frontiers | Frontiers in Built Environment

TYPE Mini Review
PUBLISHED 24 June 2025
DOI 10.3389/fbuil.2025.1622873

OPEN ACCESS

EDITED BY
Bo Xiao,
Michigan Technological University,
United States

REVIEWED BY
Yifan Wang,
Michigan Technological University,
United States

*CORRESPONDENCE
Yamem Tamut,
ymt@nerist.ac.in

RECEIVED 04 May 2025
ACCEPTED 30 May 2025
PUBLISHED 24 June 2025

CITATION
Nyokum T and Tamut Y (2025) Artificial intelligence in civil engineering: emerging applications and opportunities.
Front. Built Environ. 11:1622873.
doi: 10.3389/fbuil.2025.1622873

Artificial intelligence in civil engineering: emerging applications and opportunities

Taba Nyokum and Yamem Tamut*

Department of Civil Engineering, North Eastern Regional Institute of Science and Technology, Nirjuli, Arunachal Pradesh, India

Artificial intelligence (AI) is rapidly transforming civil engineering by harnessing vast data streams and advanced computational methods. This review provides a comprehensive survey of AI innovations in civil engineering, covering key technologies (machine learning, deep learning, natural language processing, computer vision, robotics, and generative AI) and their applications across design, construction, monitoring, transportation, geotechnical, environmental, and asset management domains. This paper discuss how AI-driven models and systems improve efficiency, safety, and sustainability, while also addressing challenges such as data limitations, model interpretability, and ethical concerns. Emerging trends—such as digital twins, smart cities, and quantum computing—are highlighted, along with the growing need for workforce skills in AI. By synthesizing recent studies, this article aims to clarify how AI is reshaping civil engineering practice and to identify opportunities and gaps for future research.

KEYWORDS

artificial intelligence, civil engineering, machine learning, infrastructure monitoring, sustainable development

1 Introduction

Civil infrastructure must now contend with aging systems, rapid urbanization, climate change, and sustainability demands. Simultaneously, data from sensors, UAVs, and IoT devices are proliferating, offering unprecedented insight into infrastructure condition and usage. Modern AI methods—including data-driven machine learning (ML) and deep learning (DL)—can capture complex nonlinear relationships in these data, often surpassing traditional analytical models in predictive accuracy (Harle, 2023; Abioye et al., 2021; Xu et al., 2021). Despite the construction industry's large scale, it has been among the slowest to digitize (Abioye et al., 2021), leaving untapped opportunities for AI-driven improvements, as highlighted in recent reviews on AI applications in construction projects (Ali and Sini, 2023). AI has begun to optimize material usage, predict structural deterioration, and manage traffic flows in real time (Harle, 2023). For example, ML models are now used to predict soil behavior and foundation performance, while AI-enabled traffic systems can forecast congestion and adjust signals dynamically (Harle, 2023; Pennetti et al., 2024). Vision-based AI inspects infrastructure (e.g., bridges, pipelines) for defects via image analysis, enabling timely repairs and higher reliability (Harle, 2023). Breakthroughs in convolutional neural networks and large language models are further enabling automated design exploration and construction reporting.

However, AI adoption in civil engineering faces significant hurdles. Many AI models require large, high-quality datasets that are often scarce or fragmented on construction sites.

The "black-box" nature of complex models raises concerns about trust and interpretability, especially in safety-critical decisions (Kamolov et al., 2024; Abioye et al., 2021). Ethical issues related to data privacy, autonomous systems, and workforce impacts are also paramount (Megdad et al., 2024; Sargiotis, 2024). Integrating AI with emerging technologies like digital twins, IoT, and blockchain holds promise for predictive maintenance and resilient infrastructure, yet practical implementation challenges remain. While previous reviews have addressed AI in civil engineering (e.g., Sargiotis, 2024; Baghbani et al., 2022), many do not reflect the latest AI paradigms such as generative design or large language models. This review fills that gap by surveying contemporary AI technologies and their civil engineering applications, highlighting both achievements and open research directions.

2 AI technologies in civil engineering

This section reviews fundamental AI methods being applied in civil engineering. We cover broad categories—machine learning, neural networks, natural language processing, computer vision, robotics, and generative AI—emphasizing their principles, capabilities, and limitations.

