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MACHINE LEARNING APPLICATIONS IN STRUCTURAL DYNAMIC RESPONSE PREDICTION OF HIGH-RISE BUILDINGS UNDER WIND AND SEISMIC EXCITATIONS: A SYSTEMATIC REVIEW

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Abstract

The prediction of structural dynamic responses in high-rise buildings under wind and seismic excitations is essential for performance-based engineering, yet traditional physics-based methods remain computationally prohibitive for real-time and large-scale applications. Machine learning has emerged as a promising alternative, but the field lacks a coherent synthesis of its diverse methodological developments and practical limitations. We conducted a systematic review following the PRISMA framework to critically map and evaluate the existing evidence on machine learning applications for this problem. Our objectives were to categorize the predominant ML architectures, identify critical gaps in validation and generalizability, and assess reported effectiveness in terms of accuracy, efficiency, and robustness. A comprehensive search across seven major databases was performed using the Population-Exposure-Outcome framework, with inclusion criteria requiring quantitative validation against physical data or high-fidelity simulations. The review reveals a rapidly expanding field where recurrent neural networks, particularly Long Short-Term Memory networks, dominate time-series prediction tasks and generally outperform feed-forward alternatives by capturing temporal dependencies. A notable methodological shift is the integration of physics-informed neural networks, which embed governing equations into the loss function and thereby improve predictive accuracy and physical plausibility, especially under data scarcity. Transfer learning has also gained traction for adapting models across building typologies and hazard scenarios. However, key challenges persist: data scarcity for extreme events, poor generalizability across diverse structural configurations, and the absence of standardized error metrics preclude meaningful cross-study comparison. We conclude that machine learning provides a computationally efficient paradigm for dynamic response prediction, with hybrid data-physics approaches showing the most promise for overcoming current limitations. Nevertheless, the gap between proof-of-concept studies and validated, generalizable tools remain substantial, primarily due to the lack of standardized development and validation frameworks. Future efforts should prioritize open benchmark datasets and performance metrics that reflect both accuracy and practical decision-making utility.

1. Introduction

High-rise buildings have become indispensable to modern urban landscapes, serving as symbols of economic prosperity and technological capability. The structural design of these slender, often flexible, systems is predominantly governed by their dynamic behavior under environmental loads, particularly wind and seismic excitations [1]. The response to these excitations—quantified in terms of accelerations, inter-story drifts, and base shears—is central to ensuring both structural integrity and occupant comfort during extreme events [2]. Accurate prediction of these dynamic responses is, therefore, a cornerstone of performance-based structural engineering, where design decisions are made based on probabilistic assessments of structural performance under a range of hazard scenarios [3].

Classical methods for predicting structural dynamic responses have traditionally relied on physics-based models. The most fundamental of these is the modal analysis method, which decomposes the structural response into a set of independent vibration modes [4]. For linear elastic systems, this approach is highly efficient. However, high-rise buildings frequently exhibit nonlinear behavior under severe wind and seismic loads due to material yielding, geometric nonlinearity, and the opening and closing of gaps in connections [5]. To capture these nonlinearities, practitioners often resort to incremental dynamic analysis (IDA), where a detailed finite element (FE) model is subjected to a set of scaled ground motion records [6]. Similarly, for wind engineering, nonlinear time-history analyses using computational fluid dynamics (CFD) are employed to simulate aeroelastic effects, where the motion of the building alters the surrounding wind field and vice versa [7]. These high-fidelity simulations, while accurate, are computationally prohibitive. A single nonlinear time-history analysis for a 50-story building can take hours to days on a high-performance computing cluster, making parametric studies for design optimization or probabilistic risk assessment practically infeasible [8].

Furthermore, the integration of real-time structural health monitoring (SHM) systems into high-rise buildings has generated vast quantities of acceleration and strain data [9]. Interpreting these data streams to provide real-time estimates of structural state and remaining useful life requires models that can be evaluated almost instantaneously. Physics-based models, with their computational overhead, are ill-suited for this task. This disconnect between the need for rapid, accurate predictions and the computational burden of traditional methods constitutes a fundamental research gap. Moreover, the models themselves often suffer from epistemic uncertainty, arising from simplifications in material constitutive laws and idealized boundary conditions [10]. These uncertainties propagate through the analysis, leading to predictions that may deviate significantly from observed structural behavior, especially under rare, extreme events for which calibration data are sparse.

Machine learning (ML) has emerged as a powerful alternative to address these challenges. Unlike physics-based models that solve governing differential equations, ML algorithms learn the complex, often nonlinear, mapping between input loads and structural responses directly from data [11]. A feed-forward neural network, for example, can be trained on a dataset of wind-load time histories and corresponding acceleration responses to produce near-instantaneous predictions for new, unseen load cases [12]. Recurrent neural networks (RNNs), and their more advanced variants such as Long Short-Term Memory (LSTM) networks, are particularly adept at modeling temporal dependencies, making them natural choices for predicting sequential response time series [13]. The ability of these models to learn from data without requiring explicit knowledge of the underlying physics offers significant advantages in terms of computational speed and ease of deployment.

However, the application of ML to structural dynamic response prediction is not without its own set of critical gaps. The most prominent issue is the scarcity of high-quality, labeled data, particularly for extreme loading events where structural damage and nonlinearity are most pronounced [14]. Training an effective ML model requires a representative dataset that spans the full range of possible loading conditions, a requirement that is rarely met due to the rarity of such events and the high cost of deploying dense sensor networks. A second major gap concerns the generalizability of trained models. An ML model trained on acceleration data from one specific building is unlikely to perform well on a different building with a different height, plan geometry, or structural system [15]. This lack of transferability severely limits the practical utility of many proof-of-concept studies. Third, the field suffers from a lack of standardized validation protocols and error metrics. Without common benchmarks, it is difficult to compare the performance of different ML architectures or to assess whether a reported improvement in accuracy is practically significant [16]. Finally, purely data-driven models operate as black boxes, offering no guarantee that their predictions respect fundamental physical laws such as conservation of energy or momentum. This can lead to predictions that are physically implausible, even if they are numerically accurate on the training data [17].

The motivation for this systematic review, therefore, is to provide a comprehensive and structured synthesis of the existing literature on ML applications for predicting the dynamic response of high-rise buildings under wind and seismic loads. We aim to critically map the predominant ML architectures that have been employed, ranging from classical neural networks to modern deep learning models and their physics-informed counterparts. Furthermore, we seek to identify the critical methodological gaps that currently hinder the transition from laboratory-scale demonstrations to validated, generalizable engineering tools. By systematically evaluating the reported effectiveness of these models in terms of accuracy, computational efficiency, and robustness, we aim to offer a balanced perspective on the state of the art. The significance of this work lies in its potential to guide future research efforts by highlighting the most promising directions, such as hybrid physics-data models, and by proposing clear recommendations for the development of standardized benchmark datasets and evaluation frameworks. The remainder of this paper is organized as follows: Section 2 details the systematic review methodology, following the PRISMA guidelines, including the search strategy, inclusion criteria, and data extraction process. Section 3 presents the results of the review, first describing the overarching research trends and then delving into specific thematic areas: deep learning for temporal dependencies, feature engineering and transfer learning, structural system-specific applications, surrogate models for fragility analysis, and physics-informed models. Section 4 discusses the implications of the findings, synthesizes the identified challenges, and proposes a roadmap for future work. Section 5 concludes the review by summarizing the principal contributions and key takeaways.

2. Methodology

2.1 Review Protocol

This systematic review was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [18], ensuring transparency and reproducibility in the search, selection, and synthesis processes. The research question was formulated using the Population-Exposure-Outcome (PEO) framework, where the population comprises high-rise buildings, the exposure encompasses wind and seismic excitations, and the outcome pertains to the prediction of structural dynamic responses. We performed a comprehensive search across seven major electronic databases: Web of Science, known for its rigorous indexing of high-impact engineering journals; Scopus, which offers broad coverage across engineering disciplines and an extensive citation network; ScienceDirect, providing access to a large repository of full-text engineering and computer science articles; IEEE Xplore, selected for its strength in computational intelligence and neural network research; SpringerLink, included for its extensive collection of civil engineering and applied mechanics publications; arXiv, chosen to capture emerging work in machine learning at the frontier of engineering applications before formal peer review; and Google Scholar, used as a supplementary source to maximize coverage and identify gray literature that might be missed by discipline-specific databases.

The search strategy employed a combination of Boolean operators and keywords derived from the PEO framework. The search string was structured as follows: ("Machine Learning" OR "Deep Learning" OR "Neural Networks" OR "Random Forest" OR "Support Vector Machine" OR "XGBoost" OR "Ensemble Learning") AND ("Structural Dynamic Response" OR "Vibration Prediction" OR "Seismic Response" OR "Wind-Induced Vibration" OR "Structural Health

Monitoring") AND ("High-Rise Buildings" OR "Tall Buildings" OR "Skyscrapers" OR "Super-Tall Structures") AND ("Wind Excitation" OR "Seismic Excitation" OR "Earthquake Loading" OR "Wind Loading"). This string was adapted for each database to comply with its specific syntax requirements. For Web of Science and Scopus, the field tags were adjusted to search within titles, abstracts, and keywords; for IEEE Xplore, the search was restricted to metadata fields; and for Google Scholar, the strategy was narrowed using exact phrase matching and date filters to manage the volume of results. The initial search was conducted in March 2024, and no publication date restrictions were imposed to capture the full historical development of this field.

2.2 Thematic Taxonomy for Study Categorization

To structure the synthesis of the included studies, we developed a thematic taxonomy that reflects the key methodological dimensions and research foci identified in the literature. This taxonomy was derived iteratively through a preliminary reading of the full texts, which revealed distinct clusters of approaches based on the core ML architecture, the nature of the problem addressed, and the integration of domain knowledge. The first dimension pertains to models that explicitly capture temporal and spatial dependencies in the structural response, predominantly through recurrent architectures such as Long Short-Term Memory networks and convolutional neural networks applied to time-series or sensor-grid data. The second dimension encompasses techniques that enhance data utility and model transferability, including feature engineering to extract salient dynamics and transfer learning to adapt models across different buildings or loading regimes. The third dimension covers studies that tailor predictions to specific structural systems, such as frame-core tube or outriggered buildings, or that simultaneously consider multiple hazards like combined wind and seismic loading. The fourth dimension groups surrogate models and probabilistic frameworks designed for fragility analysis and performance-based assessment, where the ML model replaces computationally expensive simulations to enable Monte Carlo sampling. The fifth dimension includes physics-informed and hybrid models that embed governing equations or conservation laws into the learning process, thereby imposing physical consistency on the predictions. Studies that did not fit neatly into these categories were assigned to a sixth, miscellaneous class. This taxonomy provides a coherent framework for examining the methodological evolution and comparative effectiveness of different ML approaches within the field.

2.3 Inclusion and Exclusion Criteria

Clear inclusion and exclusion criteria were established to ensure that only studies directly relevant to the research question were selected, thereby maintaining the consistency and validity of the review. Studies were considered eligible if they applied machine learning methods, including deep learning, reinforcement learning, or statistical learning algorithms, to predict the dynamic response—such as displacement, acceleration, inter-story drift, or internal forces—of high-rise buildings subjected to wind or seismic excitations. Only original research articles, conference papers, or review papers published in peer-reviewed journals or peer-reviewed conference proceedings were included. Each study had to explicitly describe the input features, output targets, and the machine learning model architecture or algorithm employed. Furthermore, studies were required to provide quantitative validation of the model against either experimental data, field monitoring data, or high-fidelity numerical simulations, such as finite element models or computational fluid dynamics analyses. Only full-text articles available in the English language were considered.

Conversely, studies were excluded if they used machine learning solely for wind load or seismic hazard characterization without linking the prediction to the structural dynamic response of a high-rise building. Studies where the primary structural system was not a building, such as bridges, dams, offshore platforms, or low-rise structures, were also excluded. We excluded studies that applied conventional control theory without employing a data-driven or machine learning prediction model as a core component. Studies focusing exclusively on structural health monitoring for damage detection or modal identification, without predicting the dynamic response under new excitations, were not included. Publications that were book chapters, technical reports, theses, or non-peer-reviewed preprints, such as those on arXiv, were excluded. Studies where machine learning was used only as a surrogate for material property modeling, without integration into a full building dynamic response framework, were similarly excluded. Finally, studies that lacked any form of validation or error metric against a known reference solution were deemed ineligible, as purely theoretical proposals without numerical or experimental verification could not be reliably evaluated.

2.4 Study Selection Process

The study selection process was conducted in multiple stages, following the PRISMA workflow to ensure rigor and traceability. Initially, all records retrieved from the seven databases were collated and imported into a reference management system. Duplicate records were identified and removed using both automated deduplication algorithms and manual inspection. We then screened the titles and abstracts of the remaining records against the inclusion and exclusion criteria. Records that clearly did not meet the criteria, such as those focusing on bridges or low-rise buildings, were excluded at this stage. For the records that passed the initial screening, full-text versions were sought for retrieval. We attempted to obtain all full texts through institutional library access, interlibrary loans, and direct author requests; reports that could not be retrieved after multiple attempts were documented and excluded. The retrieved full texts were then assessed for eligibility in detail, with each study evaluated against all inclusion and exclusion criteria. Studies that were deemed ineligible upon full-text review, for reasons such as insufficient focus on response prediction or lack of quantitative validation, were excluded and the reasons for exclusion were recorded. The final set of studies that satisfied all criteria was included in the review for data extraction and synthesis.

The quality of each included study was assessed using a custom checklist developed in accordance with the research question and established conventions in structural engineering and machine learning literature. The checklist evaluated the clarity of the research objective, the appropriateness of the machine learning model selection, the robustness of the validation approach, the reporting of error metrics, and the generalizability of the findings. Each criterion was scored on a scale, and studies scoring below a threshold were subjected to sensitivity analysis to determine their impact on the overall synthesis. The selection process is illustrated in Figure 1, which presents the PRISMA flowchart detailing the number of records at each stage. The initial search yielded a total of 975 records across all databases. After removing 406 duplicate records, 569 unique records remained for title and abstract screening. This screening process excluded 427 records that did not meet the inclusion criteria, leaving 142 reports sought for retrieval. Of these, 7 reports could not be retrieved, resulting in 135 reports assessed for eligibility through full-text review. During the eligibility assessment, 28 reports were excluded due to ineligibility, such as insufficient focus on high-rise buildings or lack of quantitative validation. Consequently, a total of 107 studies were included in the final review.

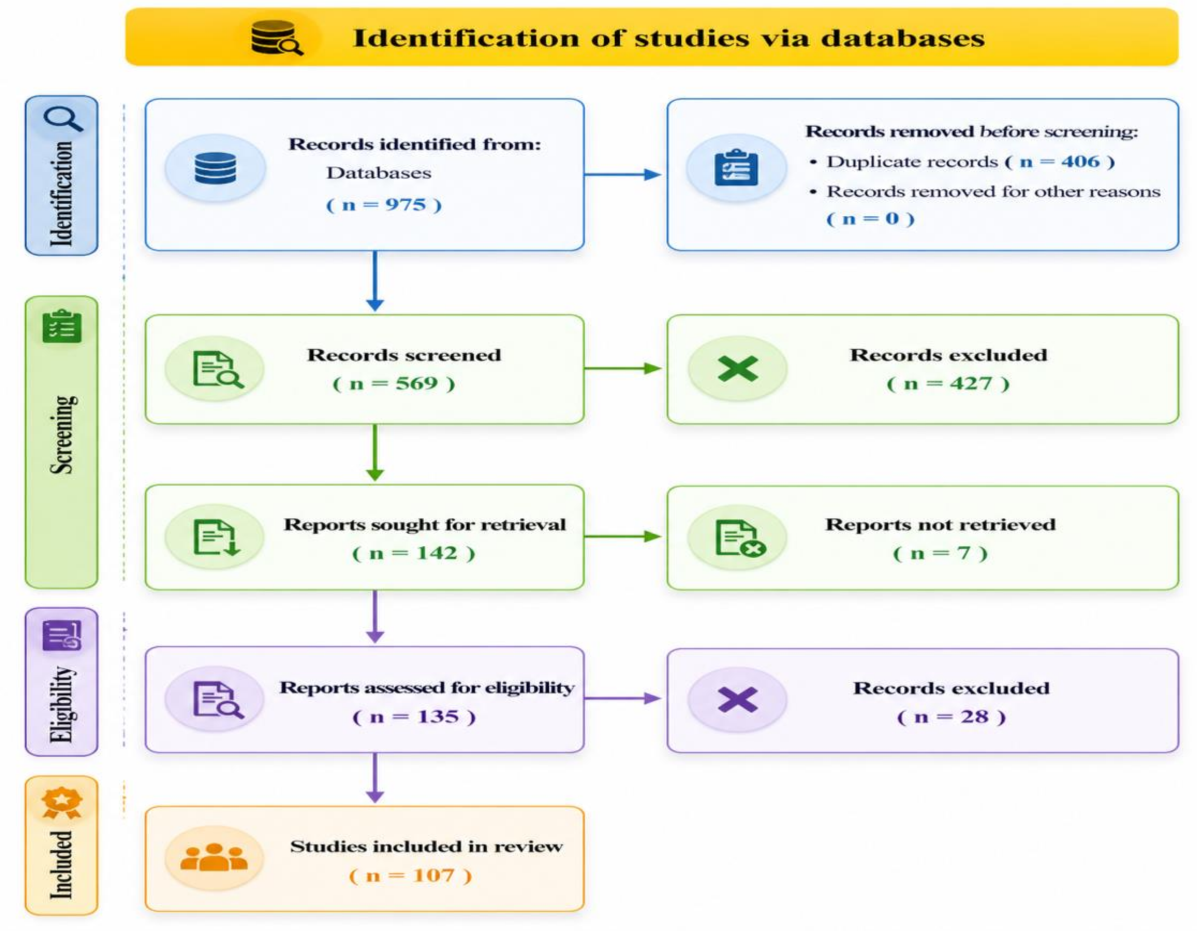

Figure 1. PRISMA flowchart illustrating the study selection process from initial database search to the final included studies.

