake engineering. Regression applications include earthquake early warning, magnitude estimation, failure probability assessment, ground-motion prediction, bridge-network functionality and resilience prediction, and cyclic resistance ratio prediction for liquefaction analysis. Classification applications include seismic detection, bridge damage prediction, seismic zone classification, vulnerability assessment, post-earthquake building usability prediction, landslide susceptibility assessment, structural damage evaluation, and seismic damage prediction. These applications show that ML is useful for structured input features requiring rapid prediction or classification to support engineering decision-making.

Among the reviewed studies, random forest, support vector machine, artificial neural network, k-nearest neighbors, and boosting-based models such as gradient boosting, XGBoost, LightGBM, CatBoost, and Extra Trees are the most frequently used ML approaches. Their popularity reflects a balance between predictive performance, robustness, computational efficiency, and ease of implementation. Random forest is commonly used in classification problems because of its stability and ability to handle nonlinear feature interactions, while boosting methods often provide strong performance by combining weak learners into more accurate ensemble models. Support vector machines remain useful for smaller or moderately sized datasets, particularly when clear class boundaries can be defined. However, performance differences among these models should be interpreted cautiously because the reported results are based on different datasets, seismic regions, input variables, evaluation metrics, and validation protocols.

The reviewed studies also show that ML performs best when the dataset is sufficiently representative, the input features are well selected, and the target problem has moderate complexity. In such cases, ML can provide fast and practical tools for early warning, vulnerability screening, damage classification, and preliminary decision support. However, several limitations remain. Many studies report data imbalance, limited sample sizes, insufficient representation of large-magnitude events, sensitivity to regional data distributions, and weak generalization across different sites or structural systems. In addition, conventional ML models often depend on manually selected features, which may limit their ability to capture complex temporal, spatial, or multimodal patterns. Overfitting is also a recurring concern, particularly when training datasets are small or highly specific to a single earthquake event, region, or structural typology.

Another important limitation is that most ML studies emphasize predictive accuracy while offering little discussion of uncertainty, explainability, robustness, and deployment readiness. This is critical because earthquake engineering is a safety-sensitive field in which false alarms, missed detections, or poorly generalized predictions can have serious consequences. Although some ML models are more interpretable than deep learning methods, their outputs still require careful engineering interpretation, especially when used for post-earthquake decisions, seismic vulnerability assessment, or infrastructure prioritization. Therefore, future ML studies should move beyond reporting accuracy alone and include uncertainty quantification, model explainability, external validation, sensitivity analysis, and benchmark comparisons across diverse datasets.

To further summarize the model distribution in Table 3, Fig. 4 presents the seven most frequently used ML models in the reviewed studies. RF and SVM appear most often, with 17 and 16 occurrences, respectively, indicating their strong popularity for structured earthquake-engineering datasets and classification-oriented tasks. KNN, ANN, XGBoost, DT, and MLP are also frequently used, reflecting the continued relevance of both conventional classifiers and ensemble-based models. This distribution suggests that ML applications in earthquake engineering remain dominated by interpretable, computationally efficient, and feature-based models. However, boosting and neural network approaches are increasingly used to improve predictive performance.

Overall, ML remains valuable in earthquake engineering, particularly for structured datasets, rapid assessment, and tasks requiring efficient computation and moderate interpretability. Its strengths include practicality, low computational cost, and suitability for decision-support workflows needing fast predictions. However, ML is not universal. Problems involving nonlinear behavior, temporal dependence, image data, multimodal inputs, or large sensor streams may require deep learning, physics-informed learning, hybrid AI, or multimodal systems. Future studies should combine ML with improved preprocessing, automated feature selection, diverse datasets, uncertainty-aware evaluation, and real-time monitoring and decision support.

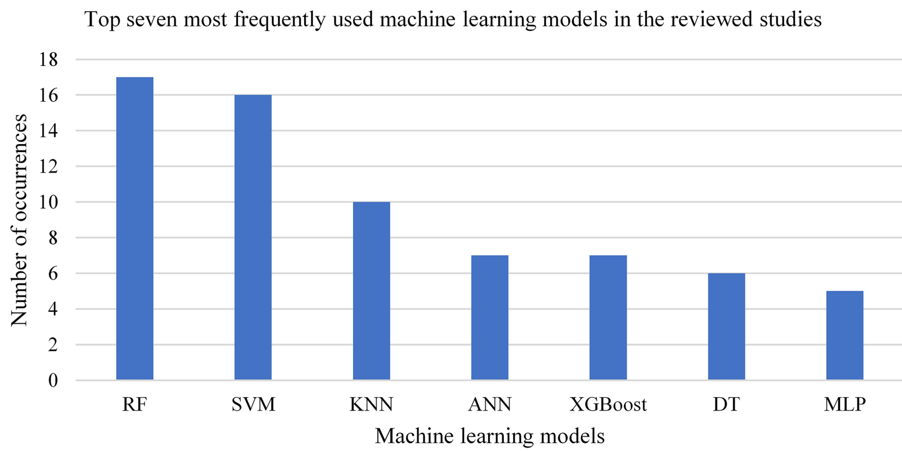

Figure 4: The seven most frequently used machine learning models in the reviewed studies.

5 Deep Learning in Earthquake Engineering

Deep learning (DL) advances conventional machine learning by automatically learning hierarchical features from complex, high-dimensional data [84–86]. Unlike traditional ML, which often relies on manually engineered inputs, DL can extract representations directly from seismic waveforms, structural response histories, images, remote sensing data, and multimodal datasets [87]. This capability is important in earthquake engineering because relevant patterns are nonlinear, time-dependent, spatially distributed, and difficult to capture with handcrafted variables. The growing availability of datasets, improved sensing technologies, and stronger computational resources have further accelerated the adoption of DL in earthquake-related research. Table 4 summarizes representative DL studies, including model types, application domains, key findings, and limitations.

Table 4: Summary of deep learning applications in earthquake engineering.

Ref.	Deep Learning Method	Application Domain	Key Findings	Limitations
[88]	Convolutional Neural Network (CNN)	Generalized seismic phase detection (Classification)	CNN achieved 99% accuracy, showing strong capability for generalized seismic phase detection.	Large labeled datasets and computational resources may be required for reliable deployment.
[89]	Pick-Net (CNN variant)	Seismic arrival-time picking (Classification)	Pick-Net achieved 85.41% accuracy for rapid seismic arrival-time picking.	Accuracy requires improvement for reliable real-time use across diverse seismic records.
[90]	Earthquake Transformer (EQ-T)	Simultaneous earthquake detection and phase picking (Classification)	EQ-T achieved 94.50% accuracy with strong performance in precision, recall, and F1-score.	Transformer-based models are computationally demanding and require large training datasets.

(Continued)

Table 4 (continued)

Ref.	Deep Learning Method	Application Domain	Key Findings	Limitations
[91]	Convolutional Neural Network (CNN)	On-site early PGA prediction for earthquake early warning (Classification)	CNN achieved 97.18% accuracy for early PGA prediction using P-wave inputs.	Deployment requires improved false-alarm control and cross-region generalizability.
[92]	CNN-SET	P-wave detection for earthquake early warning (Classification)	CNN-SET achieved high precision and recall while maintaining fast computational performance.	The model does not yet incorporate multimodal sensor or geodetic data.
[93]	Bi-LSTM, LSTM, GRU	Dynamic earthquake response prediction (Regression)	GRU outperformed RF, achieving a higher R^2 and a lower MAPE.	Interpretability is lower than that of rule-based or feature-based ML models.
[94]	EQGraphNet, MagNet, CREIME, CNQI	Earthquake magnitude prediction (Regression)	EQGraphNet achieved the best performance in magnitude prediction among the evaluated models.	Substantial overfitting requires stronger cross-validation and real-world testing.
[95]	LSTM, Bidirectional LSTM (Bi-LSTM)	Nonlinear seismic ground response prediction (Regression)	Bi-LSTM outperformed LSTM for nonlinear seismic ground response prediction.	Broader earthquake-motion datasets and PGA ranges are needed for validation.
[96]	Multi-Task Focal Mechanism Network (MTFMN)	Earthquake focal mechanism prediction (Regression)	MTFMN achieved very high predictive performance with $R^2 = 0.9998$.	Further feature fusion and architectural optimization may improve robustness.
[97]	CrackNet	Post-earthquake road crack prediction (Classification)	CrackNet achieved 0.942 accuracy using multi-scale raw and processed image inputs.	Real-time drone-based implementation still requires further validation.
[51]	RNN, CONNIP, MOIPor	On-site earthquake intensity prediction (Regression)	MOIPor achieved the best R^2 and MSE for onsite intensity prediction.	Encoder architecture and hyperparameters require further optimization.
[98]	Xception, InceptionV3, InceptionResNetV2, MobileNet, MobileNetV2, DenseNet121, NasNetMobile	Post-earthquake structural damage prediction (Classification)	MobileNet achieved the strongest classification performance among the evaluated CNN architectures.	The model classifies damage severity but not detailed damage mechanisms.
[99]	EEWNet	Real-time seismic response prediction for earthquake early warning systems (Regression)	EEWNet achieved the lowest RMSE compared with XGBoost and ANN.	Computational efficiency remains important for real-time early-warning deployment.
[100]	LSTM, Transformer, PatchTST, Patch-fusion-R	Seismic response prediction (Regression)	Patch-fusion-R achieved the lowest MAE, MSE, and RMSE values.	More parameters and higher memory usage increase computational time.

