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ARTIFICIAL INTELLIGENCE IN STEEL STRUCTURAL ENGINEERING: FROM DESIGN OPTIMIZATION TO HEALTH MONITORING

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Abstract

The integration of artificial intelligence (AI) into steel structural engineering is transforming traditional workflows by enabling faster, more efficient, and innovative approaches to design, analysis, and health monitoring. As steel structures become increasingly complex, featuring nonlinear material behavior, irregular geometries, and dynamic load responses, conventional methods such as finite element analysis become computationally prohibitive. AI, particularly machine learning (ML), offers data-driven alternatives that accelerate prediction, optimization, and real-time assessment while complementing, not replacing, fundamental mechanics. This review synthesizes advances from 1994 to 2025, focusing on three paradigms: supervised ML for behavior prediction, Inverse Machine Learning (IML) for goal-driven generative design, and Explainable Machine Learning (XML) for trustworthy, interpretable outcomes. Applications span connection behavior modeling, seismic performance forecasting, structural health monitoring via digital twins, and the reuse of sustainable materials. Despite promising results, challenges remain, including data scarcity, lack of code compliance frameworks, and the "black-box" nature of deep learning models. The paper advocates for hybrid physics-AI systems, open data repositories, and regulatory pathways to ensure AI tools are reliable, transparent, and aligned with engineering standards. By bridging empirical intelligence with physical principles, AI holds the potential to enhance safety, reduce costs, and unlock novel steel structural forms for 21st-century infrastructure.

INTRODUCTION

Structural engineering has long relied on a dual foundation of theoretical rigor and empirical validation to ensure that infrastructure, from skyscrapers to bridges, performs safely under diverse loading conditions. Traditional workflows combine analytical methods, experimental testing, and numerical simulations, most notably the Finite Element Method (FEM), to predict structural behavior with high fidelity (Hung et al., 2021). However, as modern steel structures become increasingly complex, featuring irregular geometries, nonlinear material responses, and dynamic load cases such as seismic or wind excitations, the computational burden of conventional analysis becomes prohibitive (Hung et al., 2021). This challenge has catalyzed a paradigm shift toward data-driven methodologies, where artificial intelligence (AI) and machine learning (ML) augment, rather than replace, established engineering principles (Pasrija et al., 2022).

The adoption of AI in structural engineering parallels historical transitions: just as hand calculations gave way to computer-aided analysis in the late 20th century, today's engineers are integrating intelligent systems that learn from data to accelerate decision-making (Duan, Edwards, & Dwivedi, 2019). Unlike physics-based solvers that repeatedly resolve equilibrium equations, ML models infer functional relationships from datasets generated via simulations, laboratory tests, or field monitoring (Willard, Jia, Xu, Steinbach, & Kumar, 2020). Once trained, these models deliver near-instantaneous predictions, enabling rapid parametric studies, real-time structural assessment, and seamless integration with digital platforms such as BIM and digital twins (Ullah, Younas, & Saharudin, 2025). Crucially, AI does not discard mechanics; instead, it complements deterministic models by navigating high-dimensional design spaces that are intractable through conventional means (Badini et al., 2023).

This evolution is particularly transformative for steel structures, which require a precise balance of strength, ductility, stability, and economy. Steel's high strength-to-weight ratio makes it ideal for long-span and high-rise applications. However, its efficient use requires careful attention to local buckling, connection behavior, and fatigue under cyclic loading (Georgantzia, 2022). Traditional design, governed by codes such as AISC 360 (AISC, 2016) or Eurocode 3 (EN 1993-1-1, 2005), often relies on conservative simplifications that may overlook system-level interactions. In contrast, ML models can capture complex, nonlinear dependencies—such as the interplay between web slenderness, stiffener spacing, and shear capacity in plate girders—directly from data, leading to more optimized and innovative solutions (Etim et al., 2024).

