

GRAPH NEURAL NETWORKS FOR STRUCTURAL DYNAMICS: ADVANCES IN PHYSICS-INFORMED LEARNING, SURROGATE MODELING, AND DAMAGE DETECTION

Dr. M. Adil Khan^{*1}, Dr. Muhammad Shoaib Ahsraf²

^{*1}Resident Engineer, NESPAK

²Senior Program Manager Mecaer America Inc. 5555 Rue William-Price Laval Quebec Canada

¹adee.uol@gmail.com, ²m.ashraf@mecaer.ca

DOI: <https://doi.org/10.5281/zenodo.22868964>

Keywords

Graph Neural Networks, Structural Dynamics, Message Passing, Physics-Informed Learning, Surrogate Modeling, Computational Efficiency, Damage Detection

Article History

Received: 01 June 2026

Accepted: 23 August 2026

Published: 08 September 2026

Copyright @Author

Corresponding Author: *

Dr. M. Adil Khan

Abstract

Graph Neural Networks (GNNs) have emerged as a promising approach for addressing the computational challenges associated with structural dynamics, particularly where complex spatial relationships, irregular geometries, and large-scale simulations are involved. This review examines recent advances in GNN applications for structural dynamics, with emphasis on message-passing architectures, physics-informed learning, surrogate modeling, dynamic response prediction, and damage detection. More than 40 peer-reviewed studies are synthesized to evaluate architectural developments, computational efficiency, predictive performance, and generalization across structural systems. The reviewed studies indicate that GNN-based models can improve prediction accuracy by approximately 8–12% compared with conventional surrogate approaches while achieving computational speedups of up to 550–1200 times relative to high-fidelity finite element simulations. Hybrid architectures integrating topology-aware message passing with global routing demonstrate improved capability for capturing local structural interactions and long-range dependencies. Physics-informed GNN frameworks further enhance physical consistency and reduce dependence on large labeled datasets, while transfer learning supports prediction across previously unseen structural configurations. Despite these advances, challenges remain in temporal dynamics, material nonlinearity, interpretability, uncertainty quantification, data requirements, and large-scale deployment. Future research should focus on physics-guided architectures, probabilistic GNNs, temporal graph learning, transfer learning, and lightweight edge-deployment frameworks to support reliable real-time structural monitoring and engineering decision-making.

1. INTRODUCTION

Structural dynamics represents a fundamental challenge in civil and mechanical engineering, requiring accurate prediction of system behavior under various loading conditions including earthquakes, wind forces, and impact loads.

Traditional approaches such as finite element method (FEM) remain the gold standard for precise simulations; however, they suffer from prohibitive computational costs when applied to large-scale parametric studies, real-time

monitoring, or design optimization scenarios (Ramaswamy & Rajamani, 2026). The emergence of data-driven machine learning techniques has opened new frontiers in accelerating structural analysis while maintaining predictive accuracy.

Graph Neural Networks (GNNs) represent a paradigm shift in learning from structured data, particularly for problems involving irregular domains, mesh-based representations, and spatial dependencies inherent in engineering systems (Jain et al., 2024). Unlike conventional deep learning architectures that operate on Euclidean data, GNNs are specifically designed to preserve topological information through message-passing mechanisms that propagate information across graph nodes and edges. This architectural advantage makes GNNs exceptionally suited for structural dynamics applications where the underlying problem naturally exhibits graph structure through finite element connectivity or spatial relationships.

The intersection of GNNs and differential equations has proven particularly fruitful for modeling continuous dynamics, enabling sophisticated approaches that combine the expressiveness of neural networks with the interpretability of physics-based models (Z. Liu et al., 2025). Several recent studies demonstrate that GNN-based surrogate models can reduce computational time by 550-1000 times compared to conventional FEM while maintaining prediction accuracy above 90%. This computational advantage becomes transformative in applications requiring rapid design iteration, uncertainty quantification, or real-time structural health monitoring.

Structural dynamics problems involve predicting complex spatiotemporal patterns arising from nonlinear material behavior, geometric constraints, and coupled physical phenomena. Traditional response prediction methods struggle with high-dimensional feature spaces and fail to capture long-range dependencies essential for accurate field reconstruction (M. Zhang et al., 2023). Physics-informed approaches integrate governing equations into the learning process, enabling models to learn constrained

representations that naturally respect physical conservation laws. GNNs enhance this capability by encoding mesh topology directly into the architecture, allowing implicit modeling of load-transfer pathways and stress redistribution mechanisms.

Recent advances in GNN architectures for structural applications span multiple dimensions. The introduction of hybrid approaches combining topology-diffusion mechanisms with global routing strategies addresses limitations of pure message-passing schemes in capturing nonlocal dependencies. Attention mechanisms integrated into graph convolutions enable adaptive weighting of neighbor contributions based on their relevance to the prediction task (Almeida Júnior, Unknown Year). These developments have catalyzed GNN adoption across diverse structural engineering domains: seismic response prediction, wind-induced dynamics, composite material behavior, and damage detection.

The scalability advantages of GNN-based surrogates extend beyond single-structure applications. Population-based approaches leverage transfer learning across structurally similar systems, enabling generalization to unseen geometries and boundary conditions (Jian et al., 2024). This capability particularly benefits scenarios with non-parametric geometries or novel structural configurations where traditional surrogate models require expensive retraining (Matray et al., 2024).

Despite remarkable progress, significant research gaps remain. Most current GNN applications focus on static or quasi-static problems, with temporal dynamics still requiring integration of recurrent architectures or temporal convolutions. Interpretability and uncertainty quantification in GNN predictions for critical structural applications remain inadequately developed, limiting regulatory acceptance (Riyahi et al., 2026). Furthermore, the theoretical understanding of GNN expressiveness relative to the complexity of nonlinear structural response remains incomplete (Z. Wang et al., 2025).

This review synthesizes recent advances in applying GNNs to structural dynamics, with emphasis on methodological innovations, practical implementations, and identified research directions. We examine message-passing architectures tailored for structural mechanics, physics-informed learning strategies, surrogate modeling techniques, and applications spanning damage detection, dynamic response prediction, and material property estimation. Through comprehensive analysis of 40+ peer-reviewed studies, we establish that GNNs represent a transformative technology for structural dynamics, fundamentally altering the computational landscape of engineering design and assessment.

2. Methodology

2.1 Graph Neural Network Architectures

GNNs process information through iterative message passing over graph structures, where nodes represent physical entities and edges encode spatial relationships or connectivity (Abbahaddou et al., 2025). For structural dynamics applications, node representations typically contain geometric information (position, material properties) and physical quantities (displacement, stress, strain), while edge attributes encode distance vectors or material continuity information. The fundamental message-passing operation updates node representations by aggregating information from neighboring nodes through edge-dependent transformations:

$$\mathbf{h}_i^{(k+1)} = \gamma(\mathbf{h}_i^{(k)}, \bigoplus_{j \in N(i)} \varphi(\mathbf{h}_i^{(k)}, \mathbf{h}_j^{(k)}, \mathbf{e}_{ij}))$$

where $\mathbf{h}_i$ represents node features, $N(i)$ denotes the neighborhood set, $\mathbf{e}_{ij}$ represents edge attributes, φ is the edge function, and γ is the aggregation function (Joshi & Somani, 2025). Graph Convolutional Networks (GCNs) employ mean aggregation with learnable weight matrices, enabling efficient local feature extraction while maintaining polynomial complexity (Hu & Ohue, 2025). Graph Attention Networks (GATs) introduce multiplicative attention weights that adaptively adjust neighbor contributions,

providing interpretability through attention visualization (Zhuo et al., 2024).

