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REVIEW PAPER

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ADVANCES IN STRUCTURAL ENGINEERING THROUGH ARTIFICIAL INTELLIGENCE: METHODS, CHALLENGES AND OPPORTUNITIES

Małgorzata Kurcjusz[1]✉, Rohan Raj Das[2]

[1] Institute of Civil Engineering, Warsaw University of Life Sciences – SGGW, Warsaw, Poland
[2] Institute of Structural Mechanics, Bauhaus-Universität Weimar, Weimar, Germany

ABSTRACT

This paper reviews recent advances in applying artificial intelligence (AI) in structural engineering, with a particular focus on methods, challenges, and opportunities. It examines how machine learning, deep learning, and evolutionary algorithms are transforming traditional design, analysis, and maintenance processes. The integration of AI with building information modelling (BIM), digital twins, and sensor-based monitoring systems is creating a more data-driven engineering environment. However, widespread adoption remains limited by issues such as data quality, model transparency, and a lack of validation frameworks. The study highlights the need for explainable models, ethical oversight, and standardised data practices to ensure the safe and reliable use of AI in structural applications.

Keywords: artificial intelligence, machine learning, deep learning, structural engineering, design optimisation, structural health monitoring

INTRODUCTION

Structural engineering has long relied on analytical models, empirical knowledge, and numerical simulations to design, analyse, and maintain safe and efficient structures. In recent years, the increasing complexity of structural systems and the scale of modern projects have highlighted the need for more advanced analytical and data-driven approaches beyond traditional engineering methods (Varshney, Pandey, Pandey & Singh, 2025). In this context, AI has emerged as a promising tool to help engineers make more accurate predictions, optimise designs, and automate repetitive or computationally demanding tasks (Aziz et al., 2025).

Techniques (Fig. 1) such as machine learning (ML), deep learning (DL), and evolutionary algorithms are now used across a wide range of structural engineering applications. They support tasks such as predicting structural performance under different loading conditions, detecting damage or deterioration in existing structures, optimising material use, and assisting in real-time monitoring and decision-making (Aziz et al., 2025; Bahadori-Jahromi et al., 2025). The growing integration of AI with BIM, digital twins, and sensor-based monitoring systems is further transforming the discipline into a data-driven and adaptive field (Deng, Menassa & Kamat, 2021; Azanaw, 2024).

Małgorzata Kurcjusz https://orcid.org/0000-0002-9703-2118; Rohan Raj Das https://orcid.org/0000-0003-2080-4105
✉malgorzata_kurcjusz@sggw.edu.pl

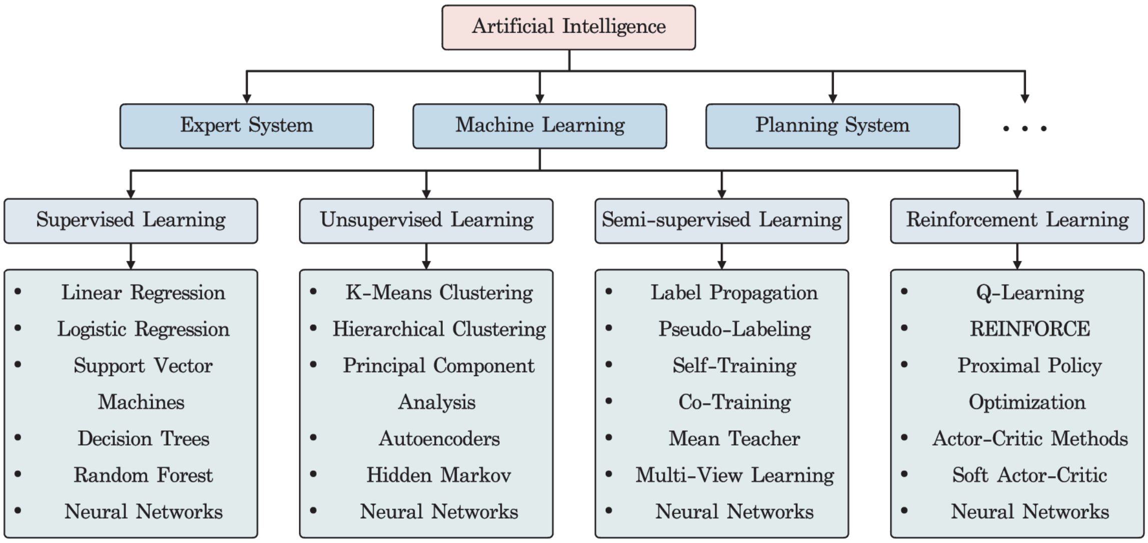

Fig. 1. Artificial intelligence and machine learning

Source: Ao, Li and Duan (2025).

The advantages of AI in structural engineering are significant. ML models can capture complex, nonlinear relationships within structural data, offering more precise and adaptable solutions than conventional analytical methods (Bahadori-Jahromi et al., 2025). DL, in particular, has proven effective in handling large datasets from sensors, images, and simulations, enabling accurate detection of structural anomalies and early warnings of potential failures (Luleci, Catbas & Avci, 2023). In parallel, optimisation algorithms inspired by natural processes, such as genetic algorithms and swarm intelligence, are helping to generate innovative structural designs that balance performance, cost, and sustainability (He, Wang & Zhang, 2025).

Despite these advancements, several challenges limit the widespread adoption of AI in structural engineering. These include limited access to high-quality labelled data, difficulties in interpreting AI models (the so-called "black box" problem), and the absence of standard frameworks for model validation and integration with existing engineering tools (Hassija et al., 2024; Bahadori-Jahromi et al., 2025). Moreover, while AI can improve both efficiency and accuracy, its outputs must always be reviewed critically by qualified engineers to ensure safety and compliance with design codes (Plevris & Hosamo, 2025).

This review provides an overview of current AI applications in structural engineering, summarising the main methods, benefits, and limitations identified in recent studies (Fig. 2). It categorises the literature into thematic areas, including design optimisation, structural analysis, material modelling, damage detection, and health monitoring, as well as discussing how AI contributes to each. The paper concludes with a discussion of future research directions, highlighting the potential of integrating AI with digital twins and physics-informed learning to reshape the future of structural engineering.

