

# Frontier AI in computational civil engineering: a review of graph, sequence, physics-informed deep learning, and beyond (2020–2025)



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## Highlights:

- A comprehensive review of frontier AI applications for computational analysis.
- Focus on GNNs, Seq2Seq models, Transformers and Physics-informed methods.
- Qualitative and quantitative synthesis of ~100 primary studies from 2020 to 2025 are performed.
- Key research gaps are identified and potential future directions are suggested.

**Abstract:** Structural computational analysis in civil engineering increasingly demands efficient, robust, and physics-aware methodologies capable of addressing non-Euclidean geometries, history-dependent behaviors, and multi-scale problems that remain challenging for conventional numerical approaches. Recent advances in frontier artificial intelligence (AI) techniques have shown promising potential to overcome these limitations. This paper presents a comprehensive review of frontier AI applications in computational structural analysis from 2020 to 2025, focusing on graph neural networks (GNNs), sequence-to-sequence (Seq2Seq) and Transformer-based architectures, and physics-informed methods. We synthesize fundamental concepts, typical model variants, and representative applications across diverse tasks, including constitutive modeling, static and dynamic structural analysis, data reconstruction, and parameter inversion. Furthermore, we identify critical research gaps and discuss potential future directions within each model family. A quantitative analysis of the reviewed studies is conducted, categorizing them by publication year, application task, and adopted model type. Common challenges regarding benchmarking, empirical–physics trade-offs, scalability and generalizability are summarized. Finally, we highlight several promising techniques for advancing intelligent structural computation and promoting practical engineering deployment.

**Keywords:** AI-based computational analysis; graph neural network; transformer; physics-informed method; civil engineering



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## 1. Introduction

Design optimization, construction control, and long-term operation and maintenance of civil engineering structures all rely heavily on computational analysis techniques. Traditional structural computational analysis in engineering primarily depends on numerical approaches represented by finite element (FE) methods, which are underpinned by deterministic computational mechanics and empirical theoretical modeling frameworks [1]. These simulations often involve loads of degrees of freedom and detailed mesh representations, making them extremely time-consuming and computationally expensive. The computational bottleneck motivates the exploration of AI techniques to complement or even replace certain stages of engineering workflows with higher efficiency in the past decade [2–4]. Early applications primarily employ classical machine learning (ML) algorithms and basic deep learning (DL) models, such as deep neural networks (DNNs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs), to tackle multi-feature datasets, uncover hidden patterns and predict structural behaviors [5,6]. While conventional AI models have shown effectiveness in relatively simple cases such as regular material characterization and component-level analysis, their applicability faces significant challenges when dealing with complex real-world engineering scenarios, such as full-range analysis of large-scale structural systems (e.g., high-rise buildings, long-span bridges, nuclear containment structures, *etc.*), highly nonlinear history-dependent behaviors of advanced new materials, and structural states inference based on fuzzy monitoring data acquired from the site.

Recently, more advanced AI paradigms with better alignment to the intrinsic nature of engineering problems have been introduced to address these limitations. Engineering computational data are generally unstructured, non-Euclidean and discrete, posing challenges for data representations with classic grid-based models such as CNNs. Graph learning represent data in graph form, enabling the corresponding GNN to capture the topological information of the structural systems and their irregular meshes more efficiently [7]. For sequential data, RNNs are first adopted to simulate sequential problems in engineering, but suffer from vanishing gradients and long-range history dependencies in dynamic structural analysis [8]. Sequence-to-sequence (Seq2seq) models [9], along with representative Transformers [10], are then adapted to tackle the problem. The attention mechanisms overcome the abovementioned shortcomings by capturing the global interactions across long sequences and focus on critical information like loading and unloading path in dynamic analysis [11]. To strengthen the capability of mining data distribution patterns, these methods have been combined with generative models to extend learning tasks from prediction to generative tasks such as data reconstruction [12]. Beyond improving data representations and model configurations, efforts have also focused on embedding mechanical information in DL models to enhance their physical interpretability and solve more sophisticated nonlinear problems. Physics-informed neural networks (PINN) explicitly integrate governing PDEs into the loss function, alleviating the “black-box” criticism of prior methods and reducing dependence on large labeled datasets [13]. Other physics-informed methods adapt the network architecture to enforce consistency with underlying mechanical principles [14,15]. Neural operator (NO) methods generalize this concept by learning mappings between input fields (loads, material properties) and output fields (displacements, stresses) across function spaces and yields mesh-free solutions that are more accurate and physically consistent [16].

Applications of AI techniques in civil engineering have surged in recent years, emerging as a new research frontier. Several review studies have systematically examined the use of classical ML algorithms and conventional DL models across diverse domains, including structural analysis [3,4,8,17], building construction [18,19], and structural health monitoring [20,21]. However, with the rapid evolution of new models and algorithms, there remains a pressing need for comprehensive reviews that synthesize the applications of state-of-the-art AI approaches in structural computational analysis, emphasizing their methodologies, advantages, and inherent limitations relative to traditional ML/DL methods.

In this paper, we review relevant works in recent years (2020–2025) and cover frontier AI techniques including GNNs, Seq2Seq\Transformer-based architectures, and physics-informed methods in the context of structural computational analysis. The remainder of this paper is organized as follows. In Section 2, we introduce the literature search, the selection criteria, and key aspects to classify the review. In Section 3–5, we review the current state-of-the-art research by summarizing the general concepts and methodology, overviewing representative applications, and presenting research gaps along with possible future directions for each model family. In Section 6, we perform a quantitative analysis based on the reviewed literature and discuss the current progress, especially regarding the common limitations of the existing research. In addition, we suggest several prospective avenues for future research on the applications of frontier AI techniques in structural computational analysis.

## 2. Literature search and selection

In this review, samples of peer-reviewed papers were collected from widely recognized academic databases, and the criteria for search and selection are presented as follows:

- (1) Literature Publication Time Range: 2020 to 2025. Since this review focuses on recent applications of frontier AI techniques in structural computational analysis, this time frame covers the latest technological trends and excludes classic methods, ensuring the reviewed research is timely and practically relevant [22].
- (2) Databases for literature search: We selected multiple authoritative academic databases to ensure comprehensive coverage of relevant studies, including Web of Science, ASCE Library, ScienceDirect, Scopus, Wiley Online Library, Engineering Village, and CNKI.
- (3) Keywords for literature search: Regarding the scope of AI models and algorithms, the search keywords encompass two categories: general terms such as “artificial intelligence”, “deep learning”, and “neural network”; and domain-specific keywords, including “GNN”, “Seq2Seq”, “Transformer”, “generative models”, “PINN”, *etc.* Other keywords focus on computational analysis and structural behaviors in civil engineering, such as “structural engineering”, “seismic performance”, “computational analysis”, *etc.* Keywords are combined to search for interdisciplinary literature, such as “GNN for computational analysis”.
- (4) Criterion for literature selection: From the initial search results, the abstracts of all retrieved papers are screened to exclude those that are not directly related to AI applications in structural engineering or lack substantial novel contributions. We select studies focusing on constitutive modeling, static and dynamic structural analysis, response reconstruction, FE surrogates and parameter inversion of construction materials, structural components, and structural systems with the aid of frontier AI techniques. Priority is given to JCR Q1/Q2 journal articles and highly cited conference papers.

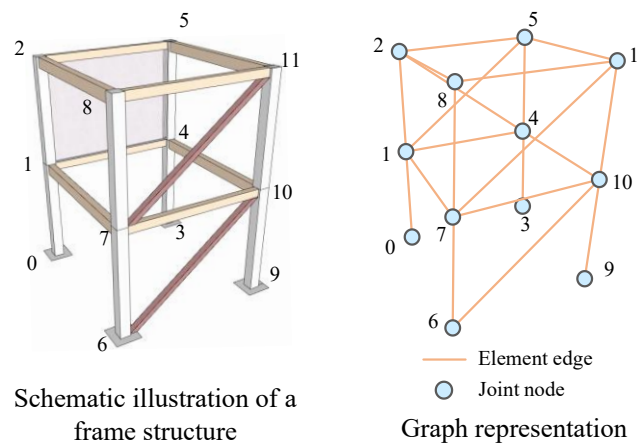
After thoroughly reading the selected articles, information including their titles, sources, authors, publication years, the AI models employed, and application tasks is systematically organized. Then the articles are further classified based on the model family, laying a foundation for subsequent analysis of articles by their methodologies and application tasks.

### 3. GNN-based applications

To achieve high-fidelity digital representation of structural systems and enable the capability transition from material/component-level analysis to structural system-level analysis, GNNs have been increasingly introduced into structural engineering in recent years [23,24]. This section first elaborates on the rationale for introducing GNNs in structural analysis, followed by basic concepts and model variants of GNNs. We then discuss various graph representation methods and provide a systematic review of GNN applications in computational analysis. Finally, we summarize the limitations of existing research and outline potential future directions.

#### 3.1. Rationale of introducing GNN

The digital representation of structural systems remains a primary challenge for AI in civil engineering. Reviewing classical numerical studies and engineering experience, the feature information of structural systems involves two aspects [4]: (1) Structural member properties: The intrinsic features of each member in the system, including member types, configurations, material properties, *etc.* (2) The topological information: The connectivity and relative locations of numerous members. Existing studies laid emphasis on the former part but neglected the latter, which results in a great loss of topological information and thus poor generalization capability across diverse structures. In contrast, the non-Euclidian graph data is suitable for representing structural systems with complex configuration, and the material/member/structure information can be stored in the feature vectors in the graph (see Figure 1). This data scheme proposed by Song *et al.* [25] can properly digitalize arbitrary structural systems while preserving their topological information with high fidelity, and facilitates further application of GNN models in computational analysis. Furthermore, the message passing and information aggregation mechanism in each layer of GNNs mimic the way forces and displacements distribute through a structure system, and the deep learning models can be trained to learn the governing mechanical laws in structural analysis.



**Figure 1.** Illustration of a frame structure and its graph representation with nodes and edges.

### 3.2. Basic concepts and model variants

GNNs are deep learning models designed to operate on graph-structured data by iteratively propagating (“message passing”) information along the edges between nodes [7]. The homogenous graph data can be formally defined as:

$$G = (V, E, A) \quad (1)$$

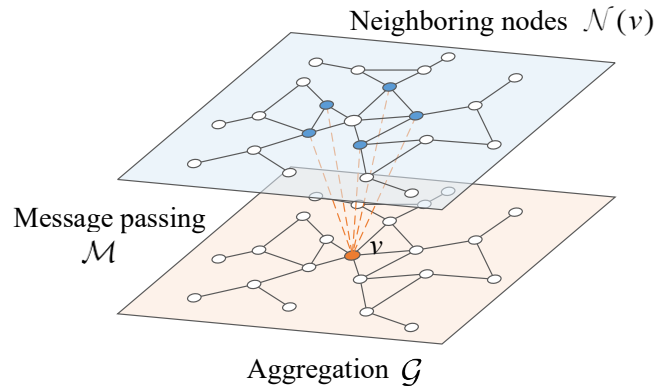
where  $V = \{v_1, v_2, \dots, v_N\}$  is the set of  $N$  nodes and  $E$  is the set of edges. Each node  $v_i$  may have an associated node feature vector  $x_i \in \mathbb{R}^d$  and each edge  $(v_i, v_j)$  may have edge feature  $e_{ij} \in \mathbb{R}^k$ . The connectivity of the graph is typically represented by an adjacency matrix:

$$A \in \{0, 1\}^{N \times N}, \quad A_{ij} = \begin{cases} 1, & \text{if } (v_i, v_j) \in E, \\ 0, & \text{otherwise.} \end{cases} \quad (2)$$

To process the graph information, the node/edge feature vectors are updated by aggregating messages from its neighboring nodes/edges with learnable functions in a basic GNN (also termed as message-passing neural network, MPNN, see Figure 2) layer [26]:

$$h'_v = \mathcal{G}(\mathcal{M}(h_u), u \in \mathcal{N}(v) \cup \{v\}) \quad (3)$$

where  $h_v / h_u$  is the hidden information of node  $v/u$  and  $\mathcal{N}(v)$  is the set of neighboring nodes of  $v$ . The learnable functions  $\mathcal{M}$  and  $\mathcal{G}$  vary in different types of GNNs. This paradigm naturally encodes the topological information of civil engineering structures, fostering surging interest in their applications to computational analysis tasks. Besides basic GNN, we summarize four prototypical GNN architectures as below:



**Figure 2.** Illustration of basic GNN layer with message passing and aggregation mechanism.

Graph Convolutional Network (GCN) [27]: GCNs are foundational GNNs that utilize convolution-like operations to aggregate features from a node and its neighbors. Through weighted summation and non-linear transformations, GCNs perform spectral-domain smoothing to encode both graph connectivity and node attributes. The update rule is formulated as:

$$h'_v = \sigma \left( W \sum_{u \in \mathcal{N}(v) \cup \{v\}} \frac{1}{\sqrt{d_v d_u}} h_u \right) \quad (4)$$

Graph Attention Network (GAT) [28]: GAT augments the basic GCN idea by learning adaptive attention weights on edges. Instead of treating all neighbors equally, a GAT layer computes an attention

coefficient for each neighbor (based on their feature vectors), and uses these coefficients to perform a weighted aggregation of neighbor features:

$$h'_v = \sigma \left( \sum_{u \in \mathcal{N}(v)} \alpha_{vu} W h_u \right) \quad (5)$$

where  $\alpha_{vu}$  are learned attention scores. This mechanism allows the network to specify different weights for different neighbors, therefore focusing on more important information in a graph effectively.

GraphSAGE [29]: GraphSAGE is another inductive GNN framework that generates node embeddings by sampling and aggregating features from a node's local neighborhood. Unlike learning fixed node embeddings during training, it learns a parameterized aggregator (e.g., mean-pooling, max-pooling) applicable to unseen nodes at test time. This flexibility is crucial for analyzing evolving or large-scale engineering systems that extend beyond the initial training distribution.

Graph Isomorphism Network (GIN) [30]: GIN replaced the usual neighbor-mean aggregator with a simple sum followed by a multi-layer perceptron (MLP), which could theoretically distinguish any two different multisets of neighbor features. As shown in the following equation, MLP denotes the MLP layer, and  $\varepsilon$  is a trainable parameter to balance self and neighbor feature contributions. Empirically, this construction makes GIN powerful in terms of distinguishing between structurally distinct designs even if they have similar local features.

$$h'_v = \text{MLP} \left( (1 + \varepsilon) h_v + \sum_{u \in \mathcal{N}(v)} h_u \right) \quad (6)$$

Heterogeneous Graph Neural Network (HGNN) [31]: HGNNs are engineered to handle heterogeneous graphs that contain multiple types of nodes and/or edges, leveraging meta-paths to represent a sequence of node types connected by edge types and captures semantic relationships between nodes [32]. To address the challenges posed by graph heterogeneity, HGNNs typically employ: (1) Type-specific transformation matrices (for projecting features of different node types into a common feature space); (2) Node-level attention mechanisms (for learning the importance of meta-path-based neighbors for each node); (3) Relation-specific message passing and type-specific aggregation modules. In summary, HGNNs extend the capabilities of basic GNNs to accommodate more complex physical entities and connections.

Other typical GNN variants include ChebNet [33], Graph Transformers [34], *etc.* Each of the above architectures operates on the same basic principle of neighborhood aggregation, but differs in the operating learnable functions. Collectively, these architectures provide versatile tools for learning mechanical response patterns of complex structural systems.