Potential limitations of this study selection process must be acknowledged. The search strategy, while comprehensive, may have been biased by the chosen keywords and databases, potentially missing studies that use different terminology for dynamic response prediction or that are indexed in less accessible sources. The exclusion of non-English publications may have introduced a language bias, as significant research contributions may have been published in other languages, particularly in regions with extensive high-rise construction such as China or Japan. The quality assessment, while systematic, inherently relies on the subjective judgment of the reviewers, and the scoring criteria may not equally capture the merits of different methodological approaches. Furthermore, the decision to exclude preprints from arXiv, while ensuring consistency in peer review quality, may have delayed the inclusion of cutting-edge work that has not yet undergone formal peer review. Finally, the focus on validation against physical data or high-fidelity simulations may favor studies with access to such resources, potentially underrepresenting theoretical advancements that lack immediate empirical grounding.

3. Results

3.1 Research Trends

The publication trajectory of machine learning applications for structural dynamic response prediction in high-rise buildings reveals a profound and accelerating shift from nascent exploration to a burgeoning field of inquiry, as shown in Figure 2. Prior to 2016, sporadic contributions laid the groundwork, with only three studies published, indicating a period of conceptual incubation where computational limitations and data scarcity constrained broader adoption. A modest but consistent increase began around 2019, with five publications, and this growth intensified dramatically from 2021 onward. The year 2021 marked a pivotal transition with 13 studies, followed by sustained activity through 2023, where annual publication counts remained in the single digits to low teens. However, the most striking surge occurred in 2024 and 2025, with 17 and 30 studies respectively, representing a near-doubling of the output from the previous peak. This explosive growth is symptomatic of several converging factors: the maturation of deep learning libraries, increased availability of computational resources, and a growing recognition within the structural engineering community of the limitations of traditional physics-based methods for real-time and large-scale analysis. The projection for 2026 already includes 10 publications, suggesting this upward trend is not a temporary spike but a sustained shift in research focus. This rapid expansion, while indicative of enthusiasm and promise, also raises critical questions about the maturity and rigor of the field, as early adopters may rush to publish proof-of-concept demonstrations without adequate validation or generalizability testing.

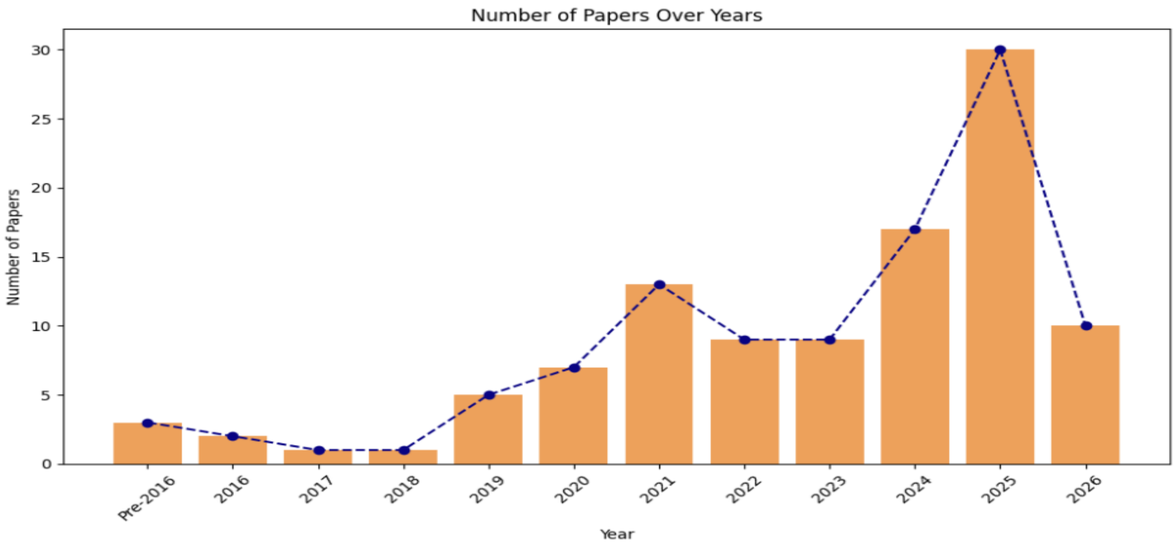

Figure 2. Research trends in the domain of Machine Learning Applications in Structural Dynamic Response Prediction of High-Rise Buildings under Wind and Seismic Excitations

The distribution of publications by year also highlights a notable gap between methodological development and practical deployment. The early phase, from 2016 to 2020, was characterized by foundational work establishing the feasibility of neural networks for predicting seismic drift or wind-induced acceleration, often using synthetic data from simplified single-degree-of-freedom systems. The subsequent surge from 2021 onwards coincides with the introduction of more sophisticated architectures, particularly recurrent models like LSTMs and convolutional neural networks, alongside the emergence of physics-informed learning. This timeline suggests that the field is still in a discovery-driven phase, where each year introduces new algorithmic variations rather than converging on a standardized toolkit. The lack of a plateau in publication counts after 2022 indicates that the field has not yet reached saturation; unresolved challenges such as data scarcity, model generalizability, and validation against real-world monitoring data continue to drive novel contributions. For instance, while early studies often reported high accuracies on training datasets, the more recent literature increasingly acknowledges the difficulty of extrapolating predictions to unseen extreme events or structurally different buildings. Therefore, the observed trends not only quantify the growth of the field but also underscore its current state of methodological pluralism, where rapid innovation coexists with persistent foundational gaps.

3.2 Overview of Included Studies

Table 1 presents the main characteristics of the included studies. The extracted information included study identification, ml model type, structural system, excitation type, output response type, data source and key enhancement strategy, where applicable.

The included studies varied in terms of their ML model types, structural systems, and excitation types. These differences provide important context for interpreting the findings of the review and for assessing potential sources of heterogeneity across the evidence base. Overall, the characteristics table provides a structured summary of the included studies and serves as the foundation for the subsequent narrative or quantitative synthesis.

Table 1. Characteristics of Included Studies

STUDY ID	ML MODEL TYPE	STRUCTURAL SYSTEM	EXCITATION TYPE	OUTPUT RESPONSE TYPE	DATA SOURCE	KEY ENHANCEMENT STRATEGY
[19]	Autoencoder-ANN	3D RC frame	Artificial ground motions	Maximum Base Shear (MBS), Maximum Inter-story Drift (MIDR), Maximum Roof Drift Ratio (RDR)	Nonlinear Time History Analysis (NL-THA) of 192,000 buildings	Unsupervised algorithms (Principal Component Analysis and Autoencoder) for dimensionality reduction and feature improvement
[20]	hybrid ML model	Special moment frames (SMFs)		maximum Inter-story drift ratio (MIDR)		improve seismic prediction and enhance the generalization of the model
[21]	Physics-Informed Neural Network (PINN)			structural stress	curated dataset of 2,500 samples with 11 engineered features	embedding elasticity and strength constraints directly into the learning process
[22]	CNN (Convolutional Neural Network)		Earthquake	Maximum ductility factor, inter-story drift ratio, maximum response acceleration	Seismic response analysis using actual earthquakes; accelerometer observation records	
[23]	ANN-SA model, Artificial	concrete shear walls	ground motions	responses of the reinforced	150 seismic records	hybrid technique

	Neural Network, Simulated Annealing			concrete shear walls	analyzed in OpenSees	(ANN-SA model)
[24]	Physics-informed machine learning (PiML) with LSTM networks	Steel moment resisting frame structures	Seismic loading	Seismic response	DesignSafe-CI Database	Integration of Newton's second law, dimensionality reduction via model order reduction and wavelet analysis, and LSTM networks for temporal dependencies
[25]	convolutional neural networks (CNNs) and recurrent neural networks (RNNs)	foundations and high-rise buildings	seismic events, wind loads, and environmental degradation	structural response data	numerical simulations and case studies	proactive maintenance, reducing life-cycle costs, and improving resilience
[26]	Deep Neural Network-Genetic Algorithm (DNN-GA)	aeroelastic tapered prism	flow-induced vibrations, Vortex-Induced Vibration (VIV), Galloping, VIV-Galloping	aerodynamic damping	synchronous, high-fidelity wind tunnel data	Genetic Algorithm optimization for aerodynamic damping based on tip response predicted by DNN
[27]	deep neural network (DNN) model, EEWnet		ground motion (seismic)	seismic responses	strong-motion database (publicly available resources)	real-time prediction based on first 3 s after P-wave arrival
[28]	Artificial Neural Network (ANN)		Seismic waves	Maximum inter-story drift ratio	Generated via analysis of a large number of seismic waves for numerous linear and nonlinear systems	Integration of structural properties and seismic intensity measures (SIMs) as inputs
[29]	stochastic polynomial	steel moment-	nonstationary	wind-induced	fiber-based 3D nonlinear	surrogate models trained

	chaos expansions	resisting frame	downburst winds	fragility functions	finite element approach in OpenSees	on $O(10^2)$ full simulations
[30]	Neural Network (DNN)	Multi-degree-of-freedom (MDOF) 2D shear models	Ambient vibration (AV) and earthquake (EQ) time-history data	Building earthquake response	Simulated data from 1197 MDOF 2D shear models, generating 32,319 training samples	Leveraging ambient vibration measurements combined with earthquake time-history data in a neural network framework
[31]	Deep Transfer Learning Model (TL-POD-LSTM)	High-rise building (square cylinder)	Wind	Longitudinal wind pressure time series	Wind tunnel experimental data	Transfer Learning (TL) combined with Proper Orthogonal Decomposition (POD) and Long Short-Term Memory (LSTM) network
[32]	Data-Driven Neural Network (DDNN) and Physics-Informed Neural Network (PINN)	Timoshenko beam model	earthquake ground motions	impulse response data (horizontal displacement)	observational data (horizontal vibration observation data)	incorporation of decoupled Timoshenko beam equation into DDNN as physical information to form a PINN
[33]	support vector machines and random forests	steel moment frames		maximum responses, median fragility, and expected annual loss	consistent database of 621 steel moment frames with varying designs and geometry	feature selection, hyperparameter tuning, cross-validation, and model inference
[34]	Deep learning-based projection model	Reinforced concrete frame; high-rise shear-wall structure			High- and low-fidelity numerical models	Multi-fidelity modeling with deep learning to predict high-fidelity results from low-fidelity simulations

[35]	artificial neural network (ANN) and long short-term memory (LSTM)	RCC	wind	displacements and drifts	codal analysis, numerical simulations, wind tunnel testing	orientation significantly affects the performance of a structure
[36]	Recurrent Neural Network (RNN) with Long Short-Term Memory (LSTM) layers		Vertical and lateral loading conditions	Vertical, lateral (X), and lateral (Y) displacements	Finite element analysis (FEA) combined with parametric modeling and multi-objective genetic algorithm	Combined finite element analysis (FEA), parametric modeling, and a multi-objective genetic algorithm to create a robust and diverse dataset
[37]	self-adaptive FNO and Fast Fourier Transform-based DeepONet (DeepFNOnet)	six-story shear building and high-rise building	stochastic ground motions and stochastic wind excitation	nonlinear time history response	high-fidelity models	FNO beyond the DeepONet to learn the discrepancy between the ground truth and the solution predicted by the DeepONet
[38]	Long Short-term Memory (LSTM)		wind loads	nonlinear structural response	scaled aeroelastic model based on experimental studies conducted at the Wind Simulation and Testing Laboratory (WiST) at Iowa State University	
[39]	Long short-term memory networks, autoencoders, and fully	Steel moment resisting frames (SMRFs)			Existing SMRF prototype structure database	Transfer learning with fine-tuning model parameters

	connected layers					
[40]	Bidirectional long short-term memory (Bi-LSTM) networks and Transformers	multi-story buildings	ground motions	floor response spectrum (FRS)	numerical simulations (OpenSees) and structural health monitoring data from real earthquake events	surrogate-modelling techniques
[41]	Random Forest, Extreme Gradient Boosting Machine, Artificial Neural Networks	Steel Moment-Resisting Frames	Non-Linear Dynamic Analysis	Maximum Inter-Story Drift Ratio	29,200 data points from 292 models generated using ETABS software	User-friendly Graphical User Interface for practical application reducing computational costs and analytical efforts
[42]	Physics-assisted fully convolutional neural network (PhyFCN)		Long-period ground motions (LPGMs)	LPGM-induced response of high-rise buildings		Encoding the complex seismic motion equation into FCN for formulating an innovative physical loss function
[43]	Temporal Convolutional Network (TCN)		long-period ground motions	ground-motion waveforms and building shaking	near-source waveform observations	time-series forecasting approach using TCN
[44]	artificial neural networks, extreme gradient boosting	Reinforced Concrete Moment-Resisting Frames (RC MRFs)	near-fault seismic excitations	Maximum Interstory Drift Ratio (IDRmax), Median of IDA curves (M-IDAs)	Incremental Dynamic Analyses (IDAs) of 165 RC MRFs with 92,400 data points	improved with innovative techniques
[45]	recurrent neural network (RNN)	11-story building structure with a semi-active tuned mass damper (TMD), and a 27-story	five historical earthquakes and five artificial ground motions	seismic responses (time history response)	finite element method (FEM) model	significantly reduced computational cost with accurate seismic responses

		building having a semi-active mid-story isolation system				
[46]	ML fusion model	reinforced concrete (RC) building	ground motion (GM)	inter-story drifts	ground motion (GM) inputs	particle swarm optimization (PSO) for GM selection and ML fusion model for EDP prediction
[47]	artificial neural networks (ANNs)	G + 15-storey reinforced concrete (RC) buildings	recent earthquake data	storey displacements, storey shear, storey drift	finite element analysis (FEA) software (ETABS)	fluid viscous dampers (FVD)
[48]	deep convolutional neural network (DCNN)	reinforced concrete buildings; steel moment-resisting frames	seismic effects	maximum interstory drift ratio (MIDR)	30 reinforced concrete buildings' time history analyses results and 38 interstory drift spectrums	using DCNN to tune the first approximation from interstory drift spectrum
[49]	multi-scale attention-based recurrent neural network	high-rise building	bidirectional ground accelerations	seismic displacement responses at all building floors	numerical and real-world data of a high-rise building	attention mechanisms
[50]	Time-series attention-based RNN encoder-decoder (TSA-RNN-ED)	tallest building in China, the Shanghai Tower; woodframe classroom on a shake table at the University of British Columbia	seismic excitation (earthquakes)	structural dynamic responses	real-world structural cases: Shanghai Tower and woodframe classroom on a shake table at the University of British Columbia	time-series attention mechanism to exploit heterogeneous but directly related hidden features between seismic loads and corresponding structural responses
[51]	ridge regression; decision tree; random			wind pressures	Commonwealth Advisory Aeronautical Research	

	forest; gradient boosting regression tree				Council standard tall building	
[52]	Long short-term memory neural network	High-rise building	Seismic (strong earthquakes)	Seismic response	20-story benchmark building mode	Decentralized control method with fault tolerance
[53]	Cascade Forward-Backward Propagation Network (CFBPN)	super high-rise building	wind-induced	structural acceleration response	wind tunnel tests, measured wind field, linear typhoon wind field model, AI-based weather forecasting	integration of linear typhoon wind field model with response NN prediction model for long-term prediction
[54]	recurrent neural network (RNN) and long short-term memory (LSTM)	structures with or without nonlinear components	seismic waves	time history response	numerical methods	time series k-means (TSkmeans) algorithm to divide label data into different clusters
[55]	Light Gradient Boosting Machine (LGBM), K-means clustering		Crosswind	Crosswind force spectra and associated crosswind responses	Wind Engineering Research Center at Tamkang University embedded in the aerodynamic database of NatHaz Modelling Laboratory	Combined with random vibration-based response analysis and multiple database-enabled design module
[56]	Multidomain feature-guided generative adversarial neural network model (MWGAN-TF)	Three-story moment-resisting frame and reinforced concrete frame structures	Seismic excitation	Seismic responses	Response data from numerical models and field measurement data of an actual building	Incorporating time, frequency, and statistical-domain feature constraints into the multiscale generative adversarial neural network