2.1 Machine learning (ML)

Machine learning (ML) encompasses algorithms that learn patterns from data to make predictions or decisions without explicit programming. ML includes supervised learning (trained on labeled examples), unsupervised learning (finding patterns in unlabeled data), and reinforcement learning. Common ML techniques such as regression models, decision trees, support vector machines, random forests, and neural networks have proven effective in civil engineering contexts (Sargiotis, 2024; Sargiotis, 2024). ML excels at capturing complex, nonlinear relationships that traditional models cannot easily represent. In practice, ML models are used to predict infrastructure service life, forecast traffic volumes, estimate soil properties from limited tests, predict material properties such as concrete compressive strength (Costa et al., 2022; Silva et al., 2023), and classify pavement distress from sensor data. For instance, convolutional neural networks (a DL subclass) can detect and classify cracks in concrete images with high accuracy (Sargiotis, 2024). ML-based risk assessment tools enable early warning systems that prioritize inspections based on predicted failure risks. These advances help optimize resource allocation and maintenance planning.

However, ML models require large, high-quality datasets, which can be scarce or noisy in construction environments. Incomplete or inconsistent data (e.g., missing sensor readings) can degrade model performance. Moreover, many ML models act as "black boxes" that offer little insight into why they make certain predictions. This opacity can be problematic in safety-critical infrastructure decisions, where engineers need interpretable rationale. For example, a deep neural network may predict a bridge failure risk but cannot explain the key factors leading to that decision. To mitigate these issues, models must be rigorously validated with independent data, and domain expertise should be integrated. Researchers are also exploring explainable AI techniques to improve trust and transparency (Megdad et al., 2024). Despite these challenges, ML remains a powerful tool for modeling civil engineering problems, provided its limitations and potential biases are carefully managed.

2.2 Artificial neural networks (ANNs)

Artificial neural networks (ANNs) are ML models inspired by the brain's structure, consisting of interconnected nodes (neurons) that adjust weights during training. Deep learning refers to neural networks with many hidden layers, capable of modeling highly complex functions. ANNs have been applied in structural analysis, materials science, and geotechnical engineering, with numerous applications detailed in recent collections (Hui et al., 2023). For example, convolutional neural networks (CNNs) are well-suited for image-based tasks, such as automated inspection of infrastructure elements to detect cracks, corrosion, or debris. Recurrent neural networks (RNNs) and long short-term memory (LSTM) networks are used for time-series data, such as traffic flow prediction (Abduljabbar et al., 2021) or electrical load forecasting. By training on historical sensor data, these models can capture dynamic trends in infrastructure usage.

Deep networks can achieve high accuracies but with heavy costs. They have a massive demand of computation resource (e.g., GPUs) and wasted lots of sample's concentration in training. Overfitting is a problem: A network with too many parameters can do little more than memorize the data unless it is regularized, and it will not generalize well unless it has been trained on a lot of data. Both as with all ML techniques, ANNs are largely of a "black box" nature and provide restricted interpretability. To avoid these limitations, we can resort to the hybrid models in which ANN predictions are combined with physics-based engineering constraints so that the generated outputs are physically plausible. Visualization methods (attention maps), simplified surrogate models are also actively studied to make deep learning more transparent in engineering applications. Overall, ANNs and deep learning provide powerful predictive capabilities in civil engineering, enabling tasks like vibration analysis of structures and automated damage recognition, albeit at the cost of increased data and resource requirements.

2.3 Natural language processing (NLP)

Natural language processing (NLP) gets computers to understand, interpret and even measure the quality of human language. Within civil engineering, NLP is being employed to automate processing of textual data such as project reports, design documents, safety logs, or regulatory codes, a domain extensively reviewed by Wu et al. (2022a) and Wu et al. (2022b). It can summarize inspection notes, classify incident reports by cause or severity, or even draft routine forms." Large language models, such as BERT or GPT-4, however, are in a league of their own. For instance, a GPT based model has been applied successfully to a construction accident reports classification, identifying patterns helpful for safety analysis (Ahmadi et al., 2024). So-called NLP tools might also be used to automatically verify code compliance by correlating formal specifications (e.g., REVIT) with regulatory text.