### 3.3. Applications in computational analysis

To synthesize the relevant literature, we first elaborate on graph representation methods, then categorize the applications of GNNs in computational analysis based on domain tasks: (1) Continuum field prediction: This task emphasizes mesh-based mechanical evaluation of continuums (e.g., beams, plates, and columns) to predict field results such as displacement, strain and stress; (2) Static structural analysis: This task focuses on static analysis of structural components and systems, encompassing elastic computation and structural behavior prediction; (3) Dynamic structural analysis: This task centers on modeling dynamic responses of structures under external stimulus (e.g., seismic or vibration responses),

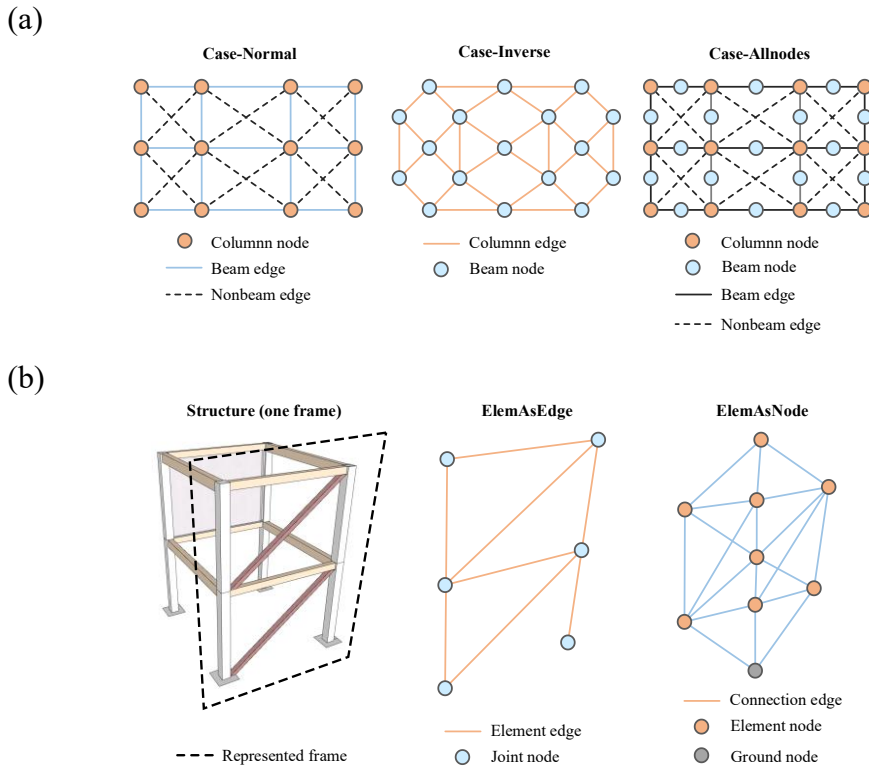
which typically feature with history-dependent effect; (4) Other applications, such as inverse problems including structural optimization and virtual sensing. Key details of representative articles are summarized in Table 1.

**Table 1.** Applications of GNN in computational analysis.

Applications	Authors	Modules	Tasks
<b>Continuum field prediction</b>	Pfaff <i>et al.</i> [35]	MPNN	Predicting displacement field of hyper-elastic plates.
	Black & Najafi [36]	MPNN	Predicting 2D displacement field of elastostatic beams.
	Maurizi <i>et al.</i> [37]	MPNN	Predicting deformed shapes, stress and strain fields in material systems.
	Gao <i>et al.</i> [38]	GCN	Solving forward and inverse partial differential equations for field prediction.
	Cao <i>et al.</i> [39]	MPNN	Predicting 3D displacement field of elastic plates.
	Fu <i>et al.</i> [40]	MPNN	Predicting stress field of cantilever beams.
<b>Static structural analysis</b>	He <i>et al.</i> [41]	GCN	Predicting deformation of elastic and hyper-elastic materials.
	Deshpande <i>et al.</i> [42]	GCN	Predicting 2D/3D displacement field of beams.
	Song <i>et al.</i> [25]	Physics-informed GIN	Elastic analysis of frame-based structures.
	Whalen & Mueller [43]	MPNN	Engineering analysis and design of trusses.
	Prachaseree <i>et al.</i> [44]	MPNN	Predicting the buckling direction of columns.
	Zheng <i>et al.</i> [45]	MPNN	Elastic analysis and safety evaluation of transmission towers.
	Nourian <i>et al.</i> [46]	MPNN	Elastic surrogate model for 2D/3D trusses.
	Parisi <i>et al.</i> [47]	Physics-informed GNN	Engineering analysis of trusses.
	Chou <i>et al.</i> [48]	GIN	Predicting the displacements, bending moments and shear forces of multi-story buildings.
	Cai & Jelovica [49]	GraphSAGE	Predicting stress distributions in stiffened panels with varying geometries.
<b>Dynamic structural modeling</b>	Tian <i>et al.</i> [50]	GAT	Searching for dominant failure mode of 2D trusses and 3D frames.
	Li <i>et al.</i> [51]	MPNN	Predicting the full-field structural dynamic response of beams.
	Chen <i>et al.</i> [52]	Physics-informed GNN	Modeling dynamics of elastic, plastic, and elastoplastic structures.
	Liu <i>et al.</i> [53]	MPNN	Modeling seismic response of a 6-story building.
	Li <i>et al.</i> [54]	HGNN	Nonlinear analysis of structures.
	Song <i>et al.</i> [55]	HGNN + Transformer	Predicting the full-range seismic responses of diverse structures.
<b>Other applications</b>	Lu <i>et al.</i> [56]	GCN	Estimating design loads of complex buildings.
	Zheng <i>et al.</i> [57]	Physics-informed GNN	Analyzing forward and inverse problems involving transmission towers.
	Yang <i>et al.</i> [58]	Ensemble GNN	Smart virtual sensing for deep excavations.
	Wang <i>et al.</i> [59]	GCN	Assessing progressive collapse regions of reinforced concrete frame structures.
	Zhang <i>et al.</i> [60]	GIN	Generating structural topology for complex architectural layouts.
	Zhang <i>et al.</i> [61]	GIN	Optimizing structural design of concrete frames.
	Zhao <i>et al.</i> [62]	MPNN	Generating beam layout design for frame structures.
	Liu & Meidani [63]	MPNN	Assessing seismic reliability of highway bridge systems.
	Son <i>et al.</i> [64]	MPNN	Localizing structural damage of a cable-stayed bridge.
	Dang <i>et al.</i> [65]	GCN	Detecting structural damage based on vibration signals.
Kim & Song [66]	GCN	Detecting structural damage based on seismic responses.	

3.3.1. Graph representation of structural systems

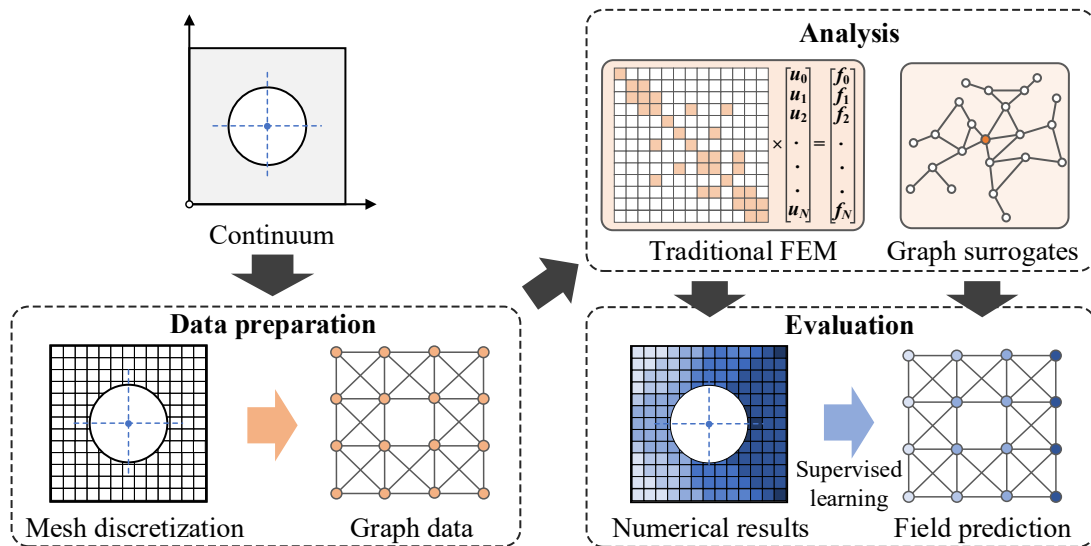
Research by Song [25] *et al.* proposed the idea of representing structural systems with graph data. They used nodes in the graph to represent structural joints and edges to correspond structural components connecting to the joints. The properties of materials and components were also embedded in the feature vectors, preserving the structural information with high fidelity. Similar works followed this approach for frame-based structures [46,48,50]. Zhao *et al.* [62] categorized graph representation methods for floor layouts into three types named Case-Normal, Case-Inverse and Case-AllNodes (see Figure 3a) according to the components referred to by nodes and edges. Chou *et al.* [48] also discussed two approaches—referred to as ElemAsEdge and ElemAsNode (see Figure 3b), where structural elements are treated as graph edges or nodes respectively—and argued that the former offers conciseness and comprehensive portrayal of a structure as graph. For continuums, the construction method followed the idea of FE meshes and represented mesh nodes with graph nodes and connected neighborhood meshes with graph edges. Pfaff *et al.* [35] designed the GNN module to encode the mesh into a multigraph with bidirectional edges. He *et al.* [41] also constructed the discretized meshes with graph nodes, but chose to define edges within a threshold distance between the nodes to ensure the graph’s locality. For feature vectors, the base material properties, the global nodal coordinates and displacements were usually considered as node features, and the connections, the distance between each node and the boundary conditions (BCs) were included in edge features [36–38,40,42].



**Figure 3.** Illustration of the different graph representation methods. **(a)** Three graph representation methods for floor layouts: (i) Case-Normal: represent columns with nodes and beams with edges; (ii) Case-Inverse: represent columns with edges and beams with nodes; (iii) Case-Allnodes: represent columns and beams as nodes and their connections as edges; **(b)** Two graph representation methods for frame structures: (i) ElemAsEdge: represent elements as edges and joint as nodes; (ii) ElemAsNode: represent all elements as nodes and their connections as edges.

### 3.3.2. Continuum field prediction

Mesh-based simulations for continua face trade-offs between accuracy and efficiency in computational analysis, especially in high-dimensional scenarios. Based on graph representations of structural meshes, recent studies suggest GNNs can be combined with numerical approaches for inferring the mechanical response of continua with higher efficiency while maintaining the accuracy (see Figure 4). Black and Najafi [36] implemented GNNs for two-dimensional elasto-static problems and produced accurate analysis given low-fidelity mesh. The results show that basic GNNs could retain physical relations between nodes using message passing mechanism and act as FE surrogates. Maurizi *et al.* [36] presented a GNN-based surrogate for learning the complex behavior of materials from simulation data. Harnessing the mesh-to-graph mapping relationship, their model could capture complex mechanical phenomena and predict deformation, stress, and strain fields in various material systems like fiber and stratified composites. He *et al.* [41] employed GCN to solve the deformation of linear elastic and hyper-elastic materials and achieved similar accuracy with shorter time compared with FE methods. Some researchers further improved the performance of vanilla GNNs by proposing strategies compatible with structured meshes. Pfaff *et al.* [35] introduced a framework named MeshGraphNets to adapt the mesh discretization during forward simulation and predict the displacement field of hyper-elastic plates accurately. By adding external edges to the graph representation, the model supports learning external dynamics such as collision and contact. Cao *et al.* [39] designed the bi-stride pooling method to tackle the reliance on labor-intensive drawing of coarser meshes. Their work allows for generality of applying GNNs to large-scale physical simulations with complex geometries. To express correlations between topologically distant nodes, Deshpande *et al.* [42] presented a novel encoder-decoder architecture named MAgNET that could capture local regularity in input meshes and reduced the graph representation to a smaller scale.

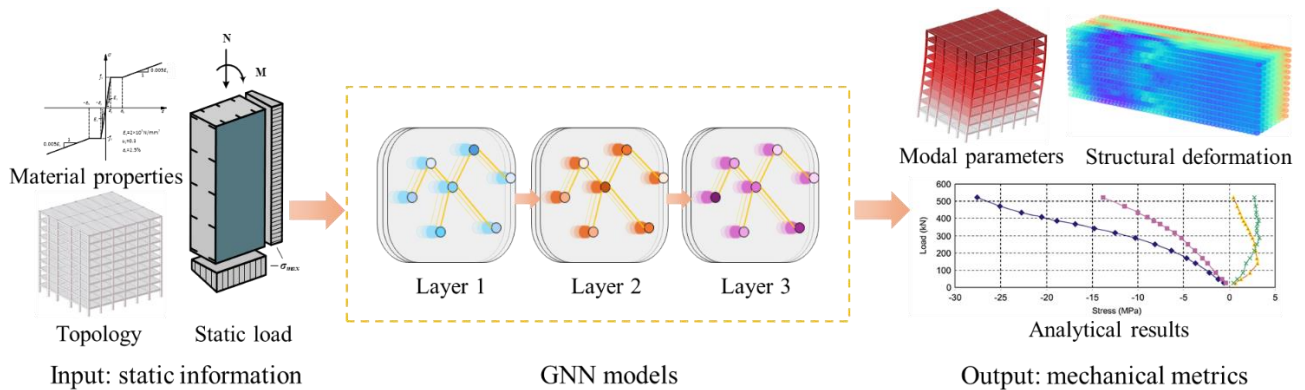


**Figure 4.** Illustration of the GNN surrogates for continuum field prediction.

### 3.3.3. Static structural analysis

GNN-based models have shown potential for modeling the mechanical behaviors of structural systems due to their ability to naturally simulate physical bodies and interactions with graph data. Researchers have employed the models to predict various mechanical metrics (see Figure 5). Song *et al.* [25]

proposed a GIN-based framework, StructGNN-E, for elastic evaluation of frame-based structures. Their work demonstrates the unique effectiveness of GNN against common DL models by ablation studies, which may be because the classical models such as CNNs or RNNs fail to capture the mechanical interactions transferred by structural components due to their Euclidean data organization. Zheng *et al.* [45] built on this concept and applied the model to the safety evaluation of transmission towers, thereby expanding its application scope. Chou *et al.* [48] added the encoder-decoder configuration to the framework and predicted the displacements, bending moments and shear forces of multi-story buildings with accuracy over 99%. They also improved its generalization on unseen structures by training the model on an extrapolated dataset comprising over 2500 structures. Whalen and Mueller [43] constructed a GNN-based surrogate model for engineering analysis and design of trusses. They also explored transfer learning across datasets of different loads and topologies and achieve 19%–48% lower prediction error with the pre-training technique. Prachaseree *et al.* [44] examined the ability of GNN message passing to predict the buckling direction of a column given its geometric structure. Their open-source dataset could facilitate the development of enhanced mechanics-specific AI methods. Cai and Jelovica [49] used GraphSAGE to predict stress distributions in stiffened panels with varying geometries. The plate domains were defined as vertices for graph construction, demonstrating the potential of representing structures of diverse geometries as graph embeddings. Tian *et al.* [50] proposed a searching algorithm for dominant failure mode (DFM) of 2D trusses and 3D frame structures based on hierarchical GAT. The approach exhibits higher computational efficiency over the traditional genetic algorithm.