(Continued)

Table 4 (continued)

Ref.	Deep Learning Method	Application Domain	Key Findings	Limitations
[49]	GoogLeNet-FC	Real-time post-earthquake damage prediction (Classification)	GoogLeNet-FC achieved higher accuracy and F1-score than RF.	Accuracy gains require higher computational time than simpler ML models.
[101]	Deep Neural Network (DNN), Deep Transfer Learning	Seismic landslide hazard assessment (Regression)	Deep transfer learning achieved a higher R^2 than DNN and existing methods.	Reduced explainability limits trust in hazard assessment applications.
[102]	PhaseNet, EQTransformer, SeismoDual	Seismic phase picking prediction (Classification)	SeismoDual achieved very high precision and recall for seismic phase picking.	Automated integration with sensor systems and data pipelines is still lacking.
[103]	RNN, LSTM, GRU, MF-LSTM, MF-GRU	Rapid seismic response prediction (Regression)	MF-GRU achieved the lowest MSE by capturing multi-level temporal features.	Strong performance may depend on extensive tuning and favorable initialization.
[104]	LSTM, LSTM-Kalman Filter	Earthquake occurrence time prediction (Regression)	LSTM-Kalman reduced MAE and RMSE compared with baseline LSTM.	Cross-validation and testing with other DL architectures are needed.
[105]	LSTM and Bi-LSTM	Location-dependent earthquake prediction in seismically active regions (Regression)	The LSTM model achieved the best accuracy, with MAE of 0.08–0.25 for time-difference prediction and 0.016–0.11 for magnitude prediction.	Broader validation across different seismic regions and real-time operational datasets is still needed.

As shown in Table 4, DL has been applied to both regression and classification tasks. Regression applications include earthquake magnitude prediction, seismic response forecasting, onsite intensity prediction, ground response prediction, and earthquake occurrence-time estimation. Classification applications include seismic phase detection, phase picking, earthquake early warning, structural damage recognition, post-earthquake damage assessment, crack detection, and focal mechanism estimation. Compared with conventional ML, DL is especially useful when the input data contains complex temporal, spatial, or image-based patterns. For example, CNN-based models are effective for image- and waveform-based classification. In contrast, recurrent models such as recurrent neural networks (RNNs), long short-term memory (LSTM), gated recurrent units (GRUs), and bidirectional LSTMs (Bi-LSTMs) are useful for sequential response prediction and time-series analysis.

The reviewed studies show that DL models often achieve strong predictive performance and, in several cases, outperform conventional ML methods. Models such as EQGraphNet, EEWNet, GoogLeNet-FC, SeismoDual, Patch-fusion-R, and LSTM-Kalman demonstrate DL's ability to capture nonlinear relationships, temporal dependencies, and multi-scale signal features. The growing use of graph-based networks, transformer-related structures, transfer learning, multi-feature fusion, and hybrid filtering strategies further indicates that progress in DL is no longer driven only by deeper architectures. Instead, recent studies increasingly combine multiple learning mechanisms to improve feature representation, temporal modeling, and prediction robustness for specific earthquake-engineering problems.

Despite these advances, several limitations remain. Many DL models require large labeled datasets, substantial computational resources, and careful hyperparameter tuning. Overfitting is also a recurring issue, especially when training data are limited, imbalanced, or strongly tied to a specific region, structure type, or earthquake scenario. In addition, DL models often behave as black boxes, making it difficult to explain why a prediction is made or how individual input variables influence the result. This is a major concern in earthquake engineering because decisions related to hazard assessment, damage evaluation, early warning, and structural safety require transparency, reliability, and engineering interpretability.

Another important challenge is the gap between benchmark performance and real-world deployment. Many DL studies report high accuracy or low prediction error under controlled datasets. Still, fewer demonstrate reliable performance under noisy sensor data, incomplete field observations, changing site conditions, or real-time operational constraints. Some models also lack direct integration with monitoring systems, sensor networks, digital twins, or automated inspection platforms. Therefore, high model accuracy alone is not sufficient to establish practical usefulness. Deployment-oriented evaluation should consider robustness, uncertainty, computational latency, false-alarm tolerance, transferability across regions, and performance under unseen earthquake and infrastructure conditions.

Future research on DL in earthquake engineering should focus on improving reliability, explainability, efficiency, and operational integration. Important directions include multimodal data fusion, transfer learning across regions and structural types, uncertainty-aware deep learning, explainable neural architectures, automated model updating, and integration with real-time sensor systems. Stronger validation strategies, including cross-validation, external testing, and benchmarking across common datasets, are also needed to ensure reproducibility and fair comparison.

To further summarize the model distribution in Table 4, Fig. 5 presents the frequency of the main deep learning model families used in the reviewed studies. CNNs and their variants are the most widely used, reflecting their strong suitability for seismic signal analysis, image-based damage detection, and feature extraction from complex datasets. LSTM and its variants are also widely applied, particularly for sequential prediction and time-series modeling of seismic or structural responses. Transformer-based models, GRUs, and RNNs appear less frequently but show growing interest in temporal modeling, attention mechanisms, and multimodal learning. Overall, this distribution indicates that deep learning applications in earthquake engineering are dominated by CNN- and LSTM-based architectures, with newer transformer-related models emerging as promising alternatives.

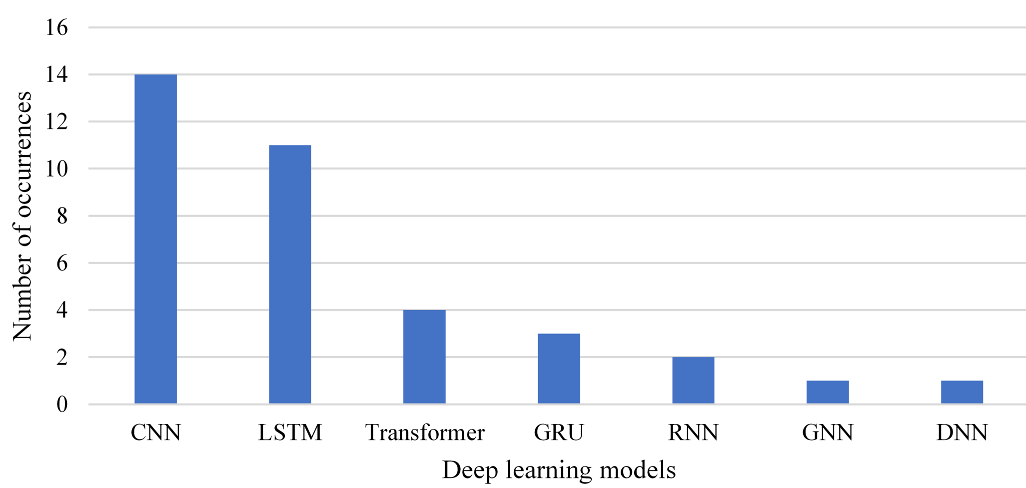

Figure 5: The top seven most frequently used deep learning models in the reviewed studies.

Overall, DL is most valuable when earthquake-engineering problems involve complex nonlinear patterns, high-dimensional inputs, or temporal dependencies; however, its future impact will depend on making these models more interpretable, robust, computationally efficient, and deployment-ready.

6 Physics-Informed and Hybrid AI Models in Earthquake Engineering

Physics-informed and hybrid AI models have emerged to address key limitations of purely data-driven ML and DL approaches, particularly their dependence on large datasets, weak generalization, and limited physical interpretability [106,107]. These models integrate data-driven learning with physical laws, engineering constraints, numerical simulations, optimization algorithms, or domain-specific knowledge [108]. In earthquake engineering, this integration is important because model predictions should remain consistent with structural dynamics, soil behavior, wave propagation, ground-motion characteristics, and seismic performance principles. By embedding physical knowledge or combining complementary models, physics-informed and hybrid AI can improve robustness, reduce data requirements, and increase trust in safety-critical engineering applications [109–111]. Table 5 summarizes representative physics-informed and hybrid AI applications in earthquake engineering.

Table 5: Summary of physics-informed and hybrid AI applications in earthquake engineering.