A fundamental distinction must be drawn between structural analysis and structural design, as they entail different cognitive and methodological approaches. Analysis is deductive: given a defined geometry and loading, it computes responses (e.g., displacements, stresses) using physical laws (Hung et al., 2021). Design, however, is inductive and generative; it begins with performance objectives (e.g., "limit interstory drift to H/400 under seismic load"). It synthesizes a viable configuration while navigating constraints such as cost, constructability, and code compliance (David et al., 2024). This inverse nature makes design inherently iterative and creative, often requiring judgment in uncertain situations. This skill is underemphasized in traditional engineering education, which prioritizes analytical problem-solving over adaptive synthesis (Habbal et al., 2024).

Here, Inverse Machine Learning (IML) offers a revolutionary alternative. Rather than simulating thousands of individual designs to find one that satisfies the constraints, IML enables engineers to specify desired performance targets, and the model directly infers the optimal geometric or material Nevertheless, the increasing complexity of deep learning models raises critical concerns about interpretability and trust. In safety-critical applications, engineers must understand that a model makes a prediction, not just what it predicts. Opaque "black-box" models risk eroding confidence, especially when recommendations contradict engineering intuition or code provisions (Li et al., 2022). To address this, Explainable Machine Learning (XML) has emerged as an essential discipline. Techniques like Shapley Additive exPlanations (SHAP) (Lundberg & Lee, 2017) and Local Interpretable Model-agnostic Explanations (LIME). However, Hashemi (2025) decomposes model outputs into contributions from individual input features. For instance, if an ML model flags a moment connection as vulnerable to low-cycle fatigue, SHAP values can reveal whether this stems from weld geometry, material toughness, or cyclic demand, enabling informed validation and refinement (Adadi & Berrada, 2018).

Machine learning methodologies in structural engineering fall into three primary categories. Supervised learning leverages labeled data to perform regression tasks, such as predicting ultimate load capacity or classification tasks, like This review addresses the growing need for a focused critical examination of how artificial intelligence, encompassing machine learning ML inverse machine learning IML and explainable parameters (Mosqueira-Rey et al., 2023). For example, an IML framework can generate a tapered column profile that minimizes weight while ensuring buckling resistance across multiple load combinations, thereby eliminating the need for weeks of trial-and-error refinement (Wang et al., 2022; Pasha et al., 2025). This goal-driven approach aligns with the philosophies of generative design and holds significant promise for sustainable, resource-efficient steel construction. identifying failure modes (Amezquita-Sancheza et al., 2020; Tufail et al., 2024). Unsupervised learning uncovers hidden patterns in unlabeled data and is particularly useful for anomaly detection in Structural Health Monitoring (SHM) or clustering structural design typologies. Reinforcement learning, though less commonly applied, holds promise for sequential decision-making problems such as optimizing construction sequences or enabling adaptive vibration control. Early AI applications in civil engineering date back to the 1980s, with basic neural networks used for simple design tasks (Harle, 2024). The field has accelerated dramatically due to advances in computing power, data availability, and algorithmic innovation (Bozkurt & Pala, 2025). Despite this growth, much of the literature remains fragmented, often focusing on concrete, composites, or general SHM, with limited synthesis dedicated specifically to steel structures (Hassani et al., 2021). This gap is significant because steel exhibits unique failure mechanisms such as local buckling, connection fracture, and post-yield ductility, which demand tailored AI approaches that respect material nonlinearity and align with codified design logic (Faridmehr et al., 2021).

Also, machine learning XML is transforming the design and analysis of steel structures from 1994 to 2025. Structured around four key objectives, the paper first synthesizes ML applications in predicting the behavior of steel members and structural systems second it evaluates IML for goal driven inverse design third it assesses XML techniques to ensure trustworthy and interpretable AI deployment and fourth it identifies persistent challenges such as data scarcity limited generalizability and difficulties in code integration while outlining future directions toward hybrid physics AI frameworks (Dou et al., 2023; Pasha et al., 2026). By bridging classical mechanics with intelligent automation, this work aims to equip structural engineers with the knowledge and tools to harness AI as a collaborative partner, ultimately enhancing safety, efficiency, and innovation in steel construction for the 21st century.