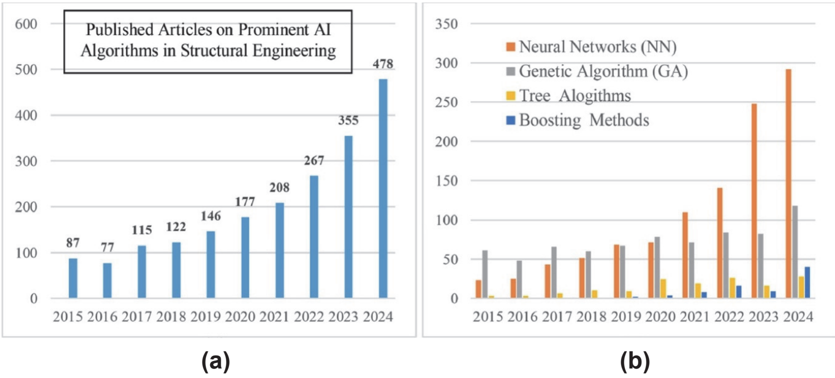

Fig. 2. Published article trends in structural engineering (Scopus-sourced, 2015–2024): (a) overall use of prominent artificial intelligence algorithms, (b) categorised by specific methods (NN, GA, tree-based, and boosting algorithms)

Source: Aziz et al. (2025).

This review adds value by providing a synthesis of AI applications across the full structural engineering lifecycle (design optimisation, material behaviour prediction, and structural health monitoring), where most existing reviews focus on only one area. It also integrates recent advances from 2023–2025, including generative models, physics-informed features, and explainable AI, offering an updated and cross-disciplinary perspective. The review is guided by three questions:

1. How are AI methods currently used across design, material performance and monitoring in structural engineering?
2. What data types and modelling approaches dominate these applications?
3. What limitations and practical barriers still restrict the wider adoption of AI in structural engineering?

METHODOLOGY

This paper is based on a structured narrative review of recent research on AI applications in structural engineering. The literature search covered the years 2019–2025 and relied on academic sources accessed through institutional subscriptions and open-access platforms, without relying on any single database. The review was guided by keyword groups such as: AI in structural engineering, machine learning for concrete, structural form finding, digital twins, structural health monitoring, generative materials design, steel additive manufacturing, computer vision construction safety, and Explainable Artificial Intelligence (XAI) for engineering.

The inclusion criteria were: (1) peer-reviewed or authoritative publications, (2) direct relevance to structural engineering or material behaviour, (3) clear use of AI/ML/DL methods, and (4) sufficient methodological detail. The exclusion criteria removed articles unrelated to structures, with weak methodological transparency, or offering no new insight.

APPLICATIONS OF AI IN STRUCTURAL ENGINEERING

Design optimisation and structural form finding

ML in structural design addresses the optimisation of structural form and element layout to reduce material use, costs, and construction clashes while preserving required safety and functionality. The workflows usually rely on BIM models, geometric parameters, material data, load cases, Finite Elements Method outputs and, in reinforcement design, graph-based representations of rebar arrangements. The main AI approaches include genetic algorithms that explore extensive design spaces, as well as graph neural networks combined with evolutionary optimisation for a clash-free reinforcement layout, as shown, for example, by Sherif, Nassar, Hosny, Safar & Abotaleb (2022) and Li, Liu, Wong, Gan & Cheng (2023). These methods are already mature at the research and pilot-application level, particularly in settings with strong BIM integration. Their limitations are high computational effort, inconsistent data standards between tools, limited automation for very complex reinforcement scenarios, and the continued need for engineers to verify results before implementation.

Material behaviour and performance prediction

Generative and predictive AI address a wide set of engineering problems in structural materials science, from discovering new material compositions to forecasting the mechanical behaviour of concrete, steel, and wood. In material discovery, the core challenge is navigating an enormous chemical design space to identify compounds with desired mechanical and thermal properties. Typical data include crystal structures, chemical compositions, thermodynamic parameters, and large simulation-derived datasets. Generative models predict formation energy, structural stability, and synthesizability, which shortens the discovery cycle, as shown by Merchant et al. (2023), Cheetham and Seshadri (2024), Ma et al. (2024), and Han and Su (2025). Ensemble learning and DL methods dominate in predicting concrete compressive strength, using datasets that combine mix proportions, curing conditions, and laboratory test results. CNNs and ANNs consistently outperform traditional regression-based approaches (Das et al., 2024; Hosseinzadeh, Samadvand, Hosseinzadeh, Mousavi & Dehestani, 2024; Muthurathinamm Alruwais, Al Mazroa & Alkharashi, 2024; Luo et al., 2025). For steel structures, the engineering problem concerns predicting mechanical performance under varying manufacturing or additive manufacturing parameters. ML models rely on data describing heat input, fibre content, microstructure, or printing conditions. CNN-based systems for steel fibre-reinforced concrete achieve higher accuracy than classical methods, while ML in metal additive manufacturing enables real-time tuning of process parameters (Gong, Zeng, Groeneveld-Meijer & Manogharan, 2022; Pakzad, Roshan & Ghalehnovi, 2023; Akbari, Zamani & Mostafaei, 2024). Similar principles apply to buckling-restrained braced frames, where ML uses physics-informed features such as eccentric loading ratios and material properties to simulate seismic response (Asgarkhani et al., 2024; Mohamed et al., 2024).