Ref.	Physics-Informed and Hybrid AI Models	Application Domain	Key Findings	Limitations
[112]	Physics-informed 1D convolutional neural network (CNN)	Seismic response modeling (Regression)	SSM-CNN achieved strong performance, with correlation index values ranging from 0.93 to 0.99.	Hyperparameter optimization was not included, limiting further improvements in performance and efficiency.
[113]	Iterative Neighborhood Component Analysis (INCA) + SVM	Earthquake classification based on seismic signals (Classification)	INCA-SVM achieved the best performance, with 99.62% accuracy and 99.57% F1-score.	The framework was limited to SVM and did not compare newer classifiers or DL models.
[114]	Quantum Machine Learning (QML) models	Post-earthquake building safety assessment (Classification)	QML showed potential for rapid post-earthquake building safety assessment in only a few training epochs.	Simplified architecture, limited iterations, and hyperparameter selection require further investigation.
[115]	AutoML–MCS–NEAT–F-PROMETHEE	Seismic design variability assessment (Decision-making tool)	The framework enabled uncertainty-aware seismic assessment at relatively low computational cost.	More advanced physics-aware or physics-informed models could improve the accuracy of multi-criteria decision-making (MCDM).
[116]	Quantum Convolutional Neural Network (QCNN)	Multiclass seismic damage detection (Classification)	QCNN outperformed nine CNN architectures, achieving 61.2% accuracy.	Accuracy remains limited and requires improved hyperparameter tuning.
[117]	Hybrid Swin Transformer Efficient U-Net (HSTEU-Net)	Earthquake-damaged building detection (Classification)	HSTEU-Net achieved the highest overall accuracy and kappa coefficient among the evaluated models.	Hyperparameter optimization was not included, limiting possible performance improvement.

(Continued)

Table 5 (continued)

Ref.	Physics-Informed and Hybrid AI Models	Application Domain	Key Findings	Limitations
[118]	Hybrid Earthquake Early Warning for Estimating Response Spectra (HEWFERS)	Ground-shaking intensity prediction (Regression and decision-making tool)	HEWFERS achieved R^2 values of 0.81 and 0.85 with interpretable XAI support.	Interactive platforms or LLM-based interfaces are still needed for practical user communication.
[119]	CNN-LSTM-Attention, CNN-LSTM, LSTM, LSTM-Attention	Seismic response prediction (Regression)	CNN-LSTM-Attention achieved R^2 = 0.99 and MAPE = 0.19%, outperforming other models.	The complex architecture increases computational cost and requires optimization.
[120]	Genetic Algorithm–MLP–ANN (GA–MLP–ANN)	Landslide susceptibility assessment (Regression)	GA–MLP–ANN achieved the highest R^2 and the lowest RMSE.	Traditional GA may be less effective than newer continuous optimization methods.
[121]	Physical Convolutional Neural Network (PhyCNN)	Seismic response prediction (Regression)	PhyCNN outperformed CNN and MLP, achieving the highest R^2 value of 0.917.	Hyperparameter optimization was not included, limiting further performance and efficiency gains.
[122]	CNN-LSTM and Physics-Based Diffusion Transformer	Ground-motion time-history prediction (Regression)	The proposed model achieved the lowest MSE and strong signal-to-noise performance.	The model showed the highest inference time among the evaluated approaches.
[123]	Particle Swarm Optimization–LSTM (PSO-LSTM)	Earthquake magnitude prediction (Regression)	PSO-LSTM achieved the best performance among the evaluated hybrid DL models.	The study was limited to LSTM and did not compare GRU or xLSTM models.
[124]	Siamese Deep Neural Network (SDNN) + Anchor Selection	Earthquake seismogram classification (Classification)	SDNN+Anchor effectively classified low-magnitude earthquakes, quakes, rockfalls, and anthropogenic noise.	Metaheuristic optimization may further improve accuracy and computational efficiency.
[125]	Slime Mould Algorithm + Deep and Cross Network (SMA-DCN)	Seismic slope stability prediction (Regression)	SMA-DCN achieved strong predictive performance, with R^2 = 0.967 and low error.	The vertical component of seismic ground motion was not considered.
[126]	Active Learning + XGBoost (AL-XGBoost)	Regional seismic risk assessment of high-speed railway bridges (Regression and classification)	AL-XGBoost achieved reliable seismic risk assessment while reducing the number of labeled samples by more than 70%.	Validation focused on high-speed railway bridges; broader bridge types and regional inventories require further testing.

As shown in Table 5, physics-informed and hybrid AI models have been applied to regression, classification, and decision-support tasks. Regression applications include seismic response prediction, ground-motion time-history simulation, earthquake magnitude estimation, landslide susceptibility assessment, and seismic slope stability prediction. Classification applications include earthquake signal classification, post-earthquake building safety assessment, multiclass seismic damage detection, damaged-building identification, and seismogram classification. Decision-support applications include uncertainty-aware seismic design assessment and hybrid early warning frameworks. These applications show that hybridization is becoming increasingly important because earthquake engineering often requires both predictive accuracy and consistency with physical or engineering principles.

The reviewed studies indicate that hybrid AI models can improve predictive performance by combining multiple sources of information or learning mechanisms. For example, physics-informed CNNs and PhyCNN frameworks improve seismic response prediction by incorporating physical consistency into the learning process. Optimization-based hybrids, such as PSO-LSTM and SMA-DCN, improve parameter search and model calibration. Other approaches, including CNN-LSTM-Attention, hybrid transformer structures, quantum-enhanced models, and AutoML-assisted decision tools, demonstrate that hybrid AI can enable more flexible, task-specific modeling. These results suggest that progress in earthquake engineering AI is moving from single-model prediction toward integrated frameworks that combine data, physics, optimization, and engineering judgment.

A major advantage of physics-informed and hybrid AI is their potential to improve reliability when data are limited or incomplete. This is particularly relevant in earthquake engineering, where strong-motion records, structural damage observations, and geotechnical failure data may be scarce, region-specific, or difficult to obtain. Physics-informed constraints can help guide the learning process and reduce physically unrealistic predictions, while hybrid models can combine complementary strengths from ML, DL, optimization, and numerical simulation. However, the effectiveness of these approaches depends strongly on how physical constraints are formulated, how model components are integrated, and whether the resulting system is validated under diverse seismic and structural conditions.

Despite their potential, several limitations remain. Many studies still rely on simplified physical assumptions, limited training data, small numbers of earthquake scenarios, or specific structural and geotechnical cases. Some models also report high accuracy without sufficient external validation, uncertainty quantification, or comparison with broader ML and DL baselines. In addition, hybrid models can be computationally expensive, difficult to interpret when multiple components are combined, and sensitive to hyperparameter choices. In several cases, the lack of hyperparameter optimization, long inference time, limited real-time integration, or absence of practical user interfaces reduces readiness for operational deployment.

Future research should focus on developing physics-informed and hybrid AI models that are not only accurate but also interpretable, computationally efficient, uncertainty-aware, and deployable in real engineering workflows. Important directions include stronger benchmarking against conventional ML and DL models, better integration with numerical simulations and digital twins, automated hyperparameter optimization, real-time sensor data assimilation, and validation across multiple seismic regions and infrastructure types. Hybrid systems should also incorporate uncertainty quantification and explainable AI to support transparent decision-making.

To further clarify the model distribution in Table 5, Fig. 6 summarizes the reviewed physics-informed and hybrid AI studies into three categories. Hybrid models combining two or more AI components represent the largest group, with eight occurrences, indicating that most studies rely on model fusion, attention mechanisms, transfer learning, or integrated learning frameworks to improve prediction and classification performance. Hybrid models that use metaheuristic or optimization algorithms appear four times, underscoring the importance of parameter tuning and model calibration in earthquake-engineering applications. Physics-informed models appear three times, indicating their growing yet still infrequent use in embedding physical consistency into AI-based seismic response and ground-motion prediction.

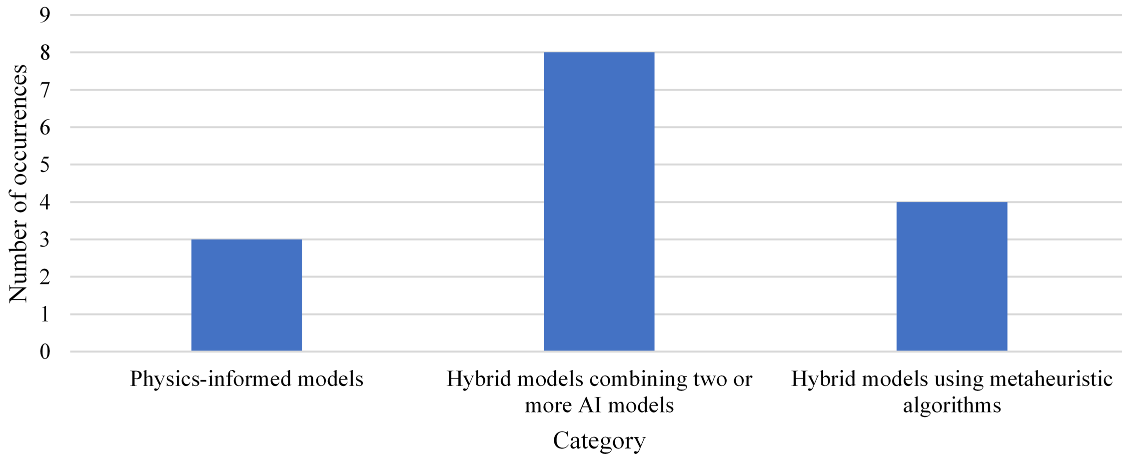

Figure 6: Categorical distribution of physics-informed and hybrid AI models in the reviewed studies.