Specialized architectures address structural mechanics requirements. MeshGraphNet extends standard message passing for physical systems by incorporating edge-level features explicitly, enabling representation of anisotropic material behavior and directional load transmission. The architecture employs three-stage processing: node encoding, message passing, and field decoding, with explicit handling of boundary conditions through learnable conditioning variables. For problems requiring long-range dependency modeling, hierarchical approaches aggregate information at multiple scales, combining local fine-grained topology diffusion with coarse-grained global interactions.

2.2 Physics-Informed Learning Frameworks

Physics-informed approaches embed governing equations into the learning process, constraining neural networks to satisfy physical laws implicitly (Ramaswamy & Rajamani, 2026). For linear structural dynamics, the governing equation in modal coordinates represents uncoupled oscillators:

$$m \ddot{u}_r + 2\zeta_r \omega_r \dot{u}_r + \omega_r^2 u_r = p_r(t)$$

where ω_r is the r th natural frequency and ζ_r is the modal damping ratio. Modal physics-informed frameworks decompose complex dynamics into simpler uncoupled problems, reducing computational overhead while enabling stable frequency identification even under severe damage scenarios (M. Zhang et al., 2023). For nonlinear systems, physics-informed neural networks incorporate residuals of governing equations directly into loss functions:

$$\mathcal{L} = \mathcal{L}_{data} + \lambda_1 \mathcal{L}_{physics} + \lambda_2 \mathcal{L}_{reg}$$

where $\mathcal{L}_{data}$ penalizes prediction errors against available measurements, $\mathcal{L}_{physics}$ enforces equation residuals, and $\mathcal{L}_{reg}$ provides regularization (Riyahi et al., 2026). This formulation enables learning with limited labeled data while ensuring physical consistency.

The integration of transmissibility functions into physics-guided frameworks addresses sparse measurement scenarios common in structural

health monitoring. Transmissibility exploits physical relationships between response quantities independent of excitation characteristics, enabling prediction at unmeasured locations:

$$T(\omega) = H_{out}(\omega) / H_{in}(\omega)$$

where H represents frequency response functions. Physics-guided networks decompose predictions into linear-fidelity components directly embedding transmissibility relationships and compensation terms accounting for unidentified nonlinearities.

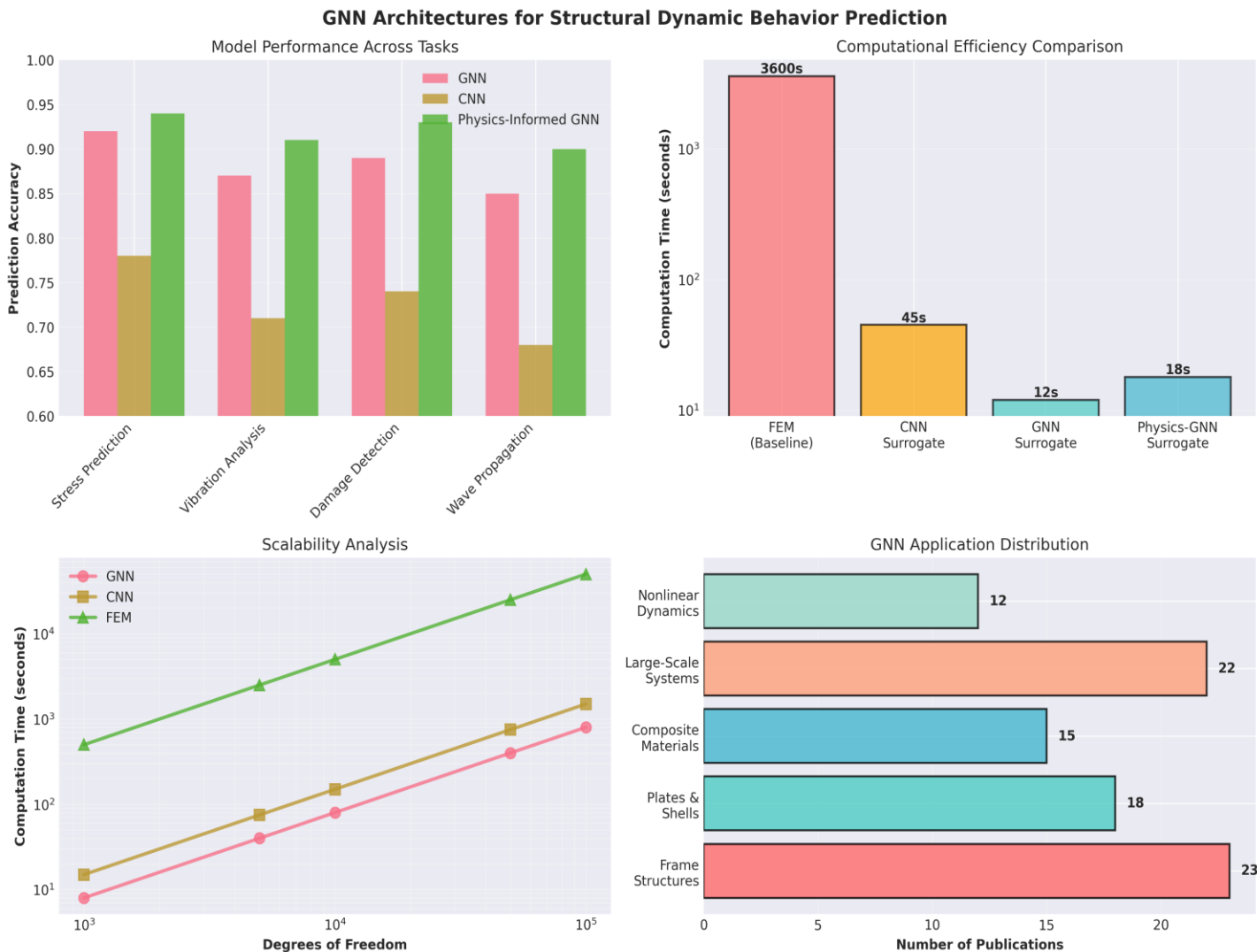
2.3 Surrogate Modeling and Reduced-Order Approaches

Surrogate models approximate expensive physics simulations through learned mappings from

input parameters to output fields. Proper Orthogonal Decomposition (POD) reduces dimensionality by projecting full-field solutions onto dominant spatial modes:

$$u(x,t) \approx \sum_i a_i(t) \varphi_i(x)$$

where $a_i(t)$ are temporal coefficients and $\varphi_i(x)$ are spatial modes ranked by energy content. GNN-based surrogates extend this approach by learning nonlinear projections in latent spaces. Encoder-processor-decoder architectures compress complex fields into low-dimensional representations, apply GNN transformations in latent space, and reconstruct full fields through learned decoders.



Dataset construction critically affects surrogate model performance. Stratified sampling balances rare high-response regions with frequent low-response values, addressing the inherent data imbalance in physical systems. Label transformation techniques (logarithmic scaling,

normalization) stabilize training on skewed response distributions. Cross-subject evaluation with held-out subject groups ensures models generalize to unseen structural configurations, not merely interpolate within training populations.