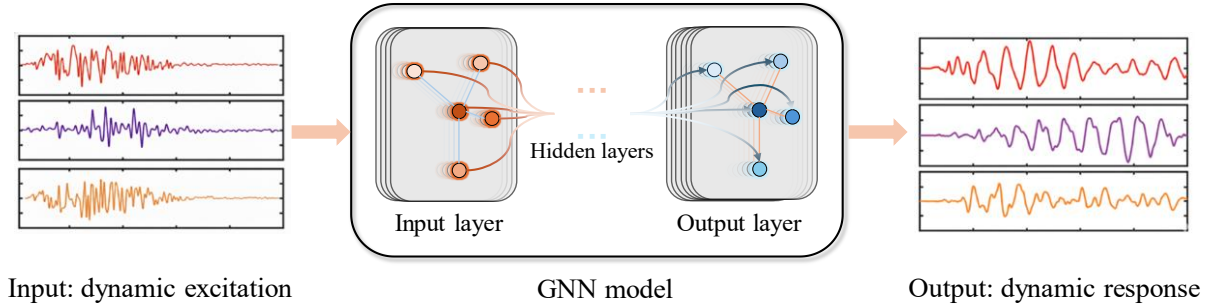


**Figure 5.** Illustration of the GNN applications for static structural analysis.

### 3.3.4. Dynamic structural modeling

Dynamic modeling of structural systems involves complex nonlinear and time-series analysis, which consumes significant computational resources when using traditional numerical approaches. In comparison, surrogate DL models can accelerate the computation and accommodate diverse scenarios without repetitive model construction, and researchers have focused on validating GNN-based frameworks to fully exploit their expressiveness and efficiency gains for predicting dynamic responses (see Figure 6). Li *et al.* [51] used GNNs to predict the full-field structural dynamic response of beams, and adopted an iterative rollout prediction scheme for sequential results. It is demonstrated that their approach could generate accurate displacements for different structures with a wide range of input parameters. Liu *et al.* [53] simulated the seismic response of a 6-story building with a GNN and explored four model variations to investigate different feature integrations. The results showed that concatenating the encoded node and

edge features achieves superior performance in predicting both displacement and acceleration. Li *et al.* [54] proposed a universal dynamic modeling method based on HGNNs, enhancing both scalability and generalization. By extracting each increment step in the dynamic analysis, their method achieves significant data augmentation without additional computation. Progress has been made, but single GNN module still face challenges such as the complexity of nonlinear constitutive laws and the historical dependence effect caused by long-time series.



**Figure 6.** Illustration of the GNN applications for dynamic structural modeling.

Some scholars have integrated physics-informed approaches, for instance, Chen *et al.* [52] introduced the physics-informed edge recurrent simulator (Piers) with graph learning to address the challenges brought by varying constitutive laws under large deformations. They initialized the module's hidden states with prior physical knowledge and assigned the physical properties of interactions as the target edge output. Extensive experimental results demonstrate that Piers can simulate the dynamics of elastic, plastic, and elastoplastic structures with smaller response prediction error than alternative baselines. More research regarding the integration of GNNs with PINNs will be discussed in detail in subsequent sections. Other studies have combined GNNs with sequence DL modules to leverage their respective advantages. Song *et al.* [55] developed a composite feature learning framework, StructGNN-N, comprising a HGNN module and a Seq2Seq module based on Transformer. The former was designed to encode structural semantics into fixed-length embeddings, while the latter was engineered to predict history-dependent responses using the embeddings and external stimuli in an end-to-end manner. By decomposing the nonlinear analysis task into structural feature-learning and dynamic feature-learning, StructGNN-N successfully predicted full-range seismic responses of large-scale structures with higher efficiency than FE methods, and exhibited generalizability across structures with diverse configurations.

### 3.3.5. Other applications

Benefiting from the expressive power of GNN models, the intelligent models have also been applied in many other scenarios. In the design phase, Lu *et al.* [56] proposed a GCN-based method to estimate design load parameters of complex building structures, which achieved the highest test accuracy when compared with a fast physical-principle-based estimation method and other AI algorithms including conventional DNNs, random forests and support vector machines. It is demonstrated that the knowledge learned using a GCN is consistent with the domain knowledge. In terms of inverse problems, Wang *et al.* [67] proposed the idea of leveraging the gradient backpropagation capability of surrogate computational GNN models to handle parameter inversion. Similar to this idea, Zheng *et al.* [57] developed a SAPIGNN-TT model for transmission tower structures, which can not only perform forward

analysis but also process the inversion of uncertain structural stiffness parameters. For construction and operation, Yang *et al.* [58] combined GNNs with real-time ensemble learning (EL) to introduce a virtual sensing method for reconstructing the settlement at unmonitored locations of excavation sites. The method could address the challenge brought by numerous environmental parameters and spatiotemporal effects, while the integration with EL effectively utilizes the streaming data to realize virtual sensing. Wang *et al.* [59] studied the progressive collapse regions of reinforced concrete frame structures with ElemAsNode graph representations and GCN. The initial failure along with primary structural information was fed into the model to simulate progressive failure propagation and predict final collapse regions. The model was applied to three RC frame structures with different layouts, demonstrating improved efficiency and reduced memory cost while maintaining consistency with FE results. Broader application scopes also include structural design and optimization [60–62], seismic reliability assessment [63], structural damage detection [64–66], *etc.* Although these are not the focus of this review, they can still preliminarily demonstrate the applicability and potential of GNNs in civil engineering.

### 3.4. Research gaps and future directions

Despite significant potential, several research gaps remain for GNN-based studies: (1) Scarcity of benchmark dataset: High-quality, open-access datasets are fundamental for training, validating and comparing data-driven models, yet public benchmark datasets remain scarce for structural engineering tasks. The paucity of shared datasets inhibits reproducibility and limits the transfer learning. (2) Limited physical interpretability: The process of graph learning is highly abstract and opaque to domain experts, which poses challenge for safety and reliability needs. (3) Scalability across topology/scale: GNN methods often exhibit inconsistent generalization capabilities when applied to unseen structures characterized by significant variations in size, topology, resolution, or BCs. This limitation is primarily attributed to architectural challenges in deep GNNs, such as over-smoothing and depth-related degradation, where repeated message-passing and aggregation homogenize the node embeddings. (4) Difficulty in capturing discontinuities: Standard GNNs implicitly assume field continuity, which is unsuitable for modeling critical structural behaviors, such as crack propagation, plastic hinge formation, and material interfaces. These phenomena exhibit abrupt discontinuities and sharp gradients in information propagation. Consequently, the repeated message aggregation mechanism tends to smooth out these localized high-frequency signals, thus failing to accurately capture the sudden physical transitions essential for robust failure analysis.

To address these limitations, we envision several promising research directions that could significantly advance the field. First and foremost, the community urgently needs to establish unified standards and comprehensive benchmarks, including standardized graph representation protocols and open, multi-institutional benchmarking datasets that can be systematically enriched through large-scale FE simulations, carefully designed field experiments, and sophisticated data augmentation strategies [24]. Equally important is the advancement of physics-aware and interpretable GNN architectures, where the path forward lies in developing hybrid mechanistics-based GNN frameworks, embedding physical laws directly into network architectures, and incorporating inductive biases that naturally enforce physical plausibility [68]. Perhaps most ambitiously, there is tremendous potential in building foundation models for structural intelligent computation by drawing inspiration from the success of large language models (LLMs). Such large-scale, pre-trained foundation models could

achieve robust cross-structural generalization capabilities and be fine-tuned for specific structural types and loading conditions, ultimately enabling truly intelligent structural analysis across diverse engineering applications.

## 4. Seq2Seq and Transformer-based applications

### 4.1. Rational of introducing Seq2Seq and Transformer architecture

Seq2Seq and Transformer-based architectures are primarily employed to address sequence-related problems in computational engineering, where the objective is to capture the temporal or history-dependent evolution of structural responses. The review by Wang *et al.* [4] define the problem as dynamic feature learning, typically manifested as mapping relationships between time-varying external stimuli (e.g., earthquake ground motions, cyclic loading histories) and the corresponding response sequences (e.g., stress-strain curves, hysteretic load-displacement relations, time-series seismic response). Another type of tasks focuses on reconstructing full-range sequences from partial data.

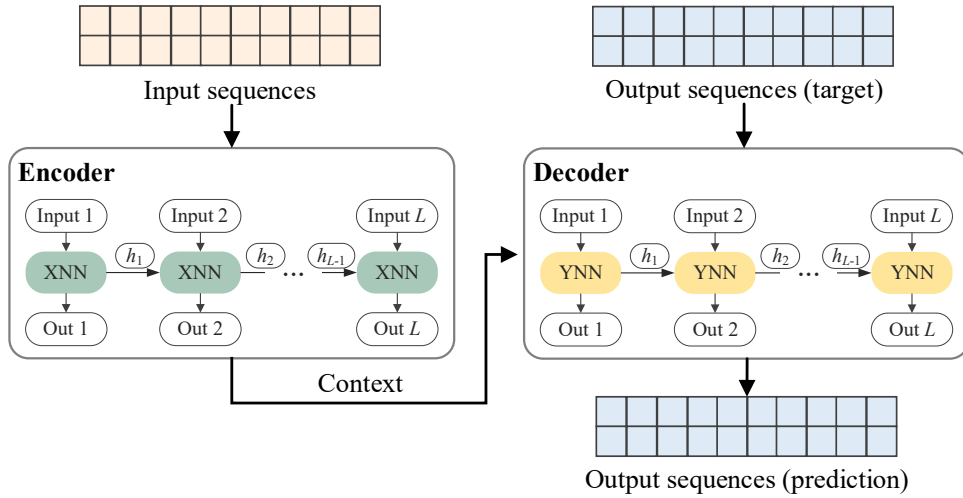
Analogous to NLP translation, where models translate sequences of words from one language to another, dynamic feature learning can be formulated as sequence-to-sequence regression tasks. The research pipeline follows three core stages: (1) Data collection and preparation. Sequential datasets are constructed or simulated. For dynamic modeling, the inputs are different time histories of external stimuli and outputs are full-range response sequences. Diverse structural configurations are added into account if the research aims at generalizability across different structures. For reconstruction tasks, a sequence is usually divided into input and output based on time windows or spatial measurement points. (2) Model configuration and training. Researchers adopt different modules within the Seq2Seq architecture or integrate Transformers with approaches such as PINNs and pre-training techniques to adapt to different application scenarios. (3) Model validation and application. The trained models are usually evaluated with unseen input sequences (generalizability across input stimuli) or diverse structures (generalizability across structures).

### 4.2. Basic concepts and model variants

Seq2Seq models were originally proposed to learn mappings between variable-length input and output sequences, and have been widely adopted in domains requiring sequential prediction (e.g. Natural Language Processing, NLP) [69]. The canonical Seq2Seq architecture consists of two key components (see Figure 7): an encoder that compresses the input sequence into a latent representation (also called the context), and a decoder that reconstructs the output sequence from this representation. This design overcomes the limitation of classical RNNs by allowing variable-length inputs and outputs, making the framework highly suitable for complex problems where input and output may differ in length. In principle, both encoder and decoder can be configured using various modules, as outlined below:

**LSTM and Gated Recurrent Unit (GRU):** The LSTM [70] network and the GRU [71] are most prevalent choices. Compared with vanilla RNNs, LSTMs and GRUs incorporate gating mechanisms that mitigate the vanishing gradient problem in long sequences. LSTM introduces separate memory cells and gating mechanisms (input, forget, and output gates) that explicitly control information flow, while GRU simplifies this structure into update and reset gates. Therefore, GRUs generally have fewer parameters

and are computationally lighter. In many engineering applications, the performance gap between two modules has been found to be relatively small [70].



**Figure 7.** Illustration of typical Seq2Seq architecture. “XNN” & “YNN” stand for arbitrary modules,  $h_i$  denotes each hidden state in the module.

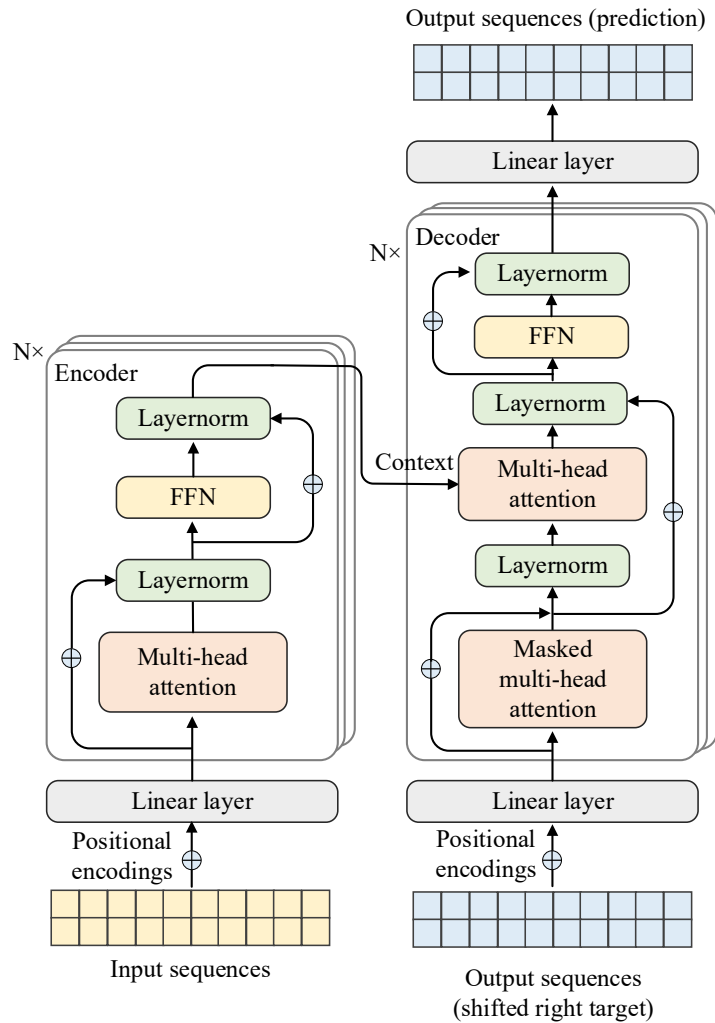
**Transformer and attention mechanism:** The limitations of recurrence-based models, particularly their difficulty in parallelization and capturing very long-range dependencies, motivated the development of another Seq2Seq architecture, Transformer [9]. As shown in Figure 8, the Transformer eliminates recurrence and instead relies on attention mechanisms, specifically the self-attention operation, to compute pairwise interactions between sequence elements. In self-attention, each element of the input sequence is first linearly projected into three vectors: a query  $\mathbf{Q}$ , a key  $\mathbf{K}$ , and a value  $\mathbf{V}$ . The attention output is then computed as:

$$\mathcal{A}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{d_k}}\right)\mathbf{V} \quad (7)$$

where  $d_k$  is the dimension of the key vectors. The dot-product  $\mathbf{Q}\mathbf{K}^T$  captures query–key similarity, the softmax function converts it into attention weights, and these weights aggregate the values to form contextual representations across the sequence. Another important technique is multi-head attention (MHA), which employs parallel projections to learn different types of internal dependencies simultaneously. MHA blocks are stacked and followed by feed-forward layers. In addition, positional encodings are introduced to retain sequence order. For structural engineering applications, the innovative architecture facilitates learning complex path-dependent behaviors.