Overall, physics-informed and hybrid AI provide an important pathway toward trustworthy earthquake-engineering models that combine data-driven flexibility with physical consistency and practical engineering reliability.

7 Large Language Models and Multimodal AI in Earthquake Engineering

Large language models (LLMs) represent a recent development in artificial intelligence that extends AI applications beyond numerical prediction toward knowledge reasoning, natural-language interaction, and decision-support assistance [127]. Unlike conventional ML and DL models, which primarily process structured numerical, waveform, or image data, LLMs are trained on large text corpora. They can generate, summarize, retrieve, and interpret technical information. In earthquake engineering, this capability is useful because relevant knowledge is often distributed across scientific papers, design codes, post-earthquake reports, reconnaissance documents, sensor records, images, and decision-support guidelines [30,128,129]. Table 6 summarizes representative LLM and multimodal AI applications related to earthquake engineering.

Table 6: Summary of large language models and multimodal AI applications in earthquake engineering.

Ref.	LLM or Multimodal AI Model	Application Domain	Key Findings
[127]	Crowdsourced data, large language model framework	Near-real-time earthquake-induced fatality estimation	The framework used crowdsourced data and large language models to enable rapid estimation of earthquake-induced fatalities.
[128]	QuakeBERT (Earthquake Bidirectional Encoder Representations from Transformers)	Earthquake impact analysis	QuakeBERT improved earthquake impact analysis from social media texts through domain-specific fine-tuning and larger training data.
[130]	Federal Emergency Management Agency (FEMA) P-58-enhanced large language model	Seismic loss estimation application and analysis	The enhanced model supported interactive seismic loss estimation through question-answering and semantic reasoning.

(Continued)

Table 6 (continued)

Ref.	LLM or Multimodal AI Model	Application Domain	Key Findings
[30]	Structural Damage Assessment Chatbot (SDAChat)	Structural damage assessment of buildings	Structural Damage Assessment Chatbot enabled image-based damage question answering, achieving an average accuracy of 76.11% across seven tasks.
[131]	Visual Question Answering (VQA) Large Language Model and Multimodal Large Language Model (MLLM)	Landslide image impact assessment	The models supported expert-level landslide image interpretation using vision-language reasoning.
[129]	Large Language Model for Structural Health Monitoring (LLM4SHM)	Structural health monitoring	The framework reduced the processing time for structural health monitoring tasks from hours to minutes through language-model-based support.
[132]	Risk Reasoning and Decision-Making for Earthquake Emergency Scenarios (R2D-EQ)	Earthquake emergency decision-making	The framework improved emergency reasoning by integrating real-time intelligence, event graphs, and retrieval-augmented generation (RAG).
[133]	Multi-Task Structural Damage Assessment Chatbot (MT-SDAChat)	Post-earthquake structural damage assessment of buildings	The chatbot supported multitask structural damage assessment through image-level and regional-level inference.
[134]	Generative Pre-trained Transformer (GPT) 5.1, Claude Sonnet 4.5, Gemini 2.5 Flash, Grok-4, Generative Pre-trained Transformer (GPT) 5-mini, Claude Haiku 4.5, Gemini 2.5 Flash Lite, and Grok-4-fast	Earthquake disaster analysis and assessment	Comparative experiments showed that the properties of synthetic data and model-specific behavior may bias disaster assessments.

As shown in Table 6, LLM-based systems have been applied to earthquake impact analysis, seismic loss estimation, structural damage assessment, landslide image interpretation, structural health monitoring, emergency decision-making, and disaster assessment. These applications indicate that LLMs are not intended to replace conventional ML or DL models. Instead, they expand the role of AI toward knowledge integration, explanation, communication, and interactive decision support. This is particularly relevant in earthquake engineering, where practitioners often need to interpret heterogeneous information under uncertain, incomplete, and time-sensitive conditions.

The reviewed studies show that domain-specific and task-oriented LLM systems can support several earthquake-engineering workflows. QuakeBERT demonstrates that fine-tuning language models on earthquake-related text can improve performance for social media-based earthquake impact analysis. SDAChat and MT-SDAChat show how multimodal LLMs can support post-earthquake structural damage assessment through image-based question answering and damage localization. LLM4SHM highlights the potential of LLMs for structural health monitoring, while R2D-EQ demonstrates the value of retrieval-augmented generation (RAG) for emergency decision-making. These examples suggest that LLMs are most promising when grounded in domain-specific data, connected to external knowledge sources, or integrated with visual and sensor-based models.

Despite these advances, LLM applications in earthquake engineering remain in their early stages. Many current studies rely on controlled datasets, synthetic scenarios, benchmark-style evaluations, or task-specific demonstrations rather than real field deployment. Their performance may be affected by hallucination, incomplete grounding, data bias, limited domain-specific training, and sensitivity to prompt design. In addition, LLMs may produce fluent explanations even when the underlying reasoning or evidence is uncertain. This is a major concern in earthquake engineering because inaccurate or unsupported outputs could affect damage interpretation, emergency response, infrastructure prioritization, and risk communication.

Another important limitation is that most LLM-based frameworks are not yet fully integrated with real-time engineering workflows. Practical deployment would require reliable connections to verified databases, sensor streams, structural analysis tools, geographic information systems, digital twins, and human-in-the-loop review processes. LLM outputs should therefore be treated as assistive interpretations rather than final engineering decisions. For safety-critical applications, model responses must be validated, traceable, uncertainty-aware, and explainable to engineers and decision-makers.

Future research should develop domain-grounded, multimodal, and retrieval-augmented LLM systems for earthquake engineering. Key directions include expanding high-quality domain datasets, integrating LLMs with structural and geotechnical models, improving visual question answering for damage assessment, linking LLMs with real-time monitoring systems, and establishing benchmarks for reliability, hallucination risk, uncertainty communication, and engineering usefulness.

To further summarize the application distribution in Table 6, Fig. 7 presents the main domains of LLM and multimodal AI studies in earthquake engineering. Disaster impact, loss, and emergency decision support represent the largest group, accounting for 56% of the reviewed studies. Structural damage assessment accounts for 22%, while landslide image interpretation and structural health monitoring each account for 11%. This distribution indicates that current LLM applications are concentrated mainly in decision-support and assessment tasks, with more limited but emerging use in SHM and geohazard interpretation.

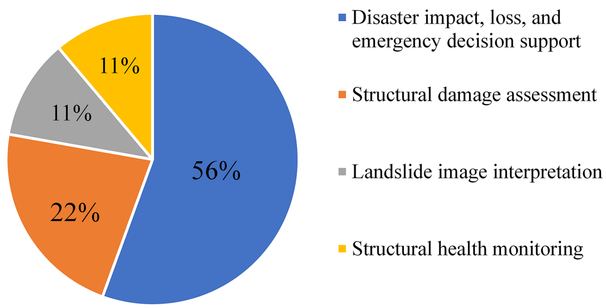

Figure 7: Application distribution of LLM-based and multimodal AI studies in earthquake engineering.

Overall, LLMs can serve as human-supervised assistants for knowledge synthesis, interpretation, and decision support. Still, their application in earthquake engineering should remain cautious, validated, transparent, and guided by expert judgment before wider practical deployment in safety-critical engineering workflows.

8 Agentic AI and Digital–Twin Workflows in Earthquake Engineering

Agentic AI represents an emerging paradigm in which artificial intelligence systems can plan, coordinate, and execute multi-step tasks by interacting with external tools, databases, simulation software, sensor systems, and domain-specific models [135,136]. Unlike conventional ML and DL models that primarily perform isolated prediction or classification tasks, agentic AI supports broader workflows through reasoning, task decomposition, tool use, and iterative feedback. In earthquake engineering, it is relevant to hazard assessment, structural analysis, damage evaluation, inspection planning, emergency response, infrastructure recovery, and digital-twin updating [137]. However, agentic AI remains in its early stages in this field and should be interpreted as a developing framework rather than a mature operational solution.

One of the primary applications of agentic AI is the automation of complex engineering workflows [138]. In earthquake engineering, tasks such as seismic hazard analysis, structural modeling, performance evaluation, and damage assessment often involve multiple sequential steps and tools [139,140]. Agentic systems can coordinate these processes by integrating simulation software, data-processing pipelines, and analytical models into a unified framework [137].

As illustrated in Fig. 8, agentic AI could support future earthquake-engineering workflows by connecting LLMs, physics-based models, numerical simulations, monitoring data, geographic information systems, digital twins, and decision-support tools.