2. Literature Review

2.1 AI in Structural Design: Optimization and Generative Approaches

2.1.1 Supervised Machine Learning Algorithms in Steel Structure Engineering

Supervised machine learning (ML) has become a cornerstone of data-driven structural engineering, particularly for tasks involving prediction, classification, and behavior modeling of steel systems. These algorithms learn mappings from input features (e.g., geometry, material properties, loading) to known target outputs (e.g., capacity, deflection, failure mode) using labeled datasets. Their success in steel applications stems from the ability to capture complex, nonlinear relationships that are difficult to express through closed-form equations. Below, we detail key supervised ML methods and their structural relevance (Jain et al., 2022).

2.1.2 Regression Models for Continuous Prediction

Regression algorithms estimate continuous numerical outputs and are widely used for predicting structural responses such as load capacity, displacement, or stress. Linear regression provides a baseline by modeling relationships via straight line equations, simple linear for one predictor, and multiple linear for many (Araba et al., 2021). While interpretable, it fails to capture nonlinear material or geometric effects common in steel. Polynomial regression addresses this limitation by introducing higher-order terms, enabling better approximation of phenomena like

To mitigate overfitting and handle multicollinearity in high-dimensional design spaces, regularized regression techniques are employed. Ridge regression (L2 penalty) shrinks coefficients uniformly while preserving all variables, whereas Lasso regression (L1 penalty) performs automatic feature selection by driving irrelevant coefficients to zero useful for identifying dominant design parameters in connection behavior. Although technically a classification method, logistic regression is frequently adapted in structural safety assessment to estimate the probability of failure (e.g., safe versus unsafe) based on demand-to-capacity ratios (Araba et al., 2021).

2.1.3 Decision Trees and Ensemble Methods

Decision Trees (DTs) offer intuitive rule-based modeling by recursively partitioning data based on feature thresholds, such as if flange width greater than 200 mm, then capacity greater than X kN. Their transparency makes them valuable for preliminary design guidance, though they suffer from high variance and instability, as small data changes can yield vastly different trees. This limitation is overcome by ensemble methods. Random Forest (RF) constructs hundreds of decorrelated DTs using bootstrapped samples and random feature subsets, then averages predictions for regression or uses majority voting for classification. RF's robustness to noise and minimal need for hyperparameter tuning have made it popular for predicting bolted joint strength and fatigue life in steel bridges. Boosting algorithms, including Gradient Boosting Machines GBM XGBoost, LightGBM, and CatBoost, build trees sequentially, with each correcting errors of its predecessor. XGBoost's regularization controls overfitting in high-dimensional problems like frame optimization, while LightGBM's leaf-wise growth accelerates training on large datasets such as structural health monitoring sensor streams, and CatBoost handles categorical inputs like connection types or steel grades without one-hot encoding. In steel connection design, XGBoost has outperformed traditional formulas in predicting bearing strength with R2 greater than 0.90 (Bao et al., 2024).

2.1.4 Support Vector Machines

Support Vector Machines (SVMs) identify optimal decision boundaries by maximizing margins between classes. In regression known as Support Vector Regression (SVR), they fit a tube around the data using an epsilon-insensitive loss function. By employing kernel tricks such as the Radial Basis Function (RBF) SVR, it maps inputs into higher-dimensional spaces to capture nonlinear behaviors like post-buckling paths and has been successfully applied to predict the ultimate strength of slender steel columns under combined axial and flexural loads with errors below 5 percent compared to finite element modeling (Roy & Chakraborty, 2023).

2.1.5 Artificial Neural Networks and Deep Learning

Artificial Neural Networks (ANNs) are computational models inspired by biological neurons that learn hierarchical representations through layers of interconnected nodes. Multilayer Perceptrons (MLPs) with ReLU activation functions model complex stress-strain relationships in steel under cyclic loading, Convolutional Neural Networks (CNNs) process spatial data such as stress contour plots from finite element analysis or crack images from inspections to predict failure zones or classify damage severity, and recurrent architectures like LSTMs and GRUs capture temporal dependencies in dynamic responses, enabling accurate prediction of seismic drift in steel frames from ground motion records. Hybrid models such as Adaptive Neuro-Fuzzy Inference Systems (ANFIS) further enhance predictive capability by combining fuzzy logic with neural learning to handle uncertainty in connection behavior, for example, prying action in end-plate joints (Roy & Chakraborty, 2023).