Wood structures pose a different engineering problem, which is strong natural variability. Models use image data showing fibre patterns, growth defects, or grain structure, supplemented with sensor readings on moisture and environmental conditions. DL and transfer learning methods allow automatic quality assessment and property prediction with limited datasets (Lukovic et al., 2024; Al-Mattarneh et al., 2025; González-Palacio, García-Giraldo & González-Palacio, 2025; Quinteros-Navarro, Quinteros, Muñoz, Ramirez & Ramirez, 2025). Neural networks combined with sensor data provide non-destructive, continuous monitoring of moisture and strength (Al-Mattarneh et al., 2025; Quinteros-Navarro et al., 2025). Across all these domains, explainable AI is gaining importance. Tools such as SHAP (SHapley Additive exPlanations) and LIME help identify which variables drive predictions, improving model transparency and trust. In concrete applications, XAI consistently highlights the influence of the water-to-cement ratio, cement content, and curing time, quantifying their contribution to predicted strength (Luo et al., 2025; Zhang et al., 2023; Zhang et al., 2024; Zheng et al., 2025).

Generative models for material discovery are rapidly advancing but still rely on extensive simulation data and expert validation. Predictive models for concrete, steel, and wood are more widely tested, yet full deployment depends on reliable datasets and integration with existing engineering workflows. Key limitations include data scarcity for specialised materials, a lack of standardised datasets, high computational costs for generative modelling, and the need for careful human verification before results are used in design or manufacturing.

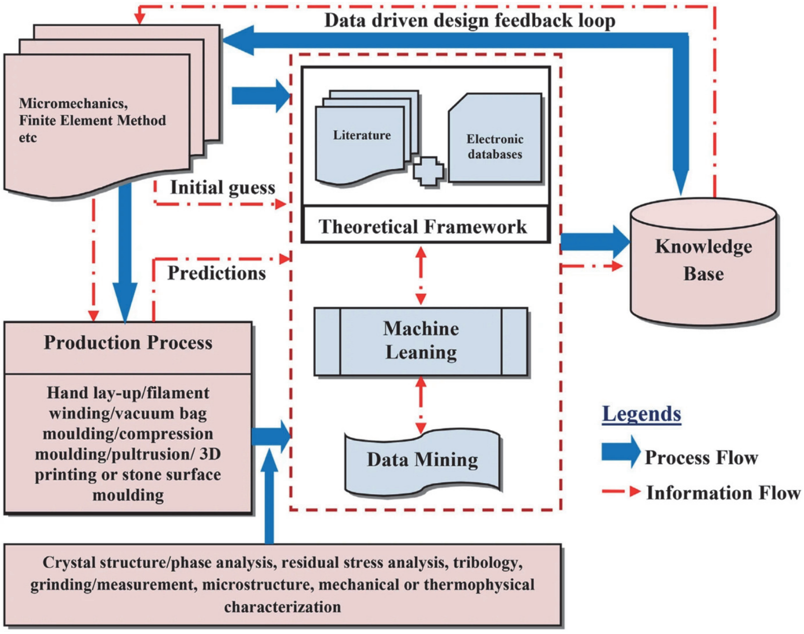

Fig. 3. Data-driven design of composite material process

Source: Okafor et al. (2023).

Damage detection and structural health monitoring

AI and Internet of Things (IoT) address a clear engineering problem: the need for continuous, accurate and non-destructive monitoring of structural performance throughout a building's life cycle. Typical data include sensor readings on temperature, humidity, vibration, strain, displacement, load response, and material degradation, complemented by BIM information and time-stamped environmental records. DL models now support ultrasonic methods for concrete, allowing real-time strength assessment without damaging the structure, as shown by Gan et al. (2025). When these data streams are combined with digital twins, engineers gain a dynamic representation of the structure. Integrating BIM models, sensor inputs, and predictive algorithms enables continuous tracking of performance and early detection of degradation trends, which supports proactive maintenance planning (Deng et al., 2021; Azanaw, 2024). AI also improves safety on construction sites: computer vision systems analyse standard camera feeds to identify unsafe behaviours or hazardous situations and generate immediate alerts, reducing accidents and downtime (Badeka et al., 2025). The maturity level of these technologies ranges from well-developed research prototypes to early industrial adoption, especially in organisations that already use BIM and sensor networks. Key limitations are inconsistent data quality from on-site sensors, limited interpretability of complex DL models, and a lack of unified validation standards that would allow engineers to trust predictions in critical decisions. Despite these challenges, AI offers substantial potential to enhance monitoring, maintenance, and structural resilience, while gradually shifting the engineer's role toward more analytical, supervisory and decision-oriented work.

Table 1. Methods, challenges and opportunities of AI in Structural Engineering

Category	Description	Example
	Methods	
Machine learning (ML), deep learning (DL)	Neural networks, support vector machines, and deep architectures are used to predict structural behaviour, damage evolution, or material properties.	Used in structural health monitoring and predictive maintenance (Flah, Nunez, Ben Chaabene & Nehdi, 2021; Spencer, Sim, Kim & Yoon, 2025).
Computer vision and image processing	Artificial intelligence-based crack, corrosion, and deformation detection using drone or camera imagery.	Automated infrastructure inspection (Tyvoniuk, Trach & Trach, 2025).
Surrogate modelling	Simplified models trained on simulation or experimental data to accelerate analysis.	Applied in topology optimisation and meta-modelling (Ao et al., 2025).
Artificial intelligence-based multi-objective optimisation	Coupling ML/DL with heuristic algorithms (e.g., particle swarm optimisation, genetic algorithms) for design optimisation under constraints.	Generative structural design systems (Ao et al., 2025).
Integration with digital twins	AI supports predictive modelling and real-time analysis in digital replicas of structures.	Enables real-time performance assessment, degradation prediction, and adaptive control in smart infrastructure systems (Azanaw, 2024; Spencer et al., 2025).
	Challenges	
Data quality and availability	Structural datasets are often incomplete, small-scale, or inconsistent, which limits model accuracy.	Need for standardised, domain-specific datasets (Bao et al., 2025; Mengesha, 2025).
Model interpretability and trust	AI, especially DL, operates as a "black box," which reduces engineers' confidence in its results.	Lack of explainable AI tools for engineering (Plevris & Hosamo, 2025; Salman, Al-Shaikhli, Ali Abbas, Ahmad & Kudus, 2025).
Reliability in real-world applications	Lab-trained models may fail in real structures due to varying conditions and noise.	Need for robust validation of field data (Zaker Esteghamati, Bean, Burton & Naser, 2025).
Integration with codes and practice (Xie, Mei & Chui, 2025)	Difficulties incorporating AI into engineering workflows and meeting design standards.	Resistance to non-traditional computational methods.
Ethical and safety considerations	AI-driven decisions affect public safety, raising questions of accountability and bias.	Ethical frameworks and human oversight required (Plevris & Hosamo, 2025).
	Opportunities	
Faster and more efficient structural design	AI enables rapid exploration of multiple design scenarios and accelerates optimisation.	Reduced design time and computational cost (Ao et al., 2025; He et al., 2025).
Early fault detection and predictive maintenance	AI predicts when structures need inspection or repair, improving safety and reducing costs.	Bridge and infrastructure monitoring (Bao et al., 2025; Spencer et al., 2025).
Material and structural optimisation	AI aids in designing lightweight, efficient structures and optimising material use.	Topology and geometry optimisation (Xie et al., 2025).
Enhanced resilience and risk management	AI helps simulate and mitigate extreme or uncertain loading scenarios.	Seismic and wind resilience analysis (Harirchian et al., 2020; Zhang et al., 2023).
Evolving role of engineers	AI automates routine analysis, allowing engineers to focus on creative and critical aspects.	Requires education and adaptation to AI-driven workflows (Plevris & Hosamo, 2025).