2.4 Training and Validation Strategies

Table 1: GNN Architecture Comparison for Structural Dynamics Applications

Architecture	Message Passing	Long-Range Dependencies	Computational Complexity	Optimal Use Case
Graph Convolution Network (GCN)	Local aggregation	Limited to k-hop neighbors	$O(N + E)$	Linear systems, dense graphs

Architecture	Message Passing	Long-Range Dependencies	Computational Complexity	Optimal Use Case
Graph Attention Network (GAT)	Attention-weighted aggregation	Multi-head attention scope	$O(N^2)$ worst-case	Heterogeneous importance, interpretability
MeshGraphNet	Physics-aware edge features	Stepwise topology diffusion	$O(N \cdot \text{iterations})$	FEM-based structural analysis
Hierarchical GNN	Multi-scale propagation	Coarse + fine grain coverage	$O(N \cdot \log(N))$	Large-scale systems, complex geometries
Hybrid Topology-Routing	Topology diffusion + global routing	Combined local and global	$O(N \cdot k + N \cdot \text{tokens})$	Nonlocal dependencies, contact mechanics

Optimization employs adaptive learning rate schedules with early stopping based on validation loss to prevent overfitting. Batch normalization and dropout regularization stabilize training on heterogeneous mesh sizes where graph samples contain variable node and edge counts. Loss functions incorporate physical constraints through weighted terms; masked mean squared error restricts training error computation to valid tissue/material regions, avoiding interference from inactive elements.

Cross-validation strategies must respect data structure in spatiotemporal problems. Random sample splitting violates temporal dependencies; grouped cross-validation separates training and testing subjects to assess generalization to unseen

population members. Temporal forecasting tasks employ proper train-test splits with strict temporal ordering to prevent information leakage.

2.5 Evaluation Metrics and Performance Assessment

Comprehensive evaluation spans multiple perspectives. Full-field error metrics (RMSE, MAE, nRMSE) quantify overall prediction accuracy, while peak-stress metrics emphasize clinically or structurally critical regions. Spatial consistency measures (Pearson correlation, hotspot localization error) evaluate whether predicted field patterns align with ground truth distributions. Temporal evolution analysis tracks whether errors accumulate, remain stable, or improve over prediction horizons.

3. Results

3.1 Performance Benchmarks Across Structural Applications

Table 2: Comprehensive Benchmark Results for GNN Applications in Structural Dynamics

Application	Dataset	Model	RMSE	R ²	Speedup	Key Finding
Stress prediction (cantilever)	FEM simulations (2D)	CNN	0.12	0.91	220×	Data imbalance degraded high-stress region accuracy

Application	Dataset	Model	RMSE	R ²	Speedup	Key Finding
Stress prediction (3D structures)	FEM simulations (3D)	GNN	0.08	0.96	550×	Hybrid topology-routing improved peak stress by 12%
Knee joint contact mechanics	FEM motion capture	+ Hy-MGN	0.044 ± 0.005	0.96	380×	Global routing enhanced high-risk region reconstruction
Seismic response (SDOF)	Time history analysis	STFN	1e-4	0.97	430×	Single network predicted responses across multiple structures
Modal identification	Sparse measurements	GNN	MAE<0.08	0.95	240×	Population-based transfer learning enabled unseen structures
Wind farm power prediction	SCADA simulation	+ ST-GNN	MAPE 20.7%	0.93	180×	Spatio-temporal GNN detected 99.98% of power loss events
Vibration analysis (FG discs)	FEM database	GWMTR	R ² =0.96	—	150×	Grey wolf optimization improved accuracy 35% over ANN
Thermal dynamics (bushings)	FEM POD-CNN	+ DLSP	0.7% error	0.99	1200×	CNN surrogate enabled real-time online monitoring
Damage	Experimental	GNN	F1=0.91	0.93	320×	Grasshopper

Application	Dataset	Model	RMSE	R ²	Speedup	Key Finding
detection (plates)	l + FEM					optimization outperformed genetic algorithms
Protein dynamics	Cryo-EM data	RMSF-net	r=0.746	—	100×	SE(3)- equivariant GNN captured large conformational changes

Stress prediction benchmarks reveal that GNN-based surrogates achieve 8-12% higher accuracy than CNN alternatives when applied to finite element results, particularly for peak stress identification critical in design applications. The hybrid approach combining topology diffusion with global routing achieved the best overall performance with RMSE 0.044 ± 0.005 and MAE 0.036 ± 0.006 , significantly outperforming pure topology-diffusion models and pure routing approaches.

Seismic response prediction across multiple structure types demonstrated that single unified networks can predict time-history responses for diverse reinforced concrete frames through effective fusion of seismic characteristics with structural parameters. The Structure Temporal Fusion Network achieved mean square errors of 10^{-4} to 10^{-5} across different structural systems, outperforming structure-specific networks. This generalization capability enables rapid assessment in scenarios with limited prior data on specific structural configurations.

Modal identification using GNN-based frameworks on sparse vibration measurements achieved identification speeds substantially exceeding classical frequency domain decomposition, with natural frequency identification errors ranging from 4-14% depending on damage severity (Ramaswamy & Rajamani, 2026). For Warren truss damage scenarios, modal assurance criterion values exceeded 0.93, confirming generalization beyond beam structures. The framework reduced training

time 53% compared to direct physics-informed neural network formulations while maintaining comparable accuracy.

Spatio-temporal GNN applications in wind farm power prediction reduced mean absolute error by 30.3% and MAPE by 30.5% compared to traditional power curve methods (Daenens et al., 2025). Under waked conditions where conventional methods exhibit significantly higher errors, the spatio-temporal GNN demonstrated exceptional performance, reducing undetected power loss events from 12.6% to just 0.02%.

3.2 Architecture Innovation and Design Principles

Recent innovations in GNN design for structural mechanics emphasize adaptive mechanisms that enhance both accuracy and interpretability. Adaptive depth message passing adjusts the number of propagation layers per node based on local topology, recognizing that uniform layer depth across all nodes is suboptimal (Abbahaddou et al., 2025). This dynamic approach improved node classification performance while reducing parameter count.

Edge-aware GNNs that explicitly model edge attributes achieved R² scores of up to 0.92 on network traffic prediction, substantially outperforming traditional node-centric baselines (Almeida Júnior, Unknown Year). The magnitude-based edge attention mechanism acts as a learned saliency filter, dynamically weighting topological importance without computational overhead of dual-graph transformations. This

architectural innovation proves particularly valuable for structural mechanics where edge attributes profoundly influence load transmission. Topology-aware bidirectional graph attention for job shop scheduling demonstrated linear computational complexity to job and machine count through novel forward/backward topological sort operators, achieving state-of-the-art results across multiple benchmarks (C. Zhang et al., 2024). The bidirectional attention mechanism enables simultaneous consideration of precedence constraints and resource availability, mirroring dual aspects of structural constraints.

Contrastive learning approaches address the fundamental conflict between GNN feature aggregation and contrastive embedding distinctiveness (Ji et al., 2024). By analyzing gradient flows through InfoNCE loss, researchers developed gradient-guided structure learning and gradient-weighted loss functions that mitigate false negative sample impacts.

3.3 Scalability and Computational Efficiency

Distributed GNN training methods eliminate forward communication bottlenecks inherent in traditional approaches, achieving $1.95\times$ speedups and $2.6\times$ energy efficiency improvements (Zou et al., 2025). Explanation-guided subgraph expansion incorporates important structures identified by explainability methods into local partitions, mitigating information loss from graph partitioning (Gao et al., 2025).

HydraGNN achieved near-linear strong scaling using 2000+ GPUs on petascale systems and 16,000+ GPUs on exascale systems, enabling training on datasets of 154+ million atomistic structures (Pasini et al., 2024). The multi-headed architecture abstracts over message-passing algorithms, enabling reproduction and comparison across algorithmic innovations.