Despite its promise, NLP faces challenges in civil engineering contexts. Technical documents often contain specialized terminology that general language models do not know by default. Domain-specific fine-tuning is required to handle engineering jargon and acronyms. Moreover, ensuring accuracy is critical when interpreting safety-critical texts; advanced models can “hallucinate” incorrect outputs if not carefully managed. For instance, an LLM might infer a wrong citation in a compliance document. Robust validation and human oversight are therefore necessary. Nonetheless, NLP greatly expands engineers' ability to leverage textual data at scale. Automated document analysis and report generation are streamlining workflows, and ongoing advances in multimodal models are poised to integrate textual and sensor data for richer insights.

2.4 Computer vision

Computer vision (CV) enables machines to interpret visual data (images and video). In civil engineering, CV has become indispensable for inspection and monitoring. CV systems are used to automatically detect structural damage (cracks, spalling, corrosion) in bridges and buildings from images or video. For example, CNN-based vision systems can identify concrete crack patterns with high accuracy (Ahmadi et al., 2024) and specialized lightweight networks like MobileNetV2 are also effectively used for crack identification on mobile platforms (Hui et al., 2023). Drones equipped with cameras use CV algorithms to map infrastructure and spot defects in hard-to-reach areas. CV is also applied in traffic monitoring (counting vehicles, detecting incidents) and in geotechnical applications (monitoring slope stability, identifying pavement distress from road images).

The key advantage of CV is its ability to process vast amounts of visual data quickly, enabling continuous, non-contact inspection that would be impractical manually. When mounted on mobile platforms or UAVs, CV enables real-time monitoring of large areas without endangering workers. However, CV models require carefully curated training datasets that account for variations in lighting, weather, and environments. A system trained in one context (e.g., sunny daytime images) may produce false positives or negatives under different conditions (e.g., shadows or rain). High-resolution images and video also demand significant computational resources for analysis. Ensuring reliability often involves techniques like ensemble modeling or thresholding to reduce false alarms. In practice, CV systems must be calibrated for specific use cases and regularly updated with new data. Despite these challenges, CV is transforming infrastructure inspection by enabling rapid, automated assessment of structures and roadways.

2.5 Robotics and autonomous systems

The integration of AI with robotics is revolutionizing construction and infrastructure maintenance. Autonomous and semi-autonomous robots are being deployed for tasks such as site surveying, hazardous inspections, earthmoving, bricklaying, welding, and demolition. For instance, unmanned aerial vehicles (UAVs) equipped with sensors can inspect high-rise structures or difficult terrain, (Liu et al., 2024), and AI-enabled robotic systems are increasingly used for broader construction inspection and maintenance tasks (Liu et al., 2024). Collecting data while keeping workers safe (Liu et al., 2024). Robotic bricklayers and 3D concrete printers demonstrate that machines can perform repetitive construction tasks with higher precision and speed than human labor. Even robotic total stations—surveying instruments—now use AI to automatically lock onto and track targets, optimizing site layout in real time (See Figure 1 and Figure 2 to see the applications of robotics).

Robots extend monitoring into dangerous or inaccessible areas and can operate continuously without fatigue, improving efficiency and safety. However, significant challenges remain. Robotic systems must be highly robust to withstand construction environments (dust, rough terrain, weather) and to ensure reliable operation. Integration of robots into human teams on site requires careful planning of human-robot collaboration and safety protocols. There are also regulatory and ethical considerations: for example, determining liability if an autonomous machine causes damage. Despite these hurdles, advances in AI and controls are rapidly enhancing robotic capabilities. As these technologies mature, intelligent robots are poised to become integral partners in construction and asset management, handling routine tasks and augmenting human workers.

2.6 Generative AI

Generative AI refers to algorithms that create new content—such as designs, images, or text—based on learned patterns. In civil engineering, generative AI is an emerging tool for automating and augmenting creative tasks. One major application is generative design, where algorithms iterate on design alternatives to meet specified criteria (loads, material limits, safety codes). By learning from existing designs, a generative model can propose novel structural layouts or architectural forms that optimize objectives (e.g., minimizing material use or maximizing daylight) while satisfying constraints (Liao et al., 2024). This approach accelerates the early design process, enabling engineers to explore unconventional yet efficient solutions that may be overlooked in manual design.