Source: own work.

CHALLENGES AND LIMITATIONS

Data quality remains one of the most critical barriers to applying AI in structural engineering. Building reliable AI models requires access to large, diverse, and high-quality datasets, yet the field continues to struggle with small sample sizes, inconsistent data collection, and a lack of standardised formats. Traditional datasets often capture only narrow case studies or laboratory conditions, limiting their usefulness for training robust surrogate models. The problem is especially acute for rare or extreme events such as earthquakes or structural failures, where historical data are scarce and incomplete (Hong, Kwon, Shin, Park & Kang, 2024; Fei, Lu, Liao & Guan, 2025; Salman et al., 2025; Varshney et al., 2025; Wala, 2025). Poor data quality can introduce bias, reduce model reliability, and lead to inaccurate predictions. Missing values, unrepresentative samples, or hidden data errors may remain undetected yet significantly increase the risk of failure in future applications. In safety-critical domains like structural engineering, even minor deficiencies in data quality can have serious or catastrophic consequences (Foidl, Felderer & Ramler, 2022; Parmar, Gupta, Chouhan & Saran, 2023; Gómez Plaza et al., 2025).

The "black-box" nature of many AI models presents another major challenge. Deep neural networks, though powerful, often lack transparency, making it difficult for engineers to understand or justify their decisions in design and safety assessments. This lack of interpretability conflicts with the core principles of professional accountability and with regulatory requirements demanding traceable, explainable design reasoning (Felderer & Ramler, 2021; Porter, Habli, McDermid & Kaas, 2024; Salman et al., 2025; Wala, 2025).

XAI has emerged as a promising response to this problem, offering methods to uncover how complex models reach their conclusions. However, implementing effective explainability in practice remains difficult, particularly for DL architectures where high accuracy often comes at the cost of interpretability. Striking the right balance between performance and transparency is essential, especially in contexts involving cultural heritage structures, public safety, or compliance with design codes (Mirzaei, Mao, Al-Nima & Woo, 2023; Geyer, Singh & Chen, 2024; Marey et al., 2024).

Another limitation lies in the computational demands of AI. Training and deploying advanced models require high-performance GPUs and substantial energy resources. While major research institutions and large engineering firms can afford such infrastructure, smaller practices and organisations in developing regions often face significant barriers to entry. GPU-accelerated computing has become indispensable for modern AI applications, but its environmental footprint and cost raise sustainability concerns (Fischer et al., 2020; Canakci et al., 2025). The issue extends beyond training: real-time structural monitoring systems must process continuous sensor data, which further increases computational load. Although edge computing offers partial relief by distributing computation across devices, it introduces new technical and operational complexities (Asadi et al., 2018; Mishra, Gangisetti & Khazanchi, 2023).

AI models in structural engineering often face difficulties when applied beyond the conditions on which they were trained. The field encompasses an extraordinary range of building types, materials, environmental contexts, and loading scenarios, which makes it challenging to create models that generalise well across all cases. Overfitting, under specification, and biases in training data remain common issues, while the omission of key variables can lead to misleading or overly confident predictions (Felderer & Ramler, 2021; Salman et al., 2025; Zaker Esteghamati et al., 2025).

Cross-validation techniques can help evaluate model robustness, but a deeper problem persists: structural engineering often involves rare, high-impact events such as extreme loading, material fatigue, or seismic failure, for which historical data are inherently scarce. In such cases, uncertainty quantification becomes essential to convey the confidence and limitations of model predictions. However, many AI frameworks still struggle to produce reliable measures of uncertainty, leaving engineers without a clear understanding of how much trust to place in automated outputs (Felderer & Ramler, 2021; Wang et al., 2022; Dalrymple et al., 2024).

Strengths	Weaknesses
– Enhanced efficiency in design and analysis as AI automates repetitive tasks, accelerates simulations, and supports real-time optimisation. – Improved accuracy and early fault detection as AI models outperform traditional statistical approaches in detecting cracks, anomalies, and material degradation. – Integration with Digital Twin systems enables predictive maintenance, continuous monitoring, and performance forecasting. – Capability to process multimodal data (images, vibration signals, environmental parameters) for holistic analysis.	– Limited availability and quality of structural datasets; many are proprietary or too small for robust model training. – Low interpretability of deep models (“black box” nature) reduces trust and transparency in safety-critical engineering contexts. – Integration challenges with existing BIM workflows, design codes, and verification procedures. – High initial cost and expertise barrier as implementation requires interdisciplinary skills (AI, structural mechanics, data engineering).
Opportunities	**Threats**
– Adoption of XAI and hybrid physics-informed models could make AI results more transparent and acceptable for regulatory frameworks. – Integration with sustainability and resilience goals, as AI-driven optimisation can reduce material use and energy consumption in design. – Development of open structural data platforms could accelerate collaboration and innovation in the field. – Growth of generative design and AI-assisted decision-making in early conceptual stages allows exploration of novel, efficient structures.	– Regulatory and legal uncertainty, lack of standards defining AI validation, liability, and model approval in engineering. – Overreliance on AI without sufficient engineering validation may lead to unsafe or non-compliant designs. – Cybersecurity risks in AI-driven monitoring systems, especially in critical infrastructure. – Potential job displacement or skill mismatch; engineers must adapt to data-centric workflows.