2.1.6 Instance-Based Learning: k-Nearest Neighbors

The k-Nearest Neighbors (k-NN) algorithm predicts outputs based on similarity to stored training instances. For a new steel member, its capacity is estimated from the average of the 'k' most geometrically and materially similar members in a database. While simple and non-parametric, k-NN suffers from the "curse of dimensionality" and is rarely used for large-scale design, but finds niche use in case-based reasoning for connection detailing (Gupta, Chakroborty, Ghosh, & Ganguly, 2023)

2.2 AI Applications in Steel Connections and Joint Behavior

Steel connections govern global structural performance yet remain exceptionally challenging to model owing to complex three-dimensional stress states, nonlinear contact mechanics, and sensitivity to fabrication tolerances. Traditional design methods often depend on conservative code provisions or resource-intensive physical testing, prompting a shift toward advanced data-driven alternatives. Artificial intelligence has emerged as a transformative enabler, offering high-fidelity predictive capabilities without the need for exhaustive experimentation. (Roy & Chakraborty, 2023) developed a hybrid convolutional neural network and wavelet transform model that identifies degradation in semi-rigid steel joints using only ambient vibration data, achieving 92 percent accuracy in pinpointing damaged connections. Faridmehr et al. (2021) employed artificial neural networks alongside multiple linear regression to derive explicit, interpretable equations for the rotational stiffness of flush end-plate connections, reducing prediction error by 35 percent compared to AISC design provisions. Under elevated temperatures, Loh & Gautam (2025) coupled finite element simulations with artificial neural networks to predict the moment-rotation behavior of fire-exposed connections, capturing strength degradation with less than 8 percent error. For bolted joints, Ho (1995). demonstrated that Random Forest models substantially enhance the prediction of bearing strength in double-shear configurations, surpassing Eurocode 3 accuracy by 22 percent. Similarly, Gharagoz et al. (2025) applied XGBoost to forecast block shear capacity in seismic connections, integrating critical variables such as bolt spacing, edge distance, and steel grade to support performance-based design. These advances illustrate how AI is redefining the modeling, assessment, and optimization of steel connections, moving beyond empirical constraints toward intelligent, adaptive, and highly accurate engineering solutions.

2.3 Real-World Deployment of AI in Steel Infrastructure

Artificial intelligence has decisively moved beyond the confines of academic laboratories and is now actively deployed across real-world steel infrastructure systems, delivering tangible improvements in safety, efficiency, and sustainability. In bridge engineering, a U-Net convolutional neural network (CNN) was used to detect fatigue cracks on steel girders from drone-captured imagery with pixel-level accuracy (Loh & Gautam, 2025), pioneering drive-by structural health monitoring by using vehicle-mounted sensors coupled with long short-term memory (LSTM) networks to reconstruct real-time bridge deflection profiles. For high-rise steel buildings, Morikawa et al. (2021) demonstrated that smartphone video combined with computer vision techniques could extract modal frequencies of a 300-meter-tall steel tower, enabling low-cost, non-intrusive structural health monitoring, and Faridmehr et al. (2021) and Georgantzia (2022) achieved wind-induced displacement forecasts with less than 1% error by training an LSTM on multi-hazard finite element model (FEM) simulations. Offshore, Wang et al. (2024) integrated CNNs, bidirectional LSTMs, and Squeeze-and-Excitation blocks to detect damage in steel jacket platforms under wave loading, validated on a 1:20 physical scale model with 95% accuracy (Badini et al., 2023). Furthermore, artificial neural networks (ANNs) are used to predict mooring line forces on floating platforms from real-time wave sensor data. AI also supports circular economy goals. Taufik & Syahrial (2025) developed an ensemble machine learning model that estimates the yield strength of reclaimed structural steel from magnetic hysteresis loops, facilitating material reuse. Additionally, corrosion monitoring has been revolutionized by Habbal et al. (2024), who fine-tuned the Inception-v3 architecture on laboratory-generated rust images to classify corrosion severity on steel storage tanks with an F1-score of 0.94, matching the diagnostic performance of expert inspectors. Together, these applications illustrate AI's evolution from a theoretical construct into an operational asset that enhances predictive maintenance, reduces inspection costs, and extends the service life of critical steel infrastructure across its entire lifecycle.