Generative AI is also being used for automation of construction reporting. For instance, AutoRepo (Pu et al., 2023) is a system connecting drone images analysis and multimodal LLM generation for site inspection report automatically. That makes documentation faster while also guaranteeing that content is complete and compliant. Generative models also examined historical accident report data to find patterns and recommend preventive measures (Ahmadi et al., 2024). Although generative AI has potential, it is in its early stage of application in civil engineering. One of the big hurdles is making sure the AI-generated designs, or documents, are up to all the necessary safety and regulatory codes. Engineers need to carefully with the AI outputs, as models can generate unattainable or non-compliant recommendations at times.

Another concern is interpretability: understanding why the AI made a particular design choice is critical for trust and refinement. As generative AI evolves, its role in civil engineering

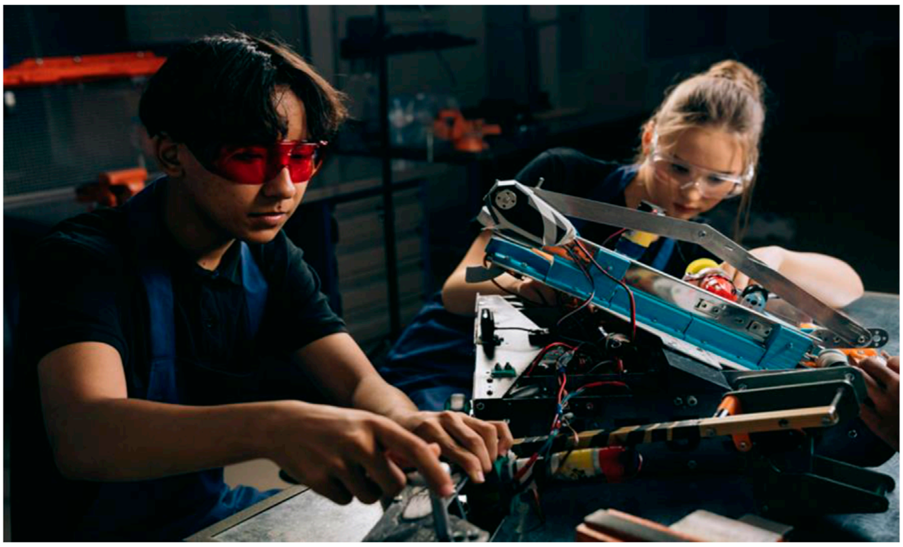

FIGURE 1
Robotics research in civil engineering. Engineering students assemble a robotic prototype in a lab. Construction robots and drones (autonomous vehicles) perform tasks such as material handling, assembly, and inspection, aiming to improve precision and safety (Liu et al., 2024).

is expected to grow—enabling rapid prototyping, intelligent reporting, and even creative urban planning—but always under the guidance of human expertise.

3 Applications of AI in civil engineering

AI is now being applied across the civil engineering lifecycle. In this section, we describe key application areas where AI is making an impact.

3.1 Design and planning

Ai is revolutionizing the way we design in-house, at the early stages of projects; AI manifests in the form of optimisation, Data driven design. Surrogate machine learning models allow a very fast screening of a multitude of design alternatives with limited computational effort, thus exploring complex parameter spaces. For instance, in sustainable building design, AI can examine building form and materials combination to reduce energy usage or carbon usea field comprehensively reviewed by Manmatharasan et al. (2025). Generative design algorithms, utilizing deep learning or genetic algorithms, can suggest new architectural shapes that meet specific performance needs such as maximization of daylight or reduction of steel (Abioye et al., 2021; Manmatharasan et al., 2025). AI also improves the process of building energy modeling by integrating data on weather, occupancy, and sensors to optimize HVAC sizing and control for energy use. Taken together, AI moves architectural and structural planning from static CAD-based methods to dynamic, multi-objective optimization. This can reduce costs and environmental impact by identifying the most efficient designs early in the process.