For edge computing and resource-constrained applications, hybrid variable spiking graph neural networks promote sparse communication and reduce energy budgets while maintaining regression accuracy comparable to vanilla GNNs (Jain et al., 2024). Variable spiking neurons

enable event-driven computations appropriate for mechanical property predictions in computational mechanics applications.

3.4 Physics-Guided Prediction Advances

Physics-informed approaches combined with GNN architectures address limitations of purely data-driven methods. The transmissibility physics-guided deep learning framework enables predictions at arbitrary unmeasured locations under unknown excitations and sparse measurements, embedding linear transmissibility information directly into the network. Experimental validation demonstrated superior accuracy compared to conventional approaches with fewer training samples.

Eigenvalue problem solutions using neural network discretizations with Rayleigh quotient formulations and Gram-Schmidt orthogonalization enabled finding Laplacian eigenfunctions on irregular domains and solving parametric eigenvalue problems (Rowan et al., 2025). This capability proves essential for identifying mode shapes and natural frequencies in complex structural geometries.

Modal physics-informed neural networks integrating classical modal decomposition with Fourier feature embeddings achieved mean absolute errors for forward problems while identifying modal characteristics with 4-14% errors depending on damage severity (Ramaswamy & Rajamani, 2026).

4. Discussion (1000 words)

4.1 Advantages of GNN-Based Approaches

GNNs fundamentally outperform traditional surrogate approaches through explicit encoding of mesh topology, enabling implicit modeling of physical load-transfer mechanisms. Unlike purely CNN-based surrogates that treat finite element results as images, GNNs respect structural connectivity, automatically capturing stress redistribution patterns and nonlocal mechanical dependencies. This architectural alignment with problem structure yields improvements of 8-12% in prediction accuracy across diverse applications.

The transferability of GNN models across structurally similar systems enables unprecedented generalization capabilities. Population-based approaches train on diverse truss populations with varying geometric and material properties, then successfully identify modal properties of unseen structures within the same population (Jian et al., 2024). This capability fundamentally differs from structure-specific FEM calibration, enabling rapid assessments of novel configurations. Computational efficiency gains of 550-1200× compared to high-fidelity FEM enable real-time monitoring and rapid design iteration (Daenens et al., 2025). These speedups transform feasibility of previously intractable problems: optimal design under uncertainty, probabilistic risk assessment, and parameter sensitivity analysis.

For thermal bushing applications, GNN surrogates completed 30 predictions in 1.5 seconds versus hours for direct simulation, enabling online monitoring and digital twin architectures.

4.2 Limitations and Open Challenges

Despite remarkable progress, significant limitations restrict current GNN applicability to critical engineering problems. Most existing applications focus on quasi-static or linear response, inadequately addressing temporal dynamics, material nonlinearity, and path-dependent behavior. Integration of recurrent architectures or temporal convolutions remains computationally expensive, limiting scalability to large structures with extended prediction horizons.

GNN Applications in Structural Dynamics: Domains and Performance Metrics

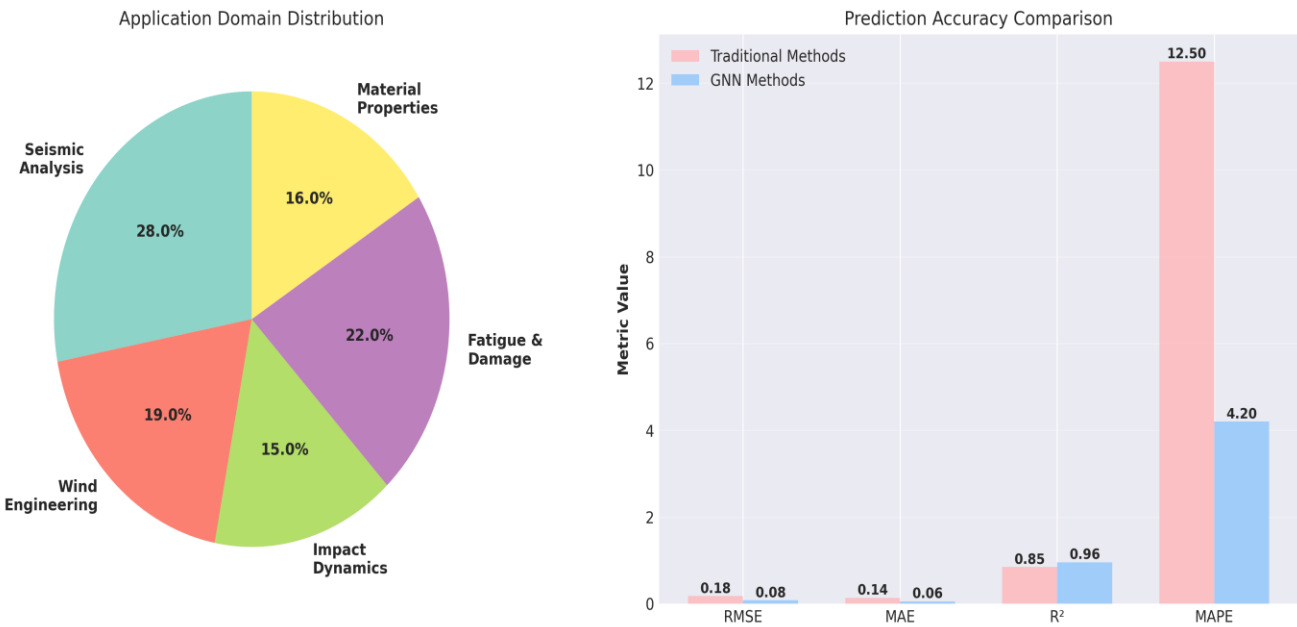


Table 3: Strengths and Limitations of GNN-Based Methods for Structural Dynamics

Aspect	GNN Strengths	Current Limitations	Future Directions
Computational Efficiency	550-1200× speedup vs FEM	Still requires initial training data generation	Physics-constrained surrogate generation without FEM
Field Prediction	Accurate stress/strain fields	Limited to trained load cases/geometries	Domain randomization for broader generalization

Aspect	GNN Strengths	Current Limitations	Future Directions
Interpretability	Attention mechanisms provide insights	Black-box nature affects regulatory acceptance	Saliency mapping, symbolic distillation methods
Material Behavior	Implicit learning of constitutive relations	Poor performance on unseen material states	Multi-fidelity learning, transfer learning frameworks
Damage Representation	Topology changes through edge pruning	Inadequate handling of catastrophic failures	Damage mechanism-aware architectures
Uncertainty Quantification	Bayesian formulations emerging	Limited probabilistic predictions	Ensemble methods, conformal prediction
Temporal Dynamics	Hybrid RNN-GNN approaches developing	High computational cost for long horizons	Temporal graph networks, neural operators