Fig. 4. SWOT analysis: Structural engineering through artificial intelligence

Source: own work.

Finally, the integration of AI introduces complex ethical and professional questions regarding accountability and oversight. When an AI-generated design or recommendation contributes to a structural failure, responsibility becomes blurred: does it rest with the developer of the algorithm, the engineer applying it, or the institution endorsing its use? This ambiguity is especially problematic given the opaque, “black-box” nature of many AI systems, underscoring the need for clear governance frameworks and continued human supervision in all safety-critical engineering decisions (Ryan, Porter, Al-Qaddoumi, McDermid & Habli, 2023; Clymer, Gabrieli, Krueger & Larsen, 2024; V Khadake, 2024).

CONCLUSIONS

As presented in Figure 4, AI is transforming structural engineering by introducing data-driven methods that enhance design, analysis, and monitoring. Techniques such as ML, DL, and evolutionary algorithms make it possible to optimise structures more efficiently, predict material behaviour with greater accuracy, and assess performance in real time. When combined with BIM, digital twins, and IoT technologies, AI enables continuous data exchange throughout the entire lifecycle of a structure, supporting predictive maintenance and more informed, sustainable decision-making.

Despite these advances, the widespread use of AI in structural engineering is still limited by several challenges, including data scarcity, limited model interpretability, the absence of consistent validation frameworks, and difficulties integrating AI with established design codes and professional practice. Maintaining transparency, ethical oversight, and human control remains vital to ensure safety and accountability in all AI-assisted processes.

Future work should aim to develop explainable and physics-informed AI models, promote open and standardised data infrastructures, and establish clear regulatory frameworks for their use. These efforts will allow AI to serve as a powerful complement (not a replacement) to engineering expertise, helping to build a safer, more efficient, and sustainable built environment.

Authors' contributions

Conceptualisation: M.K.; methodology: M.K.; validation: M.K.; formal analysis: M.K.; investigation: M.K.; resources: M.K.; data curation: M.K.; writing – original draft preparation: M.K.; writing – review and editing: M.K.; visualisation: M.K.; supervision: M.K. and R.D.; project administration: M.K.; funding acquisition: M.K.

All authors have read and agreed to the published version of the manuscript.

REFERENCES

Akbari, P., Zamani, M. & Mostafaei, A. (2024). Machine learning prediction of mechanical properties in metal additive manufacturing. *Additive Manufacturing*, *19*, 104320. https://doi.org/10.1016/j.addma.2024.104320

Al-Mattarneh, H., Ismail, R., Trrad, I., Nimer, H., Khodier, M., Jaradat, Y., Malkawi, A. B. & Mohammed, B. S. (2025). Using artificial neural networks and electromagnetic capacitive NDT sensors for wood engineering application. *HBRC Journal*, *21* (1), 211–233. https://doi.org/10.1080/16874048.2025.2471122

Ao, Y., Li, S. & Duan, H. (2025). Artificial Intelligence-Aided Design (AIAD) for Structures and Engineering: A State-of-the-Art Review and Future Perspectives. *Archives of Computational Methods in Engineering*, *32* (7), 4197–4224. https://doi.org/10.1007/s11831-025-10264-1

Asadi, K., Ramshankar, H., Pullagurla, H., Bhandare, A., Shanbhag, S., Mehta, P., Kundu, S., Han, K., Lobaton, E. & Wu, T. (2018, July 22). Building an Integrated Mobile Robotic System for Real-Time Applications in Construction. *2018 In Proceedings of the 35th ISARC, Berlin, Germany* (pp. 453–461). The International Association for Automation and Robotics in Construction. https://doi.org/10.22260/ISARC2018/0063

Asgarkhani, N., Kazemi, F., Jakubczyk-Gałczyńska, A., Mohebi, B., & Jankowski, R. (2024). Seismic response and performance prediction of steel buckling-restrained braced frames using machine-learning methods. *Engineering Applications of Artificial Intelligence*, *128*, 107388. https://doi.org/10.1016/j.engappai.2023.107388

Azanaw, Mr. G. M. (2024). Revolutionizing Structural Engineering: A Review of Digital Twins, BIM, and AI Applications. *Indian Journal of Structure Engineering*, *4* (2), 1–8. https://doi.org/10.54105/ijse.B1321.04021124

Aziz, Md. T., Osabel, D. M., Kim, Y., Kim, S., Bae, J. & Tsavdaridis, K. D. (2025). State-of-the-art artificial intelligence techniques in structural engineering: A review of applications and prospects. *Results in Engineering*, *28*, 107882. https://doi.org/10.1016/j.rineng.2025.107882

Badeka, E., Muchla, A., Koulalis, I., Ioannidis, K., Dymarski, P. & Vrochidis, S. (2025). Ladder Walking Detection via Action Recognition for Enhancing Worker Safety in Construction. In *2025 IEEE International Workshop on Metrology for Living Environment (MetroLivEnv)* (pp. 345–349). IEEE International. https://doi.org/10.1109/MetroLivEnv64961.2025.11107036

Bahadori-Jahromi, A., Room, S., Paknahad, C., Altekreeti, M., Tariq, Z. & Tahayori, H. (2025). The Role of Artificial Intelligence and Machine Learning in Advancing Civil Engineering: A Comprehensive Review. *Applied Sciences*, *15* (19), 10499. https://doi.org/10.3390/app151910499