**Variants of Transformers:** Since invented, Transformers have spawned numerous variants designed to improve the efficiency and scalability for long sequences. For example, the computational complexity of vanilla Transformers with standard attention scales quadratically with the sequence length, while the Performer by Choromanski *et al.* [72] reduces the quadratic complexity to linear through kernelization techniques. Reformer [73] mitigates the quadratic bottleneck by utilizing local attention and introduces reversible residual layers to minimize memory consumption during the training. Longformer [74] addresses the scaling challenge through a sparse attention mechanism that combines a localized sliding window with global attention tokens, making it particularly suitable for processing long-sequence problems. More recently, large-scale Transformers like the Generative Pre-trained Transformer (GPT) [75]

have demonstrated remarkable capabilities in sequence modeling and generative prediction. Although originally developed for NLP tasks, the underlying architecture offers potential for structural engineering applications.



**Figure 8.** Illustration of the vanilla Transformer architecture. “LayerNorm” denotes the layer normalization process and “FFN” stands for feed forward network.

#### 4.3. Applications in computational analysis

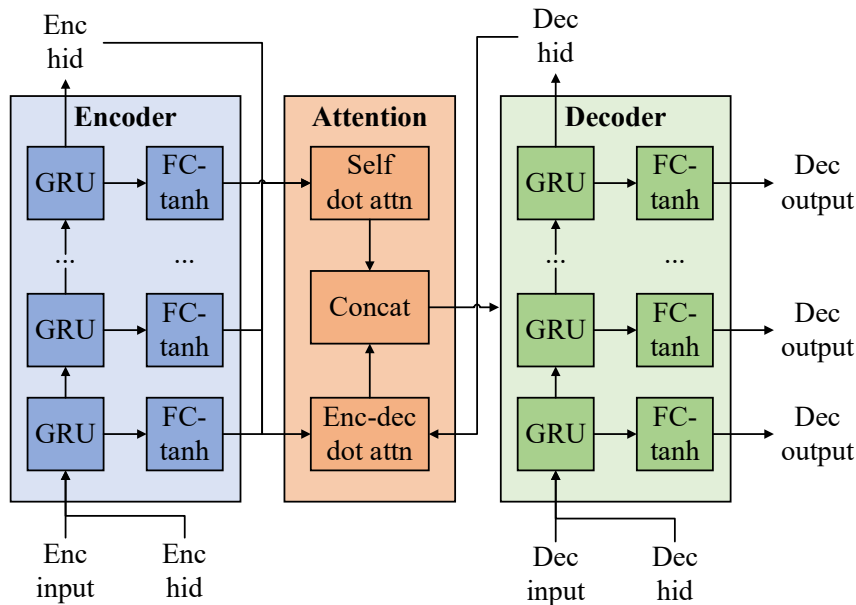
The applications of Seq2Seq family mainly concentrate on following tasks: (1) Constitutive relations modeling: learns to map the constitutive relations of construction materials or capture underlying multi-scale mechanism; (2) Dynamic structural modeling: centers on modeling dynamic responses of structures subjected to time-varying excitations; (3) Structural response reconstruction: aims to reconstruct missing, unmeasured, or full-field responses from partial observations (e.g., sparse sensor data, limited spatial samples, or truncated time windows). Key details of representative articles are summarized in Table 2.

**Table 2.** Applications of Seq2seq/Transformer models in computational analysis.

Applications	Authors	Encoder	Decoder	Tasks
<b>Constitutive relations modeling</b>	Wang <i>et al.</i> [76]	GRU + Attention	GRU	Predicting history-dependent cyclic behavior of low-yield point steel.
	Li <i>et al.</i> [77]	(a) GRU (b) GRU + Attention (c) Temporal CNN (d) Transformer (best)	GRU	Modeling constitutive relations.
<b>Dynamic structural modeling</b>	Zhongbo & Hien [78]	Pre-trained Transformer	-	Modeling elastoplastic behaviors of fiber-reinforced composite.
	Li <i>et al.</i> [79]	Attention blocks	LSTM	Forecasting structural response under seismic excitation.
	Wang <i>et al.</i> [80]	Deep & cross network + Performer	-	Hysteresis analysis of shear wall structures.
	Li <i>et al.</i> [81]	Transformer	-	Predicting seismic response of bridges.
	Meng <i>et al.</i> [82]	LSTM	LSTM	Predicting real-time seismic response of concrete structures.
	Zhou <i>et al.</i> [83]	Physics-informed Transformer	-	Predicting real-time seismic response of building structures.
	Zhang <i>et al.</i> [84]	Transformer	-	Predicting seismic response of a damped structure.
	Zhang <i>et al.</i> [85]	Transformer encoder	LSTM	Linear-elastic and elastoplastic response prediction of structures.
	Choi <i>et al.</i> [86]	CNN & LSTM & Transformer	-	Predicting seismic ground accelerations with one-dimensional wave propagation model.
	Shu <i>et al.</i> [87]	Transformer	-	Predicting generalized seismic performance of building structures.
	Meng <i>et al.</i> [88]	Physics-informed + Pre-trained Transformer	-	Predicting real-time seismic response of building structures.
	Wang <i>et al.</i> [89]	LSTM + Attention	LSTM	Predicting nonlinear time-varying deformation of an earth-rock dam.
	Yazdanpanah <i>et al.</i> [90]	Transformer	-	Predicting real-time seismic response of bridge bearings and piers.
	Liao <i>et al.</i> [91]	PINN + Transformer + GCN	-	Predicting seismic response of a five-story frame structure.
	Bao <i>et al.</i> [92]	PINN + Transformer	-	Predicting long-sequence time-history response of containment structures under mainshock-aftershock sequences.
	<b>Structural response reconstruction</b>	Xing <i>et al.</i> [93]	Transformer	-
Zhao <i>et al.</i> [94]		Transformer	-	Predicting dynamic responses of train-track-bridge interaction system.
Zhang <i>et al.</i> [95]		LSTM + Transformer	-	Prediction of bridge structure response and resilience assessment under main-aftershock.
Jiang <i>et al.</i> [96]		GRU	GRU + Attention	Reconstructing dynamic structural responses of a footbridge.
Fan <i>et al.</i> [97]		Attention + GAN	-	Reconstructing dynamic structural responses of Guangzhou New Television Tower.
Zheng <i>et al.</i> [98]		Transformer + GAN	-	Reconstructing multi-channel response of bridges under pedestrian excitations and typhoon events.
Khodaei & Bitaraf [99]		Transformer + GAN	-	Synthesizing structural dynamic data from limited measured data.
Yang <i>et al.</i> [100]		Mixed Transformer + CNN	-	Reconstructing acceleration responses of Guangzhou New Television Tower.
Dao <i>et al.</i> [101]		Multi-scale dilated Transformer	-	Reconstructing acceleration responses of Guangzhou New Television Tower.
Baharami <i>et al.</i> [102]		GRU & LSTM	GRU & LSTM	Forecasting unknown bridge response based on measured data.

### 4.3.1. Constitutive relations modeling

While basic DL modules have long been used for constitutive modeling of construction materials, some researchers have moved toward more flexible Seq2Seq encoder-decoder architectures to better capture long-range history dependent behaviors. Wang *et al.* [76] were among the first to introduce Seq2Seq framework into this field. They discussed the drawbacks of previous methods, which failed to transmit historical information stored in hidden layers for long sequences. They designed an Unrolled-Attention Sequence-to-Sequence (UA-Seq2Seq) with transferable formulations that are applicable to other materials (see Figure 9). Illustration of the UA-Seq2Seq architecture for constitutive modeling [77]. The model succeeded in characterizing main cyclic properties including the working hardening and the idiosyncratic softening of low-yield-point steel. Li *et al.* [77] used Seq2Seq framework to model high-dimensional stress-strain relationships of materials under complex loading conditions. They evaluated various encoder architectures, including GRU, GRU with attention, temporal CNN and Transformer encoder, and found the Transformer to achieve the best overall performance. For more complex behaviors of elastoplastic heterogeneous materials, Zhongbo *et al.* [78] employed a pre-trained Transformer surrogate model. Pretrained on a cheaply generated source dataset and fine-tuning to targets, the model's strain-stress predictions under random loading paths outperforms baseline RNNs.



**Figure 9.** Illustration of the UA-Seq2Seq architecture for constitutive modeling. Note: Enc (Encoder), Dec (Decoder), tanh (tanh activation function), FC (fully connected layer), dot attn (dot product attention), and concat (concatenation).

### 4.3.2. Dynamic structural modeling

Seq2Seq methods are widely used for dynamic structural modeling, notably real-time seismic and hysteresis analysis. Li *et al.* [79] employed an attention-augmented Seq2Seq architecture to predict structural responses to seismic excitation, validating it on real high-rise buildings and demonstrating efficient generation of future dynamic responses. They also introduced an accumulative-energy metric to select the most representative seismic-duration for offline training. Meng *et al.* [82] used a similar

pipeline but replaced the RNN with LSTMs, reporting prediction speeds more than  $100 \times$  faster than conventional FE simulations.

Despite these advances, establishing a reliable predictive framework remains challenging in practice because of complex causal relationships and strong interactions between input excitations and structural responses. Compared with RNN-based Seq2Seq frameworks, the Transformer architecture is better suited to capture global dependencies and to model entire sequences holistically, and has therefore attracted increasing attention. For example, Li *et al.* [81] compared a Transformer-based model with a commonly used LSTM baseline for bridge structural-response prediction and reported significant less prediction error. The Transformer architecture has also been applied to diverse tasks, including seismic-response prediction for damped structures [84], building structures [85,87], the earth-rock dam [89], bridge bearings and piers [90], train-track-bridge interaction systems [94], bridge structures [95], seismic-capacity prediction of frame-core-tube structures [93], and seismic ground-acceleration simulations [86], among others. These studies consistently report Transformer with superior performance over conventional sequential models, highlighting its strong feature-extraction capability and broad applicability.

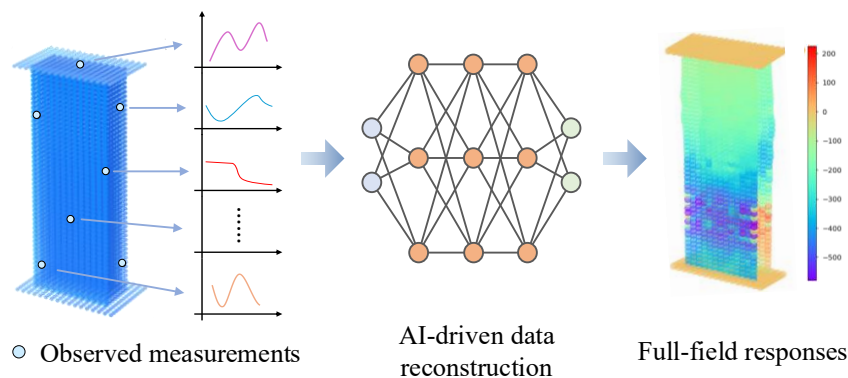
Apart from directly adopting the vanilla Transformer, several scholars have proposed modifications tailored to the structural engineering domain, typically by revising submodules or integrating complementary modules. Wang *et al.* [80] argued that vanilla Transformers, while effective for dynamic sequences and generalizing input excitations, overlook important static features such as topology, component information, and material properties. To remedy this, they incorporated the Deep & Cross Network (DCN) [103] from recommender-system research to learn cross-interactions among static features. For long-sequence, vanilla Transformers also encountered challenges regarding the computational efficiency and causal consistency during autoregressive modeling. So, they replaced the standard attention with the more computationally efficient fast attention from Performer [72] to reduce the time cost. Applied to a dataset of shear-wall structures, the proposed model PADCN-Mechformer enabled nonlinear hysteresis analysis and improved generalization across diverse configurations. For nonlinear analysis of large-scale structural systems with more complex topology, Song *et al.* [55] combined the Transformer with HGNN modules to perform graph learning on static features, broadening the application scope of the hybrid architecture. They further designed a masked response-based strategy for training the model based on partial data points to mitigate the data scarcity issue. Liao *et al.* [91] designed a novel mechanics-informed Transformer-GCN architecture for computing structural linear dynamic responses. Their work exploited the computational similarity between multi-head attention mechanism and the mode-superposition method, and innovatively replaced the adjacency matrix of GCN with the structural stiffness matrix, therefore constraining the prediction results to comply with the deformation compatibility principle.

Despite these advancements, significant challenges persist in adapting Transformers for long-sequence dynamic structural modeling. Beyond computational efficiency, a primary concern is autoregressive drift, where incremental prediction errors propagate and accumulate over extended temporal horizons. In practical applications, this manifests as a progressive decay in predictive accuracy as time step increases. Such a limitation is particularly problematic for tasks that demand high fidelity in modeling cumulative damage effects and long-term structural degradation like seismic analysis. Moreover, as sequence length increases, purely data-driven Transformers tend to prioritize empirical statistical correlations over the underlying mechanical laws [83]. Therefore, integrating physical information and governing mechanical equations into data-driven Transformers has recently attracted considerable

attention. Zhou *et al.* [83] proposed a physics estimator called Phy-Seisformer, which incorporates structural information—the story mass and stiffness—together with the Newmark- $\beta$  dynamics equation into the learning architecture. The experiment on several structures verified the model's high accuracy and faster calculation speed than FE methods. Physics-informed methods are also utilized to reduce the reliance on large training datasets. Bao *et al.* [92] developed a Physics-informed Transformer model named Phyformer for longer mainshock-aftershock sequence predictions and discussed the challenges brought by scarcity of high-quality data. Therefore, the physics constraints were embedded in the loss function to better capture structural characteristics for efficient model training with limited data.

#### 4.3.3. Structural response reconstruction

The loss of measured structural responses inevitably occurs during the construction or maintenance stage and severely hampers the safety assessment of engineering structures. It is therefore of paramount importance to reconstruct missing, unmeasured, or full-field response data from partial observations. Traditional FE-based methods are limited by the discrepancy between the real-world civil structures and the corresponding FE models, and the uncertainty of noise under extreme loading conditions [96]. On the other hand, the data-driven methods make the most of accumulated data and learn the complex mapping relationships between lost measurements and observed measurements in an end-to-end manner (see Figure 10). Characterized by numerous parameters and deep representation learning capabilities, Seq2Seq models and Transformer are employed to address the reconstruction problem as a sequence generation task. Jiang *et al.* [96] proposed a Seq2Seq framework for structural dynamic response reconstruction and virtual sensing. A soft attention mechanism was utilized to extract the potential spatiotemporal correlation and promote the bidirectional flow of information along the sequence data. They verified the effectiveness and robustness of the network based on the ambient vibration signal of a footbridge measured on-site.



**Figure 10.** Illustration of end-to-end AI-driven data reconstruction process: full-field responses are reconstructed from partially observed measurements.

Generative models, such as generative adversarial networks (GAN [104], which consisted of a generator and a discriminator), have also been introduced to yield results that are more consistent with the real data distribution. Fan *et al.* [97] introduced a self-attention enhanced GAN to reconstruct missing data based on the accurately measured ones. Their method integrated self-attention and adversarial learning to capture global spatial-temporal correlations from limited data, achieving highly accurate reconstruction under both ambient excitation and extreme typhoon loading. The study by Zheng *et al.* [98]

adopted a similar transformer-based GAN to reconstruct lost measurements from observed measurements. They adopted a Transformer backbone integrated with discrete wavelet transform for the generator and designed a customized discriminator to evaluate the authenticity of the reconstructed data. The proposed model was tested on a footbridge and achieved improved performance compared with densely connected CNNs. Transformer-based GAN has also been employed for synthesizing structural dynamic responses, addressing the critical challenge of data scarcity in structural health monitoring (SHM) [99].