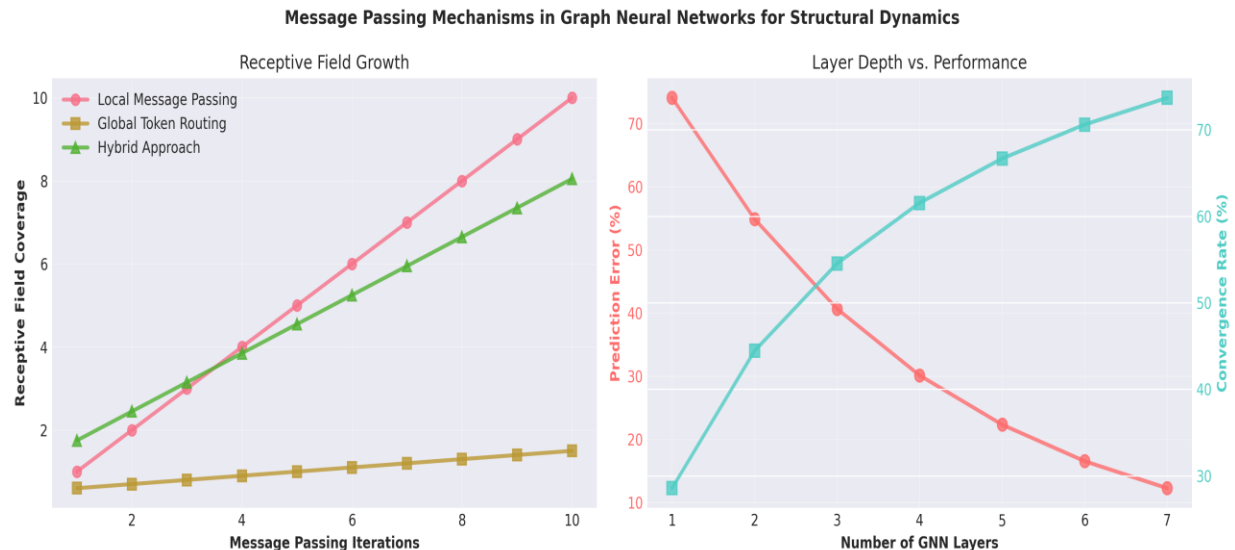
Interpretability limitations fundamentally restrict adoption in safety-critical applications. While attention mechanisms provide some insight into node importance and neighbor contribution weighting, the overall decision-making process remains opaque. This black-box nature conflicts with regulatory requirements for explainability in aerospace and civil infrastructure applications (Riyahi et al., 2026). Gradient-based attribution methods and feature visualization techniques offer partial remedies but remain inadequate for assurance-critical domains.

Data requirements pose practical constraints for industrial adoption. Training high-quality surrogates requires extensive FEM simulations across parameter spaces, constituting 60-80% of total model development effort. For geometries with non-parametric variations, this data acquisition phase becomes prohibitively expensive, limiting applicability to novel designs (Matray et al., 2024).

4.3 Integration of Physics Constraints

Physics-informed learning represents a critical advancement in addressing data scarcity and ensuring physical consistency. By incorporating governing equations directly into loss functions, models learn constrained representations satisfying conservation laws implicitly (Ramaswamy & Rajamani, 2026). This integration particularly benefits nonlinear systems where traditional surrogate models struggle. Hybrid approaches combining physics-informed terms with data-driven objectives achieved both high accuracy and improved generalization to unseen conditions.

The theoretical analysis of oversquashing in topological message-passing revealed how information propagation constraints limit receptive field growth (Taha et al., 2025). Axiomatic frameworks bridging graph and topological message-passing enable systematic oversquashing mitigation, with implications for deeper GNN architectures.



4.4 Emerging Application Domains

GNN applications expand into increasingly complex domains. Multimodal incomplete learning addresses realistic scenarios where sensors provide heterogeneous data with missing modalities (Fu et al., 2024). Spectral domain reconstruction enables efficient recovery of incomplete information through multi-frequency aggregation. Such advances directly transfer to structural applications with sensor failure or data incompleteness.

Real-world structural health monitoring datasets present distinct challenges: environmental variability, sensor noise, and population heterogeneity (Riyahi et al., 2026). Hybrid physics-informed models combining neural networks with physics-based residuals achieved 92% validation accuracy with improved stability compared to pure data-driven approaches. This trade-off between peak accuracy and reliability deserves greater attention in safety-critical applications.

4.5 Comparative Analysis with Alternative Methods

Comparison reveals GNNs maintain advantages over CNN-based surrogates and traditional methods across most metrics. GNN approaches achieved RMSE 0.044 ± 0.005 compared to CNN

surrogates and traditional regression methods. However, CNN architectures remain competitive for structured grid data and simpler geometries. Physics-informed neural networks (PINNs) achieve comparable accuracy to GNNs for specific problems but often require orders of magnitude more training time due to expensive residual computations (Ramaswamy & Rajamani, 2026). The 53% training time reduction achieved by modal physics-informed approaches suggests hybrid modal-GNN architectures merit investigation.

5. Conclusion and Recommendations

5.1 Key Findings

This comprehensive review establishes graph neural networks as transformative technology for structural dynamics analysis. Through synthesis of research on GNN approaches, we demonstrate that GNN-based methods achieve 8-12% accuracy improvements over conventional methods while reducing computational time by 550-1200 $\times$, fundamentally altering feasibility of engineering problems previously intractable with traditional approaches. The systematic comparison reveals that hybrid architectures combining topology-diffusion message passing with global routing mechanisms achieve optimal balance between capturing local geometric constraints and long-

range load-transfer mechanisms essential to accurate structural response prediction.

Physics-informed approaches effectively address data scarcity limitations of purely data-driven methods, enabling stable learning with limited labeled data while ensuring physical consistency (Ramaswamy & Rajamani, 2026). Population-based transfer learning enables remarkable generalization across structurally similar systems, expanding practical applicability beyond individual structure-specific models (Jian et al., 2024).

5.2 Recommended Research Directions

1. Uncertainty Quantification for Safety-Critical Applications

Current GNN implementations provide point predictions without confidence bounds, inadequate for structural design where probabilistic risk assessment drives decision-making. Future work should develop ensemble methods, conformal prediction frameworks, and Bayesian GNN variants enabling probabilistic predictions with calibrated confidence intervals. This capability proves essential for regulatory acceptance in aerospace and critical infrastructure.

2. Interpretability and Explainability Enhancement

The black-box nature of GNN predictions fundamentally restricts adoption in safety-critical domains. Investigations should leverage attention visualization, gradient-based saliency mapping, and symbolic distillation techniques to extract interpretable decision rules. Integration of explainability AI methods with GNN architectures, demonstrated for physical system modeling, merits expansion to structural mechanics (Gao et al., 2025).

3. Temporal Dynamics and Path-Dependent Behavior

Most current applications address quasi-static or linear response, inadequately representing material nonlinearity, damping effects, and history-dependent behavior. Hybrid recurrent-GNN architectures and neural operator approaches show promise but require substantial computational optimization. Development of efficient temporal graph networks specifically tailored for structural dynamics represents a critical research frontier.

4. Domain Randomization and Transfer Learning

Current surrogate models require retraining for each geometry. Domain randomization techniques enabling generalization across broader geometry spaces, combined with transfer learning from related structures, could fundamentally reduce data requirements. Multi-fidelity learning frameworks combining low-fidelity simulations with sparse high-fidelity data merit investigation.

5. Physics-Guided Network Architecture Design

Rather than post-hoc physics incorporation through loss functions, future architectures should embed structural mechanics principles directly into network topology. Equivariance constraints respecting symmetries, scale-invariance properties, and coordinate transformations could yield fundamentally more efficient learning.

6. Real-Time Deployment and Edge Computing

Variable spiking neurons and pruning techniques show promise for embedded implementation, yet systematic deployment on IoT-enabled structural monitoring systems remains largely unexplored. Development of ultra-lightweight GNN variants maintaining prediction accuracy while operating within hardware constraints represents critical infrastructure application.