3.2 Construction management

In construction management, AI streamlines scheduling, resource allocation, and risk management. ML models can predict project durations, cost overruns, and labor productivity by learning from historical project data. Vision systems based on computer vision (CV) can monitor sites to track worker movements and equipment usage, improving safety and productivity, with ongoing development of AI-based systems for comprehensive construction safety monitoring (Zhang et al., 2024). Natural language processing (NLP) tools extract information from contracts, reports, and manuals, reducing paperwork bottlenecks and aiding in tasks like the automated analysis of construction accident reports to identify safety patterns (Ahmadi et al., 2024). Real-time AI-driven dashboards integrate data from IoT sensors and BIM models with predictive analytics. For instance, sensor data on material deliveries can be fed into demand forecasting models to optimize inventory and workflows. Robotics and automated machinery further augment operations: self-driving earthmovers, robotic bricklayers, and UAVs performing surveys all contribute to more efficient construction processes. By making construction management more data-driven and predictive, AI helps minimize delays, reduce waste, and improve quality (Pu et al., 2023; Pu et al., 2023).

3.3 Infrastructure monitoring and maintenance

AI plays a critical role in structural health monitoring (SHM) and maintenance of infrastructure assets. Networks of sensors embedded in bridges, buildings, and roads continuously collect data on strain, vibration, temperature, and other indicators. AI models analyze this streaming data to detect anomalies and predict damage before it becomes critical. Deep learning (especially CNNs) is widely

FIGURE 2
Human–robot collaboration. A robotic arm plays chess with a human operator in a controlled environment. This illustrates the potential of AI-driven robots in construction for tasks that involve both autonomy and human oversight (Liu et al., 2024).

used for image-based inspection: for example, AI algorithms can automatically identify cracks or corrosion in bridge images with high accuracy, and similar techniques are applied for the visual inspection of cultural heritage structures (Mishra et al., 2022). Studies report detection accuracies around 97%–99% in some bridge inspection cases. Beyond detection, predictive maintenance algorithms use historical and real-time data to forecast the remaining service life of components. This enables proactive maintenance scheduling, extending asset life and improving safety. For example, if vibration data indicate accelerated wear on a bridge bearing, AI models can recommend maintenance before failure. By providing timely diagnostics and forecasts, AI-based monitoring helps infrastructure operators prioritize interventions and allocate budgets more effectively (Plevris and Papazafeiropoulos, 2024; Plevris et al., 2023).

3.4 Traffic and transportation systems

In transportation engineering, AI enhances traffic forecasting, signal control, and network planning. ML models, leveraging techniques such as LSTM networks for spatial-temporal speed prediction (Abduljabbar et al., 2021), can predict short-term traffic volumes, travel times, and congestion hotspots more accurately than traditional time-series methods, as reviewed by Afandizadeh et al. (2024). These predictions feed into adaptive signal control systems that adjust timing in real time to optimize flow. AI also supports transit planning and incident management: for instance, anomaly detection algorithms flag unusual traffic patterns or accidents from sensor and camera data. Autonomous vehicles and connected infrastructure heavily rely on AI for perception, path planning, and control, improving safety and throughput. Generative AI is beginning to impact intelligent transportation systems (ITS) by enabling more efficient scenario generation and decision support, with applications systematically reviewed by Rong et al. (2025a) and Rong et al. (2025b). For example, generative models can synthesize realistic traffic scenarios for testing control strategies or simulate incident responses to aid planning. Overall, AI applications in transportation are making mobility systems more predictive, responsive, and efficient.

3.5 Geotechnical engineering

AI is transforming geotechnical engineering by improving soil and ground behavior prediction. ML models (including ANNs and support vector machines) are used to estimate soil parameters (such as shear strength and permeability) from accessible data (borehole logs, sensor readings), reducing the need for extensive laboratory testsand to predict phenomena such as rock slope failure (Mnzool, 2024). In earthquake engineering, AI models can forecast ground motion patterns for given seismic inputs and classify structural damage post-event, aiding rapid post-disaster assessment. Hybrid approaches that combine ML with physics-based simulations are emerging to optimize foundation design and seismic resilience assessments. For instance, an ML model may predict settlement for a preliminary design, which is then refined with finite element analysis. Data scarcity remains a challenge in geotechnics, but reviews (Abdellah, 2024) indicate that AI tools are increasingly valuable for interpreting complex subsurface data. As more monitoring data become available (e.g., from instrumented sites), AI-driven analytics will continue to improve foundation design and hazard mitigation.