Some scholars argued that the vanilla transformer architecture involved redundant computations and were limited by the lack of inductive bias [105]. Yang *et al.* [100] developed a novel mixed Transformer-CNN network that connected the two modules in a parallel manner. The method was validated using the field acceleration data from the Guangzhou New Television Tower and reduced the error by 56% and 17% compared with models using only Transformer or CNN. Building upon their work, Dao *et al.* [101] designed a multi-scale dilated Transformer model which employed dilation operation to reduce computational costs and capture semantic dependencies across scales. Their model was tested on the same dataset and outperforms the former network by improving reconstruction accuracy in terms of mean squared error, relative error and the coefficient of determination. Apart from reconstructing responses with measured data from the same structure, Bahrami *et al.* [102] used a Seq2Seq framework with GRU and LSTM cells to reconstruct bridge responses using measurements from another bridge under identical truck loading. Their model, trained on real traffic data from multiple bridges, achieved over 20% lower error than linear baselines, demonstrating the feasibility of prediction with sparse measurements.

#### 4.4. Research gaps and future directions

The Seq2Seq and Transformer, as well-established frameworks for handling sequential problems, have preliminarily demonstrated its powerful expressiveness in the various fields of structural engineering; However, existing studies still exhibit certain limitations: (1) Reliance on large datasets: Seq2Seq and Transformer-based models typically contain a large number of parameters and exhibit strong data dependency. In the absence of sufficient training samples, their generalization capability may deteriorate, leading to a high risk of overfitting. (2) Insufficient exploration of training strategies: Training deep Seq2Seq/Transformer architectures poses significant challenges, particularly due to optimization instability and high computational demands [106]. Although some studies introduce physics-informed losses or pre-training schemes, systematic strategies and efficient optimization techniques remain underexplored for large-scale training. (3) Lack of spatiotemporal scaling and geometric inductive biases: Seq2Seq models are designed for token sequences; applying them to high-resolution spatiotemporal structural fields leads to prohibitive token counts and heavy computational demands. Moreover, vanilla Transformers lack mesh/geometry-aware inductive biases (e.g. rotations/translations invariance, local topological structure), which are important for physically meaningful generalization on structural domains [105]. (4) Reliance on heuristic and non-physical positional encoding: The permutation-invariant nature of the self-attention mechanism necessitates the use of positional encodings to reintroduce the critical spatiotemporal order. Defining a physically meaningful and generalizable PE for high-dimensional, irregular structural mesh data—rather than relying on arbitrary sinusoidal or learned embeddings—is a non-trivial architectural challenge. This difficulty directly impacts the model's ability to correctly encode and interpret physical relationships across the engineering domain. (5) Limitations in long-sequence structural dynamics: For

long sequence problems, the vanilla Transformer with standard attention mechanism faces multiple challenges including the computational prohibitive complexity, the autoregressive drift issue and tendency to prioritize superficial statistical correlations over underlying governing equations.

To address the aforementioned limitations, future research should explore more efficient, physically grounded, and structurally aware learning paradigms that can push the frontier of dynamic response modeling. A primary direction lies in developing data-efficient and hybrid learning frameworks that reduce the reliance on massive datasets while maintaining high generalization capability. Promising approaches include leveraging transfer [107] few-shot learning techniques [108] to harness cross-task similarities, and generating diversified synthetic data through physics-based simulations to enrich training coverage without costly experiments. Equally important is the advancement of optimization and training strategies for scalable models. Techniques such as low-rank adaptation (LoRA) [109] and parameter-efficient fine-tuning (PEFT) [110] provide efficient solutions for large structural systems, enabling stable convergence, reduced computational overhead, and improved adaptability to complex dynamic conditions. Finally, perhaps the most critical frontier is the development of mesh-aware and hybrid schemes that bridge data-driven and physics-based representations. Future efforts should explore multi-resolution tokenization methods, mesh-aware attention mechanisms (e.g., mesh-transformers [111], equivariant attention [112]), and hybrid architectures that integrate neural operators or GNNs with attention modules. In parallel, standardized benchmarks that evaluate model accuracy, efficiency, and mesh-transferability are essential to foster fair comparison and accelerate progress in this rapidly evolving domain.

## 5. Physics-informed methods

### 5.1. Basic concepts and variants

Physics-informed methods (similar terms include physics-guided, physics-integrated and physics-encoded) were first proposed to integrate physical laws (often expressed as differential equations or conservation laws) into the loss functions of neural networks by Raissi *et al.* [13]. They introduced the idea that, given sparse or partial data, one can train a DL model to approximate the solution of a partial differential equation (PDE), enforce initial conditions (ICs) and boundary conditions (BCs), and sometimes learn unknown parameters of the PDE. In the typical PINN framework (see Figure 11a), a neural network  $u(x, t; \theta, \lambda)$  is defined to represent the spatiotemporal field of interest  $f(x, t)$ , and the loss function is deliberately designed to help the network learn the underlying physics, which may contain the following terms [113,114]:

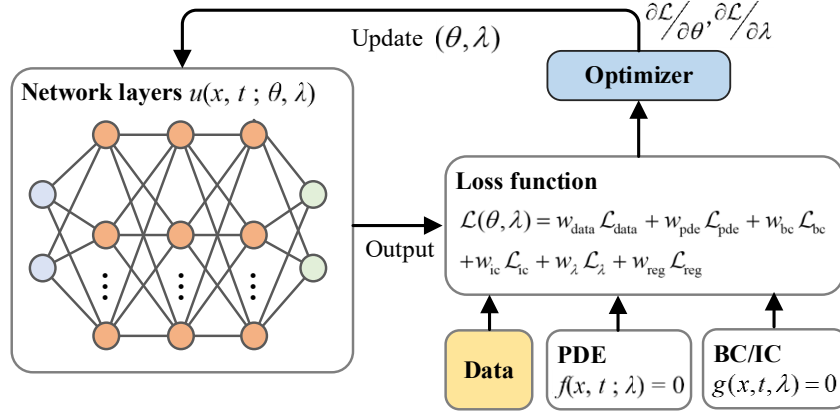
$$\mathcal{L}(\theta, \lambda) = w_{\text{data}} \mathcal{L}_{\text{data}} + w_{\text{pde}} \mathcal{L}_{\text{pde}} + w_{\text{bc}} \mathcal{L}_{\text{bc}} + w_{\text{ic}} \mathcal{L}_{\text{ic}} + w_{\lambda} \mathcal{L}_{\lambda} + w_{\text{reg}} \mathcal{L}_{\text{reg}}, \quad (8)$$

where  $\theta$  are network weights,  $\lambda$  are unknown physical parameters (if any), and  $w^*$  are scalar weights acting as hyperparameters for balancing each loss term. The meanings of each term are as follows:  $\mathcal{L}_{\text{data}}$  stands for data loss in supervised data-driven learning;  $\mathcal{L}_{\text{pde}}$  stands for PDE residual loss at collocation points (a set of known coordinates inside the PDE domain);  $\mathcal{L}_{\text{bc}} / \mathcal{L}_{\text{ic}}$  stands for BC and IC loss;  $\mathcal{L}_{\lambda}$  stands for parameter loss (if physical parameters  $\lambda$  are treated as learnable);  $\mathcal{L}_{\text{reg}}$  stands for regularization loss.

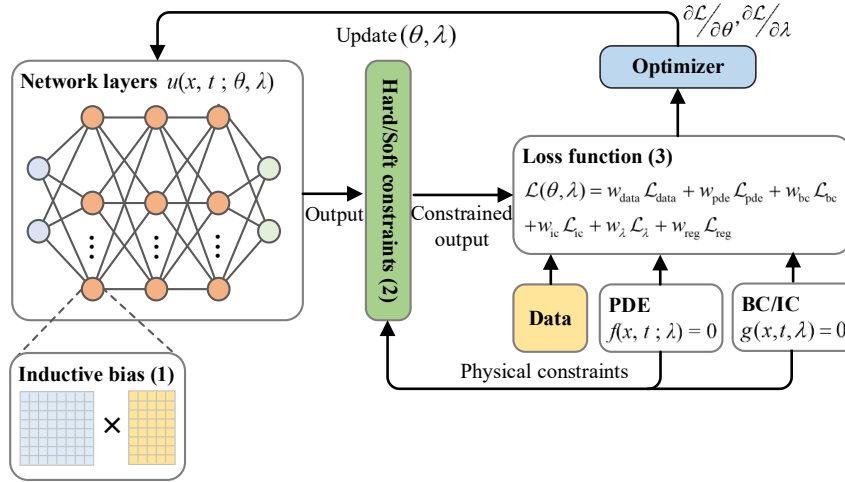
By training the network to minimize the loss function using gradient-based optimization method, the model is considered to approximate the ground-truth solution. Practical issues rise when the basic forms are applied to engineering domains, including the need to balance multiple loss terms, sensitivity to

network architecture, slower divergence speed compared to data-driven models and computational cost due to evaluating high-order derivatives. Over time, various enhancements or alternative forms have been developed to improve accuracy, efficiency and stability. Two of the most representative variants related to the reviewed studies are listed below:

(a)



(b)



**Figure 11.** Illustration of the typical physical-informed methods. **(a)** Physics incorporation in loss function; **(b)** Physics-encoded architectures, with physics incorporation in: (1) model framework as inductive bias; (2) output layer as soft/hard constraints; (3) loss function.

Weak/Energy form: The original loss function is defined as hard form, while some variants use energy or weak forms to reduce required derivative order or to better approximate gradients or integrals. The Deep Energy Method (DEM) proposed by Samaniego *et al.* [115] represents a foundational energy form. Unlike traditional residual-based PINNs, DEM replaces the standard PDE residual loss with a variational loss derived from the total potential energy functional of the system. The approaches have been successfully applied to various engineering problems including linear elasticity, elastodynamics, nonlinear hyperelasticity, *etc.* [116].

Physics-encoded architectures: In addition to loss-based physics enforcement, there exist multiple alternative approaches to encode physics information into models to enhance their interpretability. As illustrated in Figure 11b, examples include integrating FE methods, modifying the framework by designing physically plausible modules informed by domain knowledge, enforcing soft/hard constraints directly at the output layer, and employing equivariant or invariant neural architectures to respect

rotational or translational symmetries as the inductive bias. Moreover, combinations of the aforementioned variants have also been developed.

**Physics-informed neural operators (PINOs):** Unlike conventional neural networks that are often tied to specific grid resolutions, NOs are designed to provide mesh-independent solutions, making them particularly suitable for approximating complex PDEs in structural mechanics. For instance, the Fourier Neural Operator (FNO) by Li *et al.* [117] utilizes the Fast Fourier Transform to perform spectral convolutions that quickly identify broad physical patterns across an entire field. Another successful example is the Deep Operator Network (DeepONet) proposed by Lu *et al.* [118], which can evaluate solutions at any arbitrary point within the domain, thus decoupling the input excitation from the evaluation coordinates. Building upon the success of FNOs, Li *et al.* [119] proposed the PINO to further integrate physical constraints into the operator learning framework. PINOs have since become a powerful paradigm to simulate complex physical systems, enabling resolution-invariance and robust generalization, rather than being limited to point-wise solutions on a fixed discretization in traditional PINNs. Once trained, PINOs provide instantaneous inference of the entire solution field for new parameters or ICs, compared with iterative optimization process for every new problem instance required by traditional PINNs [120]. The variational-informed NOs (VINO) proposed by Eshaghi *et al.* [121] is another potential variant that shifts the optimization goal from minimizing the point-wise PDE residual to minimizing the total system energy over the entire solution function space. By embedding the global energy principles instead of local equations, VINOs are more effective for simulating systems with discontinuous or complex BCs.

Compared with conventional data-driven paradigms, physics-informed methods exhibit several distinctive characteristics: (1) **Data efficiency:** By constraining the hypothesis space with prior information, these models achieve accurate predictions with significantly fewer labeled samples. (2) **Physical interpretability:** Incorporating physical principles improves extrapolation beyond the training domain and enhances the interpretability and reliability of the learned representations. (3) **Computational Cost:** Evaluation of PDE residuals and derivatives results in higher training costs and slower convergence speed. (4) **Condition-specific:** Unlike data-driven models, which can generalize across certain variations, a trained PINN is typically tailored to specific conditions and must be retrained if these conditions change. (5) **Solution to inverse problems:** Physics-informed methods are appropriate for solving both forward and inverse problems; (6) **Hybrid Potential:** The physics-informed methods are usually combined with other techniques such as supervised learning and NOs to leverage respective strengths, offering a balanced framework for complex engineering problems.

## 5.2. Applications in computational analysis

Based on the intended tasks, physics-informed methods can be classified into several categories: (1) Constitutive modeling & calibration; (2) FE–PINN hybrids & surrogates; (3) Dynamic structural modeling. Key details of representative articles are summarized in Table 3.

**Table 3.** Applications of physics-informed methods in computational analysis, where “LF” stands for loss function, “MF” stands for model framework and “OL” for output layers.