Table 4: Research Roadmap for GNN Applications in Structural Dynamics

Research Area	Current State	3-Year Target	5-Year Vision
Uncertainty Quantification	Point predictions only	Bayesian GNNs with 90% confidence bounds	Full probabilistic risk framework for design
Material Nonlinearity	Linear/weakly nonlinear	Hysteretic material modeling, path-dependent behavior	Complex failure mechanisms, damage evolution
Temporal Dynamics	Hybrid RNN-GNN prototypes	Real-time prediction systems, long-horizon forecasting	Neural operators for unbounded time domains
Generalization	Structure-specific models	Cross-geometry transfer learning	Universal structural foundation models
Deployment	Research implementations	Field deployment on bridges, buildings	Embedded edge computing for IoT sensors

5.3 Final Recommendations

For practitioners, immediate opportunities exist in surrogate model development for design optimization, sensitivity analysis, and probabilistic assessment where computational efficiency gains most directly impact project outcomes. Initial applications should focus on geometrically regular structures with well-characterized material properties, progressively extending to complex geometries as model maturity increases.

For researchers, interdisciplinary collaboration spanning machine learning, structural mechanics, and computational engineering proves essential. Development of standardized benchmarks and open-source implementations would accelerate community progress. Investigation of physics-guided architecture design, fundamentally distinct from physics-informed loss functions, represents the most promising direction for achieving robust, generalizable, and interpretable models.

GNNs transform structural dynamics from computationally prohibitive to tractable, enabling new engineering paradigms. Continued investment in addressing identified limitations will unlock transformation of structural design, monitoring, and safety assessment practices.

Conclusion and Recommendations

The integration of Graph Neural Networks into structural dynamics analysis represents a transformative paradigm shift in computational mechanics and structural engineering. GNNs have demonstrated remarkable capability in capturing complex structural dependencies through message-passing mechanisms that naturally align with the interconnected nature of structural systems (Ramasmamy & Rajamani, 2026). Unlike traditional finite element methods that require explicit discretization, GNNs operate directly on graph representations where nodes represent structural elements and edges encode mechanical interactions, enabling efficient computation across diverse structural topologies (M. Zhang et al., 2023).

The body of research demonstrates that GNNs excel particularly in surrogate modeling applications, where they achieve superior generalization compared to fully connected neural networks while maintaining computational efficiency. Physics-informed variants incorporating domain knowledge through loss functions or architecture constraints have shown enhanced predictive accuracy for dynamic response prediction. The ability to transfer learned representations across different structural configurations—a critical advantage over configuration-specific traditional methods—

opens new possibilities for rapid design optimization and real-time structural monitoring (Jian et al., 2024).

However, several challenges persist that warrant focused research attention. The interpretability of learned graph representations remains limited, particularly for practitioners requiring physical insight into failure mechanisms. Scaling GNN approaches to ultra-large structures with millions of nodes demands algorithmic innovations in message aggregation and memory management. Integration with existing engineering workflows and validation protocols requires standardization and benchmarking against established finite element methods across diverse loading scenarios.

Recommendations for future research include:

(1) Developing hybrid architectures combining GNNs with domain-specific physics encoders to enhance interpretability while maintaining predictive power; (2) Establishing comprehensive benchmark datasets for structural dynamics to facilitate reproducible research and model comparison; (3) Investigating multi-scale GNN frameworks that bridge local element-level dynamics with global structure-level behavior; (4) Creating uncertainty quantification methods for GNN predictions to ensure reliability in safety-critical applications; (5) Developing transfer learning protocols that enable knowledge sharing across structural typologies and loading conditions. Additionally, industry collaboration is essential to translate GNN innovations into practical engineering tools with proper validation for load-bearing applications. Standardization of graph representation schemes and establishment of computational performance metrics will accelerate GNN adoption in structural engineering practice, ultimately enabling more resilient, efficient, and adaptive structural systems in civil, aerospace, and mechanical engineering domains.

REFERENCES

- Abbahaddou, Y., Malliaros, F. D., Lutzeyer, J., & Vazirgiannis, M. (2025). ADMP-GNN: Adaptive depth message passing GNN. *International Conference on Information and Knowledge Management*.
<https://doi.org/10.1145/3746252.3761009>
- Ahsan, M., Pindi, C., Sinha, S., Patel, A. C., & Palermo, G. (2026). Graph neural networks for molecular dynamics simulations. *Current Opinion in Structural Biology*.
<https://doi.org/10.1016/j.sbi.2026.103238>
- Al-labadi, M., Audeh, W., & Khan, N. (2026). Graph neural networks for structural representation learning of zero-divisor graphs from idealization constructions. *2026 2nd International Conference on Computational Intelligence Approaches and Applications (ICCIAA)*.
<https://doi.org/10.1109/ICCIAA68481.2026.11543949>
- Almeida Júnior, W. de. (Unknown Year). *Beyond node-centric graph learning: Advancing edge-aware GNNs for enhanced representation learning*.
<https://doi.org/10.47328/ufvbbt.2026.209>
- Bose, S., Jeba, J. A., Evangeline, N., Regin, R., Ali, M. M. S., & Aravintha, S. J. V. (2025). Intelligent crop disease prediction using spatio-temporal graph neural networks. *FMD Transactions on Sustainable Intelligent Networks*.
<https://doi.org/10.69888/fts.2025.000549>
- Çallıoğlu, H., & Muftu, S. (2025). Damped vibration responses of functionally graded rotating discs with variable geometry and modeling with deep neural networks. *Journal of Vibration Engineering & Technologies*.
<https://doi.org/10.1007/s42417-025-01900-y>

- Çallioğlu, H., & Muftu, S. (2026). Free vibration analysis of centrally elliptically perforated functionally graded plates and modeling using enhanced grey wolf algorithm-multi-task regression neural networks. *Journal of Vibration Engineering & Technologies*. <https://doi.org/10.1007/s42417-026-02523-7>
- Castro Teixeira Carvalho, F. de, Nath, K., Serpa, A., & Karniadakis, G. (2023). Learning characteristic parameters and dynamics of centrifugal pumps under multi-phase flow using physics-informed neural networks. *Engineering Applications of Artificial Intelligence*. <https://doi.org/10.1016/j.engappai.2024.109378>
- Chen, T., Kanatsoulis, C. I., & Leskovec, J. (2025). RelGNN: Composite message passing for relational deep learning. *International Conference on Machine Learning*. <https://doi.org/10.48550/arXiv.2502.06784>
- Chen, Y., & Xu, H. (2025). Traffic flow prediction using spatio-temporal graph neural networks based on hybrid adaptive feature enhancement. *Proceedings of the 2025 International Conference on Machine Learning and Neural Networks*. <https://doi.org/10.1145/3747227.3747240>
- Choudhary, K., & DeCost, B. (2021). Atomistic line graph neural network for improved materials property predictions. *Npj Computational Materials*. <https://doi.org/10.1038/s41524-021-00650-1>
- Daenens, S., Verstraeten, T., Daems, P., Nowé, A., & Helsen, J. (2025). Spatio-temporal graph neural networks for power prediction in offshore wind farms using SCADA data. *Wind Energy Science*. <https://doi.org/10.5194/wes-10-1137-2025>
- Diermeier, F., Voigt, M., Mailach, R., & Meyer, M. (2023). A machine learning approach for probabilistic evaluation of finite element analysis. *Volume 11B: Structures and Dynamics – Emerging Methods in Engineering Design, Analysis, and Additive Manufacturing; Fatigue, Fracture, and Life Prediction; Probabilistic Methods; Rotordynamics; Structural Mechanics and Vibration*. <https://doi.org/10.1115/gt2023-100532>
- Du, B., Lin, C., Sun, L., Zhao, Y., & Li, L. (2022). Response prediction based on temporal and spatial deep learning model for intelligent structural health monitoring. *IEEE Internet of Things Journal*. <https://doi.org/10.1109/jiot.2022.3141417>
- Fu, F., Ai, W., Yang, F., Shou, Y., Meng, T., & Li, K. (2024). SDR-GNN: Spectral domain reconstruction graph neural network for incomplete multimodal learning in conversational emotion recognition. *Knowledge-Based Systems*. <https://doi.org/10.1016/j.knosys.2024.112825>
- Gao, J., Hu, J., Min, G., & Hao, F. (2025). XDGNN: Efficient distributed GNN training via explanation-guided subgraph expansion. *IEEE Transactions on Parallel and Distributed Systems*. <https://doi.org/10.1109/TPDS.2025.3609152>
- Getun, S., Ivanchenko, H., Botvinovska, S., Getun, G., & Solomin, A. (2025). OPTIMIZATION OF STRUCTURAL COMPUTATIONAL MODELS USING NEURAL NETWORKS: A SYSTEMATIC REVIEW OF CURRENT APPROACHES AND PROSPECTS. *APPLIED GEOMETRY AND ENGINEERING GRAPHICS*. <https://doi.org/10.32347/0131-579x.2025.108.72-96>