3.6 Water resources and environmental engineering

AI is also applied in water and environmental infrastructure. In water distribution networks, ML algorithms forecast demand patterns and detect leaks by learning from flow and pressure sensor data. AI-driven models integrate diverse inputs—weather forecasts, soil moisture sensors, topography—to improve flood prediction accuracy. For example, by combining real-time rainfall data with terrain models, AI can predict flood extent faster than conventional hydrologic models. In wastewater treatment and environmental compliance, AI optimizes process controls (e.g., adjusting aeration in a treatment plant to save energy). In environmental monitoring, AI analyzes sensor data to predict air quality, noise, and pollution trends, supporting sustainable planning. These AI applications help manage water resources more efficiently and mitigate environmental risks (Harle, 2023).

3.7 Infrastructure asset management

In asset management, AI enables advanced digital twin platforms that integrate sensor data, structural models, and analytics to monitor infrastructure health continuously. Predictive analytics identify which assets (bridges, pipelines, etc.) are likely to fail or need maintenance soon, allowing managers to prioritize interventions and budget effectively. The ethical use of AI is critical here: data governance and transparency must ensure that decisions (like closing a bridge) are justified and based on accurate information. By handling large-scale data and complex networks, AI-driven management systems are transforming how public agencies maintain assets. This leads to safer, longer-lasting infrastructure and more efficient use of limited maintenance funds (Abioye et al., 2021). See Supplementary Table S1 for case studies of AI applications in civil engineering, showing domain, AI method, and performance. These examples illustrate the high accuracy achieved in practice.

4 Challenges in AI adoption for civil engineering

Despite its promise, AI adoption in civil engineering faces several substantial challenges. Data quality and availability are primary barriers. Construction and infrastructure data are often sparse, inconsistent, or proprietary, making it difficult to train robust AI models. Sensor malfunctions, changes in instrumentation, and fragmented data systems lead to gaps and noise in the data. Obtaining sufficient labeled data for training is especially hard for rare events (e.g., structural failures), limiting supervised learning approaches (Abioye et al., 2021).

Another challenge is model transparency. Many powerful AI models (especially deep neural networks) are "black boxes" whose internal decision processes are opaque. In civil engineering—where safety is paramount—engineers must trust and understand model outputs. The field is responding with a focus on explainable AI (XAI) methods that make AI decisions more interpretable. This involves techniques like feature importance analysis and surrogate models that approximate complex networks.

Integration and interoperability also hinder deployment. New AI tools must fit into established engineering workflows, software, and standards. Often, AI systems developed in research are not easily plugged into legacy project management or design systems. There is also cultural resistance: many engineers are trained in traditional methods and may be skeptical of AI. A shortage of AI-literate personnel compounds this issue, as training is needed for engineers to work effectively with AI.

Practical constraints on construction sites add further hurdles. Reliable computing and connectivity (e.g., for cloud AI services) are not always available on remote or rapidly changing job sites. The initial cost of adopting AI technologies (drones, sensors, computing infrastructure) can be high, and the return on investment may be uncertain, deterring smaller firms.

Finally, ethical and governance issues are increasingly critical. Civil engineering projects impact public safety and resources, so data privacy and algorithmic bias must be managed carefully. For example, AI models trained on non-representative data could misjudge risks in certain communities. This underscores the need for robust standards, transparency, and oversight in AI systems. Addressing these challenges requires collaboration among engineers, data scientists, policymakers, and educators to build the data infrastructure, guidelines, and expertise needed for responsible AI integration.

5 Future directions of AI in civil engineering

Looking ahead, AI's role in civil engineering is poised to expand in several key directions. Smart cities and urban systems will increasingly rely on AI to manage interconnected infrastructure (transportation, energy, utilities, buildings) in an integrated way. AI-driven digital twins of entire cities will enable planners to simulate and optimize complex systems in real time, improving sustainability and resilience. For example, an urban digital twin could optimize traffic flow, energy usage, and emergency response simultaneously.