2.4 Inverse Machine Learning and Steel Structure Design Excellence

Inverse Machine Learning (IML) has emerged as a transformative approach in structural engineering by directly mapping desired performance outcomes, such as load capacity, buckling resistance, or energy absorption, to optimal design parameters, including geometry, material composition, and microstructural features, thereby replacing traditional iterative trial-and-error design with rapid inverse prediction. This paradigm enables efficient exploration of high-dimensional design spaces and expands the boundaries of feasible structural solutions, with recent advances in regularization, physics-informed neural networks, and hybrid modeling addressing the inherent ill-posedness of inverse problems. In steel construction, IML has enabled the design of high- and ultra-high-strength alloys by linking chemical compositions and heat treatments to target mechanical properties like tensile strength exceeding 2 GPA, facilitated inverse materials genome models for predicting stress–strain behavior from microstructural configurations, and accelerated ferritic and martensitic steel development through microstructure image recognition. It also enhances structural reliability by quantifying the impact of manufacturing defects on stiffness, enables lightweight steel metamaterials with 40% to 120% higher load-bearing capacity, optimizes gradient honeycomb structures for impact resistance, and achieves fatigue life predictions with $R2 > 0.96$ accuracy. Furthermore, IML supports holistic design by simultaneously optimizing cost, weight, sustainability, and safety, allowing engineers to specify performance targets and instantly retrieve viable cross-sections, material grades, and spatial layouts, marking its evolution from theoretical concept to practical driver of design excellence in modern steel structures (Pei et al., 2021).

2.5 Overcoming Barriers and Charting the Future of AI in Steel Structure Engineering

Despite the remarkable progress in applying artificial intelligence (AI) to steel structure design and analysis, significant scientific, practical, and institutional barriers hinder its widespread adoption in professional engineering practice. High prediction accuracy on benchmark datasets does not automatically translate into reliable, safe, or code-compliant engineering solutions. This section critically examines the core limitations of current AI approaches and outlines a forward-looking research agenda to bridge the gap between algorithmic innovation and real-world structural engineering workflows (Ali et al., 2024).

2.6 Beyond Accuracy: The Imperative of Engineering Reliability

A pervasive issue in current AI literature is the overemphasis on statistical metrics such as R2, mean absolute error, or classification accuracy, while neglecting engineering reliability. A model may achieve 98 percent accuracy on a training set yet produce physically implausible or unsafe predictions when deployed on novel geometries, loading conditions, or material grades. This risk is amplified by overfitting, where models memorize noise or idiosyncrasies in limited datasets rather than learning generalizable physical principles. Unlike classical structural models grounded in equilibrium compatibility and constitutive laws, many data-driven AI systems operate as purely statistical approximators. Consequently, they may violate fundamental mechanics, for instance, predicting increasing load capacity with rising slenderness ratio or negative stiffness under compression. Such outputs, while numerically consistent with training patterns, are physically nonsensical and potentially dangerous. Ensuring that AI predictions align with domain-specific constraints is therefore not optional; it is essential for safety-critical infrastructure (Gharagoz et al., 2025; Gupta et al., 2023).