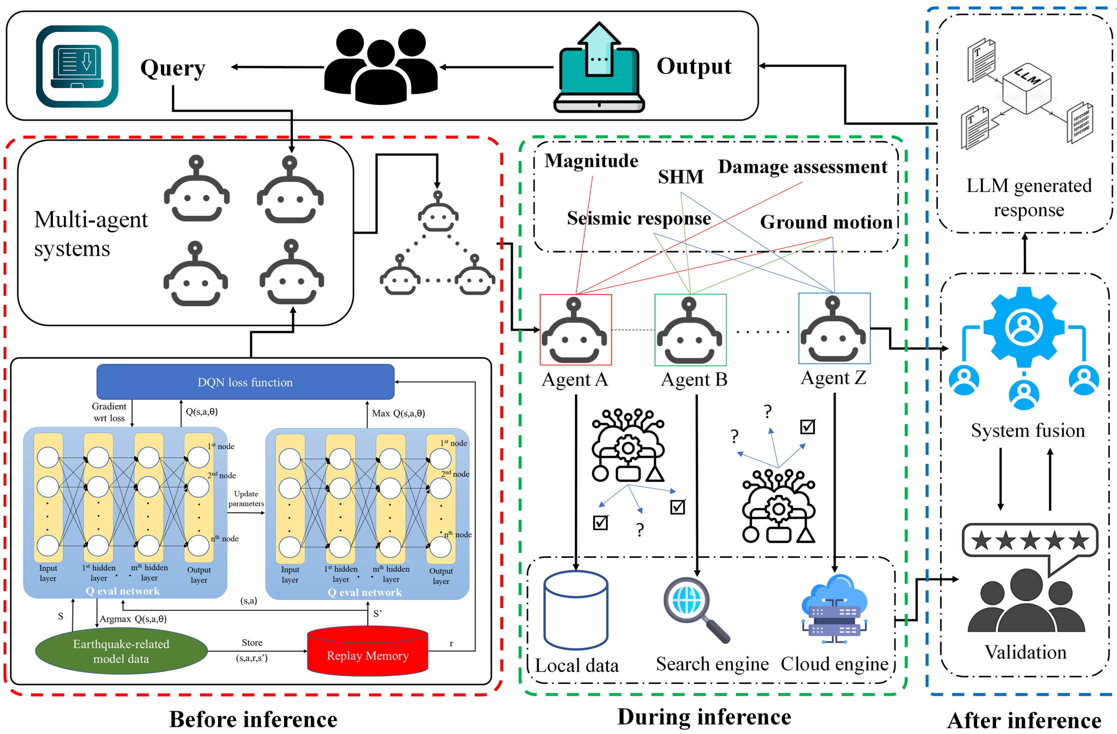

Figure 8: Potential framework for agentic AI in earthquake engineering.

As shown in Fig. 8, an agentic system could retrieve seismic records, select appropriate ground motions, run structural analyses, summarize response results, compare damage indicators, and generate preliminary engineering reports. In post-earthquake situations, such systems could help prioritize inspections, organize field information, update digital twins, and support resource allocation. These capabilities suggest that agentic AI may improve efficiency and coordination in complex workflows, particularly when multiple data sources and engineering tools must be integrated.

A key potential advantage of agentic AI is its compatibility with digital twins and intelligent infrastructure systems. Digital twins require continuous data exchange between physical assets, sensor networks, analytical models, and decision-support platforms [141,142]. Agentic AI can potentially coordinate these components by monitoring incoming data, triggering model updates, and recommending follow-up actions [56]. In seismic applications, this could support real-time structural health monitoring, rapid post-earthquake condition assessment, and adaptive maintenance planning. Nevertheless, such applications require reliable data pipelines, validated models, robust uncertainty handling, and strict human supervision before they can be considered suitable for operational use.

Despite its potential, agentic AI introduces important risks and challenges in earthquake engineering. Because agentic systems may combine multiple models, tools, and data sources, errors can propagate across the workflow and become difficult to detect. Hallucinated reasoning, incorrect tool selection, poor data interpretation, weak validation, cybersecurity vulnerabilities, and lack of accountability are especially concerning in safety-critical applications. In addition, autonomous outputs may appear authoritative even when they are based on incomplete or uncertain information. Therefore, agentic AI should not be used as an independent decision-maker in earthquake engineering. Instead, it should operate within human-in-the-loop frameworks where engineers can verify assumptions, review intermediate outputs, and approve final decisions.

Another challenge is the absence of standardized validation protocols for agentic AI in earthquake engineering. Traditional evaluation metrics such as accuracy, precision, recall, or error values are insufficient for assessing multi-step agentic workflows. Evaluation should also consider task reliability, traceability, uncertainty communication, tool-use correctness, computational latency, robustness under noisy data, and performance under emergency constraints. For real-world deployment, agentic systems must also comply with engineering standards, data governance requirements, cybersecurity practices, and institutional decision-making procedures. These issues are particularly important when agentic AI is connected to sensor networks, digital twins, structural analysis tools, or emergency-response platforms.

Future research should focus on developing trustworthy, transparent, and human-supervised agentic AI systems for earthquake engineering. Important directions include validated tool-use frameworks, benchmark tasks for seismic workflows, integration with digital twins and monitoring systems, uncertainty-aware reasoning, explainable multi-step decision processes, and cybersecurity-aware deployment. Agentic AI should also be tested under realistic earthquake scenarios, including incomplete data, time pressure, conflicting information, and changing infrastructure conditions.

Overall, agentic AI offers a promising pathway toward coordinated and adaptive earthquake-engineering workflows, but its practical value will depend on reliability, validation, transparency, and responsible human oversight.

9 Discussion

9.1 Cross-Paradigm Comparison and Application Trends

The reviewed studies show that AI applications in earthquake engineering have evolved from task-specific predictive models toward more integrated, multimodal, and decision-oriented systems. Fig. 9 summarizes the broader distribution of AI applications across earthquake-engineering problems and provides an overview of how ML, DL, physics-informed AI, hybrid AI, and LLMs contribute to different stages of seismic analysis, damage assessment, monitoring, and decision support. This distribution indicates that AI is no longer limited to a single application area but is increasingly being explored across the full earthquake-engineering lifecycle.

Machine learning remains the most established and practically accessible AI paradigm, especially for structured datasets and classification-oriented tasks. ML models are widely used for seismic vulnerability assessment, damage classification, landslide susceptibility assessment, building usability prediction, bridge damage screening, and resilience-related evaluation. Their strengths include low computational cost, simple implementation, and moderate interpretability. However, performance depends on feature selection, data quality, and dataset representativeness, making ML most suitable for well-defined engineering problems with structured input variables.