Applications	Authors	Basis models	Physics integration	Tasks
<b>Constitutive modeling &amp; calibration</b>	Pishro <i>et al.</i> [122]	DNN	LF	Modeling local bond stress-slip relationship at the steel bar-UHPC interface.
	Wang <i>et al.</i> [123,124]	GNN	LF	Predicting mechanical response of concrete with morphed honeycomb configurations.
	Wang <i>et al.</i> [125]	GRU	LF	Modeling the elastoplastic constitutive relation of steel material
	Li <i>et al.</i> [126]	DNN	MF & LF	Predicting elastoplastic behaviors of unidirectional fiber-reinforced composites.
	Roy <i>et al.</i> [127]	DNN	LF	Solving the non-associative Drucker–Prager elastoplastic model with isotropic hardening.
<b>FE–PINN hybrids &amp; surrogates</b>	Lin <i>et al.</i> [128]	CNN	LF	Calibrating the mesoscale peridynamic constitutive model of concrete.
	Anton <i>et al.</i> [129]	DNN	MF & OL & LF	Calibrating linear elastic and hyperelastic constitutive models.
	Abueidda <i>et al.</i> [130]	DNN	LF	Simulating 3D elastic and hyperelastic beam bending.
	Rao <i>et al.</i> [131]	DNN	LF	Solving elastodynamics problems without labeled data.
	Kapoor <i>et al.</i> [132]	DNN	LF	Simulating Euler–Bernoulli and Timoshenko beams on Winkler foundations.
	He <i>et al.</i> [133]	DNN	LF	Solving partial differential equations in computational structural mechanics.
	Haghighat <i>et al.</i> [134]	DNN	LF	Inversion and surrogate modeling in solid mechanics.
	Xu <i>et al.</i> [135]	DNN	LF	Solving inverse problems in linear elasticity and hyperelasticity under different loading scenarios.
	Yao <i>et al.</i> [136]	CNN	MF	Solving multi-physics and multi-phase mechanical problems.
	He <i>et al.</i> [137]	DNN	MF & LF	Solving path-dependent elastoplasticity problems with energy-based method.
	Badia <i>et al.</i> [138]	DNN	MF & OL & LF	Solving forward and inverse PDE-constrained problems.
	Zhang <i>et al.</i> [139,140]	DNN	MF & OL & LF	Modeling elastic and elastoplastic solid mechanics.
	Xu <i>et al.</i> [141]	DNN	MF & LF	Inversion of elastic homogeneous materials and heterogeneous material parameters, load, and elastoplastic model parameter.
<b>Dynamic structural modeling</b>	Sun <i>et al.</i> [142]	DNN	LF	Solving potential problems and elastostatic problems with complex-shaped region, infinite/semi-infinite region, and heterogeneous materials.
	Zhang <i>et al.</i> [143]	DNN	LF	Solving 2D elastostatic and piezoelectric problems.
	Zhang <i>et al.</i> [144]	CNN	LF	Predicting seismic response of a 6-story reinforced concrete building.
	Zhang <i>et al.</i> [145]	LSTM	LF	Modeling nonlinear systems with rate-independent hysteresis.
	Liu <i>et al.</i> [146]	LSTM	LF	Predicting seismic response of a 6-story steel building.
	Bond <i>et al.</i> [147]	LSTM	LF	Predicting seismic response of nonlinear steel moment-resisting frames.
	Wu <i>et al.</i> [148]	LSTM	LF	Predicting seismic response of nonlinear layered shear models: a 5-DOF system and a 7-DOF system.
	Liang <i>et al.</i> [149]	DNN	LF	Forward simulation and parameter inverse identification issues in structural dynamics under moving loads.
	Eshkevari <i>et al.</i> [150]	RNN	MF	Predicting seismic response of a 4-DOF shear building with elastic–perfectly plastic or nonlinear elastic stiffness.
	Su <i>et al.</i> [151]	LSTM	MF & LF	Predicting dynamic response of nonlinear structures: a 5-DOF system with nonlinear springs, a 5-DOF Bouc-Wen system and a 7-story reinforced concrete building with 6 dampers.
	Chen <i>et al.</i> [152]	DNN	LF	Solving various structural vibration problems.
	Du <i>et al.</i> [153]	DNN	LF	Solving undamped and damped vibration problems.
	<b>Other applications</b>	Lee <i>et al.</i> [154]	DNN	LF
Zou <i>et al.</i> [155]		DNN	LF	Solving various structural vibration problems.
Moradi <i>et al.</i> [156]		DNN	LF	System identification and input estimation of dynamic systems.
Teloli <i>et al.</i> [157]		DNN	LF	Model parameter identification of beam-like structures under vibration.
Söyleyici <i>et al.</i> [158]		DNN	LF	Simulation and parameter identification of beam structures under vibration.
Liu <i>et al.</i> [159]	DNN	LF	Simulation and parameter identification of T-shaped tower structures under vibration.	

### 5.2.1. Constitutive modeling & calibration

Owing to the inherent complexity of constitutive equations, physics-informed methods are particularly well-suited for constitutive modeling and parameter calibration tasks for construction material (concrete, steel, fiber composites, *etc.*) modeling, such as inferring constitutive relationships or identifying material

parameters from displacement or strain measurements. Representative studies in structural engineering incorporate equilibrium equations and deformation compatibility conditions into the DL framework, thereby improving the physical interpretability and generalization performance of the resulting models. For example, Pishro *et al.* [122] addressed the lack of accurate local bond stress–slip models for steel–UHPC interfaces by developing a UHPC-PINN model. The micromechanics compatibility constraints were incorporated. Based on 144 monotonic pullout tests and FE-calibrated data, the study solved the inverse problem with the proposed model and a genetic algorithm, showing the former yielded more precise and consistent estimates than the latter. Wang *et al.* [123,124] developed hybrid physics-informed GNN to model mechanical behaviors of hollow concrete with morphed honeycomb configurations. They incorporated Hooke’s law into the loss function and trained the model on FE data calibrated by tests, providing a fast, interpretable surrogate for configuration design.

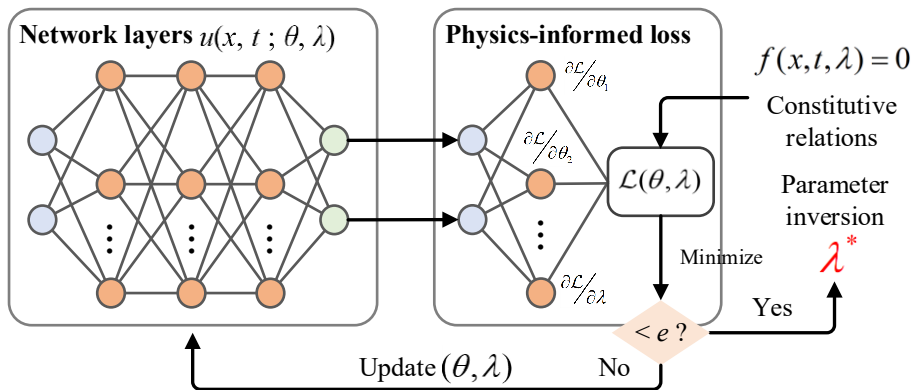
Physics-informed methods have also been reported with better performance on small datasets. Wang *et al.* [125] proposed a theory-aided few-shot learning algorithm with GRU modules for elastoplastic constitutive relation modeling. They embedded classical elastoplastic equations as priors into deep networks without requiring explicit constitutive forms or solvers. They introduced an overfitting-correction training strategy to stabilize optimization on scarce data. Validated on a type of steel, the approach improved generalization, outperforming a pure data-driven model by 38.9%. Li *et al.* [126] developed a mechanics-informed model to predict elastoplastic behaviors of unidirectional fiber-reinforced composites. Stress–strain decompositions were embedded in the model, and previous-step stress was included as an additional input to capture loading-path history, enabling accurate predictions even with a small dataset. Roy *et al.* [127] proposed a physics-infused NN for solution of the non-associative Drucker–Prager elastoplastic model with isotropic hardening. They designed a physics-augmented multi-objective loss incorporating constitutive laws, yield criterion, flow rule, and Kuhn–Tucker conditions, enabling accurate and stable elastoplastic solutions. Using transfer learning, the model efficiently adapts to different stresses and materials with limited data.

For calibration tasks, Lin *et al.* [128] employed both forward (parameter-to-behavior) and reverse (behavior-to-parameter) physics-informed CNNs to efficiently calibrate mesoscale peridynamic concrete models. The elastic modulus formula from peridynamic theory was incorporated in the loss function to link mesoscale material parameters with macroscale mechanical behaviors. Validated using OpenSees-generated datasets, the methods achieved fast and accurate calibration without solving complex inverse problems. Anton *et al.* [129] used a parametric PINN framework for calibrating constitutive models from full-field displacement data. By treating material parameters as network inputs and carefully designing the output layer, the PINN learned a parameterized PDE solution offline and served as a fast surrogate for deterministic and Bayesian calibration online. Tested on linear elastic and hyperelastic models with synthetic and experimental data, the method achieved near real-time performance, outperforming traditional FE-based calibration.

### 5.2.2. FE-PINN hybrids & surrogates

FE-PINN hybrids have matured from proof-of-concept PINNs into practical, numerically informed frameworks that blend FE ideas with neural network surrogates to solve forward and inverse problems in solid and structural mechanics. Several studies emphasized meshless or strong-form PINNs with physics-encoded loss functions for structural surrogates. For example, Abueidda *et al.* [130] developed

a meshless deep collocation method (DCM) for 3D solid mechanics, addressing linear elasticity, hyperelasticity, and von Mises plasticity. Physics information was embedded via the strong-form PDEs and BCs into the loss function. The meshfree approach avoids FE discretization and data generation, enabling rapid, accurate predictions of displacement fields across the domain. Rao *et al.* [131] addressed the computational elastodynamics problems (static, dynamic, wave propagation in truncated domains) with PINN and without labeled data.  $\mathcal{L}_{\text{pdc}}$ ,  $\mathcal{L}_{\text{bc}}$  and  $\mathcal{L}_{\text{ic}}$  were included in the loss function. Kapoor *et al.* [132] introduced a transfer learning–enhanced causal PINN for simulating Euler–Bernoulli and Timoshenko beams on Winkler foundations. By embedding beam PDEs into a causality-respecting loss and reusing pretrained weights to reduce training cost, their method improved generalizability, accelerated convergence, and accurately handled noisy or varied ICs. He *et al.* [133] proposed a multi-level PINN for structural mechanics PDEs. They decomposed high-order PDEs into several lower-order geometric, constitutive, and equilibrium equations, each solved by separate subnetworks. Linked through a unified physics-based loss, the meshless framework enhanced accuracy and efficiency in beam and shell bending simulations. Since the structural parameters could be defined as trainable parameters in FE & PINN hybrids, these frameworks are also widely adopted for inversion problems (see Figure 12). Haghghat *et al.* [134] applied the framework as inversion modeling surrogates in solid mechanics, where the loss function contained momentum balance and constitutive relations. Validated on FE data, their method enables sparse-data learning and robust parameter inversion. Xu *et al.* [135] proposed a transfer-learning–based PINN for inverse problems with linear elasticity and hyperelasticity. The unknown BCs/loads were treated as learnable parameters and inferred by the trained model.



**Figure 12.** Illustration of physical-informed parameter inversion.

More recent studies systematically incorporated FE principles, such as element discretization, weak/variational forms, element interpolation, and FE-generated training data, into the model architecture or loss functions to improve stability, accuracy, and applicability. Yao *et al.* [136] proposed a physics-guided deep CNN for predicting the mechanical response of materials and structures. By mapping FE analysis operations onto the convolution kernels (defined as FEA convolution), inductive bias is incorporated in the network architecture. With integrated interpretability of FE methods and efficiency of data-driven learning, their model demonstrated superior performance in multi-physics and multi-phase problems. He *et al.* [137] extended the DEM to solve path-dependent elastoplasticity problems. The principle derived from the discrete variational formulation of plasticity was encoded as an energy-based loss function and coupled it with the radial return algorithm to enforce the Kuhn–Tucker consistency. Using FE shape functions and Gauss quadrature, the method achieved accurate, data-free

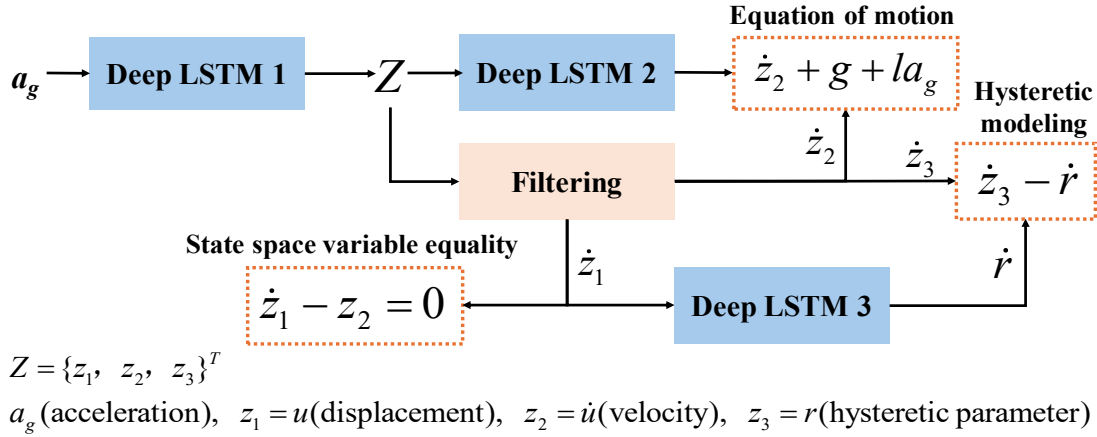
elastoplastic solutions comparable to FE results. Badia *et al.* [138] proposed FE interpolated neural networks (FEINNs) to solve both forward and inverse PDE-constrained problems. By mapping neural networks onto FE spaces, the researchers facilitated the enforcement of BCs at the mesh level and incorporated variational formulations into the training objective. FEINNs showed superior generalization and higher accuracy than standard FE. Research by Zhang *et al.* [139,140] and Xu *et al.* [141] both developed hybrid FE-integrated neural networks as forward and inverse analytical surrogates for elastic and elastoplastic solids. By embedding weak-form principles including Gaussian integration, shape functions and strain–displacement matrices and employing an incremental scheme for plasticity, FEINN effectively handled complex BCs and material nonlinearity. Other studies incorporate exact boundary integral equations (BIEs) into model training and the loss function, transferring unknowns to the boundary via BIEs to reduce training cost [142,143].

### 5.2.3. Dynamic structural modeling

Dynamic modeling is challenging due to nonlinear material and geometric behaviors, high-dimensional coupled equations, and strong sensitivity to boundary and loading uncertainties, requiring fine temporal–spatial resolution and high computational cost for accurate and stable predictions. In the preceding text, we have reviewed a subset of studies that employed physics-informed methods to simulate dynamic problems. The incorporation of physical principles into loss function has shown its potential to overcome challenges brought by complex mechanical behaviors and scarce data. Zhang *et al.* [144] proposed a physics-guided CNN (PhyCNN) for data-driven seismic response modeling. The model combined data loss with physics-based loss, using a graph-based tensor differentiator to compute time derivatives. Trained on 100 ground motion records, the model accurately predicted the interstory displacements of a six-story reinforced concrete building, showing close agreement with historical measurements. In another study, they designed a physics-informed LSTM (PhyLSTM, see Figure 13) for metamodeling of nonlinear systems with rate-dependent hysteresis [145]. Liu *et al.* [146] proposed another physics-informed LSTM (PI-LSTM) for structural response modeling of several cases of nonlinear systems and compared the model with PhyCNN and PhyLSTM. By adding the previous structural response to each step input, they declared that PI-LSTM achieved higher accuracy than PhyCNN in predicting displacement, velocity, and restoring force, and comparable displacement and velocity accuracy to PhyLSTM while outperforming it in restoring force prediction. Similarly, physics-informed LSTM models have been adopted in other studies for seismic response prediction, for example by Bond *et al.* [147] and Wu *et al.* [148].

Beyond loss function adjustments, certain studies have embedded the principles of dynamic structural modeling into the network architecture as an inductive bias, which further enhance the model's capability to simulate realistic mechanical behaviors. Eshkevari *et al.* [150] analyzed the causality of dynamic systems and designed a special RNN (DynNet) aligned with common dynamic numerical solvers. The DynNet module integrates inputs through linear layers and uses a ResNet [160] block for capturing structural nonlinearities. The module iteratively predicts structural states over time, requiring only ground motions and ICs for inference. Validated on a four-DOF shear building, DynNet accurately predicted displacement, velocity, acceleration, and internal force time histories at all DOFs. As discussed earlier, Zhou *et al.* [83] designed a physics estimator to extract the floor mass and stiffness as output features for further prediction. Since the computation process utilized the structure properties and the structural dynamic equation was embedded, the prediction relied on physical information and data rather

than purely data. Su *et al.* [151] combined the vanilla LSTM with a devised single convolution layer (SCL) module based on an explicit time-domain scheme for dynamic response prediction of nonlinear structures. The LSTM module was trained to learn the nonlinearity of restoring force, and the SCL module was designed to encode the linearity of the primary structure as prior physical knowledge. By retrieving the weights of SCL module, the model, termed as E-PINN, is capable of decoupling the linear and nonlinear evolution mechanisms embedded in the nonlinear system to reduce the learning overhead. Validated on three cases and compared with PhyLSTM [145], the lightweight E-PINN achieved higher accuracy in predicting the nonlinear hysteretic force and displacement with 10% less training time.