[57]	Physics-guided neural network with adaptive multi-level fusion outputs	Reinforced concrete (RC) frame structure	Seismic (earthquake)	Structural seismic response (acceleration time-history) and floor response spectra (FRS)	Numerical data of five RC frame structures, measured data of an RC frame shaking table test, and monitoring data of an RC frame structure under earthquake	Incorporating floor response spectra (FRS) into the loss function as a physical constraint
[58]	Polynomial Chaos Kriging	multiple-degree-of-freedom shear model	multi-hazards of earthquake and wind	multi-hazard dynamic responses		global sensitivity analysis using Sobol' indices
[59]	state-of-the-art deep learning architectures adapted from the image classification domain		ground motions	nonlinear structural seismic responses		physics-informed input representations and scientific training strategies, including hybrid transfer-learning framework
[60]		reinforced concrete (RC) columns	cyclic loading and ground motions	lateral seismic response	experimental data	integration of machine learning with a hysteretic model for data-driven parameter computation
[61]	Artificial neural networks (ANNs)	Reinforced concrete frame buildings	seismic loads	displacement	ETABS	
[62]	physics-informed recurrent neural networks	multi-degree-of-freedom (MDOF) systems	seismic (earthquake)	dynamic response		physics-informed
[63]	Generative Pre-trained Transformer (GPT)		Seismic loads	Displacement, acceleration, and	Corpus of seismic data and structural engineering principles	Physics-informed data-driven large model

				inter-story drift		
[64]	Multiple-surrogate models		wind	probabilistic performance		
[65]	Kriging surrogate models		wind			life-cycle cost optimization
[66]	temporal neural network	six-story steel building	earthquakes		finite element models carefully calibrated with experimentally measured data	rolling window strategy, data fusion, temporal neural network architecture, length- and magnitude-agnostic loss function
[67]	Gaussian Process (GP), support vector machines (SVM), backpropagation feed-forward neural network (BP-FNN), random forest (RF), gradient tree boosting (GTB), adaptive boosting (AdaBoost), Extreme gradient boosting (XGBoost), Light gradient boosting machines (LightGBM), categorical	steel trusses	El Centro earthquake	seismic lateral deflection		

	boosting (CatBoost)					
[68]	artificial neural network (ANN) and extreme gradient boosting (XGBoost)	planar steel moment-resisting frames	ground motions	maximum top and interstory drifts	22,464 nonlinear dynamic analyses on 36 steel moment frames with different structural characteristics subjected to 624 ground motions	
[69]	K-nearest neighbors, naïve Bayes, decision tree, random forest, adaptive boosting, extreme gradient boosting, light gradient boosting, category boosting	steel moment frames	240 ground motions	seismic damage states (green, yellow, red per ATC-20)	DesignSafe cyberinfrastructure database (468 steel moment frames) and 240 ground motions	Shapley additive explanations (SHAP) for input variable importance and graphical user interface for convenient access
[70]	Neural Networks (NNs)	Reinforced concrete	Ground earthquake excitation and white-noise random excitation	Frequency response functions (FRFs)	Shaking table test of a 1:20 scale model	Principal component analysis (PCA) for dimensionality reduction and noise elimination
[71]	Multilayer perceptron ANN models with back-propagation training algorithm		wind	base shear and base bending moment in along- and across-wind direction	Indian Wind Code (IWC), IS 875 (Part 3):2015	parametric study to predict dynamic wind response for configurations on which IWC is silent; design charts developed
[72]	Artificial Neural Network (ANN)		Dynamic along-wind	Dynamic along-wind base shear and base	Indian Wind Standard IS 875 (Part 3): 2015	Simplified empirical equation as a function of

				bending moment		aspect ratio, side ratio, wind velocity, and terrain category; charts for story shear force and story bending moments
[73]	convolutional neural network			dynamic structural response		safety network
[73]	Convolutional neural network (CNN)	tall building	wind load	strain (maximum and minimum strains of columns)	wind tunnel test of a building model	input map configuration combining top-level wind-induced displacement in time and frequency domains, and wind data in the frequency domain
[74]	Convolutional neural network (CNN)	reinforced concrete frame structure	earthquake	displacement responses	numerical study on the ASCE benchmark model and experimental study on a reinforced concrete frame structure	data generation method based on data overlapping with the same data pool
[75]	Neural network (NN)	Multi-degrees-of-freedom (MDOF) structures; planar reinforced concrete building structure	Artificial earthquakes (AEQs)	Maximum inter-story drift ratio and maximum displacement	Artificial earthquakes generated based on probabilistic vibration theory	Introduction of a resonance area parameter to represent the relationship between ground motion and target structure in the frequency domain
[76]	Pyramid-LSTMA (P-LSTMA)	high-rise buildings	earthquake, wind	structural responses	numerically simulated and real-world recorded data	pyramid hierarchical multi-scale feature fusion, LSTM-based

						temporal memory, and attention mechanism
[77]	Gaussian process regression		Seismic waves	Maximum displacement		Correlation analysis normalizing variables with peak ground acceleration
[78]	Convolutional Neural Network (CNN)	Reinforced concrete frame	Ground motion (earthquake)	Strain response	Shaking table test of a 3-story reinforced concrete frame specimen	Use of seismic intensity measures (singular value matrix, Arias Intensity, cumulative absolute velocity) as input data in addition to time history ground motion data
[79]	Nonlinear autoregressive exogenous model (NARX)-based recurrent neural network (NN) model	1:20-scaled 38-story highrise building structure; five-story steel frame	Seismic excitations and ambient vibrations; different levels of the Kobe earthquake			Adroit integration of empirical mode decomposition (EMD) for noise removal, mutual information (MI) index for determining optimum number of neurons, and Bayesian regularization (BR) for training
[80]	Artificial Neural Networks	high-rise buildings	wind load		structural analysis of different multi degree of freedom (MDF) systems	optimal tuning of tuned mass dampers
[81]	Artificial Neural	Concrete moment-	Earthquake events (time-	Demand parameters	111 earthquake events from	Bayesian Optimization (BO) algorithm

	Networks (ANNs)	resisting buildings	history analyses)		the SAC project, uniformly scaled from 0.1 g to 1.5 g	to tune the architecture of the NNs
[82]	ANN, CNN, LSTM, hybrid ANN–LSTM	high-rise structures with smart material technologies including shape memory alloys (SMA), fiber-reinforced polymers (FRP), and damping systems		inter-story drift ratio, base shear, damage index, energy dissipation capacity	quantitative simulation-based research design integrating finite element modeling	AI-driven predictive analytics with smart material technologies
[83]	Deep Learning	frame and frame-core tube structure	earthquakes or typhoons	dynamic responses	detailed finite element models	introducing equivalent stiffness parameters representing horizontal and vertical members into the Lumped Parameter Model (LPM) and using Displacement Interaction Coefficients (DInC) as input features to identify LPM's stiffness parameters
[84]	Artificial Neural Networks (ANN), Support Vector Machines (SVM), Genetic Algorithms (GA)	outrigger systems	seismic loads	lateral displacement, inter-story drift, energy dissipation	empirical data and synthetic simulations	closed-loop optimization cycle combining supervised learning, reinforcement-based refinement, and structural simulations

						(pushover and time-history analysis) to automatically identify optimal outrigger configuration
[85]	CNN-LSTM-ATT	Moment frame and shear wall-frame structures	Earthquake	Seismic response (dynamic response, nonlinear behaviors)	Finite element models	Transfer learning with fine-tuning
[86]	Long Short-Term Memory neural networks	skeletal structures	seismic loads	displacements	simulated and real data	integration of modal analysis with Long Short-Term Memory neural networks
[87]	Artificial Neural Networks	Multi-storey steel structures	Earthquake ground accelerations	Drift and base shear	Finite element analysis (Ansys) simulations	Parametric study with 3793 simulations using 18 input and 9 output parameters
[88]	kernel-based machine learning methods	type and combination of lateral force resisting systems	spatially explicit ground motions from the Northridge earthquake	peak floor accelerations and peak story drift ratios	Nonlinear response history analyses	Using measurements from limited locations within a subset of buildings, the full-profile response demands for all buildings in a portfolio are reconstructed
[89]	Artificial Neural Network (ANN)	reinforced concrete building	earthquake load	acceleration, velocity and displacement (story drift)	structural analysis of 34 provinces in Indonesia	
[90]	Artificial Neural Network	multi-storey reinforced concrete building	Ground acceleration	Acceleration, velocity and displacement (story drift)	Modal response spectrum analysis	

[91]	Artificial Neural Network	multi-story reinforced concrete building	earthquake load	story drift	Modal response spectrum analysis	
[92]	Autoregressive Neural Network (ARNN)	nonlinear column, damper-equipped structure, base-isolated building	earthquake ground motion	time-history response	Non-linear Time History Analysis (NLTHA) records	efficient fragility curve generation through cost-effective Monte Carlo Simulation (MCS) by partitioning single time history records into multiple training data sets and incorporating modal analysis to extract structural periods
[93]	hybrid deep learning techniques; long short-term memory (LSTM) neural networks; hybrid convolutional-LSTMs (ConvLSTM) neural networks		acceleration time-series of the base/ground	nonlinear multi-component seismic responses; capacity curves	measured seismic responses	pre-processing data and structuring the architecture of deep neural networks; Fast Fourier Transform (FFT) Butterworth filter and discrete wavelet transform (DWT) decomposition; decimation to reduce features; enhancements to the architecture of the network to reduce training time and improve accuracy

[94]	Deep Neural Networks (DNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Levenberg–Marquardt Recurrent Neural Networks (LM-RNN)	BRI ANX building	strong ground motions	acceleration response of multiple floors	sensors near and inside structures	a new proposed algorithm for all learning models; training with a new selection of hyperparameters; window of N-past features; parametric studies of windowing, down-sampling, batching, network structure, number of training epochs, and dropout rates
[95]		steel moment frame	ground motions	structural response	Nonlinear finite element analyses under 240 ground motions	Shapley additive explanations (SHAP) for feature importance inspection and selection of a reduced set of features
[96]	Decision Tree, Random Forest, Multi-Layer Perceptron (MLP)	Reinforced concrete (RC) framed buildings with facade elements, soft storeys, and shear walls	Gravity, wind, and seismic loading	Storey displacement, inter-storey drift, story shear, base reactions, and dynamic characteristics	Dataset generated from numerical simulations using ETABS	Incorporation of shear wall systems
[97]	deep learning	tall buildings	wind	nonlinear structural dynamic response		knowledge-enhanced
[98]	Artificial Neural Network	Double skin composite	Earthquake loads	Hysteretic behavior (force-	Comprehensive dataset generated	Integration of physical mechanisms

	(ANN), Transformer-based end-to-end deep learning model	wall (DSCW)		displacement constitutive relationship)	from fiber-based uniaxial material model and experimental data	(physical mechanisms into the force-displacement constitutive relationship) with data-driven approaches
[99]	Natural Frequency-Based Fourier Feature Physics-Informed Neural Network (NF-FF-PINN)		broadband earthquake excitations	displacement L2 error		Embedding structural natural frequencies into the Fourier feature mapping to align neural representation spectrum with physical frequency content, eliminating manual parameter tuning
[100]	machine learning (ML) techniques			wind pressure	wind tunnel experiments	transfer learning, Bayesian hyperparameter optimization (BO), SHapley Additive exPlanations (SHAP) analysis
[101]	Kriging metamodels	High-rise buildings with outrigger systems	Seismic and wind loads	Dynamic response	Three-dimensional (3D) finite element models developed using ANSYS	Sensitivity analysis to determine the most sensitive input parameters
[102]	DNNs and Transformer	Frame-core tube (FCT) structures	Seismic loads	Capacity points, full sets of capacity points, pushover curves	Random finite element analyses using OpenSees, validated with ETABS and SAP2000	Iterative data expansion and hyperparameter tuning

[103]	Deep Neural Networks (DNNs)	High-rise buildings with outrigger systems (one-outrigger systems, three types of outrigger systems including damped outrigger systems)	Seismic loads (two types of seismic hazards)	Inter-story drift and top acceleration	Existing database	Model-agnostic analysis using partial dependence plot and SHapley Additive exPlanations; fragility estimation
[104]	Recursive long short-term memory (LSTM) network	Multilayer frame structures	Seismic excitation	Nonlinear structural time history responses	Measured ground motions and multilayer frame structures	Recursive prediction principle
[105]	Multilayer Perceptron and Random Forest	high-rise shear wall structures	ground motion records	maximum interstory drift angle and maximum floor acceleration	incremental dynamic analysis method	SHapley Additive exPlanations
[106]	Artificial Neural Network	tall building	wind	vibration responses	cyber-physical system in wind tunnel	active aerodynamic modification, intelligent optimization algorithms, and actuator screening framework
[107]	deep neural network	nonlinear frame structure, linear frame structure, instrumented shear-wall structure	seismic	structural time history responses	numerical simulations, shake-table testing, field-sensing records	Iterative Self-training Enhanced Transfer Learning (ISTL) with self-training for sample augmentation and output conditional distribution regularization

						for domain adaptation
[108]	Genetic Algorithm (GA) and Artificial Neural Network (ANN) with deep learning	tubular structures			ZEUS-NL open-source code	amalgamating Weka's capability of data preprocessing with deep learning
[109]	Artificial Neural Network	Tall Buildings and Towers	Wind loads			Surrogate modeling
[110]	Long short-term memory networks			seismic response	C-library data, B-library data	Genetic algorithm
[111]	long short-term memory (LSTM) network	nonlinear hysteretic system, real-world building with field sensing data, steel moment resisting frame	seismic	nonlinear structural seismic response	available datasets, field sensing data	dynamic K-means clustering approach for unsupervised learning to generate informative datasets and improve prediction accuracy with limited data
[112]	Physics-guided convolutional neural network (PhyCNN)	building	seismic events (earthquakes)	seismic response prediction for serviceability assessment	seismic input-output datasets from simulation or sensing	physics constraints (e.g., law of dynamics) to guide network outputs, alleviate overfitting, reduce need for big datasets, and improve robustness; also K-means clustering for unsupervised partitioning of limited datasets

[113]	time-delay neural network	frame structure	seismic	drift peak amplitudes, maximum amplitudes		accuracy evaluation method considering drift peak amplitudes and maximum amplitudes in each intensity as performance parameters
[114]	end-to-end network with adaptive multilevel fusion output incorporating autoencoder concept	reinforced concrete frames	ground motions records	structural seismic time-history responses	four actual buildings with different construction time, occupancy types, and floor sizes	adaptive multilevel fusion output
[115]	Multilayer Perceptron (MLP)	single-degree-of-freedom system, vehicle-bridge coupled system, high-rise building	forced vibrations, wind-induced vibrations	dynamic response	numerical simulations, real-world monitoring data of a high-rise building dynamic response during Typhoon Hato	embedding resonance effect into the design of the multilayer perceptron (MLP) loss function
[116]	random forest, extreme gradient boosting (XGBoost), convolutional neural network based on large receptive field, seismic wave transformer (SWT) model based on transformer	damped structure	ground motions	maximum inter-storey displacement	comprehensive database consisting of 13,855 structural responses to ground motions	aggregation model (AM)-based structural response prediction method

	network, aggregation model (AM)					
[117]	multi-fidelity meta-learning algorithm	high-rise shear wall buildings	seismic	seismic response	multi-fidelity datasets (numerical simulations and field monitoring data)	incremental data learning and model updates
[118]	Improved Inception module, inverse neural networks, physics-informed variational autoencoder		wind	wind-induced responses, wind load sequences	full-scale nonlinear finite element analysis results, real health monitoring data	Kriging interpolation, physics-informed variational autoencoder
[119]	Improved Inception-based neural network	ultra-high-rise structures	seismic	structural displacement fields	finite element calculations	solution space-based method for generating training data using Markov chains, Improved Inception-based module, displacement field prediction method using key nodes and Kriging interpolation
[120]	Back Propagation (BP) Artificial Neural Network (ANN)	composite tall building	simultaneous earthquake and wind events		finite element (FE) analysis of tall buildings under concurrent seismic and wind excitations	incorporating both epistemic and aleatory uncertainties into fragility estimates using hybrid AI-Bayesian methodology
[121]	LSTM, PSO-LSTM		windstorm	displacement	field measurements including strain and acceleration responses, original GPS-	particle swarm optimization (PSO) for hyperparameter optimization of LSTM model

					measured signals from a 600-m-high skyscraper during Typhoon Kompasu	
[122]	Phy-Seisformer	masonry structure, reinforced concrete irregular structure, reinforced concrete frame structure	seismic wave	structural response	finite element calculations	incorporates physical information of the structure into the model
[123]	long short-term memory neural network (LSTM)	four-degree-of-freedom system; Canton Tower		structural response	Simulated responses of a four-degree-of-freedom system and real-world responses of the Canton Tower	compressive sensing (CS) combining with LSTM (LSTM+CS)
[124]	Gated Recurrent Units model		typhoon	displacement	wind pressure data collected from the building model in a wind tunnel test; FEM simulations	combining machine learning models with finite element method

3.3 Deep Learning for Capturing Temporal and Spatial Dependencies in Structural Responses

The prediction of structural dynamic responses intrinsically involves modeling dependencies across both time and space. Time-series accelerations, displacements, and drifts are governed by the temporal evolution of the structural state under external excitations. Simultaneously, the response at one location in a building is correlated with responses at other locations through the structural connectivity and modal properties. Deep learning models, particularly those based on recurrent and convolutional architectures, have been extensively adopted to capture these intertwined temporal and spatial dependencies in high-rise buildings under wind and seismic excitations. The studies in this category are summarized in Table 2, which organizes the key methodological characteristics of the included research.