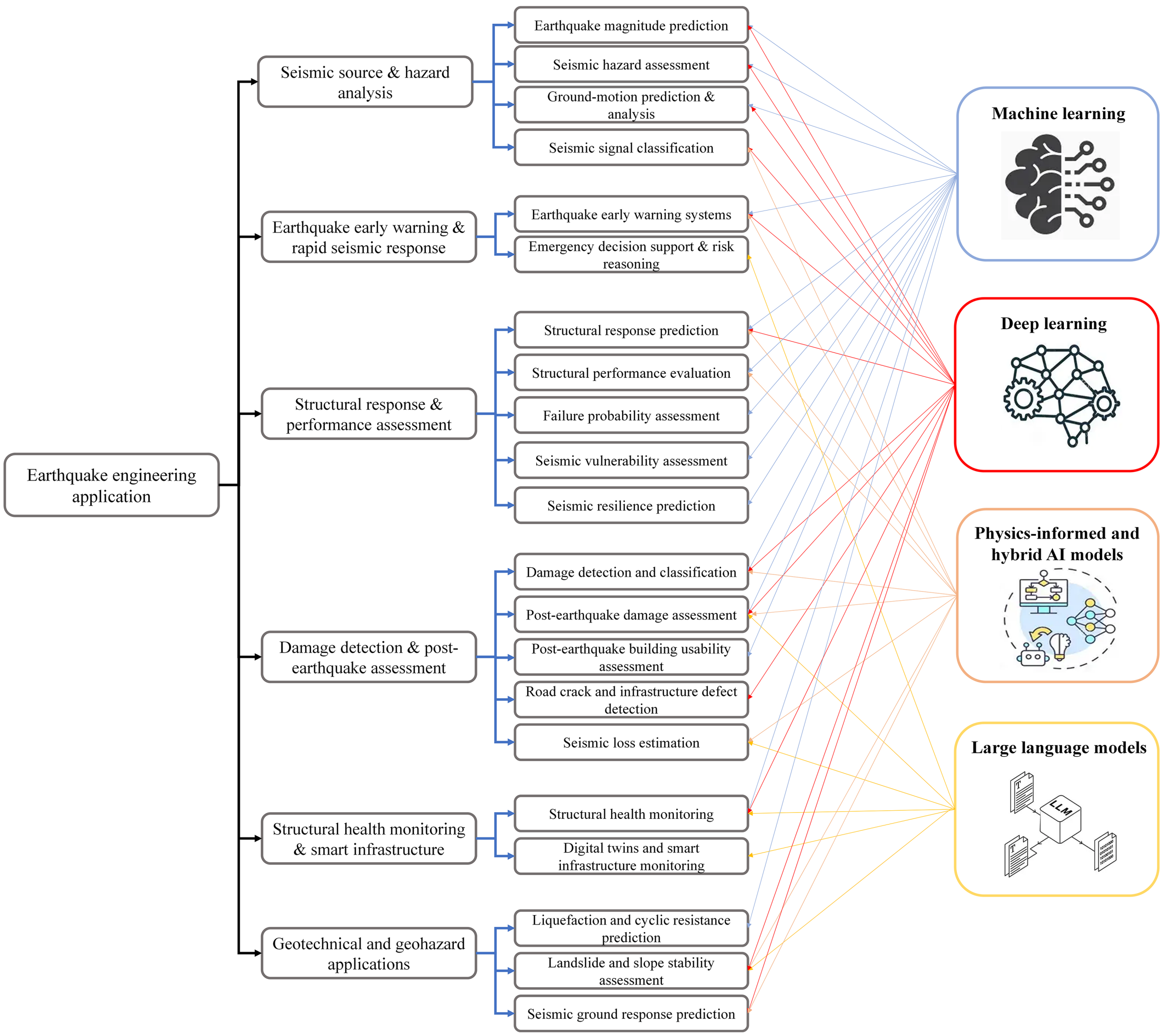

Figure 9: Mapping of AI models to earthquake engineering application domains.

Deep learning extends conventional ML by automatically extracting features from complex, high-dimensional, temporal, and image-based datasets. Reviewed studies show that DL is widely applied to seismic phase picking, earthquake early warning, structural response prediction, damage recognition, crack detection, and ground response modeling. Compared with ML, DL is better suited for waveforms, images, sensor signals, and sequential structural-response data. However, it requires larger datasets, greater computational resources, stronger validation, and improved interpretability for safety-critical engineering applications.

Physics-informed and hybrid AI models mark an important shift from purely data-driven prediction to physically consistent, engineering-aware modeling. These approaches are relevant for seismic response prediction, ground-motion simulation, slope stability assessment, structural safety evaluation, and hybrid early-warning frameworks. Their main advantage is combining learning algorithms with physical laws, numerical simulation, optimization, and domain knowledge. This can improve robustness and reduce unrealistic predictions, although effectiveness depends on physical assumptions, integration strategy, and validation across seismic conditions.

LLMs, multimodal AI, and agentic AI are newer, less mature paradigms that extend AI beyond prediction and classification. LLM-based systems can support literature synthesis, technical reporting, visual question answering, structural damage interpretation, SHM, and emergency decision support. Agentic AI further expands this role by coordinating tools, databases, simulations, sensors, and digital twins within multi-step workflows. However, these paradigms require validation, grounding, human supervision, and safeguards against hallucination, bias, and unreliable autonomous reasoning.

Fig. 10 further illustrates the distribution of earthquake-engineering applications across AI paradigms. ML is concentrated in classification and structured assessment, whereas DL is more common for signal, image, and time-series applications. Physics-informed and hybrid AI primarily support response prediction and physically constrained modeling, whereas LLMs and agentic AI primarily support interpretation, interaction, decision support, and workflow automation. These trends show that future progress will depend on selecting or combining methods according to data type, physical complexity, interpretability, computational cost, and deployment needs.

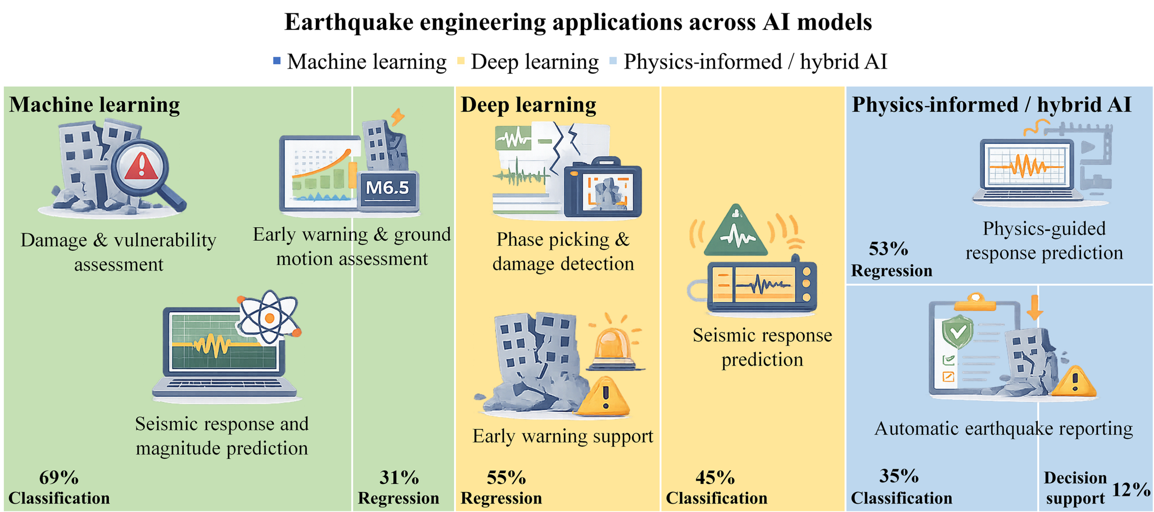

Figure 10: Distribution of earthquake engineering applications across AI models.

To further support cross-paradigm comparison, Table 7 summarizes the reviewed AI paradigms in terms of data requirements, interpretability, computational cost, scalability, robustness, and deployment readiness. This comparative framework highlights the practical trade-offs among ML, DL, physics-informed and hybrid AI, LLMs, multimodal AI, and agentic AI. It provides a structured basis for selecting suitable approaches for different earthquake-engineering tasks.

Table 7 shows that no single AI paradigm is universally superior across all evaluation criteria. ML remains the most practical for structured and computationally efficient tasks, whereas DL is stronger for high-dimensional signals, images, and time-series data. Physics-informed and hybrid AI provide better physical consistency and robustness, while LLMs and agentic AI expand AI toward interpretation, interaction, and workflow automation. Therefore, future earthquake-engineering applications should select or combine AI paradigms according to data availability, physical complexity, interpretability needs, computational constraints, and deployment requirements.

Table 7: Comparative assessment of AI paradigms in earthquake engineering.

AI Paradigm	Data Requirements	Interpretability	Computational Cost	Scalability	Robustness	Deployment Readiness
Machine learning	Low to moderate; suitable for structured tabular datasets with engineered features.	Moderate to high, especially for tree-based models and feature-importance analysis.	Low to moderate, making it suitable for rapid screening and preliminary decision support.	Moderate; scalable for structured data but limited for complex multimodal inputs.	Moderate; performance depends strongly on feature quality and data balance.	Relatively high for structured assessment tasks but requires external validation and uncertainty-aware evaluation.
Deep learning	High; usually requires large labeled waveform, image, sensor, or time-series datasets.	Low to moderate; black-box behavior remains a major concern without explainable AI methods.	Moderate to high due to complex architectures, training demands, and memory requirements.	High for large-scale waveform, image, and sensor-data applications.	Moderate; powerful for complex patterns but sensitive to overfitting and dataset shift.	Moderate; promising for real-time systems but requires robustness testing, latency control, and operational integration.
Physics-informed and hybrid AI	Moderate; can reduce data dependence by incorporating physical laws, simulations, or optimization.	Moderate to high when physical constraints or explainable components are explicitly included.	Moderate to high, depending on simulation coupling, optimization strategy, and model complexity.	Moderate; scalability depends on computational efficiency and integration with numerical models.	High potential because physical constraints can reduce unrealistic predictions and improve generalization.	Moderate; strong potential for engineering use, but broader benchmarking and real-world validation are still needed.
Large language models and multimodal AI	High; requires domain-specific text, image, sensor, or retrieval databases for reliable grounding.	Moderate; outputs are readable, but reasoning may be difficult to verify without traceable evidence.	Moderate to high, especially for large models, multimodal processing, and retrieval-augmented workflows.	High for knowledge synthesis, reporting, visual question answering, and interactive decision support.	Low to moderate; affected by hallucination, bias, prompt sensitivity, and incomplete grounding.	Low to moderate; useful as assistive tools but not yet reliable as independent engineering decision-makers.
Agentic AI	High; requires validated tools, databases, sensor streams, simulation models, and workflow-specific knowledge.	Low to moderate; multi-step reasoning and tool use require traceability and human review.	High because agents may combine LLMs, simulations, databases, digital twins, and iterative workflows.	High potential for coordinating complex, multi-step earthquake-engineering workflows.	Low to moderate at present; errors can propagate across tools and workflow stages.	Low at present; remains early-stage and requires validation, cybersecurity, governance, and human-in-the-loop control.