Bao, Y., Sun, H., Xu, Y., Guan, X., Pan, Q. & Liu, D. (2025). Recent advances in structural health diagnosis: a machine learning perspective. *Advances in Bridge Engineering*, *6* (1), 7. https://doi.org/10.1186/s43251-024-00155-z

Canakci, B., Liu, J., Wu, X., Cheriere, N., Costa, P., Legtchenko, S., Narayanan, D. & Rowstron, A. (2025). Good things come in small packages: Should we build AI clusters with Lite-GPUs? In *Proceedings of the Workshop on Hot Topics in Operating Systems* (pp. 127–135). New York: Association for Computing Machinery. https://doi.org/10.1145/3713082.3730390

Cheetham, A. K. & Seshadri, R. (2024). Artificial Intelligence Driving Materials Discovery? Perspective on the Article: Scaling Deep Learning for Materials Discovery. *Chemistry of Materials*, *36* (8), 3490–3495. https://doi.org/10.1021/acs.chemmater.4c00643

Clymer, J., Gabrieli, N., Krueger, D. & Larsen, T. (2024). *Safety Cases: How to Justify the Safety of Advanced AI Systems*. *arXiv:2403.10462*. https://doi.org/10.48550/arXiv.2403.10462

Dalrymple, D., Skalse, J., Bengio, Y., Russell, S., Tegmark, M., Seshia, S., Omohundro, S., Szegedy, C., Goldhaber, B., Ammann, N., Abate, A., Halpern, J., Barrett, C., Zhao, D., Zhi-Xuan, T., Wing, J. & Tenenbaum, J. (2024). Towards Guaranteed Safe AI: A Framework for Ensuring Robust and Reliable AI Systems. *arXiv:2405.06624*. https://doi.org/10.48550/arXiv.2405.06624

Das, P., Kashem, A., Islam, M., Ahmed, A., Haque, M. A. & Khan, M. (2024). Alkali-activated binder concrete strength prediction using hybrid-deep learning along with shapely additive explanations and uncertainty analysis. *Construction and Building Materials*, *435*, 136711. https://doi.org/10.1016/j.conbuildmat.2024.136711

Deng, M., Menassa, C. C. & Kamat, V. R. (2021). From BIM to digital twins: a systematic review of the evolution of intelligent building representations in the AEC-FM industry. *Journal of Information Technology in Construction*, *26*, 58–83. https://doi.org/10.36680/j.itcon.2021.005

Fei, Y., Lu, X., Liao, W. & Guan, H. (2025). Data enhancement for generative AI design of shear wall structures incorporating structural optimization and diffusion models. *Advances in Structural Engineering*. https://doi.org/10.1177/13694332251353614

Felderer, M. & Ramler, R. (2021). *Quality Assurance for AI-based Systems: Overview and Challenges*. https://doi.org/10.1007/978-3-030-65854-0_3

Fischer, L., Ehrlinger, L., Geist, V., Ramler, R., Sobiezky, F., Zellinger, W., Brunner, D., Kumar, M. & Moser, B. (2020). AI System Engineering – Key Challenges and Lessons Learned. *Machine Learning and Knowledge Extraction*, *3* (1), 56–83. https://doi.org/10.3390/make3010004

Flah, M., Nunez, I., Ben Chaabene, W. & Nehdi, M. L. (2021). Machine Learning Algorithms in Civil Structural Health Monitoring: A Systematic Review. *Archives of Computational Methods in Engineering*, *28* (4), 2621–2643. https://doi.org/10.1007/s11831-020-09471-9

Foidl, H., Felderer, M. & Ramler, R. (2022). *Data Smells: Categories, Causes and Consequences, and Detection of Suspicious Data in AI-based Systems*. *arXiv:2203.10384*. https://doi.org/10.48550/arXiv.2203.1038

Gan, X., Wang, W., Jiang, C., Ye, L., Chen, F., Zhou, T. & Zhao, Y. (2025). Ultrasonic detection and deep learning for high-precision concrete strength prediction. *Journal of Building Engineering*, *104*, 112372. https://doi.org/10.1016/j.jobe.2025.112372

Geyer, P., Singh, M. M. & Chen, X. (2024). Explainable AI for engineering design: A unified approach of systems engineering and component-based deep learning demonstrated by energy-efficient building design. *Advanced Engineering Informatics*, *62*, 102843. https://doi.org/10.1016/j.aei.2024.102843

Gong, X., Zeng, D., Groeneveld-Meijer, W. & Manogharan, G. (2022). Additive manufacturing: A machine learning model of process-structure-property linkages for machining behavior of Ti-6Al-4V. *Materials Science in Additive Manufacturing*, *1* (1), 6. https://doi.org/10.18063/msam.v1i1.6

González-Palacio, M., García-Giraldo, J. M. & González-Palacio, L. (2025). Integrating AI and sustainable materials: machine learning approaches to wood structural behavior. *Agronomy Research*, *23*, 2025. https://doi.org/10.15159/AR.25.073

Gómez Plaza, M., Granados Cañete, F. J., López Yajamin, E. X., Díaz Martín, D., Olalla Caballero, B. & Palma Bautista, A. M. (2025). Enhancing AI applications for European public bodies: A data quality-centric approach. *International Journal of Engineering Business Management*, *17*. https://doi.org/10.1177/18479790251367820

Han, N. & Su, B.-L. (2025). AI-driven material discovery for energy, catalysis and sustainability. *National Science Review*, *12* (5). https://doi.org/10.1093/nsr/nwaf110

Harirchian, E., Kumari, V., Jadhav, K., Raj Das, R., Rasulzade, S. & Lahmer, T. (2020). A Machine Learning Framework for Assessing Seismic Hazard Safety of Reinforced Concrete Buildings. *Applied Sciences*, *10* (20), 7153. https://doi.org/10.3390/app10207153