Sustainability and resilience will drive AI research. AI will be essential for designing infrastructure resilient to climate change (floods, heat, storms) and for optimizing resource use to meet net-zero goals, reflecting AI's growing influence on sustainable development in civil engineering (Manzoor and Chen, 2021). AI-powered models will better predict climate-related impacts (e.g., flood risk under different scenarios) and help integrate renewable energy into infrastructure (e.g., optimizing solar/wind installations on buildings and bridges). As a result, AI can reduce carbon footprints and enhance disaster preparedness.

In advanced computing, quantum computing may become a game-changer for civil engineering AI. Quantum algorithms have the potential to solve optimization and simulation problems that are currently intractable. For instance, quantum-enhanced AI could dramatically accelerate structural optimization and logistical planning processes, enabling engineers to solve complex design problems much faster (Ploennigs et al., 2024).

Meanwhile, developing the workforce and education is crucial as AI adoption grows. Civil engineers will need new skills in data science, machine learning, and AI ethics. Educational institutions should update curricula to include AI and data analytics topics, preparing a new generation of engineers who can effectively employ AI tools (Reid, 2024).

In summary, while AI is already transforming civil engineering practice, its future promises even deeper integration into smart infrastructure, climate resilience, and novel computing paradigms. Meeting this promise will require continued research in AI methods tailored to engineering needs, development of standards and best practices, and cultivation of interdisciplinary expertise. With careful guidance and collaboration, AI can help civil engineers build safer, more efficient, and more sustainable infrastructure for the future.

6 Conclusion

Artificial intelligence is rapidly reshaping civil engineering by providing new data-driven methods for design, construction, monitoring, and maintenance. Advances in ML, deep learning, NLP, computer vision, robotics, and generative AI are enabling tasks that were previously difficult or impossible, from automated damage detection to generative structural design. These technologies are improving efficiency, safety, and sustainability across civil engineering domains (Abioye et al., 2021; Harle, 2023).

At the same time, practical challenges—data scarcity, model transparency, integration into workflows, and ethical concerns—must be addressed for AI's full potential to be realized. Future progress will hinge on building better data infrastructures, developing explainable AI methods, fostering interdisciplinary collaboration, and training engineers in AI skills. Emerging trends such as smart cities, resilient infrastructure, and quantum-enhanced computation point to an exciting future where AI tools and traditional engineering expertise work together to tackle society's infrastructure challenges. By systematically overcoming adoption barriers and guiding innovation, the civil engineering community can ensure that AI becomes an integral and trusted part of building the world around us.

Author contributions

TN: Visualization, Conceptualization, Writing – original draft. YT: Writing – review and editing, Supervision.

Funding

The author(s) declare that no financial support was received for the research and/or publication of this article.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declare that no Generative AI was used in the creation of this manuscript.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fbuil.2025.1622873/full#supplementary-material

References

Abdellah, W. S. (2024). "A review of applications of artificial intelligence in geotechnical engineering," in *Proceedings of ARCSMGE 2024*.

Abduljabbar, R. L., Dia, H., Tsai, P.-W., and Liyanage, S. (2021). Short-term traffic forecasting: an LSTM network for spatial-temporal speed prediction. *Future Transp.* 1 (1), 21–37. doi:10.3390/futuretransp1010003

Abioye, A. J., Oyedele, L. O., Akanbi, L., Ajayi, O. O., Davila Delgado, J. M., Bilal, M., et al. (2021). Artificial intelligence in the construction industry: a review of present status, opportunities and future challenges. *J. Build. Eng.* 44, 103299. doi:10.1016/j.jobe.2021.103299

Afandizadeh, H., Zhang, Z., and Recker, W. (2024). Deep learning algorithms for traffic forecasting: a comprehensive review and comparison with classical ones. *J. Adv. Transp.* 2024, 9981657. doi:10.1155/2024/9981657

Ahmadi, E., Muley, S., and Wang, C. (2024). Automatic construction accident report analysis using large language models. *J. Intelligent Constr.*, 1–10. doi:10.26599/JIC.2024.9180039

Ali, M. R., and Sini, S. (2023). Application of artificial intelligence in construction projects: a comprehensive review. *J. Civ. Eng. Manag.* 29 (6), 1255–1269. doi:10.3846/jcem.2023.16712