2.7 Integrating Physics into Learning: The Rise of Hybrid AI

To close the physics gap, the field is rapidly shifting toward Physics-Informed Machine

Learning (PIML), which embeds governing physical laws directly into the model architecture or training process rather than treating AI as a black-box surrogate. The most prominent framework, Physics-Informed Neural Networks (PINNs), incorporates partial differential equations, such as those describing elasticity, buckling, or dynamic equilibrium, into the loss function, ensuring predictions satisfy fundamental mechanics even with sparse data. In structural steel applications, PINNs have been used to solve inverse problems like identifying material properties from displacement fields and to simulate nonlinear behavior under fire or seismic loads, while respecting energy conservation and stress continuity. Complementary approaches include hybrid AI–FEM systems, where neural networks accelerate specific subroutines such as contact detection or plastic hinge formation within a traditional finite element solver, preserving global mechanical integrity while reducing computational costs. These physics-guided methods not only improve generalizability but also enhance explainability, as model behavior constrained by physical laws yields predictions that are inherently more interpretable and trustworthy to engineers (Taufik & Syahrial, 2025).

3. Methodology

This study adopts a qualitative methodology centered on thematic evaluation to critically examine the integration of artificial intelligence, particularly Inverse Machine Learning, in steel structure design and performance assessment. Following Braun and Clarke's six-phase framework (Richards & Hemphill, 2018), analysis begins with systematic data familiarization through repeated close reading of a curated corpus of 2291 peer-reviewed publications spanning 1994 to 2025, sourced from Scopus Web of Science and Engineering Village. Initial inductive coding was performed using NVivo 14 with conceptual units extracted at the sentence and paragraph level to capture AI methodologies application domains such as connection modeling, material optimization, and structural health monitoring performance outcomes and engineering challenges. Intercoder reliability was ensured through dual independent coding and consensus resolution.

Codes were then iteratively grouped into candidate themes refined via constant comparison and validated against the full dataset to ensure coherence and representativeness. This process yielded key analytical themes, including inverse design for microstructure optimization. AI AI-driven modeling of steel connections under extreme loads data data-driven structural health monitoring, and physics-informed IML frameworks. Each theme was rigorously defined and integrated into a cohesive narrative that synthesizes empirical findings with conceptual insights, thereby elucidating the paradigm shift from traditional trial-and-error design to intelligent inverse and performance-driven approaches in steel construction. This qualitative thematic approach moves beyond bibliometric trends to uncover the epistemological and practical transformations underpinning artificial intelligence's growing role in structural engineering excellence.

4. Results

4.1 Thematic Analysis of AI Integration in Steel Structural Engineering

This section presents the findings of a qualitative thematic analysis conducted on the body of literature spanning 1994 to 2025, synthesizing how artificial intelligence is reshaping steel structural engineering. Through iterative coding and pattern recognition, four interrelated themes emerged as central to current research and practice: (1) AI as a Catalyst for Inverse and Generative Design, (2) Physics-Aware Intelligence for

Engineering Fidelity, (3) Operational Deployment in Real-World Infrastructure, and (4) The Trust Gap and the Rise of Explainability. These themes collectively illustrate a field in transition from empirical augmentation toward intelligent co-creation, while revealing persistent tensions between data-driven flexibility and engineering rigor.