Table 2. Characteristics of included studies focusing on deep learning models for temporal and spatial dependencies

STUDY ID	TEMPORAL DEPENDENCY CAPTURE MECHANISM	MODEL ARCHITECTURE TYPE	PHYSICS INTEGRATION METHOD
[119]	N/A	Improved Inception-based neural network	N/A (data-driven)
[121]	LSTM memory cell	LSTM and PSO-LSTM	N/A (data-driven)
[122]	Autoregressive training strategy, self-attention mechanism	Phy-Seisformer (transformer-based)	Physical information of the structure incorporated into the model architecture
[123]	LSTM memory cell	LSTM	Compressive sensing embeds physical information into prediction process
[124]	Gated Recurrent Unit (GRU)	GRU	Finite element method provides benchmark responses
[30]	N/A	DNN in image format	N/A (data-driven)
[31]	LSTM memory cell	POD-LSTM with transfer learning	Physics via Proper Orthogonal Decomposition (POD) for feature extraction
[32]	Impulse response fitting with virtual source	DDNN and PINN	Decoupled Timoshenko beam equation incorporated as physical information
[35]	LSTM memory cell	ANN, LSTM	SHAP analysis for model interpretability
[36]	LSTM memory cell	RNN with LSTM layers	Finite element analysis for data generation
[37]	N/A	FNO, DeepONet, DeepFNOnet	N/A (data-driven)
[38]	LSTM memory cell	LSTM	Experimental data for validation
[40]	Bi-LSTM and Transformer self-attention	Bi-LSTM, Transformer	N/A (data-driven)
[43]	Temporal convolutional network (TCN)	TCN	N/A (data-driven)
[45]	Recurrent neural network (RNN)	RNN	Finite element model for comparative baseline
[48]	N/A	Deep CNN (DCNN)	Interstory drift spectrum used as physics-informed first approximation
[49]	Recurrent neural network with multi-scale attention	Multi-scale attention-based RNN	Nonlinear time history analysis for data generation
[50]	RNN encoder-decoder with time-series attention	TSA-RNN-ED	N/A (data-driven)
[52]	LSTM memory cell	LSTM for decentralized control	Lyapunov stability theory for control stability constraints
[53]	N/A	Cascade Forward-Backward Propagation Network (CFBPN)	Linear typhoon wind field model integrated with NN for long-term prediction
[54]	RNN and LSTM memory cell	RNN and LSTM	TSkmeans clustering for data grouping

[56]	Multidomain feature-guided generative adversarial network	MWGAN-TF	Statistical-domain feature constraints (CNCSI indicator)
[57]	N/A	Physics-guided neural network with autoencoder	Floor response spectra (FRS) used as physical constraint in loss function
[22]	N/A	CNN using wavelet spectrum input	Wavelet transform of accelerometer records
[62]	Physics-informed RNN	Physics-informed RNN	Physics-informed (equations of motion)
[63]	Transformer (GPT architecture)	GPT-based SeisGPT	Physics-informed data-driven large model
[66]	Rolling window strategy, temporal neural network	Temporal neural network	Neural network trained on FEM data calibrated with experiments
[73]	N/A	CNN	Safety network concept using correlation between nearby buildings
[73]	N/A	CNN	Input map combining time and frequency domain data
[76]	LSTM-based temporal memory	Pyramid-LSTMA (P-LSTMA)	N/A (data-driven)
[24]	LSTM memory cell	Physics-informed ML (PiML)	Newton's second law, equation of motion
[79]	NARX-based recurrent neural network, empirical mode decomposition	NARX-based RNN	Mutual information for feature selection, Bayesian training
[81]	N/A	ANN with Bayesian Optimization	HAZUS-based simplified model for demand estimation
[82]	LSTM memory cell	ANN, CNN, LSTM, hybrid ANN-LSTM	Integration with smart material technologies
[83]	N/A	Lumped Parameter Model (LPM) with deep learning	Displacement Interaction Coefficients (DInC), equivalent stiffness parameters
[85]	LSTM memory cell with attention	CNN-LSTM-ATT	Transfer learning for model adaptation
[86]	LSTM memory cell	Two-phase neuro-modal method (LSTM + modal analysis)	Modal analysis integrated with LSTM
[25]	RNN	CNN and RNN	N/A (data-driven)
[88]	N/A	Kernel-based ML	Nonlinear response history analysis for data generation
[93]	LSTM and ConvLSTM memory cells	Hybrid ConvLSTM	Fast Fourier Transform and discrete wavelet transform filtering
[94]	RNN, LSTM, LM-RNN	DNN, RNN, LSTM, LM-RNN	Fourier spectrum comparison for validation
[97]	Deep learning (knowledge-enhanced)	Knowledge-enhanced deep learning model	Structural dynamics knowledge integrated into learning process
[99]	N/A	Natural Frequency-based Fourier Feature PINN (NF-FF-PINN)	Natural frequencies embedded into Fourier feature mapping for physics-informed learning

[102]	Transformer self-attention	DNN and Transformer	N/A (data-driven)
[104]	Recursive LSTM memory cell	Recursive LSTM network	Recursive prediction principle emulating numerical integration
[27]	N/A	DNN (EEWnet)	Earthquake early warning principles, nonlinear time history analysis for data generation
[107]	N/A	Deep neural network with iterative self-training	Transfer learning enhanced with output conditional distribution regularization
[110]	LSTM memory cell	LSTM with genetic algorithm and CNN integration	Lyapunov stability theory for control design
[111]	LSTM memory cell	Deep LSTM network	Dynamic K-means clustering for data selection
[112]	N/A	Physics-guided CNN (PhyCNN)	Dynamics laws applied as constraints to network outputs
[113]	Time-delay neural network	Time-delay neural network	Accuracy evaluation method considering drift peaks and amplitudes
[114]	N/A	End-to-end network with adaptive multilevel fusion	Autoencoder concept for feature learning
[115]	N/A	Multilayer Perceptron (MLP)	Resonance effect embedded into loss function
[116]	N/A	Transformer (SWT), CNN, XGBoost, aggregation model	Aggregation model combining physics-based partitioning with ML
[118]	N/A	Improved Inception module, variational autoencoder	Physics-informed variational autoencoder for wind load inversion
[119]	N/A	Improved Inception-based neural network	Solution space-based training data generation using Markov chains
[121]	LSTM memory cell	LSTM and PSO-LSTM	Particle swarm optimization for hyperparameter tuning
[122]	Autoregressive training strategy, self-attention mechanism	Phy-Seisformer (transformer-based)	Physical information of the structure incorporated into the model architecture
[123]	LSTM memory cell	LSTM	Compressive sensing embeds physical information into prediction process
[124]	Gated Recurrent Unit (GRU)	GRU	Finite element method provides benchmark responses

The analysis of the studies in Table 2 reveals several dominant architectural patterns and methodological trends. Long Short-Term Memory networks and their variants constitute the most widely adopted class of models for capturing temporal dependencies, appearing in over twenty of the included studies. For instance, the PSO-LSTM model developed by a group of researchers was used to enhance the accuracy of GPS-measured displacement measurements of a 600-m skyscraper during Typhoon Kompasu, achieving a demonstrable improvement over standard LSTM by optimizing hyperparameters through particle swarm optimization [121]. Similarly, a recursive LSTM network was specifically designed to predict nonlinear structural seismic responses for arbitrary lengths and sampling rates, explicitly emulating the recursive prediction principle of traditional numerical integration methods [104]. This model was validated on multilayer frame structures and measured ground motions, showing good accuracy and generalization capability. In another study, deep LSTM networks were combined with a dynamic K-means clustering approach for unsupervised learning to generate the most informative datasets, thereby improving prediction accuracy and robustness even with limited training data for nonlinear hysteretic systems and a real-world building with field sensing data [111].

The evolution from simple LSTM to more complex hybrid architectures is evident. The CNN-LSTM-ATT model, which integrates convolutional layers for feature extraction, LSTM for temporal sequence learning, and an attention mechanism for focusing on salient information, was introduced for seismic response prediction of moment frame and shear wall-frame structures [85]. Through transfer learning, this model was fine-tuned to predict seismic response across different target buildings, demonstrating that model-based transfer learning significantly enhances prediction accuracy. The TSA-RNN-ED model implemented a time-series attention mechanism within an RNN encoder-decoder architecture to exploit heterogeneous hidden features between seismic loads and corresponding structural responses, and was systematically evaluated on the Shanghai Tower, the tallest building in China, as well as a woodframe classroom on a shake table [50]. This architecture demonstrated reliable regression of excitation-response interactions for real-time forecasting. Moreover, the Pyramid-LSTMA architecture combined a hierarchical pyramid for multi-scale feature fusion with LSTM-based temporal memory and an attention mechanism to capture both rapid transients and long-term temporal dependencies in structural responses under seismic and wind hazards, and was validated on a 32-story residential building in Los Angeles and Guangzhou's 303 m Leatop Plaza during a typhoon [76].

Convolutional and transformer-based architectures offer alternative strategies for spatial and temporal modeling. Several studies employed convolutional neural networks with varying input representations. The physics-guided convolutional neural network (PhyCNN) incorporated dynamics laws as constraints to network outputs, thereby alleviating overfitting and reducing the need for large training datasets while improving robustness for more reliable prediction [112]. The MWGAN-TF model innovatively incorporated time, frequency, and statistical-domain feature constraints into a multiscale generative adversarial neural network to capture the joint non-stationarity of seismic responses, and it was verified using response data from numerical models and field measurement data of an actual building [56]. The SeisGPT model, based on the Generative Pre-trained Transformer architecture, was trained on a diverse corpus of seismic data and structural engineering principles to generate predictive responses, including displacement, acceleration, and inter-story drift, in real time with high accuracy and computational efficiency [63].

The integration of physics into deep learning models represents a significant advancement. Physics-informed recurrent neural networks were proposed for evaluating the dynamic response of multi-degree-of-freedom systems, with a focus on seismic response of nonlinear structures, where the predicted response was compared to finite element analysis to assess efficacy [62]. The Natural Frequency-based Fourier Feature PINN embedded structural natural frequencies into the Fourier feature mapping to theoretically align the neural representation spectrum with the physical frequency content of the structure, eliminating manual parameter tuning and enhancing multi-frequency response accuracy under broadband earthquake excitations [99]. The PIML approach leveraging the resonance effect, a crucial piece of physical information, into the design of the MLP loss function was validated through numerical simulations and real-world monitoring data of a high-rise building during Typhoon Hato, where it significantly outperformed pure ML algorithms even with a small dataset and effectively captured the resonance effect in wind-induced vibrations [115].

Several studies addressed specific challenges such as data scarcity, long-term prediction, and real-time application. The LSTM+compressive sensing method was proposed to mitigate prediction divergence that increases as prediction length grows, embedding physical information into the prediction process, and it demonstrated high prediction performance with limited data and minimal costs using simulated responses of a four-degree-of-freedom system and real-world responses of the Canton Tower [123]. The iterative self-training enhanced transfer learning method leveraged self-training to augment abundant samples without additional experiments while integrating domain adaptation to enhance learning from augmented knowledge, improving prediction performance by up to 60% over conventional direct training in experiments involving numerical simulations, shake-table testing, and field-sensing records [107]. The improved inception-based neural network for real-time displacement field prediction of ultra-high-rise structures used a solution space-based method for generating training data using Markov chains and key nodes with Kriging interpolation, achieving correlation coefficients exceeding 0.992 for ultra-high-rise structures at computational speeds up to 43,700 times faster than conventional finite element calculations [119].

3.4 Feature Engineering, Transfer Learning, and Data-Driven Enhancement

The success of machine learning models for structural dynamic response prediction is critically contingent upon the quality, dimensionality, and representativeness of the input features and training data. Raw sensor signals, such as acceleration time histories, often contain redundant information and noise, which can degrade model performance and increase computational cost. Consequently, a substantial body of research has focused on developing systematic approaches to feature engineering, dimensionality reduction, and data augmentation. Furthermore, the high cost of generating labeled data for each new building or loading scenario has motivated the adoption of transfer learning techniques, which allow knowledge gained from one domain to be applied to a related but different domain. This subsection synthesizes the studies that explicitly address these data-centric enhancement strategies, as summarized comprehensively in Table 3.

Table 3. Characteristics of included studies focusing on feature engineering, transfer learning, and data-driven enhancement.

STUDY ID	PRIMARY ENHANCEMENT STRATEGY	DIMENSIONALITY REDUCTION / FEATURE SELECTION	INPUT FEATURE TYPE	DATA SOURCE & SIZE
[19]	Unsupervised learning (PCA, Autoencoder) coupled with ANN	PCA, Autoencoder (unsupervised)	Building characteristics, ground motion parameters	NL-THA; >192,000 buildings
[28]	Integration of structural properties and seismic intensity measures (SIMs)	N/A	Structural properties, time/freq/energy SIMs	Generated via analysis of many linear/nonlinear systems
[117]	Multi-fidelity meta-learning algorithm	Incremental data learning	Numerical simulations, field monitoring data	Multi-fidelity datasets; small-sample field monitoring
[119]	Solution space-based data generation using Markov chains	N/A	Seismic records	Finite element calculations

[121]	Particle swarm optimization for LSTM hyperparameter tuning	N/A	Strain, acceleration, measured GPS displacement	Field measurements from 600m skyscraper
[123]	Compressive sensing (CS) combined with LSTM (LSTM+CS)	Compressive sensing	Structural response time histories	Simulated (4DOF) and real (Canton Tower)
[30]	Leveraging ambient vibration (AV) measurements with earthquake data	N/A	AV and EQ time-history data	1197 MDOF 2D shear models; 32,319 samples
[31]	Transfer learning (TL) combined with proper orthogonal decomposition (POD) and LSTM	Proper Orthogonal Decomposition	Longitudinal locations of pressure time series	Wind tunnel experimental data
[33]	Comprehensive feature selection, hyperparameter tuning, cross-validation	Feature selection (varied across models)	Design parameters (height, period, etc.)	621 steel moment frames
[20]	Hybrid ML model for improved seismic prediction and generalization	N/A	Structural design parameters	NLTHA for three SMFs (4, 8, 12 stories)
[39]	Model-based transfer learning (fine-tuning) across different story numbers	Autoencoders, feature engineering	High-dimensional features from SMRF database	SMRF prototype database with varying story numbers
[41]	Data generation via Non-Linear Dynamic Analysis; GUI development	N/A	Structural configurations	ETABS; 29,200 data points from 292 models
[44]	Improved algorithms with innovative techniques	N/A	Structural features	92,400 data points from 165 RC MRFs
[46]	Particle swarm optimization (PSO) for GM selection; ML fusion model	PSO for GM selection	Ground motion records	High-rise RC building
[51]	Comparison of four ML algorithms for wind pressure prediction	N/A	Wind pressure data	Standard tall building wind tunnel data
[55]	K-means clustering for force spectrum understanding; LGBM model	K-means clustering	Crosswind force spectra, aspect ratio, side ratio	NatHaz aerodynamic database

[54]	Time series k-means (TSkmeans) for data clustering	TSkmeans clustering	Acceleration records, structural responses	Numerical method data
[56]	Multidomain feature guidance (time, frequency, statistical) in GAN	N/A	Seismic response time-frequency data	Numerical models and field measurements
[59]	Physics-informed inputs (response diagrams) and scientific training strategies	N/A	Response diagrams of SDOF systems	N/A
[69]	SHAP for feature importance; RF model selection	SHAP for feature importance	Spectral accelerations at selected periods	DesignSafe DB; 468 frames, 240 GMs, 112,320 data points
[70]	Principal component analysis (PCA) for dimensionality reduction and noise elimination	PCA	Frequency response functions (FRFs)	Shaking table test; 1:20 scale 38-story building
[73]	Input map combining time/freq domain displacement and wind data	N/A	Top-level displacement (time/freq), wind data (freq)	Wind tunnel test data
[74]	Data generation method based on data overlapping	N/A	Time histories of acceleration responses	ASCE benchmark model; shaking table test of RC frame
[75]	Introduction of 'resonance area' parameter	N/A	GM characteristics (mean period, PGA, resonance area)	2700 Artificial earthquakes
[78]	Use of seismic intensity measures (SIMs) as additional input	N/A	GM time history, SIMs (Arias Intensity, CAV)	Shaking table test of 3-story RC frame
[79]	Integration of EMD, mutual information (MI), and Bayesian regularization	Mutual information (MI) for neuron optimization	Structural response signals	1:20 scaled 38-story building; five-story steel frame
[81]	Bayesian optimization (BO) for ANN architecture tuning	BO algorithm	Earthquake records, building parameters	111 earthquake events (SAC project)
[83]	Equivalent stiffness parameters for macro-scale model; DInC as input features	N/A	Displacement Interaction Coefficients (DInC)	Detailed finite element models
[85]	Transfer learning for model finetuning across different buildings	N/A	Seismic response data	Finite element models of various parameters; actual structures