To complement the publication trend and cross-paradigm analyses, Table 8 summarizes the thematic evolution of AI applications in earthquake engineering from 2016 to 2026. This descriptive mapping shows how the field has progressed from conventional ML-based prediction and classification toward advanced DL, physics-informed and hybrid AI, multimodal learning, LLM-based interpretation, and agentic AI-supported workflows. Although this study does not aim to provide a full scientometric network analysis, the thematic evolution provides additional bibliometric-style evidence of how research priorities have shifted over time.

Table 8: Thematic evolution of AI applications in earthquake engineering from 2016 to 2026.

Period	Dominant AI Paradigms	Main Application Themes	Emerging Research Focus
2016–2019	Conventional ML and early DL	Seismic detection, earthquake prediction, ground-motion modeling, vulnerability assessment, and early damage classification	Feature engineering, structured datasets, basic classification and regression models, and early comparison between ML and traditional approaches
2020–2022	ML, DL, and early hybrid models	Earthquake early warning, seismic signal processing, structural response prediction, SHM, liquefaction assessment, and image-based damage detection	Automatic feature extraction, waveform analysis, sensor-based monitoring, early XAI discussion, and improved model validation
2023–2024	Advanced DL, transfer learning, multimodal learning, and hybrid AI	Post-earthquake damage assessment, landslide susceptibility, bridge and building damage evaluation, resilience assessment, and rapid response	Larger datasets, multimodal inputs, transfer learning, real-time prediction, model generalization, and domain-specific adaptation
2025–2026	Physics-informed AI, hybrid AI, LLMs, multimodal AI, digital twins, and agentic AI	Structural response prediction, ground-motion simulation, visual question answering, emergency decision support, digital-twin integration, and automated workflows	Trustworthy AI, uncertainty quantification, XAI, human-in-the-loop systems, retrieval-augmented reasoning, deployment readiness, and responsible autonomy

Table 8 indicates that AI research in earthquake engineering has shifted from model-centered prediction toward integrated, trustworthy, and deployment-oriented systems. Earlier studies mainly emphasized predictive accuracy for structured or signal-based tasks, whereas recent studies increasingly focus on multimodal data integration, physical consistency, uncertainty communication, explainability, and operational use. This evolution supports the broader argument of this review: future earthquake-engineering AI should not only improve model performance but also enhance reliability, transparency, and practical decision support.

9.2 Data Quality, Generalization, and Benchmarking

Despite the rapid development of AI applications in earthquake engineering, data-related limitations remain a major barrier to reliable and practical use. Many reviewed studies rely on datasets that are limited in size, region-specific, imbalanced, or collected under controlled conditions. This issue is particularly important in earthquake engineering because destructive earthquakes are rare, large-magnitude records are limited, and post-earthquake damage observations are often incomplete, inconsistent, or difficult to standardize. As a result, models that perform well on benchmark datasets may not generalize reliably to different seismic regions, structural systems, soil conditions, construction practices, or infrastructure inventories.

Generalization is therefore one of the most critical challenges across ML, DL, physics-informed (PI) models, LLMs, and agentic AI. Many models are trained and tested using data from specific earthquakes, building types, sensor networks, or geographic areas. Although these models may achieve high accuracy within the original dataset, their performance can decrease when exposed to unseen ground motions, unfamiliar structural typologies, noisy monitoring data, incomplete field observations, or different damage mechanisms. This limitation is especially important for safety-critical earthquake-engineering applications, where predictions must remain reliable under rare but high-consequence events. Future studies should therefore emphasize external validation, cross-region testing, transferability analysis, and datasets that better represent diverse seismic and infrastructure conditions.

Benchmarking also requires further improvement. Reported performance indicators, such as accuracy, F1-score, R^2, RMSE, and MAE, are often difficult to compare across studies because they are obtained from different datasets, tasks, input features, hazard levels, validation strategies, and evaluation protocols. A model with high accuracy on a simple or balanced dataset may not be more useful than a model with lower accuracy on a complex, imbalanced, or real-world dataset. Therefore, model evaluation should move beyond performance values alone and consider dataset complexity, physical plausibility, robustness, computational cost, transferability, uncertainty, and readiness for engineering deployment. Standardized open-access datasets and common benchmarking protocols would greatly improve reproducibility, fair comparison, and practical confidence in AI-based earthquake-engineering models.

9.3 Uncertainty Quantification, Explainability, and Trustworthy AI

Uncertainty quantification remains essential but underdeveloped in AI-based earthquake engineering. Uncertainty can arise from ground-motion variability, structural modeling assumptions, material properties, soil conditions, sensor noise, damage-state ambiguity, incomplete field observations, and limited training data. However, many studies still report deterministic outputs without prediction confidence, uncertainty ranges, or probabilistic interpretation. This limits their usefulness for emergency response, structural safety assessment, infrastructure prioritization, and risk-informed decisions. Future AI systems should include probabilistic prediction, prediction intervals, Bayesian inference, ensemble learning, or uncertainty-aware frameworks so that engineers can interpret both outcomes and confidence levels.

Explainability is equally important because earthquake-engineering decisions require transparency, accountability, and engineering interpretation. Conventional ML models may provide moderate interpretability through feature importance, decision rules, or sensitivity analysis. In contrast, DL models, LLMs, multimodal AI, and agentic AI systems are often more difficult to interpret. In safety-critical applications, black-box predictions are insufficient if engineers cannot understand why a damage classification, seismic response prediction, or decision recommendation was produced. Therefore, explainable artificial intelligence (XAI) methods, including feature attribution, attention visualization, sensitivity analysis, counterfactual explanation, physical constraints, and traceable reasoning, should be incorporated during model development, validation, and deployment.

Fig. 11 summarizes the relationship between technical limitations, AI model development, trustworthy evaluation, and engineering outcomes. As shown, imbalanced datasets, noisy measurements, heterogeneous infrastructure conditions, incomplete observations, and operational variability can directly affect model training and prediction reliability. To reduce these risks, AI systems should be evaluated through a trustworthy framework that emphasizes validation, robustness, uncertainty quantification, explainability, and interpretability.

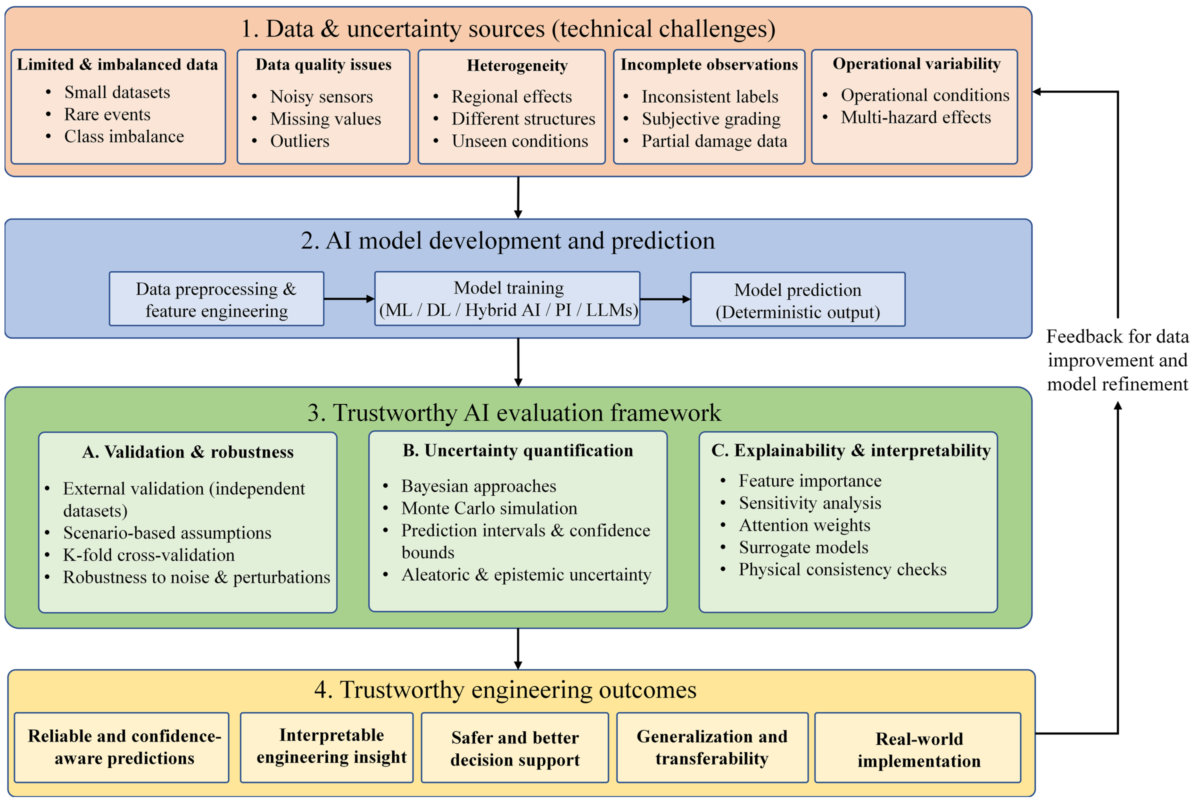

Figure 11: Framework for uncertainty-aware and explainable AI evaluation in earthquake engineering.