Hassija, V., Chamola, V., Mahapatra, A., Singal, A., Goel, D., Huang, K., Scardapane, S., Spinelli, I., Mahmud, M. & Hussain, A. (2024). Interpreting Black-Box Models: A Review on Explainable Artificial Intelligence. *Cognitive Computation*, *16* (1), 45–74. https://doi.org/10.1007/s12559-023-10179-8

He, Z., Wang, Y-H. & Zhang, J. (2025). Generative AIBIM: An automatic and intelligent structural design pipeline integrating BIM and generative AI. *Information Fusion*, *114*, 102654. https://doi.org/10.1016/j.inffus.2024.102654

Hong, S., Kwon, Y., Shin, D., Park, J. & Kang, N. (2024). DeepJEB: 3D Deep Learning-based Synthetic Jet Engine Bracket Dataset. *arXiv:2406.09047*. https://doi.org/10.48550/arXiv.2406.09047

Hosseinzadeh, M., Samadvand, H., Hosseinzadeh, A., Mousavi, S. S. & Dehestani, M. (2024). Concrete strength and durability prediction through deep learning and artificial neural networks. *Frontiers of Structural and Civil Engineering*, *18* (10), 1540–1555. https://doi.org/10.1007/s11709-024-1124-9

Li, M., Liu, Y., Wong, B. C. L., Gan, V. J. L. & Cheng, J. C. P. (2023). Automated structural design optimization of steel reinforcement using graph neural network and exploratory genetic algorithms. *Automation in Construction*, *146*, 104677. https://doi.org/10.1016/j.autcon.2022.104677

Lukovic, M., Ciernik, L., Müller, G., Kluser, D., Pham, T., Burgert, I. & Schubert, M. (2024). Probing the complexity of wood with computer vision: from pixels to properties. *Journal of The Royal Society Interface*, *21* (213). https://doi.org/10.1098/rsif.2023.0492

Luleci, F., Catbas, F. N. & Avci, O. (2023). Generative adversarial networks for labeled acceleration data augmentation for structural damage detection. *Journal of Civil Structural Health Monitoring*, *13* (1), 181–198. https://doi.org/10.1007/s13349-022-00627-8

Luo, D., Wang, K., Wang, D., Sharma, A., Li, W. & Choi, I. H. (2025). Artificial intelligence in the design, optimization, and performance prediction of concrete materials: a comprehensive review. *Npj Materials Sustainability*, *3* (1), 14. https://doi.org/10.1038/s44296-025-00058-8

Ma, J., Cao, B., Dong, S., Tian, Y., Wang, M., Xiong, J. & Sun, S. (2024). MLMD: a programming-free AI platform to predict and design materials. *Npj Computational Materials*, *10* (1), 59. https://doi.org/10.1038/s41524-024-01243-4

Marey, A., Arjmand, P., Alerab, A. D. S., Eslami, M. J., Saad, A. M., Sanchez, N. & Umair, M. (2024). Explainability, transparency and black box challenges of AI in radiology: impact on patient care in cardiovascular radiology. *Egyptian Journal of Radiology and Nuclear Medicine*, *55* (1), 183. https://doi.org/10.1186/s43055-024-01356-2

Mengesha, G. (2025). *Integrating AI in Structural Health Monitoring (SHM): A Systematic Review on Advances, Challenges, and Future Directions*. https://doi.org/10.2139/ssrn.5004977

Merchant, A., Batzner, S., Schoenholz, S. S., Aykol, M., Cheon, G. & Cubuk, E. D. (2023). Scaling deep learning for materials discovery. *Nature*, *624* (7990), 80–85. https://doi.org/10.1038/s41586-023-06735-9

Mirzaei, S., Mao, H., Al-Nima, R. R. O. & Woo, W. L. (2023). Explainable AI Evaluation: A Top-Down Approach for Selecting Optimal Explanations for Black Box Models. *Information*, *15* (1), 4. https://doi.org/10.3390/info15010004

Mishra, A., Gangisetti, G. & Khazanchi, D. (2023). Integrating Edge-AI in Structural Health Monitoring domain. *arXiv:2304.03718*. https://doi.org/10.48550/arXiv.2304.03718

Mohamed, H. S., Qiong, T., Isleem, H. F., Tipu, R. K., Shahin, R. I., Yehia, S. A., Jangir, P., Arpita, & Khishe, M. (2024). Compressive behavior of elliptical concrete-filled steel tubular short columns using numerical investigation and machine learning techniques. *Scientific Reports*, *14* (1), 27007. https://doi.org/10.1038/s41598-024-77396-5

Muthurathinam, R. V., Alruwais, N., Al Mazroa, A. & Alkharashi, A. (2024). Optimizing concrete compressive strength prediction with a deep forest model: an advanced machine learning approach. *Matéria (Rio de Janeiro)*, *29* (4). https://doi.org/10.1590/1517-7076-rmat-2024-0569

Okafor, C. E., Iweriolor, S., Ani, O. I., Ahmad, S., Mehfuz, S., Ekwueme, G. O., Chukwumuanya, O. E., Abonyi, S. E., Ekengwu, I. E. & Chikelu, O. P. (2023). Advances in machine learning-aided design of reinforced polymer composite and hybrid material systems. *Hybrid Advances*, *2*, 100026. https://doi.org/10.1016/j.hybadv.2023.100026

Pakzad, S. S., Roshan, N. & Ghalehnovi, M. (2023). Comparison of various machine learning algorithms used for compressive strength prediction of steel fiber-reinforced concrete. *Scientific Reports*, *13* (1), 3646. https://doi.org/10.1038/s41598-023-30606-y

Parmar, D. S., Gupta, P., Chouhan, C. & Saran, H. K. (2023). Data-centric AI: Prioritizing Data Quality Over Model Complexity. *International Journal of Innovative Research in Computer and Communication Engineering*, *11* (07). https://doi.org/10.15680/IJIRCCE.2023.1107004

Plevris, V. & Hosamo, H. (2025). Responsible AI in structural engineering: a framework for ethical use. *Frontiers in Built Environment*, *11*. https://doi.org/10.3389/fbuil.2025.1612575