[88]	Kernel-based ML; reconstruction of demands with limited sensors	Kernel methods (limited sensor use)	Peak floor accelerations and drift ratios from limited locations	Nonlinear RHA; portfolio of tall buildings (Northridge)
[91]	ANN using modal response spectrum analysis; high prediction rate	N/A	Earthquake parameters, soil condition, building geometry	Modal analysis; 1080 training, 405 testing datasets
[92]	Autoregressive NN; partition of single time history into multiple datasets	N/A	Modal periods, windowed earthquake data, structural response	NLTHA records; 10-300 records for fragility
[93]	Filtering (FFT, DWT) and decimation for dimension reduction	Decimation, FFT/DWT filtering	Acceleration time-series (three components)	Field sensing data (practical industrial building)
[94]	Hyperparameter optimization (windowing, down-sampling, batching, dropout)	Down-sampling	Base/ground acceleration	Sensors in BRI ANX building (historic events)
[95]	SHAP for feature importance; reduced feature set retraining	SHAP for feature selection	Acceleration response spectrum	Nonlinear FE analyses; high-rise steel moment frames
[100]	Transfer learning with Bayesian hyperparameter optimization and SHAP	Bayesian optimization	Spatial coordinates of measurement points	Wind tunnel data from rectangular and square columns
[105]	SHAP for contribution analysis; MLP and RF models	SHAP for feature importance	Ground motion intensity, structural parameters	IDA for high-rise shear wall structures
[107]	Iterative self-training enhanced transfer learning (ISTL); sample augmentation	Self-training for sample augmentation	Structural time history response data	Numerical simulations, shake-table test, field-sensing records
[108]	GA for nonlinear structural modeling; ANN with deep learning for fragility	GA for model parameter selection	Structural and dynamic demand parameters	ZEUS-NL; tubular structures
[110]	Genetic algorithm for LSTM hyperparameter optimization	GA for hyperparameter optimization	Seismic response data (C-library, B-library)	Benchmark model data
[111]	Dynamic K-means clustering for unsupervised data selection	Dynamic K-means clustering	Seismic inputs (acceleration records)	Available datasets, field sensing data
[44]	Feature engineering emphasizing structural features	N/A	Structural features, ground motion parameters	IDA of 165 RC MRFs

[33]	Feature selection from design parameters	Feature selection (explicit)	Height, number of stories, period, beam inertia	621 steel moment frames
[83]	Macro-scale modeling with deep learning; DInC input features	N/A	DInC under each mode shape	Detailed FE models of frame and frame-core tube
[59]	Physics-informed inputs (response diagrams) for image classification adaptation	N/A	Response diagrams (linear SDOF histories)	N/A
[79]	Mutual information for neural network architecture optimization	Mutual Information	Structural response signals	38-story highrise building model; five-story steel frame
[28]	Integration of structural properties and seismic intensity measures	N/A	SIMs (time, frequency, energy), structural properties	Generated dataset of linear and nonlinear systems
[121]	PSO for hyperparameter optimization of LSTM	PSO for hyperparameter optimization	Strain, acceleration, GPS displacement	Field measurements from skyscraper during typhoon

The studies in Table 3 reveal that dimensionality reduction and feature selection are employed to address the challenges of high-dimensional input spaces and limited training data. A prominent approach is the use of unsupervised learning techniques for data preprocessing. For example, one study systematically coupled Principal Component Analysis and Autoencoders with an Artificial Neural Network to reduce the dimensionality of input features derived from over 192,000 building models analyzed via nonlinear time history analysis [19]. The Autoencoder-ANN model demonstrated the highest performance compared to the PCA-ANN and standalone ANN models, indicating that the non-linear dimensionality reduction capability of autoencoders is more effective at preserving relevant information for seismic response prediction than the linear projection of PCA. In another work, the 'resonance area' parameter was proposed to explicitly encode the frequency-domain relationship between a ground motion and a target structure as a novel input feature for a neural network, showing that this physics-informed parameter enhances the model's ability to estimate seismic responses by directly incorporating the dynamic characteristics of the structure [75].

Transfer learning emerges as a critical strategy to overcome the fundamental limitation of data scarcity, especially when adapting models to new buildings or loading conditions. One study proposed a model-based transfer learning method for data-driven seismic response prediction of steel moment-resisting frames with varying story numbers [39]. By pre-training on a source task (five-story frames) and fine-tuning with minimal data on target tasks (nine-, fourteen-, and nineteen-story frames), the method significantly improved prediction accuracy in data-scarce conditions while maintaining generalizability. A different study developed a hybrid transfer-learning framework that enabled effective fine-tuning of deep learning models for different structural systems using limited datasets, thereby enhancing both prediction accuracy and generalization capability by combining physical insights with advanced ML techniques [59]. The TL-POD-LSTM framework also combined transfer learning with proper orthogonal decomposition and LSTM to predict longitudinal wind pressure time series on a high-rise building using data from very few sensors, achieving a determination coefficient improvement from 0.194 to 0.976 when using only four taps at the target domain [31].

Beyond simple pre-training and fine-tuning, more sophisticated data-driven enhancement methods have been developed. The multi-fidelity meta-learning algorithm proposed for seismic response prediction of high-rise shear wall buildings enabled incremental data learning and model updates across datasets of varying fidelities, including multiple numerical simulations and field monitoring data [117]. Under small-sample field monitoring scenarios, this method reduced overall prediction errors by 40.4% compared to typical transfer learning approaches, demonstrating superior learning capabilities in limited-data settings. The iterative self-training enhanced transfer learning method took a further step to augment samples without additional experiments, combining self-training with output conditional distribution regularization to improve prediction performance by up to 60% over conventional direct training [107]. Another novel approach used compressive sensing to embed physical information into the prediction process of an LSTM model, thereby mitigating the prediction divergence that typically increases with prediction length; this method achieved high performance with limited data and minimal costs as verified on both simulated and real-world structural responses [123].

Several studies focused on optimizing the selection and representation of input features to maximize model performance. The integration of structural and seismic properties was systematically investigated by using seismic intensity measures representing time domain information, frequency domain information, and energy characteristics of seismic waves as inputs to an ANN, with separate models built for linear and nonlinear systems [28]. The results showed that the inclusion of all three classes of SIMs, combined with structural properties, yielded the best prediction performance for maximum inter-story drift ratio. Similarly, the use of structural seismic intensity measures such as singular value matrix, Arias Intensity, and cumulative absolute velocity as additional inputs to a CNN, alongside time history ground motion data, was found to improve strain response prediction performance in shaking table tests [78].

The importance of model interpretability in feature engineering is underscored by the use of SHAP analysis in multiple studies. One study used SHAP to inspect the importance of input variables for predicting seismic damage states of steel moment frames, finding that spectral accelerations at 1 and 2 seconds strongly influenced prediction because the first natural periods of the considered frames fell in this range [69]. Another study applied SHAP for feature importance inspection in predicting structural responses of high-rise steel moment frame buildings, leading to the selection of a reduced set of features that confirmed the importance of the acceleration response spectrum [95]. SHAP analysis of multilayer perceptron and random forest models for high-rise shear wall structures revealed that peak ground acceleration was the most significant parameter impacting structural response [105].

Clustering and data partitioning strategies have also been employed to enhance model training and prediction. The time series k-means algorithm was used to divide label data into different clusters to enhance the generalization of RNN and LSTM models for predicting responses of structures with or without nonlinear components [54]. The dynamic K-means clustering approach was specifically developed as an unsupervised learning algorithm to generate the least but most informative datasets for training LSTM networks, improving prediction accuracy and robustness, particularly when training data was limited [111]. For wind engineering applications, K-means clustering was employed to advance the understanding of crosswind force spectrum characteristics of tall buildings, with the effects of ground roughness, aspect ratio, and side ratio on the force spectra discussed based on clustering results [55].

Particle swarm optimization and genetic algorithms have been leveraged as data-driven enhancement tools. PSO was used to optimize the hyperparameters of an LSTM model for improving GPS displacement measurement accuracy of a high-rise building under windstorm conditions, with the resulting PSO-LSTM model demonstrating superior performance in enhancing the accuracy of displacement measurements during a Tropical Storm [121]. In another study, PSO was integrated with a machine learning fusion model to select ground motions that may induce maximum inter-story drifts, thereby facilitating the generation of more accurate fragility curves for a high-rise RC building [46]. A method that fused a genetic algorithm with an LSTM network for high-rise building vibration intelligent control demonstrated that the GA optimized hyperparameters and achieved good prediction results, with the fitness value representing the controller loss function converging after 80 iterations [110]. Additionally, GA was used for nonlinear structural modeling of tubular structures, coupled with an ANN developed using deep learning, to reduce computational demand for fragility assessment [108].

The macro-scale modeling approach proposed to capture bending-shear coupled dynamic behavior in high-rise structures used equivalent stiffness parameters representing horizontal and vertical members and Displacement Interaction Coefficients as input features to identify a Lumped Parameter Model's stiffness parameters via deep learning [83]. This method efficiently reproduced dynamic characteristics of frame and frame-core tube structures. A study demonstrated that through the integration of empirical mode decomposition for noise removal, mutual information for determining the optimum number of neurons in the hidden layer, and Bayesian regularization for training, a NARX-based recurrent neural network could achieve accurate response prediction for large structures while maintaining low computational burden for real-time applications [79].

Collectively, these studies demonstrate that the path to robust and practical machine learning models for structural dynamic response prediction is not solely about architecting deeper or wider networks. Instead, it critically depends on the thoughtful curation and transformation of input data, the strategic transfer of knowledge across domains, and the systematic enhancement of training processes. Feature engineering techniques that embed physical understanding—such as the resonance area parameter or multidomain feature constraints—consistently outperform purely data-driven representations. Transfer learning provides a pragmatic solution to the chronic problem of data scarcity, while advanced optimization and data augmentation methods further push the boundaries of what can be achieved with limited high-fidelity samples. However, the diversity of enhancement strategies, and the lack of a unified framework for comparing their efficacy, highlight the need for future research to establish standardized benchmarks that isolate and evaluate the contribution of each enhancement component.

3.5 Structural System-Specific and Multi-Hazard Response Prediction

The vast majority of the machine learning studies reviewed focus on predicting the global dynamic response of generic building models, often idealized as multi-degree-of-freedom shear frames or moment-resisting frames. However, real-world high-rise buildings exhibit a diverse array of structural systems, each with distinct load-resisting mechanisms, dynamic characteristics, and failure modes. Furthermore, these buildings are often subjected to multiple hazards concurrently or sequentially, such as the combined action of wind and seismic loads, or the escalation of damage from a mainshock to aftershocks. The effective application of ML in these contexts demands models that are either tailored to specific structural systems or capable of learning the multi-faceted physics of multi-hazard scenarios. This subsection synthesizes the studies that directly address these challenges of structural system-specific and multi-hazard response prediction. The relevant studies are summarized in Table 4.

Table 4. Characteristics of included studies focusing on structural system-specific and multi-hazard response prediction.

STUDY ID	STRUCTURAL SYSTEM SPECIFICITY	HAZARD TYPE(S)	PREDICTION TASK	VALIDATION APPROACH	APPLICATION FOCUS

[117]	High-rise shear wall buildings	Seismic	Seismic response prediction	Multi-fidelity datasets (numerical and field monitoring); noise robustness test	Post-earthquake loss assessment; pre-event vulnerability identification
[120]	Composite tall building	Multi-hazard (Earthquake + Wind)	Fragility estimates	Unknown (surrogate model for FE)	Uncertainty quantification (epistemic & aleatory); resilience assessment under multiple hazards
[122]	Masonry structure; RC irregular structure; RC frame structure (11 & 21 story)	Seismic wave	Real-time structural response prediction	Ablation study; comparative experiment; 5000x speedup over FE	Damage assessment; structural health monitoring; resilience assessment
[35]	Rectangular RCC high-rise building	Wind	Displacement and drift at each story	Wind tunnel testing; codal and numerical validation	Performance-based wind design in Indian wind zones
[36]	General high-rise structure	Vertical and lateral loading	Displacement time series (vertical, lateral X, Y)	FEA-generated dataset; R^2 > 0.99 on test data	Structural health monitoring in seismic areas
[38]	Tall building (150 m)	Wind (long-duration)	Nonlinear structural response under sustained wind	Aeroelastic wind tunnel test data	Performance-based wind engineering for long-duration winds
[45]	11-story with semi-active TMD; 27-story with mid-story isolation	Seismic	Time history response simulation	FEM comparison; unseen ground motions	Optimal design of semi-active control systems
[47]	G+15 RC building with fluid viscous dampers	Seismic	Storey displacement, shear, drift	FEA (ETABS) results used for training	Seismic vulnerability assessment with retrofitting
[50]	Shanghai Tower (tallest in China); woodframe classroom	Seismic excitation	Online structural response forecasting	Real-world case studies	Early warning system for extreme loads
[52]	20-story benchmark high-rise building	Seismic (strong	Seismic response control (decentralized)	Simulation with noise and sensor failure	Fault-tolerant control system for large

		earthquakes)			complex structures
[53]	Kingkey 100 (super high-rise)	Typhoon (wind)	Long-term wind-induced acceleration response	Measured typhoon data; wind tunnel tests	Proactive emergency response during typhoons
[56]	3-story moment-resisting frame; RC frame structure	Seismic	Structural seismic response reconstruction	Numerical models and field measurement data	Safety assessment of structures under earthquakes
[57]	Five RC frame structures; RC frame shaking table test	Seismic	Acceleration time-history reconstruction	Multiple real-world datasets; damage assessment of NSCs	Non-structural component damage evaluation
[22]	General building (damage identification)	Earthquake	Max ductility, inter-story drift, acceleration	Real earthquake records; CNN with wavelet input	Immediate post-earthquake damage identification
[58]	Super high-rise structures (MFS model)	Multi-hazard (Earthquake + Wind)	Dynamic response prediction (sensitivity analysis)	Monte Carlo simulation; PCK surrogate	Global sensitivity analysis for uncertainty propagation
[60]	RC columns	Cyclic loading and ground motions	Lateral seismic response	Experimental data as ground truth	Component-level response prediction
[61]	20- and 40-story RC frame buildings	Seismic	Displacement	ETABS simulations	Understanding structural behavior under seismic loads
[67]	Steel trusses	Earthquake (El Centro)	Seismic lateral deflection	Nine ML algorithms evaluated; experimental validation	Structural reliability analysis (future)
[68]	Planar steel moment frames (1-19 stories)	Ground motions	Maximum top and interstory drift	22,464 analyses; R^2 = 0.975 (XGBoost)	Performance-based seismic design
[69]	Steel moment frames (1-19 stories)	240 Ground motions	Seismic damage state (green/yellow/red)	112,320 data points; RF, XGBoost; SHAP	Rapid post-earthquake damage assessment
[71]	General tall building	Wind	Base shear and base bending moment	Indian Wind Code (IWC) comparison	Design charts for configurations not in code

[72]	General tall building	Along-wind	Dynamic along-wind base shear/moment	IWC (IS 875)	Simplified empirical equation for wind response
[73]	General tall building (wind tunnel model)	Wind	Column strain (max/min)	Wind tunnel test data; comparative CNN	Structural health monitoring under wind
[74]	ASCE benchmark model; RC frame (experiment)	Earthquake	Displacement responses	Numerical and shaking table tests	Seismic response prediction
[76]	32-story residential building; Leatop Plaza, Guangzhou (303 m)	Earthquake; Typhoon	Dynamic response reconstruction	Real-world data under seismic and typhoon events	SHM under extreme events with data loss
[78]	3-story RC frame (shaking table test)	Earthquake (ground motion)	Strain response of members	Experimental data	Strain response prediction using GM data
[80]	General high-rise building	Wind	Optimal TMD tuning	Multi-degree-of-freedom models	Optimal design of passive control devices
[82]	High-rise structures with SMA, FRP, dampers	Seismic	Drift, base shear, damage index, energy dissipation	K-fold cross-validation; ANN, LSTM, hybrid	AI-assisted seismic assessment with smart materials
[84]	Outrigger systems in tall buildings	Seismic	Lateral displacement, drift, energy dissipation	Pushover and time-history analysis; ANN, SVM, GA	Optimal outrigger design in earthquake-prone regions
[87]	Multi-storey steel structures	Seismic	Drift and base shear	FEA (Ansys) validation; 3793 simulations	Performance-based seismic engineering; digital twins
[89]	Multi-story RC building	Earthquake	Acceleration, velocity, story drift	Indonesian seismic code; 96% prediction accuracy	Rapid building condition identification
[90]	Multi-story RC building	Ground acceleration	Acceleration, velocity, story drift	Modal response spectrum analysis (Indonesia)	Seismic-resistant building design
[91]	Multi-story RC building (Sumatra)	Earthquake	Story drift	95% prediction accuracy	Building condition identification and maintenance