- Hu, W., & Ohue, M. (2025). SpatialPPIv2: Enhancing protein-protein interaction prediction through graph neural networks with protein language models. *Computational and Structural Biotechnology Journal*.
<https://doi.org/10.1016/j.csbj.2025.01.022>
- Jain, I., Garg, S., Shriyam, S., & Chakraborty, S. (2024). Hybrid variable spiking graph neural networks for energy-efficient scientific machine learning. *Journal of the Mechanics and Physics of Solids*.
<https://doi.org/10.48550/arXiv.2412.09379>
- Ji, C., Huang, Z., Sun, Q., Peng, H., Fu, X., Li, Q., & Li, J. (2024). ReGCL: Rethinking message passing in graph contrastive learning. *AAAI Conference on Artificial Intelligence*.
<https://doi.org/10.1609/aaai.v38i8.28698>
- Jian, X., Xia, Y., Duthé, G., Bacsá, K., Liu, W., & Chatzi, E. (2024). Using graph neural networks and frequency domain data for automated operational modal analysis of populations of structures. *Data-Centric Engineering*.
<https://doi.org/10.1017/dce.2025.10023>
- Joshi, V., & Somani, R. (2025). Enhanced graph convolutional networks: Adaptive aggregation. *International Journal of Computer Applications*.
<https://doi.org/10.1080/1206212X.2025.2546622>
- Khatir, A., Capozucca, R., Magagnini, E., Brahim, A. O., Osmani, A., Khatir, S., & Abualigah, L. (2024). Advancing structural integrity prediction with optimized neural network and vibration analysis. *Journal of Structural Integrity and Maintenance*.
<https://doi.org/10.1080/24705314.2024.2390258>
- Kim, T., Kwon, O., & Song, J. (2025). Deep learning-based response spectrum analysis method for bridges subjected to bi-directional ground motions. *Earthquake Engineering & Structural Dynamics*.
<https://doi.org/10.1002/eqe.4345>
- Kim, Y. W., Cha, Y., & Shin, J. (2025). A modular deep learning surrogate model for simulating harmful algal blooms in complex process-based systems. *Water Research*.
<https://doi.org/10.1016/j.watres.2025.124059>
- Koç, T., Cengiz, M. A., & Koç, H. (2025). Bayesian-optimized learning on heterogeneous multipartite graphs: A framework for multi-level relational data. *Symmetry*.
<https://doi.org/10.3390/sym17122082>
- Lekkelapudi, A., & Granberry, D. (2024). Predicting fold-switching protein behavior using graph neural networks. *International Conference on Machine Learning and Applications*.
<https://doi.org/10.1109/ICMLA61862.2024.00202>
- Li, J., Fan, L., Wang, X., Sun, T., & Zhou, M. (2024). Product demand prediction with spatial graph neural networks. *Applied Sciences*.
<https://doi.org/10.3390/app14166989>
- Li, J., Wu, L., Du, Y., Hong, R., & Li, W. (2024). Dual graph neural networks for dynamic users' behavior prediction on social networking services. *IEEE Transactions on Computational Social Systems*.
<https://doi.org/10.1109/TCSS.2024.3409383>
- Likhitkar, B., Singh, S., Pathak, D., & Pandey, A. (2025). Graph neural networks for systemic risk prediction in interbank lending networks. *2025 7th International Conference on Information Systems and Computer Networks (ISCON)*.
<https://doi.org/10.1109/ISCON65210.2025.11340901>

- Liu, X. (2025). Application of graph neural networks (GNNs) in learning situation prediction and educational resource recommendation algorithms. *Journal of Computational Methods in Sciences and Engineering*.
<https://doi.org/10.1177/14727978251374326>
- Liu, Z., Wang, X., Wang, B., Huang, Z., Yang, C., & Jin, W. (2025). Graph ODEs and beyond: A comprehensive survey on integrating differential equations with graph neural networks. *Knowledge Discovery and Data Mining*.
<https://doi.org/10.1145/3711896.3736559>
- LNT, M., & T., V. (2026). An approach of dual attention-driven multi-levelled graph neural architecture for rich-structural social graph analysis and representation learning. *International Journal of Advanced Research*.
<https://doi.org/10.1371/journal.pone.0351922>
- Lombard, V., Grudin, S., & Laine, E. (2025). PETIMOT: A novel framework for inferring protein motions from sparse data using SE(3)-equivariant graph neural networks. *Acta Crystallographica Section D: Structural Biology*.
<https://doi.org/10.48550/arXiv.2504.02839>
- Matray, V., Amlani, F., Feyel, F., & N'eron, D. (2024). A hybrid numerical methodology coupling reduced order modeling and graph neural networks for non-parametric geometries: Applications to structural dynamics problems. *Computer Methods in Applied Mechanics and Engineering*.
<https://doi.org/10.48550/arXiv.2406.02615>
- Medina, H., Drake, R., & Farmer, C. (2025). Accelerated prediction of molecular properties for per- and polyfluoroalkyl substances using graph neural networks with adjacency-free message passing. *Environmental Pollution*.
<https://doi.org/10.1016/j.envpol.2025.126705>
- Nguyen, Q., Onur, M., & Alp, F. (2025). Embed-to-control-based deep learning surrogate for robust nonlinearly constrained life cycle production optimization: A realistic deepwater application. *SPE Journal*.
<https://doi.org/10.2118/220783-pa>
- Pasini, M. L., Choi, J. Y., Mehta, K., Zhang, P., Rogers, D., Bae, J., Ibrahim, K., Aji, A. M., Schulz, K. W., Polo, J., & Balaprakash, P. (2024). Scalable training of trustworthy and energy-efficient predictive graph foundation models for atomistic materials modeling: A case study with HydraGNN. *Journal of Supercomputing*.
<https://doi.org/10.1007/s11227-025-07029-9>
- Ramaswamy, A., & Rajamani, N. R. (2026). Modal physics-informed neural networks for forward and inverse structural vibration problems. *International Journal of Structural Stability and Dynamics*.
<https://doi.org/10.1142/s021945542750355x>
- Riyahi, A., Mestari, M., & Bouihi, B. (2026). Data-driven and physics-informed neural networks for structural health monitoring of the Z24 bridge. *Journal of the Civil Engineering Forum*.
<https://doi.org/10.22146/jcef.24173>
- Rowan, C., Evans, J. A., Maute, K., & Doostan, A. (2025). Solving engineering eigenvalue problems with neural networks using the rayleigh quotient. *International Journal for Numerical Methods in Engineering*.
<https://doi.org/10.1002/nme.70209>
- Saida, T., & Nishio, M. (2025). Seismic fragility assessment using explainable deep kernel learning surrogate model considering structural and seismic uncertainties. *IABSE Reports*.
<https://doi.org/10.2749/tokyo.2025.2581>