Porter, Z., Habli, I., McDermid, J. & Kaas, M. (2024). A principles-based ethics assurance argument pattern for AI and autonomous systems. *AI and Ethics*, *4* (2), 593–616. https://doi.org/10.1007/s43681-023-00297-2

Quinteros-Navarro, D., Quinteros, A., Muñoz, V., Ramirez, H. & Ramirez, W. (2025). Learning Model Based on Artificial Intelligence to Determine Wood Quality: A Systematic Review. *Ingénierie Des Systèmes d Information*, *30* (2), 427–436. https://doi.org/10.18280/isi.300214

Ryan, P., Porter, Z., Al-Qaddoumi, J., McDermid, J. & Habli, I. (2023). What's my role? Modelling responsibility for AI-based safety-critical systems. *arXiv:2401.09459*. https://doi.org/10.48550/arXiv.2401.09459

Salman, M. R., Al-Shaikhli, M., Ali Abbas, H., Ahmad, H. H. & Kudus, S. A. (2025). A critical review of deep learning applications, challenges, and future directions in structural engineering. *International Journal for Computational Civil and Structural Engineering*, *21* (1), 146–156. https://doi.org/10.22337/2587-9618-2025-21-1-146-156

Sherif, M., Nassar, K., Hosny, O., Safar, S. & Abotaleb, I. (2022). Automated BIM-based structural design and cost optimization model for reinforced concrete buildings. *Scientific Reports*, *12* (1), 21616. https://doi.org/10.1038/s41598-022-26146-6

Spencer, B. F., Sim, S.-H., Kim, R. E. & Yoon, H. (2025). Advances in artificial intelligence for structural health monitoring: A comprehensive review. *KSCE Journal of Civil Engineering*, *29* (3), 100203. https://doi.org/10.1016/j.kscej.2025.100203

Tyvoniuk, V., Trach, R. & Trach, Y. (2025). Integration of Probability Maps into Machine Learning Models for Enhanced Crack Segmentation in Concrete Bridges. *Applied Sciences*, *15* (6), 3201. https://doi.org/10.3390/app15063201

V Khadake. (2024). AI Ethics and Responsible AI Development: Navigating the Ethical Landscape of Artificial Intelligence. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, *10* (6), 1494–1508. https://doi.org/10.32628/CSEIT241061187

Varshney, R. K., Pandey, N. K., Pandey, A. K. & Singh, A. N. (2025). Exploring Artificial Intelligence & Machine Learning Applications in Structural Engineering Trends and Challenges. *2025 International Conference on Next Generation Information System Engineering (NGISE)*, 1–6. https://doi.org/10.1109/NGISE64126.2025.11085231

Wala, R. (2025). An ethical framework for AI in structural engineering: from promise to practice. *The Structural Engineer*, *103* (10), 10. https://doi.org/10.56330/PTFH2233

Wang, Q., Dai, Y., Ma, Z., Ni, Y., Tang, J., Xu, X. & Wu, Z. (2022). Towards probabilistic data-driven damage detection in SHM using sparse Bayesian learning scheme. *Structural Control and Health Monitoring*, *29* (11). https://doi.org/10.1002/stc.3070

Xie, H., Mei, Q. & Chui, Y. H. (2025). AI applications for structural design automation. *Automation in Construction*, *179*, 106496. https://doi.org/10.1016/j.autcon.2025.106496

Zaker Esteghamati, M., Bean, B., Burton, H. V. & Naser, M. Z. (2025). Beyond Development: Challenges in Deploying Machine-Learning Models for Structural Engineering Applications. *Journal of Structural Engineering*, *151* (6). https://doi.org/10.1061/JSENDH.STENG-13301

Zhang, M., Guo, T., Zhu, R., Zong, Y., Liu, Z. & Xu, W. (2023). Damage identification of seismic-isolated structure based on CAE network using vibration monitoring data. *Engineering Structures*, *283*, 115873. https://doi.org/10.1016/j.engstruct.2023.115873

Zhang, Y., Ren, W., Chen, Y., Mi, Y., Lei, J. & Sun, L. (2024). Predicting the compressive strength of high-performance concrete using an interpretable machine learning model. *Scientific Reports*, *14* (1), 28346. https://doi.org/10.1038/s41598-024-79502-z

Zheng, H., Huang, Y., Wu, K., Wang, B., Hu, Q., Wang, D., Sun, B. & Antwi-Afari, M. F. (2025). A comparative analysis of explainable artificial intelligence (XAI) models for predicting concrete elastic dynamic modulus. *Smart Construction*. https://doi.org/10.55092/sc20250025

POSTĘPY W INŻYNIERII KONSTRUKCJI DZIĘKI SZTUCZNEJ INTELIGENCJI: METODY, WYZWANIA I MOŻLIWOŚCI

STRESZCZENIE

W artykule przedstawiono przegląd aktualnych zastosowań sztucznej inteligencji (AI) w inżynierii budowlanej ze szczególnym uwzględnieniem metod, wyzwań i perspektyw rozwoju. Omówiono, w jaki sposób techniki uczenia maszynowego, uczenia głębokiego i algorytmów ewolucyjnych zmieniają tradycyjne podejścia do projektowania, analizy i utrzymania konstrukcji. Integracja AI z BIM, bliźniakami cyfrowymi i systemami czujników przyczynia się do tworzenia bardziej zintegrowanego i opartego na danych środowiska inżynierskiego. Powszechne wdrożenie AI ograniczają jednak problemy z jakością danych, interpretowalnością modeli oraz brak ujednoliconych standardów walidacji. W opracowaniu podkreślono potrzebę rozwoju wyjaśnialnej sztucznej inteligencji, wprowadzenia nadzoru etycznego oraz standaryzacji danych, co umożliwi bezpieczne i odpowiedzialne wykorzystanie AI w praktyce inżynierskiej.

Słowa kluczowe: sztuczna inteligencja, uczenie maszynowe, uczenie głębokie, inżynieria konstrukcji, optymalizacja projektowania, monitorowanie stanu konstrukcji