[92]	Nonlinear column; damper-equipped structure; base-isolated building	Earthquake	Time-history response	Three numerical examples; ARNN for fragility	Efficient fragility curve generation via MCS
[96]	15-story RC framed buildings (facade, soft storey, shear wall)	Gravity, wind, seismic	Displacement, drift, shear, base reactions	ETABS; Decision Tree, RF, MLP	Seismic design and retrofit decision-making
[98]	Double skin composite wall (DSCW)	Earthquake	Hysteretic behavior (force-displacement)	Experimental data; SHAP analysis	Seismic performance assessment of composite structures
[101]	High-rise buildings with outrigger systems (3 types)	Seismic and Wind	Dynamic response and fragility	3D FE models (ANSYS); sensitivity analysis	Fragility estimates for seismic and wind loads
[103]	High-rise buildings with one-outrigger system (3 types)	Seismic	Inter-story drift and top acceleration	Comparison with kriging and probabilistic models; SHAP	Fragility estimation of outrigger systems
[106]	Scaled tall building (wind tunnel)	Wind	Vibration response mapping	Cyber-physical system in wind tunnel; GA, PSO, SA	Adaptive wind-induced vibration control
[111]	Nonlinear hysteretic system; real-world building; steel MRF	Seismic	Nonlinear structural seismic response	Three proof-of-concept studies	Seismic fragility analysis; reliability assessment
[113]	4 frame structures (20 stories)	Seismic	Drift peak amplitudes	Accuracy evaluation method; 80%+ explanation	Efficient seismic response simulation
[114]	Four actual buildings (varying construction time, occupancy, size)	Ground motion records	Seismic time-history response	Comparison to MDOF method; good generalization	Urban-scale seismic hazard prediction
[115]	Single-DOF; vehicle-bridge system; high-rise building (Typhoon Hato)	Wind (typhoon); forced vibration	Dynamic response; structural fragility	Real-world monitoring data; PIML outperforms pure ML	Structural reliability and fragility under climate change

Studies focusing on specific lateral load-resisting systems reveal that the choice of ML architecture must be informed by the underlying structural mechanics. For instance, high-rise shear wall buildings, which resist lateral loads primarily through cantilever wall action, were the subject of a multi-fidelity meta-learning algorithm that integrated heterogeneous data sources, including floor-based and component-based numerical models, as well as field monitoring data [117]. The algorithm, designed to work with small-sample field monitoring data, not only reduced prediction errors by 40.4% over conventional transfer learning but also demonstrated robustness to noise in input features. This system-specific approach effectively addressed the challenge of data scarcity, a common problem for unique structural typologies where extensive monitoring data are not available. For super high-rise structures with outrigger systems, a specific type of lateral system used to connect the core to perimeter columns, kriging metamodels were developed for three distinct outrigger types to predict dynamic responses under both seismic and wind loads, and these metamodels were then used to generate fragility estimates [101]. Deep neural networks were then benchmarked against these kriging models for the same seismic scenario, with the DNNs demonstrating high sensitivity to the seismic hazard features (earthquake magnitude and rupture distance) and providing the basis for fragility curves that quantitatively showed the effectiveness of damped outrigger systems in reducing seismic fragilities [103]. An integrated ANN-SVM-GA framework was specifically tailored for the optimal design of outrigger systems, achieving a 46.67% reduction in lateral displacement and a 33.33% improvement in energy dissipation, and demonstrating code-adaptability across different seismic zones [84].

The response of building systems equipped with smart materials and supplemental damping devices represents another category of system-specific prediction. For a G+15 story RC building equipped with fluid viscous dampers at various locations, an ANN was trained on finite element analysis results to predict seismic vulnerability indicators such as storey displacements, storey shear, and storey drift, offering a fast and generalizable method for assessing the effectiveness of retrofitting strategies [47]. For structures with semi-active control devices, specifically a magnetorheological damper and a semi-active tuned mass damper, an RNN model was developed to simulate the nonlinear dynamic response of the controlled structure, thereby reducing the computational cost of iterative simulations needed for control system optimization [45]. This RNN model was tested on an 11-story building with a semi-active TMD and a 27-story building with a mid-story isolation system, accurately predicting seismic responses for both seen and unseen ground motions. The use of shape memory alloys, fiber-reinforced polymers, and damping systems in high-rise structures was assessed through an AI-driven framework integrating ANN, CNN, LSTM, and hybrid ANN-LSTM models, with the hybrid model achieving the highest predictive accuracy (R^2 = 0.96) for earthquake demand parameters and quantifying a 39% reduction in damage indices for the smart-material-integrated structures [82].

System-specific ML models have also been developed for steel framing systems, which exhibit ductile, energy-dissipating behavior. For steel moment-resisting frames, a comprehensive study evaluating nine ML algorithms for predicting seismic drift responses found that tree-based ensemble methods, particularly CatBoost and LightGBM, consistently outperformed Gaussian Process, SVM, and BP-FNN models across all considered truss types and loading scenarios [67]. In another extensive effort, an ANN and an XGBoost model were trained on 22,464 nonlinear dynamic analyses of 36 planar steel moment frames subjected to 624 ground motions [68]. The XGBoost model achieved a coefficient of determination (R^2) of 0.975 for maximum top drift and 0.962 for maximum interstory drift, identifying peak ground velocity as the most influential input variable. This study culminated in a practical graphical user interface for preliminary seismic drift estimation. Furthermore, for rapid post-earthquake damage state classification of steel moment frames—assigning tags of green, yellow, or red per ATC-20 guidelines—a random forest model achieved 98% prediction accuracy on a testing dataset, with spectral accelerations at periods of 1 and 2 seconds identified as the most critical input features through SHAP analysis [69].

Several studies have addressed the prediction of responses from building systems incorporating more complex components. For instance, a machine learning-aided model was developed to simulate the hysteretic behavior of double skin composite walls, a key lateral-force-resisting component in high-rise steel-concrete composite structures [98]. By combining a fiber-based material model with an artificial neural network, the model outperformed a Transformer-based deep learning model, particularly under asymmetric loading conditions, because the ANN model integrated physical mechanisms directly into the force-displacement constitutive relationship. The application of ML to systems with tuned mass dampers was demonstrated for optimal tuning under wind loads, where an ANN was trained on patterns from structural analyses of different multi-degree-of-freedom systems to find optimal TMD mechanical properties without iterative computations [80].

Studies focusing on multi-hazard scenarios are comparatively rarer but address the critical need for resilience assessment under combined threats. A hybrid AI-Bayesian methodology was proposed for fragility estimates of tall composite buildings subjected to simultaneous earthquake and wind events, using a BP-ANN surrogate to replace computationally expensive FE analyses for uncertainty quantification [120]. This approach incorporated both epistemic uncertainty, via Bayesian updating of demand model parameters, and aleatory uncertainty, via Monte Carlo sampling of material and geometric properties, and its application highlighted the importance of accounting for both uncertainty types in multi-hazard fragility estimates. A global sensitivity analysis of super high-rise structures under multi-hazards was performed using polynomial chaos Kriging as a surrogate model for the dynamic response [58]. This study revealed that epistemic uncertainty parameters, such as bending stiffness, density, and damping ratio, dramatically affect the dynamic responses under concurrent earthquake and wind loads, and that the variation levels of these parameters have a remarkably greater influence on sensitivity indices than the type of probability distribution assumed.

The prediction of responses for specific structural systems under a single hazard has also been advanced by models that can account for the complex interaction between loading and structural behavior. For the Shanghai Tower during seismic events, the TSA-RNN-ED model demonstrated that a time-series attention mechanism could effectively capture the time-varying correlation between ground motion and structural response [50]. For wind hazard, an intelligent long-term prediction method was validated on the Kingkey 100 super high-rise building during Super Typhoon Mangkhut, using a Cascade Forward-Backward Propagation Network that predicted structural acceleration responses with a correlation coefficient exceeding 0.99 [53]. By integrating this neural network with a linear typhoon wind field model and AI-based weather forecasting, long-term structural response predictions were achieved, enabling a shift from reactive emergency measures to proactive decision-making. Similarly, the Pyramid-LSTMA architecture was validated on both a 32-story residential building subjected to seismic events and the 303 m Leatop Plaza in Guangzhou during a typhoon, demonstrating its robustness in reconstructing dynamic responses under multiple hazard types [76].

The influence of architectural and structural features on seismic behavior was systematically studied for 15-story RC framed buildings with facades, soft storeys, and shear walls [96]. Among the ML models evaluated (Decision Tree, Random Forest, and Multi-Layer Perceptron), the Decision Tree and Random Forest regressors demonstrated superior predictive accuracy (R^2 up to 0.95) for key performance indicators such as storey displacement, inter-storey drift, and base shear. The study revealed that shear wall-equipped models exhibited a 60-70% reduction in roof displacement and inter-storey drift, alongside a 120-140% increase in base shear capacity compared to frame-only configurations, while soft storeys amplified deformation demand in the absence of shear walls. This work bridges the gap between system-specific architectural features and data-driven structural response prediction.

The majority of studies reviewed have focused on predicting either seismic or wind-induced responses individually. However, the need for unified frameworks capable of seamless predictions under both hazards is increasingly recognized. The physics-informed deep learning model, Phy-Seisformer, was tested on multiple building types including an 11-story RC irregular structure and a 21-story RC frame structure, demonstrating that the integration of structural physical information into the model architecture enabled high-precision predictions at speeds at least 5,000 times faster than finite element calculations across different building types [122]. This cross-system validation is crucial for establishing the generalizability of a single model to varying building typologies. Furthermore, a macro-scale modeling approach using deep learning, which introduced equivalent stiffness parameters and displacement interaction coefficients as input features, successfully captured the dynamic behavior of both frame and frame-core tube structures for earthquake and typhoon hazards, demonstrating a unified method for rapid response estimation across distinct structural systems [83].

The studies summarized in Table 4 also highlight the progression from single-building, single-hazard case studies towards more integrated and system-specific approaches. The research on steel moment frames [68] [69] demonstrates how ML can be systematically used for a single, well-defined structural typology across thousands of parametric configurations. The work on outrigger systems [84] [101] [103] illustrates how ML can be embedded in the design optimization loop for a specific lateral system. In contrast, the multi-hazard studies [120] [58] represent an important but still nascent direction where ML is used to tackle the combined effects of wind and earthquakes. The composite tall building study [120] specifically addressed the quantification of both epistemic and aleatory uncertainties for multi-hazard fragility analysis, providing a Bayesian framework that directly enhances the reliability of resilience assessments.

Similarly, the structural fragility analysis using a PIML approach that embeds the resonance effect showed significant changes in the fragility of a high-rise building under climate change projections from 1985 to 2045, demonstrating the long-term value of this combined approach [115]. The application of ML to building portfolios, rather than individual structures, has also been explored using kernel-based methods that reconstruct full demand profiles from limited sensor locations during the Northridge earthquake, demonstrating the potential for city-scale rapid damage assessment [88].

The evidence suggests that while the field is progressing towards more nuanced, system-aware models, the validation of these models for multi-hazard scenarios remains a significant gap. Most studies validate against a single hazard event or a single building system. The few studies that address multi-hazard often rely on simplified models, such as the multiple-degree-of-freedom shear model used for global sensitivity analysis [58]. Future work should aim to develop ML models that are not only tailored to specific structural systems but are also rigorously validated under multi-hazard conditions, using high-fidelity models or field data from actual multi-hazard events.

3.6 Surrogate and Probabilistic Models for Fragility and Performance

A substantial portion of the literature is dedicated to developing surrogate models that replace computationally expensive finite element simulations for probabilistic performance assessment, particularly for generating fragility curves and estimating expected losses. These surrogate models enable the efficient propagation of uncertainties through the analysis chain, a task that would be computationally prohibitive with direct Monte Carlo simulation using high-fidelity models. The studies in this category are characterized by their explicit goal of not just predicting response, but of quantifying the probability of exceeding a given performance limit state under uncertain loads and structural properties. The key characteristics of these studies are summarized in Table 5.

Table 5. Characteristics of included studies focusing on surrogate and probabilistic models for fragility and performance.

STUDY ID	PROBABILISTIC/FRAGILITY FOCUS	SURROGATE MODEL TYPE	UNCERTAINTY QUANTIFICATION APPROACH	VALIDATION/APPLICATION SCALE
[21]	Structural reliability (probability of failure)	Physics-informed neural network	Monte Carlo simulation with surrogate prediction	Generic structural element (stress-based failure)
[23]	Response prediction (seismic demand model)	ANN with simulated annealing	Sensitivity analysis of input variables	15, 20, 25, 30-story RC shear wall buildings
[28]	Seismic response prediction (maximum inter-story drift)	ANN	N/A (deterministic prediction)	General linear and nonlinear structural systems
[29]	Wind-induced fragility functions	Stochastic polynomial chaos expansions	Non-parametric fragility from statistical dependence of EDP on IMs	60-story CAARC steel moment frame under downburst winds
[33]	Median fragility and expected annual loss	SVM, random forest, etc.	Cross-validation and statistical performance metrics	621 steel moment frames
[34]	Fragility curves	Deep learning-based multi-fidelity model	High-fidelity prediction from low-fidelity data	RC frame and high-rise shear-wall structure
[41]	Seismic limit-state capacity (M-IDR as proxy)	RF, XGBoost, ANN	N/A (deterministic mapping)	SMRFs on soil type D
[44]	Seismic limit-state capacity and performance assessment	ANN, XGBoost	N/A (deterministic mapping)	165 RC MRFs
[46]	Fragility curves	ML fusion model (PSO-assisted)	PSO for GM selection; ML for EDP prediction	High-rise RC building
[47]	Seismic vulnerability assessment	ANN	N/A (deterministic mapping)	G+15 RC building with dampers
[48]	MIDR estimation for performance assessment	DCNN with interstory drift spectrum	N/A (deterministic mapping)	30 RC buildings; 30 steel MRFs
[55]	Crosswind response prediction (deterministic)	LGBM with random	N/A (deterministic prediction)	Rectangular tall buildings

		vibration theory		
[58]	Global sensitivity analysis (parametric)	Polynomial chaos Kriging (PCK)	Sobol' indices for sensitivity	Super high-rise multi-degree-of-freedom shear model
[64]	Probabilistic performance assessment	Multiple surrogate models	N/A (comparison of surrogates)	Wind-excited tall buildings
[65]	Life-cycle cost optimization	Kriging surrogate models	N/A (deterministic optimization)	39-story building with dampers
[67]	Seismic lateral deflection prediction (deterministic)	CatBoost, LightGBM, etc.	N/A (deterministic prediction)	Steel trusses
[68]	Seismic drift prediction (deterministic)	ANN, XGBoost	N/A (deterministic prediction)	Planar steel moment frames
[69]	Seismic damage state classification (green/yellow/red)	RF, XGBoost, LightGBM	SHAP for feature importance	468 steel moment frames; 240 GMs
[70]	Seismic damage identification	NN with PCA-compressed FRFs	PCA for noise elimination	1:20 scale 38-story building (shaking table)
[71]	Dynamic wind response (design charts)	ANN	N/A (deterministic prediction)	Tall buildings (Indian Wind Code)
[72]	Dynamic along-wind base shear/moment (design charts)	ANN	N/A (deterministic prediction)	Tall buildings (Indian Wind Code)
[75]	Seismic response prediction	NN	N/A (deterministic prediction)	MDOF structures; planar RC building
[77]	Fragility curves for regional damage assessment	Gaussian process regression	Fragility curves from GPR-based displacement model	Six-floor and 13-floor buildings; regional application (Gyeonjgu, Korea)
[80]	Optimal TMD tuning (performance optimization)	ANN	N/A (deterministic optimization)	Generic high-rise buildings
[84]	Seismic performance optimization (outrigger systems)	ANN, SVM, GA	N/A (deterministic optimization)	Outrigger systems in tall buildings
[87]	Seismic response prediction (drift, base shear)	ANN	N/A (deterministic prediction)	Multi-storey steel structures
[92]	Fragility curves	Autoregressive neural network (ARNN)	Monte Carlo simulation with ARNN-predicted time histories	Nonlinear column; damper-equipped structure; base-isolated building

[96]	Seismic behavior prediction (parametric study)	Decision Tree, RF, MLP	N/A (deterministic prediction)	15-story RC buildings with facades, soft storeys, shear walls
[101]	Fragility estimates for outrigger systems	Kriging metamodels	Sensitivity analysis	High-rise buildings with 3 types of outrigger systems
[103]	Fragility estimates for outrigger systems	Deep neural networks	SHAP for global and local model explanation	High-rise buildings with outrigger systems (3 types)
[105]	Seismic fragility analysis of shear wall structures	Multilayer perceptron, random forest	SHAP for contribution analysis	Three high-rise shear wall structures
[108]	Fragility assessment for tubular structures	GA + ANN (deep learning)	N/A (deterministic mapping)	Tubular structures
[109]	Structural fragility analysis under wind loads	ANN surrogate modeling	N/A (comparison with Monte Carlo)	Tall buildings and towers
[111]	Seismic fragility and reliability	Deep LSTM with dynamic K-means clustering	N/A (deterministic prediction)	Nonlinear hysteretic system; real-world building; steel MRF
[113]	Seismic response prediction (drift peaks)	Time-delay neural network	N/A (deterministic prediction)	4 frame structures (20 stories)
[114]	Seismic response prediction	End-to-end network with adaptive multilevel fusion	N/A (deterministic prediction)	Four actual buildings (varying sizes)
[115]	Structural fragility under climate change	Multi-layer perceptron with resonance loss	Fragility curves derived from PIML predictions	High-rise building (Typhoon Hato)
[116]	Seismic response prediction (damped structure)	XGBoost, SWT, aggregation model	N/A (aggregation model improves accuracy)	Damped structure with 13,855 responses
[117]	Seismic response prediction (fragility application)	Multi-fidelity meta-learning	Noise robustness test	High-rise shear wall buildings
[120]	Fragility estimates (multi-hazard)	BP-ANN	Bayesian statistics for epistemic uncertainty; Monte Carlo for aleatory uncertainty	Representative composite tall building

The studies in Table 5 reveal that the transition from deterministic response prediction to probabilistic fragility assessment is achieved through several distinct methodological pathways. The most direct approach involves replacing the computationally expensive finite element model with a trained ML surrogate, which is then queried thousands or millions of times within a Monte Carlo simulation to generate fragility curves. For example, the autoregressive neural network (ARNN) model was designed explicitly for this purpose, with a unique input layer incorporating modal analysis to extract structural periods, windowed earthquake data, and structural responses [92]. This ARNN enabled a single time history record to be partitioned into multiple training datasets, enhancing the efficiency of the Monte Carlo simulation for fragility generation, and was validated on three numerical examples including a nonlinear column, a damper-equipped structure, and a base-isolated building. Similarly, the use of stochastic polynomial chaos expansions as a surrogate for wind fragility analysis showed that non-parametric fragility functions could be accurately approximated with relatively small training datasets, even for vector-valued intensity measures, on a 60-story CAARC steel frame subjected to nonstationary downburst winds [29].