**Figure 13.** Illustration of PhyLSTM model architecture with three deep LSTM networks.

Physics-informed methods have also been widely adopted for structural vibration analysis. Chen *et al.* [152] developed an advanced time-marching PINN (AT-PINN) to solve accuracy degradation with the simulation time in solving vibration equations. They embed vibration PDEs and ICs/BCs into the loss function. Du *et al.* [153] employed a similar model to analyze both undamped and damped vibrations, and conducted an ablation study on the model parameters. Lee *et al.* [154] explored optimal strategies for constructing PINNs in the context of cantilever dynamics. They incorporated the second-order nonlinear term and decomposed the solution into spatial domain and temporal domain. The model was trained to describe the final prediction on the two decomposed bases, providing valuable guidelines for constructing PINNs in the realm of structural dynamics problems. Zou *et al.* [155] constructed a parameter-balanced Fourier feature PINN model to address the large differences in the physical parameter scales and high vibration frequencies in real structures. Fourier feature mapping was introduced to transform the traditional time-domain input into time-frequency domain input to enhance the expression capability and solution accuracy. Along with forward simulation, the inverse identification problems are also studied with PINNs. For example, Liang *et al.* [149] proposed two respective frameworks for forward simulation and parameter inverse identification in structural dynamics under moving loads. They integrated DNNs with forward and inverse Fourier transform, alleviating the spectral bias problem of the model. In numerical experiments for inverse identification, the proposed models produce better results than baseline traditional PINN. More applications can be found in the field of SHM, which lies beyond the main focus of this review; we therefore list only a representative subset of the related literature for reference [156–159].

### 5.3. Research gaps and future directions

Physics-informed methods have been increasingly adopted in civil structural engineering for tasks ranging from constitutive modeling and parameter calibration to FE surrogates and dynamic response simulation. Despite these advances, these practical challenges remain [161]. First, the lack of compatible governing equations fundamentally limits their applicability in structural computation. The governing mechanisms of structural systems involve the equilibrium equations, kinematic compatibility equations, and constitutive relations. While the first two can be effectively solved using mature and general numerical approaches such as the FE method, the constitutive equations in civil engineering are typically phenomenological and data-fitted, rarely expressed in differential form—particularly in nonlinear or elasto-plastic domains. Consequently, unlike fields such as fluid dynamics where the underlying PDEs are difficult to solve and physics-informed approaches offer clear advantages, structural computation already benefits from well-established solvers. Thus, physics-informed methods provide limited added value and exhibit weak universality in this context. Second, sensitivity to BCs and ICs remains a critical issue. Physics-informed models are originally formulated to solve PDEs under specific BCs/ICs, yet these conditions often vary significantly in engineering settings. Without guidance from supervised data, the models typically require retraining whenever conditions change, hindering their practical scalability. Third, robustness to noisy and incomplete data has not been sufficiently investigated. Most existing studies rely on synthetic or noise-free data, whereas real structural measurements inevitably contain noise, missing information, or sensor bias, exposing the fragility of current approaches in field applications. Finally, computational scalability remains a major bottleneck. Evaluating physics residuals densely across large 3D or fine-mesh domains is computationally expensive, which restricts most existing research to small-scale or low-dimensional problems. Efficient implementations and domain-decomposition strategies are still needed before these methods can be extended to realistic structural systems.

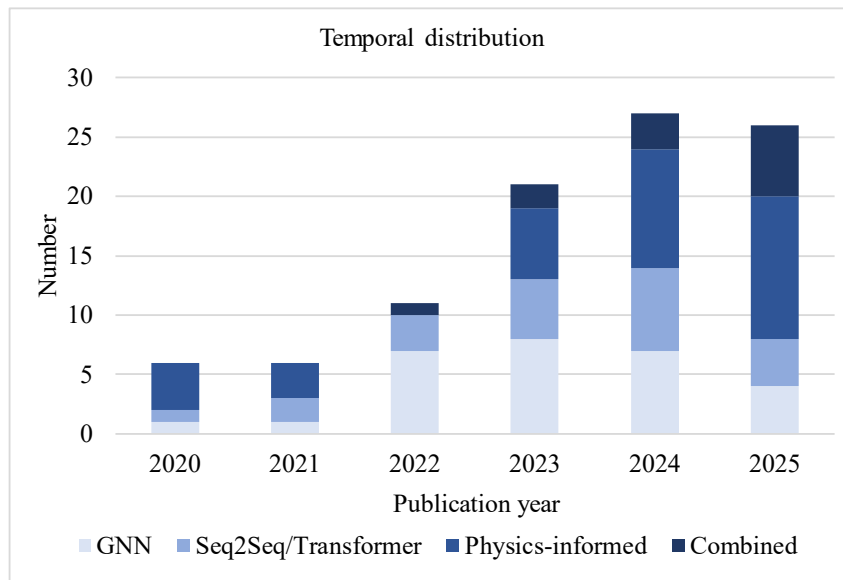
Looking ahead, future research on physics-informed learning for structural computation should focus on addressing issues of boundary sensitivity, data robustness, and computational scalability, which are more attainable and directly relevant to practical applications. To improve adaptability to varying BCs and ICs, promising directions include designing hybrid and adaptive training frameworks that couple physics constraints with supervised data-driven learning, allowing models to flexibly adjust loss weighting or solution strategies as BCs change. Enhancing model robustness requires integrating uncertainty quantification and data assimilation techniques into the physics-informed framework, enabling the model to actively learn from noisy or incomplete measurements. Approaches such as Bayesian inference, probabilistic PINNs [162], and sequential filtering (e.g., Kalman or ensemble methods) can progressively refine predictions and maintain physical consistency in real-world sensing environments. In parallel, improving computational scalability remains critical for applying these methods to large and complex structural systems. Domain decomposition and hierarchical training strategies offer an effective pathway, allowing parallel computation and local adaptation within subdomains while preserving global physical continuity. Incorporating efficient solvers or operator-learning modules can further accelerate residual evaluations and enable multi-scale modeling [163]. Collectively, these directions hold the potential to make physics-informed methods more robust, efficient, and practically applicable to the diverse and uncertain conditions encountered in civil structural engineering.

## 6. Discussion and extension

### 6.1. Quantitative analysis of the collected literature

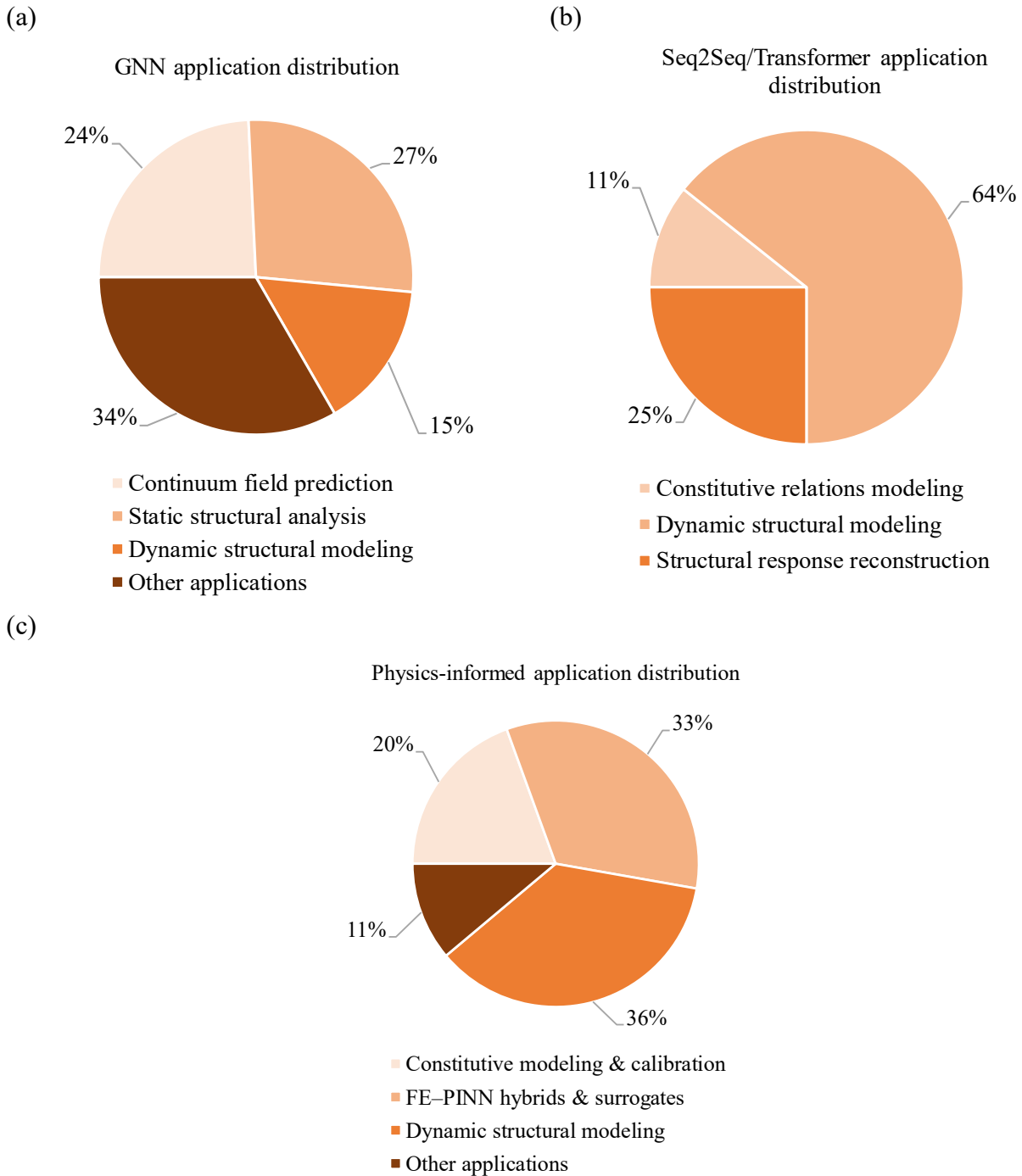
To provide an objective overview of the current research landscape, a quantitative analysis has been conducted on collected publications related to frontier AI applications in structural engineering from 2020–2025. The selected works are categorized according to multiple dimensions, including publication year, application task, and module type.

**Temporal Distribution:** As shown in Figure 14, the number of publications has exhibited a steady increase since 2020, indicating growing academic interest in frontier AI algorithms and models. Beginning in 2022, there was a notable increase in publications, particularly those employing physics-informed methods, indicating growing recognition of the importance of integrating domain knowledge into learning architectures. The combined methods are also increasing from 2023 onward, suggesting a paradigm shift toward methods that leverage advantages of different models and balance data efficiency and physical interpretability.



**Figure 14.** Temporal distribution of the collected publications (2020–2025).

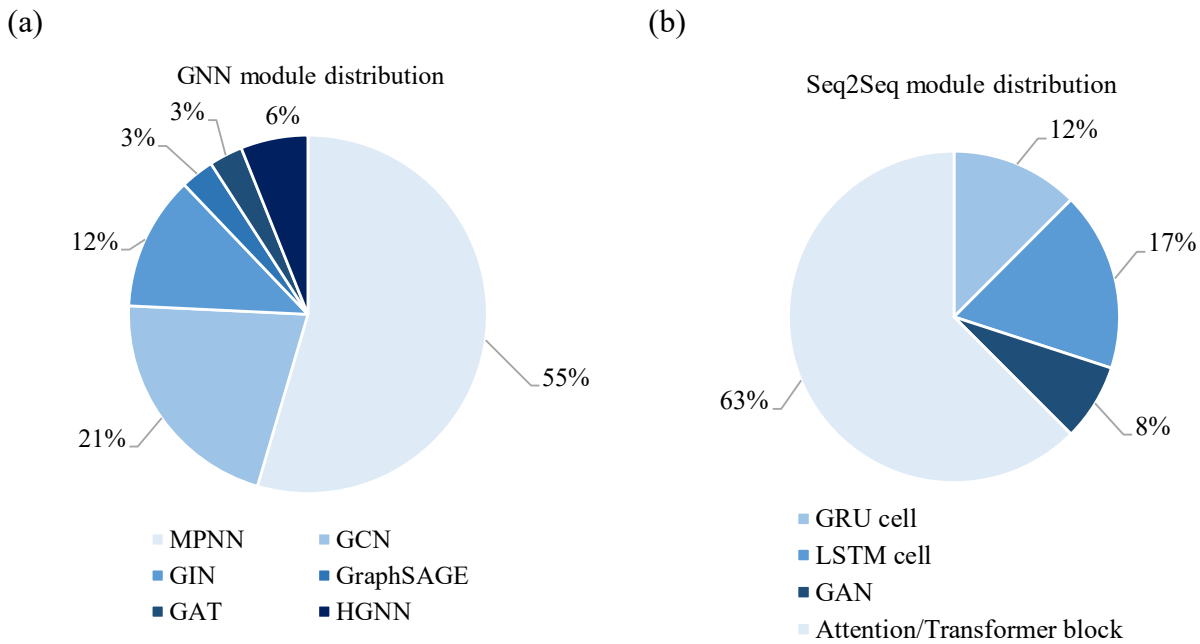
**Application task:** The reviewed studies have been roughly divided into several categories according to the application tasks and domains. As shown in Figure 15a, GNNs have been evenly explored across a broad spectrum of structural-engineering tasks, which reflects their natural advantages for problems defined on meshes or networks in civil engineering. Figure 15b highlights that Seq2Seq and Transformer architectures are predominantly applied to dynamic modeling problems ( $\approx 64\%$ ) and response reconstruction ( $\approx 25\%$ ), consistent with their design for sequence modelling and long-range temporal dependencies. A small portion ( $\approx 11\%$ ) addresses constitutive relation tasks, where sequence-aware encoders can capture loading–unloading paths and path-dependent material behavior. Figure 15c summarizes application areas for physics-informed approaches. Dynamic structural modeling constitutes the largest share ( $\approx 36\%$ ), followed closely by FE-PINN hybrids & surrogates ( $\approx 33\%$ ). This pattern underscores a maturing field in which domain knowledge is systematically fused with learning to produce accurate, interpretable surrogates.



**Figure 15.** Distribution among application tasks of the collected publications. **(a)** GNN; **(b)** Seq2Seq/Transformer; **(c)** Physics-informed method.

Module type: Figure 16a summarizes the prevalence of GNN module types. Likely due to their simplicity and computational efficiency, the basic MPNN and GCN (55% + 21%) dominate the surveyed GNN-based applications, reflecting their flexibility as generic aggregation–update paradigms for diverse structural tasks. GIN modules account for about 12%, while more complex GraphSAGE, GAT and HGNN take smaller shares, indicating that more expressive and hierarchical modules are yet to be explored. Figure 16b shows the module types of encoders and decoders in Seq2Seq/Transformer-based studies. Transformer blocks leveraging attention mechanisms are the most widely employed, followed by conventional GRU and LSTM architectures. Some studies focusing on response reconstruction

further incorporate GANs to enhance prediction fidelity. Overall, Seq2Seq/Transformer frameworks tend to integrate multiple module types rather than relying on a single architecture, aiming to combine their respective advantages in modeling and generation tasks.