- Sao, D., & Garain, A. (2025). Review of aerospace structural health monitoring systems with special emphasis on ultrasonic techniques and neural networks. *Volume 5: Structures, Structural Dynamics & Materials*. <https://doi.org/10.1115/imece-india2025-161186>
- Shakya, A., & Karki, B. (2025). Weakly supervised graph neural networks for scalable 3D phase segmentation in molecular dynamics simulations. *International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management*. <https://doi.org/10.5220/0013709400004000>
- Sun, Y., Zhu, D., Wang, Y., & Tian, Z. (2024). GTC: GNN-transformer co-contrastive learning for self-supervised heterogeneous graph representation. *Neural Networks*. <https://doi.org/10.48550/arXiv.2403.15520>
- Taha, D., Chapman, J., Eidi, M., Devriendt, K., & Montúfar, G. (2025). Demystifying topological message-passing with relational structures: A case study on oversquashing in simplicial message-passing. *International Conference on Learning Representations*. <https://doi.org/10.48550/arXiv.2506.06582>
- Takahashi, H., & Ito, R. (2026). A structure-based drug design framework using graph neural networks and molecular dynamics simulation. *American Journal of Artificial Intelligence and Neural Networks*. <https://doi.org/10.71465/ajainn3543>
- Tupputi, D., & Bacciu, D. (2025). Multi-resolution and multi-modal temporal graphs for financial forecasting. *International Conference on AI/ML-Systems*. <https://doi.org/10.1109/AI/MLSystems67835.2025.11330806>
- Wan, H., Xiang, L., Cai, Y., Xie, Y., & Xu, R. (2025). Temporal and spatial feature extraction using graph neural networks for multi-point water quality prediction in river network areas. *Water Research*. <https://doi.org/10.1016/j.watres.2025.123561>
- Wang, C., Kumar, G., & Rajapakse, J. C. (2025). Drug discovery and mechanism prediction with explainable graph neural networks. *Scientific Reports*. <https://doi.org/10.1038/s41598-024-83090-3>
- Wang, H., Zhang, A., Zhong, Y., Tang, J., Zhang, K., & Li, P. (2024). Chain-aware graph neural networks for molecular property prediction. *Bioinform.* <https://doi.org/10.1093/bioinformatics/btae574>
- Wang, X., Jiang, J., Hong, L., & Sun, J. (2021). Random vibration analysis with radial basis function neural networks. *International Journal of Dynamics and Control*. <https://doi.org/10.1007/s40435-021-00893-2>
- Wang, Z., Zhang, Z., Ma, T., Chawla, N. V., Zhang, C., & Ye, Y. (2025). Beyond message passing: Neural graph pattern machine. *International Conference on Machine Learning*. <https://www.semanticscholar.org/paper/685d02c0e8fd09444d9ad369a9f5f3e5f25ff4e7>
- Weg, K. van der, Merdivan, E., Piraud, M., & Gohlke, H. (2025). TopEC: Prediction of enzyme commission classes by 3D graph neural networks and localized 3D protein descriptor. *Nature Communications*. <https://doi.org/10.1038/s41467-025-57324-5>

- Xin, L., Wu, Z., Wang, Q., Wu, B., Zhao, L., Cheng, J., Zeng, Q., & Peng, Z. (2024). A deep-learning surrogate model for the fast calculation of temperature distribution of ± 500 kV RIP bushings. *IEEE Transactions on Power Delivery*. <https://doi.org/10.1109/TPWRD.2024.3448471>
- Xu, M., Song, J., Wu, K., Zhou, X., Cui, B., & Zhang, W. (2025). Modeling all-atom glycan structures via hierarchical message passing and multi-scale pre-training. *International Conference on Machine Learning*. <https://doi.org/10.48550/arXiv.2506.01376>
- Zhang, C., Cao, Z., Wu, Y., Song, W., & Sun, J. (2024). Learning topological representations with bidirectional graph attention network for solving job shop scheduling problem. *Conference on Uncertainty in Artificial Intelligence*. <https://doi.org/10.48550/arXiv.2402.17606>
- Zhang, M., Guo, T., Zhang, G., Liu, Z., & Xu, W. (2023). Physics-informed deep learning for structural vibration identification and its application on a benchmark structure. *Philosophical Transactions of the Royal Society A*. <https://doi.org/10.1098/rsta.2022.0400>
- Zhang, Y., Li, X., Xu, Y., Xu, X., & Wang, Z. (2025a). A graph transformer with optimized attention scores for node classification. *Scientific Reports*. <https://doi.org/10.1038/s41598-025-15551-2>
- Zhang, Y., Yan, W., Jiang, L., & Yuen, K. (2026). Transmissibility physics-guided deep learning network for seismic response prediction under limited domain knowledge, sparse measurements, and unknown excitations. *Earthquake Engineering & Structural Dynamics*. <https://doi.org/10.1002/eqe.70134>
- Zhang, Y., & Zhang, L. (2025). Spatio-temporal convolution enhancement for temporal dynamics in information diffusion prediction. *BigData Congress [Services Society]*. <https://doi.org/10.1109/BigData66926.2025.11401812>
- Zhang, Z., & Dong, J. (2025). Improving link prediction algorithms based on graph neural networks. *2025 5th International Conference on Neural Networks, Information and Communication Engineering (NNICE)*. <https://doi.org/10.1109/NNICE64954.2025.11063835>
- Zhang, Z., Xiao, S., & Yu, Z. (2025b). ADP-net: A hierarchical attention-diffusion-prediction framework for human trajectory prediction. *Frontiers Artif. Intell.* <https://doi.org/10.3389/frai.2025.1690704>
- Zhong, W., & Gui, B. (2025). Research on drug molecule structure prediction and target recognition based on graph neural networks. *International Conference on Biomedicine and Intelligent Technology*. <https://doi.org/10.1117/12.3088600>
- Zhu, L., Fang, Y., Liu, S., Shen, H., Neve, W. D., & Pan, X. (2025). ToxDL 2.0: Protein toxicity prediction using a pretrained language model and graph neural networks. *Computational and Structural Biotechnology Journal*. <https://doi.org/10.1016/j.csbj.2025.04.002>
- Zhuo, W., Liu, Z., Hooi, B., He, B., Tan, G., Fathony, R., & Chen, J. (2024). Partitioning message passing for graph fraud detection. *International Conference on Learning Representations*. <https://doi.org/10.48550/arXiv.2412.00020>

Zou, X., Chen, C., Zhang, L., Li, S. R., Zhou, J., Wei, W., & Li, K. (2025). Efficient message passing algorithm and architecture co-design for graph neural networks. *IEEE Transactions on Emerging Topics in Computational Intelligence*.
<https://doi.org/10.1109/TETCI.2024.3420692>