A conceptually related but more sophisticated approach is the use of multi-fidelity modeling to further reduce computational cost. The deep learning-enhanced multi-fidelity approach uses high- and low-fidelity numerical models to generate small and large sample responses, respectively [34]. A deep learning-based projection model is then trained with the limited high-fidelity data to learn the correlations between the two fidelity levels, allowing the trained model to predict high-fidelity results from low-fidelity simulations. This approach was validated on a reinforced concrete frame and a high-rise shear-wall structure, demonstrating that it can effectively accelerate seismic analyses for fragility curve generation without compromising accuracy. The multi-fidelity meta-learning algorithm proposed for high-rise shear wall buildings represents a significant advancement in this direction, as it integrates heterogeneous data sources—floor-based and component-based numerical models, as well as field monitoring data—into a single predictive framework that can be updated incrementally [117]. In small-sample field monitoring scenarios, this method reduced overall prediction errors by 40.4% compared to typical transfer learning approaches.

Several studies have focused on the explicit quantification of epistemic and aleatory uncertainties within the fragility framework. The hybrid AI-Bayesian methodology proposed for tall buildings under concurrent earthquake and wind events addresses both uncertainty types directly [120]. The aleatory uncertainty, associated with the inherent randomness of material properties and structural characteristics, is handled by using a BP-ANN surrogate model that can be rapidly evaluated in a Monte Carlo loop. The epistemic uncertainty, due to incomplete knowledge of the demand model parameters, is quantified through Bayesian statistics, which yields posterior probability distributions for the unknown parameters. This dual approach was applied to a representative composite tall building, demonstrating the importance of incorporating both uncertainty types for reliable multi-hazard fragility estimates. The polynomial chaos Kriging (PCK) method was used for a different form of epistemic uncertainty quantification—parametric sensitivity analysis [58]. By combining PCK as a surrogate with Sobol' indices for global sensitivity analysis, this study identified the most influential input parameters on the multi-hazard dynamic response of super high-rise structures, providing engineers with a clear understanding of which uncertainties most critically affect performance.

The studies that prioritize model explainability are also noteworthy in this context. For the prediction of median fragility and expected annual loss for a steel building inventory, a comprehensive comparison of eight ML algorithms found that support vector machines and random forests provided the highest accuracy, with an average R^2 of 0.93 and 0.91 over different performance outputs, respectively [33]. Crucially, an examination of the explainability of these best models revealed that height, number of stories, fundamental period, and the minimum of the beams' moment of inertia were the most influential input parameters across multiple PBEE outputs, providing design-oriented insights. SHAP analysis was used to objectively quantify the contribution of each input feature to the predicted fragility of high-rise shear wall structures, identifying peak ground acceleration as the most significant parameter [105]. For outrigger systems, model-agnostic analysis using partial dependence plots and SHAP revealed that the DNN predictions for inter-story drift and top acceleration were extremely sensitive to variations in earthquake magnitude and rupture distance [103]. These explainability techniques transform the black-box ML surrogate into a tool that can provide engineering insights, which is critical for adoption in performance-based design.

A further important development is the use of surrogate models for optimization within a performance-based framework. The life-cycle cost optimization of wind-excited tall buildings used a set of Kriging surrogate models to analyze a large number of different structural properties and damping device characteristics, with the combination that minimizes life-cycle cost taken as the optimal configuration [65]. This procedure was demonstrated on a wind-sensitive 39-story building, showing that the accuracy of the Kriging surrogates depended on the number of input variables considered, with an average root mean square error of 2.5% for floors without dampers and 5% for floors with damping devices. This approach directly connects the prediction of dynamic response to economic decision-making, which is the ultimate goal of performance-based engineering.

The studies summarized in Table 5 also reveal a clear methodological evolution from simple surrogate models used for deterministic response prediction to more sophisticated frameworks that incorporate multi-fidelity data, explicit uncertainty quantification, and model explainability. A key insight is that the choice of surrogate model is often less critical than the framework within which it is embedded. For instance, while the ANN surrogate used for wind fragility analysis [109] and the Gaussian process regression used for regional damage assessment [77] are different algorithms, both enable the computationally efficient generation of fragility curves that would be infeasible with direct Monte Carlo. The GPR-based model was specifically constructed to estimate maximum displacement from seismic activities and then used to construct fragility curves for regional damage assessment in Gyeonjgu city, South Korea, demonstrating that surrogate models can be scaled from individual buildings to city-wide applications. Similarly, the end-to-end network with adaptive multilevel fusion output was validated on four actual buildings with different construction times, occupancies, and floor sizes, showing good generalization for urban-scale seismic hazard prediction [114]. The time-delay neural network was used to predict drift peak amplitudes, achieving over 80% explanatory power as a performance parameter for limit-state assessment [113].

The diversity of approaches in this category reflects the complexity of moving from a deterministic prediction to a probabilistic decision-support tool. However, a critical gap is evident: many studies still validate their surrogate models only against the same type of data used for training (i.e., numerical simulations), without rigorous testing against field monitoring data from actual extreme events. The few studies that do incorporate real-world data, such as the multi-fidelity meta-learning algorithm [117] or the PIML model validated against Typhoon Hato monitoring data [115], stand out as examples of more realistic validation. Furthermore, the lack of a standardized benchmark for comparing the accuracy and efficiency of different surrogate modeling approaches for fragility analysis hinders the identification of best practices. Future work should prioritize the development of open-access benchmark datasets that include both numerical simulation results and field monitoring data for a variety of high-rise building types, along with standardized protocols for generating and evaluating fragility curves from surrogate models.

3.7 Physics-Informed and Hybrid Physics-Data Models

A profound methodological shift has occurred within the field, moving from purely data-driven models toward the systematic integration of physical laws and domain knowledge into the learning process. This class of models, broadly termed physics-informed machine learning, seeks to constrain the vast hypothesis space of neural networks by embedding governing differential equations, conservation laws, or other physical principles directly into the model architecture or loss function. The central motivation for this integration is to address the fundamental limitations of purely data-driven approaches: their lack of generalizability outside the training distribution, their propensity to violate physical plausibility, and their heavy dependence on large, high-fidelity datasets. By imposing physical consistency, these models promise improved accuracy, enhanced robustness to data scarcity, and predictions that remain physically interpretable even for unseen loading scenarios. This subsection synthesizes the studies that explicitly adopt such physics-informed or hybrid physics-data approaches, and their key methodological characteristics are summarized in Table 6.

Table 6. Characteristics of included studies focusing on physics-informed and hybrid physics-data models.

STUDY ID	PHYSICS INTEGRATION MECHANISM	CORE ML ARCHITECTURE	PHYSICS INTEGRATION LOCATION	VALIDATION APPROACH	APPLICATION SCENARIO
[21]	Elasticity and strength constraints embedded into the learning process	Physics-Informed Neural Network (PINN)	Loss function (constraints)	Benchmark against RF, GB, XGBoost, SVR, MLP; physics residuals	Near-real-time structural stress simulation for digital-twin workflows
[24]	Newton's second law of motion; dimensionality reduction via model order reduction and wavelet analysis	Physics-informed machine learning (PiML) with LSTM networks	Loss function (equation of motion)	Comparison with existing physics-guided LSTM; archetype steel moment frames (DesignSafe-CI)	Seismic response modeling of nonlinear steel moment resisting frames
[29]	Stochastic polynomial chaos expansions for non-parametric fragility	Stochastic polynomial chaos expansions	Model formulation (statistical dependence)	Comparison with full nonlinear time-history analysis	Wind fragility analysis of high-rise buildings under downburst winds
[32]	Decoupled Timoshenko beam equation (horizontal displacement only) incorporated as physical information	Data-Driven Neural Network (DDNN) transformed into PINN	Loss function / model architecture	Comparison of shear-wave velocity (Cs) and longitudinal-wave velocity (Cl) estimates	Seismic damage identification in super high-rise buildings using SHM data

[34]	Multi-fidelity modeling (high- and low-fidelity physics simulations)	Deep learning-based projection model	Training data (multi-fidelity correlation)	Validated on RC frame and high-rise shear-wall structure; parametric study of training factors	Seismic assessment and fragility curve generation
[37]	Neural operators (DeepONet, FNO) for infinite-dimensional function space mapping; self-adaptive FNO and DeepFNOnet for discrepancy learning	Deep operator network, Fourier neural operator, DeepFNOnet	Model architecture (operator learning)	Comparison with high-fidelity models; two problems: shear building and high-rise building	Stochastic nonlinear time history response prediction under earthquakes and wind
[42]	Complex seismic motion equation encoded into FCN as an innovative physical loss function	Physics-assisted fully convolutional neural network (PhyFCN)	Loss function (seismic motion equation)	Numerical examples on two different buildings; comparison w/o physics; R^2 improvement >28% with single sample	Prediction of long-period ground motion responses for high-rise buildings
[57]	Floor response spectra (FRS) incorporated in the loss function as a physical constraint	Physics-guided neural network with autoencoder	Loss function (FRS constraint)	Five RC frames (numerical), shaking table test (experimental), and monitoring data under earthquake	Structural seismic response reconstruction and damage assessment of non-structural components
[59]	Response diagrams (linear SDOF histories) as physics-informed input representations	State-of-the-art deep learning architectures (adapted for image classification)	Input representation (response diagrams)	Systematic evaluation of optimizers and learning rate schedules; hybrid transfer-learning framework	Rapid structural seismic response prediction

[60]	Integration of ML with a hysteretic model; hybrid optimization for parameter identification	Modified hysteretic model; hybrid optimization; two data-driven solvers	Model architecture (ML predicts parameters for physics-based model)	Comparison with classical methods (fiber model); experimental data as ground truth	Lateral seismic response prediction of RC columns
[62]	Physics-informed (equations of motion)	Physics-informed recurrent neural network (RNN)	Model architecture / loss function	Comparison with finite element analysis	Seismic response evaluation of nonlinear multi-degree-of-freedom systems
[63]	Physics-informed data-driven large model (SeisGPT)	Generative Pre-trained Transformer (GPT) with deep neural networks	Training data (corpus of structural engineering principles)	Comprehensive validation; comparison with FEM; real-time capability	Real-time prediction of building dynamic behavior under seismic forces
[98]	Integration of physical mechanisms into the force-displacement constitutive relationship; fiber-based material model; modified Bouc-Wen model	Artificial neural network (ANN); Transformer-based DL model	Model architecture (ML predicts parameters for physics-based hysteretic model)	Experimental data; SHAP analysis; comparison with end-to-end Transformer	Hysteretic response prediction of double skin composite walls
[99]	Structural natural frequencies embedded into Fourier feature mapping; elimination of manual tuning for multi-frequency response	Natural Frequency-Based Fourier Feature PINN (NF-FF-PINN)	Input representation (Fourier features with natural frequencies)	Numerical validations; relative displacement L2 error <2%; noise analysis vs. Newmark method	Structural dynamic response prediction under broadband earthquake excitations
[112]	Dynamics laws (e.g., equation of motion) applied as constraints to network outputs	Physics-guided convolutional neural network (PhyCNN)	Loss function / output constraints	Three case studies (numerical and experimental); comparison w/o physics guidelines	Data-driven seismic response modeling and serviceability assessment

[115]	Resonance effect embedded into the MLP loss function	Multilayer Perceptron (MLP)	Loss function (resonance effect)	Numerical simulations; real-world Typhoon Hato monitoring data; parameter analysis	Structural dynamic performance modeling; long-term fragility under climate change
[116]	Physics-informed inputs (response diagrams)	XGBoost, CNN, Transformer (SWT), aggregation model	Input representation (seismic wave transformer)	13,855 structural responses; comparison of multiple ML models	Seismic response prediction of damped structures
[118]	Physics-informed variational autoencoder for wind load inversion	Improved Inception module; inverse neural networks; physics-informed variational autoencoder	Model architecture (autoencoder with physics)	Full-scale FE analysis and real health monitoring data; theoretical validation	Real-time wind response prediction and load inversion for skyscrapers
[122]	Physical information of the structure incorporated into the Phy-Seisformer model	Phy-Seisformer (transformer-based)	Model architecture (structural parameters embedded)	Ablation study; comparative experiment; three building types; 5000x speedup over FE	Real-time structural response prediction for post-earthquake assessment and SHM
[115]	Resonance effect embedded into the MLP loss function for wind-induced vibration	Multi-layer perceptron (MLP)	Loss function (resonance effect)	SDOF, vehicle-bridge system; real high-rise Typhoon Hato data; PIML outperforms pure ML	Structural dynamic performance modeling; fragility under climate change
[117]	Multi-fidelity physics simulations integrated via meta-learning	Multi-fidelity meta-learning algorithm	Training data (multi-fidelity meta-learning)	Small-sample field monitoring data; 40.4% error reduction over transfer learning	Seismic response prediction of high-rise shear wall buildings

The analysis of Table 6 reveals several distinct strategies for integrating physics into machine learning for structural dynamic response prediction. The most common strategy is to embed a physical constraint into the loss function of the neural network, thereby penalizing predictions that violate the governing equations of motion. For instance, the physics-informed machine learning (PiML) method for nonlinear steel moment resisting frames constrains the model's solution space within known physical bounds through three main features: dimensionality reduction via combined model order reduction and wavelet analysis, LSTM networks for temporal dependencies, and Newton's second law as a constraint in the loss function [24]. This approach allows the model to learn system nonlinearities and confine solutions within physically interpretable results, enabling training with sparse data while enhancing accuracy, interpretability, and robustness. The physics-assisted fully convolutional neural network (PhyFCN) similarly encodes the complex seismic motion equation into the FCN to formulate an innovative physical loss function [42]. Even when only one training sample is available, this physics-assisted mechanism sharply increased the R^2 value by 28.4% while decreasing the mean squared error by 60.2% and the mean absolute error by 37.6%, demonstrating the profound impact of imposing physical constraints when data are extremely scarce. The physics-guided convolutional neural network (PhyCNN) applies dynamics laws, such as the law of dynamics, as constraints to the network outputs, thereby alleviating overfitting issues, reducing the need for big training datasets, and improving the robustness of the trained model for more reliable prediction [112].