**Figure 16.** Distribution of applied modules of the collected publications. (a) GNN; (b) Seq2Seq/Transformer.

## 6.2. Progress and common limitations

This review examined recent progress in applications of frontier AI models and algorithms to computational analysis. GNNs excel where topology and local connectivity matter. They naturally encode mesh or network structure, handle heterogeneous element properties, and scale to component-level or system-level tasks with locality-aware aggregation. Seq2Seq and Transformer-style architectures are especially effective for sequential or temporal problems. They capture long-range dependencies in time series, enable accurate prediction and response reconstruction. Physics-informed methods provide a complementary capability to data-driven models by incorporating governing equations, BCs/ICs, FE principles or conservation laws into the model framework and loss functions. They offer the benefits of reducing data requirements, improving physical interpretability and facilitating inversion tasks. The hybrids of these models and conventional methods have driven considerable progress in computational tasks such as constitutive modeling, FE surrogates, dynamic modeling, *etc.*

Nevertheless, certain challenges that hinder the practical application of AI techniques persist. In addition to the research gaps discussed above, we highlight several common limitations:

**Scarcity of benchmark dataset and evaluation metric:** While the fields of NLP and CV have established relatively systematic benchmark datasets and evaluation frameworks, such standardized resources remain largely absent in the domain of computational analysis. Due to the economic costs and labor involved in obtaining large-scale datasets, most studies in recent years still rely on proprietary or small-scale datasets, which makes cross-comparison between different models difficult. A rough overview of the reviewed literature indicates that fewer than 10% of the works provide open access to their data or code, hindering the reproducibility of proposed methods. Furthermore, evaluation metrics

are often inconsistent; some studies report accuracy on specific target variables, while others focus on prediction error or physical constraint violations. This inconsistency complicates the identification of truly superior methods and slows down progress in the field.

**Empirical–physics trade-off:** Existing models in structural engineering face a fundamental trade-off between data-driven paradigm and incorporating physical information. Purely data-driven models may learn the data distribution efficiently but lack physical interpretability and fail to generalize beyond the training manifold. On the other hand, physics-informed methods ensure the conformity to governing equations but are sensitive to altered BCs/ICs, limiting flexibility to learn novel patterns. Although some studies have explored approaches that combine data-driven learning with physics-informed methods [164], a critical optimization trade-off emerges: the competing objectives between data-fidelity loss and physics-informed loss can lead to stiff gradients and non-convex loss landscapes, making convergence challenging. Therefore, a comprehensive and systematic hybrid training strategy is yet to be developed.

**Scalability and generalizability:** Many models perform well on small-scale structures or specific datasets, but their performance on large-scale structures or unseen data needs to be evaluated. Scalability issues arise from the rapidly increasing computational cost and memory demand as the number of nodes and elements grows with system size, or as the number of time steps expands from linear to nonlinear analysis. Although GNNs can handle multi-graph and large-graph tasks to some extent, they might suffer from over-smoothing caused by repeated message-passing and aggregation; Seq2Seq and Transformer models require auxiliary techniques to cope with long sequences that exceed their configured context window; and physics-informed methods are particularly sensitive to changes in BCs/ICs. Together, these limitations hinder the scalability of current approaches. The limited generalizability may primarily stem from the scarcity of available data and the lack of systematic training strategies; addressing this requires expanding and diversifying training datasets and adopting techniques from NLP/CV fields, such as unsupervised/self-supervised learning or pretraining.

### 6.3. Practical implications for engineers

Frontier AI techniques examined in this study, including GNNs, Seq2Seq/Transformers and physics-informed methods, have been the focus of considerable scholarly interest across the research community. To facilitate the transition of these techniques from academic research to engineering practice, several practical dimensions must be addressed:

**Role in engineering FE workflow:** FE approaches remain the dominant paradigm for engineering computational analysis. The exploration of AI techniques is not intended to fully discard FE approaches; rather, they serve as a complementary framework to address inherent numerical limitations. The most prevalent role follows an experimental–numerical–AI pipeline, where experimental data is combined with high-fidelity FE simulations to yield AI-based surrogates [4]. Deployed through engineering-ready GUI for automated design and analysis tasks, these surrogates could significantly enhance computational efficiency by offering instant predictions and data export [165]. On the other hand, conventional FE strictly predicated on explicit mathematical formulations cannot directly resolve the analysis where governing equations or constitutive laws of construction materials are partially unknown. In these contexts, AI acts as a phenomenological modeling tool capable of discovering latent relationships directly from experimental or observational data. Furthermore, AI excels in structural parameter

calibration (e.g., calibration of constitutive models [128]) and inverse design problems (e.g., optimization of cable forces [167]), where the engineers can bridge the gap between raw sensor data and actionable mechanical insights in ways that traditional “forward” FE approaches cannot.

**Safety-critical design:** For engineering applications where structural failures pose severe risks to safety, the “black-box” nature of data-driven AI models might compromise numerical robustness and lead to instability. Unlike general predictive tasks, these high-stakes applications necessitate robust uncertainty quantification (UQ) to provide reliable confidence intervals for engineering decisions. Engineers must synthesize deterministic AI predictions with traditional failure mode analysis, redundancy strategies, and established structural codes. Consequently, AI is positioned as a powerful auxiliary tool for rapid design screening and real-time early warning systems, while the final safety closure must remain firmly anchored in fundamental mechanical principles and human expertise.

**Validation requirements for code compliance:** To bridge the gap between AI innovation and professional adoption, establishing rigorous validation protocols for code compliance is essential. Current engineering codes (e.g., Eurocodes, ACI) are predicated on semi-probabilistic safety formats and explicit mechanical models. Therefore, AI-based models must demonstrate that their predictions consistently align with or remain more conservative than code-mandated benchmarks across a wide range of design parameters [166]. Validation requirements should include statistical verification against large-scale experimental datasets, UQ to provide reliable confidence intervals and the incorporation of partial safety factors within the AI training objective. Furthermore, “white-box” verification is necessary to ensure that the model does not violate fundamental physical laws like the equilibrium equations.

**Potential integration with BIM or digital twins:** The integration of AI techniques with building information modeling (BIM) and digital twins (DT) transforms structural management from static design to dynamic lifecycle oversight. For engineers, AI could serve as the efficient “analytical engine” within a DT framework, fusing real-time sensor telemetry and inspection data to enable smart virtual sensing [58]. By embedding AI surrogates directly into BIM environments, engineers can move beyond reactive repairs toward predictive maintenance strategies. This workflow creates a continuous feedback loop where real-world performance data updates the DT, providing instant decision support for safety assessments and asset management [169,170].

**Feasibility of engineering deployment:** At present, practical deployment of frontier AI techniques for computational analysis remains underexplored, primarily due to the scarcity of open-source code and standardized benchmark datasets in this field. Some researchers have developed engineering GUIs for automated design [165], others have established online platforms for DT workflows [169]. Given that most frontier AI techniques are developed using the Python ecosystem and PyTorch library [3], their inherent flexibility and universality facilitate seamless integration with the application programming interfaces (APIs) of various FE, CAD and BIM software. Consequently, future researchers are encouraged to draw inspiration from broader AI communities by open-sourcing research outputs and integrating models into professional engineering platforms.

#### 6.4. Prospective avenues

Beyond the reviewed frontiers, several more sophisticated techniques merit focused research in the future:

**Generative models:** Generative models have emerged as powerful tools for a wide range of generation tasks. As discussed earlier, GAN models consist of two competing networks—a generator that creates synthetic samples and a discriminator that learns to distinguish real from generated data. Through adversarial training the generator gradually learns the target data distribution and produces outputs that are probabilistically close to it. Diffusion models are another class of generative models that have gained significant attention recently. They gradually transform random noise into structured data through a sequence of denoising steps, typically trained by reversing a diffusion process that adds noise to data. Compared with GANs, diffusion models offer more stable optimization and can generate more realistic and diverse outputs. They have become the dominant foundation for many state-of-the-art techniques in the computer vision (CV) field [171]. Such models are valuable for generative engineering tasks: structural design [172], data augmentation [174,175] and reconstruction [176], physical field estimation [177].

**Meta-learning:** Although meta-learning is still an emerging topic in civil engineering, it represents a transformative frontier for overcoming data-scarcity challenges in computational analysis. Often described as “learning to learn,” meta-learning aims to identify an optimal model initialization that allows for rapid adaptation to new tasks with minimal high-fidelity samples. While foundational algorithms like Model-Agnostic Meta-Learning (MAML) [178] established the theoretical framework, recent advancements have tailored these techniques for solving PDEs, including meta-learning-based initialization method to improve training efficiency of PINNs [179], and meta-learning methods for solving newly given PDEs without updating model parameters [180]. In the context of structural analysis, the few-shot capabilities offer immense potential for predicting the responses of unseen structural configurations or complex geometries where generating large-scale training datasets is computationally prohibitive.

**Explainable AI (XAI):** As the “black-box” nature of data-driven AI models poses significant challenges for high-stakes safety-critical design and decisions, XAI has emerged as a crucial frontier to bridge the gap between algorithmic prediction and physical interpretability [181]. Current research primarily utilizes post-hoc interpretability techniques, such as SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME), to quantify feature importance of model parameters in tasks like mechanical behavior modeling [182], seismic assessment and retrofit [184], and SHM tasks [186]. These methods allow engineers to verify whether a model’s decision aligns with established design codes and physical intuition, reducing the risk of erroneous or biased influence [183]. The next generation of XAI is expected to shift from mere statistical correlation to mechanical causation. For example, Symbolic Distillation techniques offer a potential pathway to extract human-readable, closed-form analytical formulas from complex AI surrogates that can be directly compared with engineering design codes [187].

**Large analysis models (LAMs):** The next major leap for structural computational intelligence lies in the development of LAMs—industry-scale foundation models trained from extensive, domain-specific datasets that cover diverse engineering scenarios such as buildings, bridges, tunnels, and offshore structures [188]. Unlike existing task-specific or project-level models that are narrowly trained for

individual structural forms or datasets, LAMs aim to eliminate the current “one project, one model” fragmentation by leveraging the pre-training and fine-tuning paradigm that has revolutionized natural language and vision domains [189]. Through large-scale pre-training on heterogeneous numerical and experimental data, followed by task-oriented adaptation, LAMs are expected to encode generalizable representations of structural behavior across multiple materials, loading conditions, and boundary configurations. Such models would provide a unifying computational foundation for the entire civil engineering industry, bridging the gap between research prototypes and engineering practice. Once trained, a LAM could serve as a universal surrogate for structural analysis, capable of rapidly predicting responses under unseen conditions or supporting design optimization and reliability evaluation. More importantly, the establishment of large, open, high-quality datasets is a prerequisite for this development. These datasets should integrate simulation outputs (e.g., multi-scale FE analysis, dynamic time-history results) with field monitoring, inspection records, and experimental data, forming a comprehensive data ecosystem to support sustainable model evolution. Ultimately, the LAM paradigm has the potential to transform structural analysis into a data-informed, AI-driven discipline, where computational intelligence becomes a widely adopted, standardized engineering tool.

**Multimodal analysis models (MAMs):** The rapid proliferation of multimodal data in the built environment—ranging from SLAM-based point clouds to drone imagery, thermal scanning, and vibration sensing—has created unprecedented opportunities for data-rich structural assessment [190]. However, current structural modeling workflows remain largely decoupled from these multimodal sources: visual or spatial data are mainly used for qualitative inspection, while quantitative performance evaluation still relies on separate physics-based simulations. This disconnect prevents the full utilization of real-world sensing information for structural computation and decision-making. Future research should therefore focus on establishing the concept of MAMs [191], which seamlessly link multimodal perception data with structural response computations. By integrating attention-based fusion mechanisms, geometric encoders, and physics-guided inference modules, MAMs can learn consistent representations between observed multimodal features and underlying mechanical behavior. Such models would enable the transformation from data-level understanding (e.g., detecting cracks, corrosion, or deformation patterns) to computation-level prediction (e.g., stress redistribution, residual capacity, or dynamic response). This integration would allow more precise, continuous, and automated evaluation of structural performance and safety risks throughout the lifecycle—from construction monitoring to long-term operation and urban renewal. In the broader context of DTs and smart infrastructures, MAMs could serve as the computational backbone that unifies perception, simulation, and control, unlocking a new paradigm of multimodal, physics-informed structural intelligence.

## 7. Conclusions

Over the past five years, artificial intelligence has become an increasingly integral part of computational structural engineering, offering new paradigms for modeling, simulation, and design optimization. This review has systematically synthesized recent advances (2020–2025) in the applications of frontier AI models—covering graph neural networks (GNNs), sequence-to-sequence (Seq2Seq) and Transformer-based architectures, physics-informed methods, and several emerging hybrid approaches. The review has sought not only to summarize current achievements but also to identify research gaps

and outline future directions toward more generalizable, interpretable, and scalable structural computation. The main conclusions can be summarized as follows.

- (1) AI has reshaped the foundations of computational analysis in structural engineering. Traditional numerical approaches, though mature, are constrained by phenomenological constitutive assumptions and problem-specific modeling. AI-based approaches provide new data-driven and hybrid paradigms capable of directly learning structure–response relationships from data or simulations, thereby greatly improving modeling flexibility, efficiency, and the potential for real-time computation.
- (2) Advanced AI models exhibit complementary advantages in structural computation. GNNs enable direct learning on graphs and meshes, showing strong competence in structural topology representation and field prediction with reduced computational cost. Seq2Seq and Transformer frameworks excel at capturing temporal and hysteretic dependencies, supporting constitutive and dynamic response modeling. Physics-informed learning, meanwhile, enhances data efficiency and physical interpretability by embedding governing equations as soft constraints in the model’s loss function.
- (3) Each model family still faces fundamental limitations in scalability, data dependence, and robustness. GNNs remain challenged by limited benchmark datasets and graph generalization issues; Transformers require large-scale training data and efficient optimization strategies; and physics-informed methods suffer from sensitivity to BCs, limited computational scalability, and weak universality due to the lack of physically complete governing equations in structural mechanics.
- (4) Cross-disciplinary integration marks the next frontier. Recent research has started moving toward hybrid and pre-trained paradigms that unify the strengths of different AI models and conventional simulation methods. The development of LAMs, trained on extensive datasets encompassing buildings, bridges, tunnels, and other structures, could provide a shared computational foundation for the industry and overcome the current “one project, one model” limitation. Simultaneously, MAMs are expected to bridge perception and computation by integrating point-cloud, image, *etc.*, with simulation-based structural response modeling, unlocking the full potential of digital sensing and intelligent operation.

In summary, AI-driven computational structural analysis is evolving from task-specific modeling toward general, intelligent, and multimodal systems. With continued advances in algorithms, computing power, and data availability, future structural computation will become not only faster and more efficient, but also more adaptive, interpretable, and seamlessly integrated into the digital engineering ecosystem. This transformation will ultimately redefine how structures are analyzed, designed, monitored, and optimized across their entire lifecycle.

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## Authors' contribution

Conceptualization, Linghan Song, Jiansheng Fan and Chen Wang; methodology, Linghan Song, Jiansheng Fan and Chen Wang; investigation, Linghan Song and Chen Wang; resources, Linghan Song; data curation, Linghan Song, Shenxiang Zeng and Chen Wang; writing—original draft preparation, Linghan Song; writing—review & editing, Linghan Song and Chen Wang; visualization, Linghan Song and Shenxiang Zeng; supervision, Jiansheng Fan and Chen Wang; project administration, Jiansheng Fan and Chen Wang; funding acquisition, Jiansheng Fan and Chen Wang. All authors have read and agreed to the published version of the manuscript.

## Conflicts of interest

The authors declare no conflict of interest.

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