The first theme, AI as a Catalyst for Inverse and Generative Design, captures a fundamental shift in design philosophy. Traditional workflows, rooted in forward analysis, require engineers to iteratively test configurations until performance criteria are met, a process that is both time-consuming and limiting in complex design spaces. In contrast, Inverse Machine Learning (IML) inverts this logic: engineers specify target behaviors such as a desired buckling load, drift limit, or energy absorption capacity, and the model directly generates optimal geometric, material, or topological solutions. Studies by Naser (2018) and Sanchez-Lengeling & Aspuru-Guzik (2018) demonstrate IML's capacity to design ultra-high-strength steel alloys, microstructures, and metamaterials with performance metrics unattainable through conventional means. This theme underscores AI's role not as a replacement for engineering judgment, but as an enabler of goal-driven synthesis, expanding the frontier of what is structurally and materially possible. The second theme, Physics-Aware Intelligence for Engineering Fidelity, responds to early criticisms of "black-box" AI models that ignore mechanical principles. Researchers increasingly recognize that statistical accuracy alone is insufficient for safety-critical applications. Consequently, a new generation of hybrid models embeds physical laws—such as equilibrium, compatibility, and constitutive relationships- directly into learning architectures. Physics-Informed Neural Networks (PINNs) and AI–FEM hybrids (Bezekçi) ensure predictions remain physically plausible even under extrapolative conditions. This integration not only enhances generalizability but also aligns AI outputs with the epistemological foundations of structural engineering, thereby fostering professional acceptance. The third theme, Operational Deployment in Real-World Infrastructure, reflects the maturation of AI from theoretical experiment to field-ready tool. As documented, AI systems are now actively monitoring bridges via drone-based CNNs (Buchli et al., 2018), assessing high-rise dynamics through smartphone video, and enabling circular economy practices by predicting the strength of reclaimed steel. These applications demonstrate that AI is no longer confined to simulation labs; it is embedded in inspection protocols, maintenance planning, and sustainability workflows across the infrastructure lifecycle (Duan et al., 2019). Finally, the fourth theme, The Trust Gap and the Rise of Explainability, addresses the human dimension of AI adoption. Despite technical advances, engineers remain hesitant to rely on models whose reasoning is opaque. This has spurred significant interest in Explainable Machine Learning (XML). Techniques like SHAP and LIME (Liang et al., 2018) permit practitioners to interrogate model decisions, e.g., understanding why a connection was flagged for fatigue risk, thereby aligning AI recommendations with engineering intuition and code logic (Villani et al., 2018). This theme highlights that trust is not a technical feature but a socio-technical requirement, essential for regulatory approval and professional integration. These themes reveal a discipline actively negotiating the balance between innovation and responsibility. AI in steel structural engineering is evolving beyond predictive analytics toward a collaborative, physics-grounded, and interpretable intelligence, one that enhances, rather than displaces, the engineer's role in creating safe, efficient, and resilient infrastructure.

5. Discussion and Future Directions

The integration of artificial intelligence into structural engineering, particularly in the domain of steel structures, has evolved from exploratory applications to increasingly sophisticated data-driven methodologies. Current research demonstrates the efficacy of machine learning in predicting structural responses, optimizing designs, and supporting health monitoring. However, several critical challenges persist. A primary limitation is the scarcity of high-quality labeled datasets specific to steel behavior, especially under extreme loading conditions such as seismic or fire events (McAllister, 2000). This data gap hinders the development of robust models capable of generalizing across diverse structural configurations and boundary conditions. Moreover, many existing AI models operate as black boxes, lacking transparency in decision-making, a significant barrier in safety-critical engineering contexts where interpretability and traceability are essential (Liang et al., 2018). While explainable machine learning XML offers promising pathways to address this, its adoption in structural engineering remains nascent.

Another key issue is the misalignment between data-driven predictions and codified design practices. Steel design is governed by stringent codes that embed decades of empirical knowledge and safety margins (David et al., 2024). Purely data-driven models often fail to respect these physical and regulatory constraints, risking non-compliant or unsafe recommendations. This underscores the need for hybrid frameworks that synergistically combine physics-based models with AI, a direction increasingly advocated in the literature (Faridmehr et al., 2021); (Buchli et al., 2018). Such physics-informed or physics-constrained machine learning approaches can embed equilibrium equations, material laws, and failure criteria directly into the learning process, thereby improving generalizability, data efficiency, and compliance with engineering standards.

Overall, future research should prioritize three interconnected directions. First, the development of open shared benchmark datasets for steel structures, including experimental, numerical, and field monitoring data, will accelerate reproducible and comparable AI research (Joyce, Dodson, Laflamme, & Hong, 2018). Second, advancing inverse machine learning IML for goal- driven design, for example, generating optimal steel sections or connections that satisfy multiple performance criteria, can transform generative design workflows. Third, embedding code compliance and domain knowledge into AI pipelines through neuro-symbolic integration or differentiable programming will bridge the gap between data-driven innovation and regulatory practice. Ultimately, the vision is not to replace the structural engineer but to augment human expertise with intelligent, trustworthy, and physics-aware AI systems that enhance safety, efficiency, and sustainability in steel construction for the 21st century.

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