A second major strategy involves embedding physical information directly into the input representation or the model architecture itself, rather than solely through the loss function. The Natural Frequency-based Fourier Feature PINN (NF-FF-PINN) framework embeds structural natural frequencies into the Fourier feature mapping, theoretically aligning the neural representation spectrum with the physical frequency content of the structure [99]. This approach eliminates the manual parameter tuning required by standard Fourier feature mappings and significantly enhances multi-frequency response accuracy, achieving a relative displacement L2 error below 2% and stable convergence within 5×10^3 iterations for broadband earthquake excitations. The Phy-Seisformer model explicitly incorporates the physical information of the structure into the transformer-based architecture, enabling higher-precision predictions that are at least 5000 times faster than finite element calculations for different types of building structures, including a four-story masonry structure, an eleven-story RC irregular structure, and a twenty-one-story RC frame structure [122]. The physics-informed variational autoencoder model for skyscraper wind response prediction and load inversion represents an architectural integration of physics, where the autoencoder is trained in a physics-informed manner to reconstruct wind load sequences in real time from limited sensor inputs, thereby accounting for the non-unique relationship between wind-induced response sequences and wind load sequences [118]. For seismic damage identification in super high-rise buildings, a Timoshenko beam model was incorporated into a data-driven neural network as physical information to form a PINN, enabling the highly reliable estimation of both shear-wave velocity and longitudinal-wave velocity, which decrease when structural damage occurs [32].

A third, highly innovative strategy uses a hybrid modeling approach where ML is used to predict the parameters of a physics-based constitutive or hysteretic model, rather than predicting the response directly. The machine learning-aided model for simulating the hysteretic behavior of double skin composite walls represents this approach: a fiber-based uniaxial material model incorporating softening was proposed first to replicate the primary damaging mechanisms, a comprehensive dataset was generated, and then the modified Bouc-Wen model was used to calibrate hysteretic curves via optimization [98]. The artificial neural network was then trained to predict these consistent hysteretic parameters (CHPs) directly from the geometric and material properties of the wall, thereby integrating physical mechanisms into the force-displacement constitutive relationship. The SHAP analysis confirmed that the geometric parameters significantly influence the CHPs, highlighting the interdependence among Bouc-Wen model parameters. Similarly, the data-driven method for predicting the lateral seismic response of RC columns integrates ML with a hysteretic model: the ML model computes the parameters that govern the nonlinear properties of the lateral response from a training set composed of experimental data, and the hysteretic model then uses these parameters to output the lateral stiffness and perform the seismic analysis [60]. This approach significantly outperformed classical fiber beam-column methods in both generalized prediction capabilities and computational efficiency.

The studies in Table 6 also reveal a spectrum of how deeply physics is integrated, from loss function constraints to architectural modifications to hybrid physics-ML parameterization. The PIML approach that embeds the resonance effect into the MLP loss function was validated through both numerical simulations and real-world monitoring data from a high-rise building during Typhoon Hato [115]. The results demonstrated that PIML significantly outperforms pure ML algorithms, even with a small dataset, and can effectively capture the resonance effect in wind-induced vibrations. The model was then used for a parametric analysis comparing dynamic performance under different wind speeds and frequency conditions, and finally for analyzing long-term structural fragility considering climate change, which showed significant changes in fragility from 1985 to 2045. This progression from embedding physics to performing a practical, long-term reliability analysis demonstrates the value of physics-informed models for decision-making.

The operator learning approaches, such as DeepONet and FNO, take a different perspective by learning the mapping between infinite-dimensional function spaces [37]. The self-adaptive FNO and the Fast Fourier Transform-based DeepONet (DeepFNOnet) were proposed for predicting the nonlinear time history response of structural systems exposed to natural hazards. In the DeepFNOnet architecture, an FNO is employed beyond the DeepONet to learn the discrepancy between the ground truth and the solution predicted by the DeepONet. This approach achieved high accuracy while being orders of magnitude faster than their corresponding high-fidelity models for both a six-story shear building subject to stochastic ground motions and a high-rise building subject to stochastic wind excitation, explicitly accounting for the stochastic nature of the excitations.

The evidence from the reviewed studies strongly supports the conclusion that physics-informed and hybrid models consistently outperform their purely data-driven counterparts, particularly in scenarios characterized by data scarcity or the need for extrapolation to unseen loading conditions. However, a critical observation is that the validation of these models is often limited to numerical simulations of simple structural systems. Few studies, such as those validated against real health monitoring data from skyscrapers [118] or Typhoon Hato monitoring data [115], demonstrate the performance of physics-informed models on actual full-scale structures under real environmental loads. The gap between proof-of-concept on idealized numerical problems and validated performance on real-world, complex structures remains a significant barrier to widespread engineering adoption. Furthermore, the computational overhead associated with computing the physics loss function, particularly for complex three-dimensional finite element models, is rarely quantified or compared with the cost of simply running a larger purely data-driven model. Future research should prioritize the development of benchmark problems that include both synthetic and field data, where the performance of different physics-informed approaches can be systematically compared, and where the computational cost-accuracy trade-off can be rigorously evaluated.

4. Discussion

Taken together, the findings synthesized in this systematic review reveal a rapidly evolving field where machine learning has transitioned from a niche computational curiosity to a central tool in the quest for efficient and accurate prediction of structural dynamic responses in high-rise buildings. The evidence consistently indicates that the field is not converging on a single best methodology, but is instead characterized by a productive pluralism of approaches, each with distinct strengths and limitations. Recurrent architectures, particularly Long Short-Term Memory networks, have emerged as the dominant class of models for capturing the temporal evolution of structural states, consistently outperforming feed-forward alternatives in time-series prediction tasks. This dominance is not surprising given the inherently sequential nature of structural dynamic responses, where the state at the current time step depends on a history of prior states and excitations. The emergence of attention mechanisms and transformer-based architectures further underscores the field's trajectory toward models that can learn long-range dependencies and selectively focus on the most informative portions of the input sequence.

A critical pattern that emerges across the reviewed studies is the consistent advantage of hybrid physics-data models over purely data-driven approaches. Whether through embedding governing equations into the loss function, designing physics-informed input representations, or using machine learning to parameterize physics-based constitutive models, these hybrid methods demonstrate superior accuracy, robustness to data scarcity, and physical plausibility. This finding has profound implications for the future direction of the field. It suggests that the path forward does not lie in developing ever-larger deep learning models trained on ever-larger datasets, but rather in thoughtfully combining the complementary strengths of physics-based reasoning and data-driven learning. The pure data-driven approach, while powerful, operates as a black box that can produce predictions that are numerically accurate but physically inconsistent, particularly when extrapolating to unseen loading regimes. In contrast, physics-informed models embed the fundamental laws of mechanics into the learning process, thereby constraining the solution space and providing a form of regularization that is especially valuable when training data are scarce.

The practical implications of these findings are substantial. For practicing structural engineers, the reviewed literature provides a clear roadmap for integrating ML into performance-based design workflows. Surrogate models, particularly those built using ensemble methods like random forests and gradient boosting, have been shown to replace computationally expensive finite element simulations with minimal loss of accuracy, enabling rapid parametric studies and Monte Carlo simulations for fragility analysis. This capability directly addresses the fundamental computational bottleneck in probabilistic performance-based engineering, where the high cost of nonlinear time-history analyses has historically limited the scope of uncertainty propagation. The development of user-friendly graphical user interfaces in several studies represents an important step toward democratizing these tools. However, the literature also sounds a cautionary note: the generalizability of these models across different building typologies, hazard scenarios, and data qualities remains a significant limitation. An ML model trained on a steel moment frame building in a low-seismicity region cannot be assumed to perform well on a reinforced concrete shear wall building in a high-seismicity region, and the evidence suggests that systematic transfer learning or domain adaptation is necessary to bridge these gaps.

The implications for researchers are equally important. The review reveals that the field lacks standardized benchmark datasets and evaluation protocols, a deficiency that precludes meaningful cross-study comparison and hinders the identification of best practices. The absence of common error metrics means that a reported mean absolute error of 5% in one study cannot be meaningfully compared to a root mean square error of 0.03 in another, as these metrics are sensitive to the scale and distribution of the target variable. Similarly, the lack of publicly accessible open datasets for diverse building types and loading conditions means that each research group is forced to generate its own training data, often using simplified numerical models, which limits the reproducibility and generalizability of the findings. The establishment of such benchmarks, analogous to the ImageNet dataset in computer vision or the GLUE benchmark in natural language processing, would be transformative for the field, enabling rigorous comparison of different architectures and facilitating the development of models that can be reliably deployed across a range of real-world applications.

Several consistent themes of contradiction and unresolved tension emerge from the synthesis. The most prominent is the tension between model accuracy and model interpretability.

Deep learning models, particularly LSTMs and transformers, consistently achieve high predictive accuracy, but their black-box nature makes it difficult for engineers to understand why a particular prediction was made or to trust the model's output for critical design decisions. The studies that employed SHAP analysis or other explainability techniques demonstrate that interpretation is possible, but these methods are post-hoc approximations that do not guarantee that the model's internal representations are physically consistent. A second tension exists between the desire for generalizable models and the specificity required for accurate predictions on individual buildings. Models trained on datasets spanning a wide range of structural configurations tend to have lower accuracy for any specific configuration compared to a model that has been fine-tuned on that configuration. Transfer learning provides a partial solution, but the optimal strategy for selecting source tasks and the amount of fine-tuning data required remain open questions.

A notable limitation of the current evidence base is the heavy reliance on synthetic data from numerical simulations for model development and validation. While these simulations are essential for generating the large datasets required by deep learning, they necessarily embed the assumptions and simplifications of the numerical model into the training data. An ML model trained on finite element analysis results can only learn the physics captured by that particular numerical formulation; it cannot learn unmodeled phenomena such as soil-structure interaction, non-structural component behavior, or the complex three-dimensional effects of aeroelasticity. When such models are deployed on real structures, their predictions may deviate from measured behavior in ways that are difficult to anticipate. The small number of studies that validate their models against field monitoring data, such as the work on the Shanghai Tower, the Canton Tower, and the building monitored during Typhoon Hato, serve as important benchmarks for the field, but they remain the exception rather than the norm.

The methodological limitations of this review must be acknowledged when interpreting its findings. The search strategy, while comprehensive across seven major databases, may have introduced a selection bias toward English-language publications, potentially underrepresenting significant research contributions published in other languages, particularly in countries with extensive high-rise construction and strong structural engineering communities such as China and Japan. The exclusion of preprints and non-peer-reviewed reports, while ensuring a baseline level of quality control, may have delayed the inclusion of cutting-edge work that has not yet completed the peer review process. The thematic taxonomy developed for categorizing the included studies, while systematic, necessarily imposes a discrete structure on what is a continuous and overlapping methodological landscape. Some studies could reasonably be classified under multiple themes, and the assignment of a study to a single category may obscure the richness of its contributions. The quality assessment, while conducted using a structured checklist, involved subjective judgments by the reviewers regarding the clarity of objectives, the appropriateness of validation approaches, and the completeness of reported error metrics. Despite these limitations, the review provides the first comprehensive synthesis of this rapidly growing field, and the patterns and gaps identified are robust to alternative categorization schemes.

Several unresolved challenges and contradictions within the literature warrant explicit discussion. The first relates to the role of data augmentation and synthetic data generation. While several studies demonstrate that techniques such as overlapping time windows, compressive sensing, or generative adversarial networks can effectively expand limited datasets, the extent to which these synthetic samples introduce artifacts or biases that degrade model performance is not systematically explored. The second challenge concerns the trade-off between model complexity and computational cost. The most accurate models, such as deep LSTMs with attention mechanisms or multi-scale convolutional architectures, require substantial computational resources for training and inference. For real-time structural health monitoring applications, this computational overhead may be prohibitive, and simpler models like random forests or linear regression may be more practical. The literature rarely quantifies this trade-off or provides guidance on selecting the appropriate model complexity for a given application. A third, and perhaps most fundamental, contradiction concerns the validation of physics-informed models. While the physics loss function ensures that the model's predictions satisfy the governing equations of motion, these equations are themselves approximations of the true physical behavior. A model that perfectly satisfies the equations of a simplified finite element representation may not be more accurate than a purely data-driven model that has been trained on high-fidelity experimental data, because the physics imposed may be incomplete or incorrect. This raises the question of when physics-informed learning is genuinely beneficial versus when it constrains the model in a way that degrades its ability to learn from data.

The research gaps identified in this review point toward several important directions for future work. There is a pressing need for the development of large-scale, open-access benchmark datasets that include high-fidelity numerical simulations, wind tunnel experiments, and, critically, field monitoring data from instrumented high-rise buildings under real wind and seismic events. Such datasets would enable the systematic comparison of different ML architectures and validation protocols, moving the field beyond proof-of-concept demonstrations and toward rigorous, reproducible science. Future research should also explore the application of physics-informed models to more complex structural systems beyond the simplified shear frames and moment-resisting frames that dominate the current literature. High-rise buildings with outrigger systems, diagrid structures, or tuned mass dampers represent important real-world applications where current models have only begun to be tested. The understudied area of multi-hazard scenarios, where buildings are subjected to combined wind and seismic loads, aftershock sequences, or concurrent environmental and operational loads, represents a critical frontier. The few studies that address multi-hazard prediction highlight the substantial challenges in modeling the coupled physics, but also the potential for ML methods to provide computationally efficient solutions that would be infeasible with traditional simulations.

The role of uncertainty quantification in ML-based predictions also deserves greater attention. Most studies in the review report point estimates of response quantities without providing measures of prediction uncertainty. This is a significant limitation for engineering practice, where decisions must account for the inherent variability in loading, material properties, and modeling assumptions. Bayesian neural networks, Monte Carlo dropout, or ensemble methods that naturally provide prediction intervals are promising avenues for future research. Furthermore, the temporal dynamics of structural performance under long-duration wind events, as opposed to the short-duration pulse of an earthquake, warrant dedicated study. The few wind-focused studies in the review demonstrate that capturing the evolving, low-frequency nature of wind-induced vibrations, including aeroelastic coupling and cumulative fatigue effects, requires models that can maintain accuracy over thousands of time steps without divergence.

The integration of ML with structural health monitoring systems represents a natural and important application domain that remains underexplored. Real-time sensor data streams from instrumented high-rise buildings provide a continuous source of validation data for ML models, and the models, in turn, can provide real-time estimates of structural state and safety that inform emergency response decisions. The studies that demonstrated real-time prediction capabilities, with computation times thousands of times faster than finite element analysis, suggest that ML is ready for deployment in early warning systems. However, the robustness of these models to sensor noise, data loss, and sensor failure has not been systematically evaluated, and the integration of ML predictions into decision-support workflows for building managers and emergency responders remains an open challenge. Future research should focus on the development of resilient, fault-tolerant prediction systems that can maintain acceptable accuracy even under degraded sensor conditions.

Finally, the economic and practical feasibility of deploying ML models in structural engineering practice requires careful consideration. The cost of generating high-quality training data through extensive laboratory testing or high-fidelity simulations is substantial, and for many existing buildings, such data may not be available. Transfer learning and multi-fidelity methods offer promising avenues for reducing this cost, but their practical implementation requires a level of computational expertise that may not be present in typical structural engineering firms. The translation of ML models from research papers into user-friendly software tools that integrate with existing design workflows, such as ETABS or SAP2000, is an essential step that has only begun to be addressed by a handful of studies. The development of graphical user interfaces, automated hyperparameter tuning, and standardized output formats will be critical for bridging the gap between the research community and practicing engineers. Without such tools, the promising results demonstrated in the literature will remain confined to academic laboratories, and the potential of ML to transform structural dynamic response prediction will remain unrealized.

5. Conclusion

This systematic review mapped 107 studies to critically evaluate the landscape of machine learning applications for predicting structural dynamic responses of high-rise buildings under wind and seismic excitations. Our synthesis confirms that recurrent neural networks, particularly LSTM architectures, have become the foundational tools for capturing temporal dependencies in structural responses, consistently outperforming traditional feed-forward networks. However, the most significant finding is the demonstrated superiority of hybrid physics-data models over purely data-driven approaches; embedding governing equations into the loss function or using ML to parameterize physics-based models improves accuracy and robustness under data-scarce conditions. These findings advance the field by clarifying that methodological progress depends not on model scale but on thoughtful integration of domain knowledge.

The practical implications of our work are twofold. For structural engineers, the reviewed evidence provides validated pathways to replace computationally prohibitive nonlinear time-history analyses with surrogate models for probabilistic fragility assessment, enabling rapid uncertainty propagation in performance-based design. For researchers, the review identifies critical gaps that must be addressed before ML can transition from proof-of-concept to validated engineering tool. The absence of standardized benchmark datasets and error metrics prevents meaningful cross-study comparison, while the overreliance on synthetic training data from simplified numerical models limits real-world applicability. Furthermore, data scarcity for extreme events, poor generalizability across diverse structural configurations, and insufficient validation against field monitoring data remain unresolved challenges.

Future research should prioritize three directions: first, developing open-access benchmark datasets that include high-fidelity simulations, experimental data, and field monitoring records from instrumented high-rise buildings under real hazard events; second, systematically evaluating physics-informed models on complex structural systems such as outrigger and diagrid frames under multi-hazard scenarios; and third, integrating uncertainty quantification into ML predictions to provide decision-relevant confidence intervals rather than point estimates. The field stands at a pivotal juncture where thoughtful methodological development, guided by the gaps identified here, can transform ML from a promising research tool into a practical instrument for enhancing the safety and resilience of high-rise structures worldwide.

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