Overall, data quality, generalization, uncertainty, and explainability are closely interconnected. Poor or biased data weaken generalization, limited generalization increases uncertainty, and insufficient explainability makes uncertainty harder to interpret. Addressing these issues requires moving from accuracy-centered model development toward trustworthy AI systems that are validated, transparent, uncertainty-aware, and physically meaningful. This shift is essential because AI-supported outputs may influence infrastructure safety, emergency response, risk prioritization, and community resilience.

9.4 Deployment Readiness, Ethical–Legal Issues, Safety, and Human Supervision

A major challenge for AI in earthquake engineering is the gap between model capability and real-world deployment. Although many studies report high accuracy or low prediction error under controlled conditions, practical implementation remains limited by noisy sensor data, incomplete field observations, changing structural conditions, regional differences, and real-time operational constraints. Deployment-ready AI systems must therefore be evaluated not only by predictive performance but also by robustness, latency, scalability, maintainability, uncertainty communication, and compatibility with existing engineering workflows. For earthquake engineering, these requirements are especially important because AI outputs may influence structural safety assessment, emergency response, infrastructure prioritization, and resilience planning.

From a practical engineering perspective, AI supports different earthquake-engineering domains in complementary ways. In bridge engineering, it can assist rapid damage screening, portfolio-level vulnerability assessment, bridge-network functionality and resilience prediction, fragility analysis, and prioritization of post-earthquake inspection or retrofit actions. In geotechnical earthquake engineering, AI can support liquefaction assessment, seismic slope stability evaluation, landslide susceptibility mapping, ground-response prediction, and site-specific hazard interpretation when field data are incomplete or spatially variable. For structural damage assessment, AI can improve image-based recognition, sensor-based SHM, usability evaluation, and rapid safety classification.

Operational deployment also requires stronger integration between AI models and engineering infrastructure. Many existing studies remain offline or benchmark-oriented, with limited connection to real-time monitoring systems, sensor networks, geographic information systems, digital twins, inspection platforms, or structural analysis software. Future AI systems should be designed as components of broader decision-support environments rather than standalone predictive tools. This requires reliable data pipelines, automated model updating, standardized input formats, and validation procedures that reflect realistic earthquake scenarios. In this context, digital twins can serve as an important platform for integrating sensor data, physics-based models, AI predictions, and human decision-making.

Ethical and safety considerations are central to the use of AI in earthquake engineering. Errors in seismic risk assessment, damage classification, early warning, or emergency decision support may have serious social, economic, and safety consequences. Therefore, AI systems must be developed with attention to accountability, transparency, fairness, cybersecurity, data privacy, and risk communication. Bias in training data may lead to unreliable predictions for underrepresented regions, construction types, or infrastructure systems. Similarly, cyber vulnerabilities may become critical when AI systems are connected to sensor networks, digital twins, or emergency-response platforms. These issues require governance frameworks that define responsibilities, validation requirements, and acceptable levels of automation.

Human supervision remains essential for all safety-critical AI applications in earthquake engineering. AI systems should assist engineers by organizing information, identifying patterns, estimating uncertainty, and supporting scenario analysis, but final decisions should remain under expert control. This is particularly important for LLMs and agentic AI systems, which may generate fluent explanations or autonomous recommendations even when their outputs are incomplete, uncertain, or insufficiently grounded. Human-in-the-loop workflows should therefore include verification of assumptions, review of intermediate outputs, traceability of model reasoning, and clear procedures for approving or rejecting AI-supported recommendations.

Fig. 12 presents a conceptual roadmap for rethinking earthquake engineering in the AI era. The roadmap emphasizes a transition from isolated, model-centric development toward integrated, interpretable, human-supervised, and deployment-ready systems. Rather than treating ML, DL, physics-informed and hybrid AI, LLMs, and agentic AI as separate research directions, future earthquake-engineering frameworks should combine their complementary strengths within trustworthy decision-support ecosystems. By advancing toward validated, uncertainty-aware, and operationally integrated AI systems, earthquake engineering can better support resilient infrastructure, rapid post-earthquake response, and safer communities.

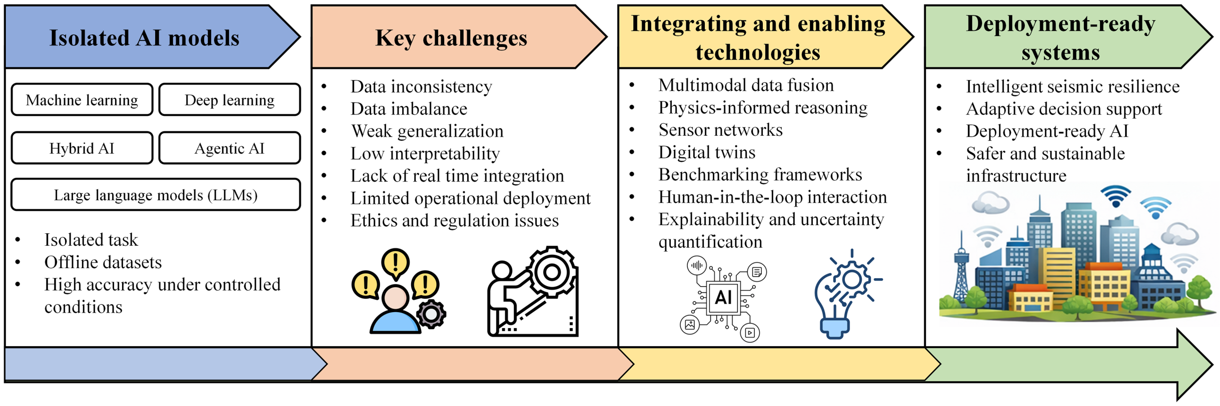

Figure 12: Conceptual roadmap for rethinking earthquake engineering in the AI era.

10 Conclusions

This study provides a systematic synthesis of artificial intelligence applications in earthquake engineering, covering the progression from conventional machine learning and deep learning to physics-informed and hybrid AI, large language models, multimodal AI, and agentic AI. The reviewed studies show that AI has become increasingly important across the earthquake-engineering lifecycle, including seismic hazard assessment, earthquake prediction, earthquake early warning, ground-motion modeling, structural response prediction, damage assessment, structural health monitoring, geotechnical earthquake engineering, post-earthquake reconnaissance, and decision support. Overall, the field is shifting from isolated predictive models toward more integrated, multimodal, and decision-oriented AI systems.

Each AI paradigm offers distinct strengths and limitations. Machine learning remains valuable for structured datasets, rapid assessment, and computationally efficient classification or regression tasks. Deep learning is well-suited to complex waveforms, images, sensor signals, and time-dependent structural response data, but often requires large datasets and careful validation. Physics-informed and hybrid AI models provide an important pathway for combining data-driven learning with engineering knowledge, physical constraints, optimization, and numerical simulations. Meanwhile, large language models, multimodal AI, and agentic AI expand the role of AI toward knowledge interpretation, human–AI interaction, workflow automation, and decision-support assistance. However, these emerging paradigms remain in their early stages in earthquake engineering and require careful grounding, validation, and human supervision.

Several cross-cutting challenges must be addressed before AI can be reliably deployed in safety-critical earthquake-engineering applications. These include limited and imbalanced datasets, weak generalization across regions and structural systems, inconsistent benchmarking, insufficient uncertainty quantification, limited explainability, and the gap between benchmark performance and real-world operational use. Reported model accuracy alone is insufficient to demonstrate practical readiness, as AI systems must also be robust, interpretable, uncertainty-aware, computationally efficient, and compatible with engineering workflows. These requirements are especially important for applications involving structural safety, emergency response, infrastructure prioritization, and resilience planning.

Future research should prioritize developing trustworthy, deployment-ready AI systems for earthquake engineering. Key directions include standardized, open-access datasets; common benchmarking protocols; external validation across diverse seismic regions and infrastructure types; uncertainty-aware modeling; explainable AI; multimodal data fusion; real-time integration with monitoring systems; and stronger coupling with digital twins. For large language models, multimodal AI, and agentic AI, future work should focus on domain-grounded models, retrieval-augmented workflows, validated tool-use frameworks, cybersecurity-aware deployment, and human-in-the-loop control. Overall, the future of AI in earthquake engineering should not be defined only by higher predictive accuracy but by the development of reliable, transparent, physically meaningful, and human-supervised systems that support safer and more resilient infrastructure.

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Ethics Approval: Not applicable.

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