Baghbani, A., Baghbani, H., Shalchiyan, M. M., and Kiany, K. (2022). Utilizing artificial intelligence and finite element method to simulate the effects of new tunnels on existing tunnel deformation. *J. Comput. Cogn. Eng.* 3 (2), 166–175. doi:10.47852/bonviewJCCE2202307

Costa, G., da Silva, F., and Chang, T. (2022). Machine learning-based prediction of the compressive strength of Brazilian concretes: a dual-dataset study. *Sensors* 22 (8), 3129. doi:10.3390/s22083129

Harle, S. M. (2023). Advancements and challenges in the application of artificial intelligence in civil engineering: a comprehensive review. *Asian J. Civ. Eng.* 25, 1061–1078. doi:10.1007/s42107-023-00760-9

Hui, L., Ibrahim, A., and Hindi, R. (2023). Artificial neural networks applied in civil engineering. *Appl. Sci.* 13 (2), 1131. doi:10.3390/app13021131

Kamolov, M., Mohebbi, M., Zamanifekri, A., and Davoudinejad, A. (2024). Machine learning methods in civil engineering: a systematic review. *Ann. Math. Comput. Sci.* 39 (2), 121–153. doi:10.56947/amcs.v21.277

Liao, W., Huang, S., Hu, K., Tang, Z., and Fan, B. (2024). Generative AI design for building structures: current state and future directions. *Smart Struct. Syst.* 34 (2), 123–145. doi:10.1016/j.autcon.2023.105187

Liu, Y., Adeli, H., Haron, N. A., and Wang, H. (2024). Robotics in the construction sector: trends, advances, and challenges. *J. Intelligent & Robotic Syst.* 110, 72. doi:10.1007/s10846-024-02104-4

Liu, Y., Wu, H., Zhang, X., and Chen, G. (2024). AI-enabled robotic systems for construction inspection and maintenance. *Automation Constr.* 152, 104807.

Manmatharasan, P., Bitsuamlak, G., and Grolinger, K. (2025). AI-driven design optimization for sustainable buildings: a systematic review. *Energy Build.* 332, 115440. doi:10.1016/j.enbuild.2025.115440

Manzoor, A., and Chen, C. (2021). Influence of AI in civil engineering toward sustainable development—systematic review. *Int. J. Civ. Eng.* 19 (7), 2220–2234. doi:10.3390/asi4030052

Megdad, M. M. M., Abueleiwa, M. H. S., Al Qatrawi, M., El-Tantaw, J., Harara, F. E. S., Abu-Nasser, B. S., et al. (2024). Ethics in AI: balancing innovation and responsibility. *Int. J. Acad. Pedagogical Res. (IJAPR)* 8 (9), 20–25.

Mishra, D., Gupta, R., and Yanev, P. (2022). Deep learning-enabled visual inspection for cultural heritage structures. *Appl. Sci.* 12 (19), 10215. doi:10.1016/j.culher.2024.01.005

Mnzool, M. (2024). Prediction of rock slope failure based on multiple machine learning algorithms. *Therm. Sci.* 28 (6A), 4907–4916. doi:10.2298/TSCI2406907M

Pennetti, F. I., Boyles, S. D., and Work, D. B. (2024). Predictive real-time traffic management in large-scale networks using model-based artificial intelligence (Report No. FHWA-HRT-23-107). Washington, DC: Federal Highway Administration. Available online at: https://rosap.ntl.bts.gov/view/dot/74165.

Plevris, T., Michini, B., Laflamme, S., and El-Ali, M. (2023). Artificial intelligence in structural health monitoring for infrastructure maintenance and safety. *Appl. Sci.* 13 (20), 10622. doi:10.3390/app132010622

Plevris, V., and Papazafeiropoulos, G. (2024). AI in structural health monitoring for infrastructure maintenance and safety. *Infrastructures* 9 (12), 225. doi:10.3390/infrastructures9120225

Ploennigs, J., Berger, M., Mevissen, M., and Smarsly, K. (2024). "Quantum computing in civil engineering: potentials and Limitations," in Accepted for publication in Proceedings of the International Conference on Computing in Civil and Building Engineering (ICCCBE) 2024. doi:10.48550/arXiv.2402.14556

Pu, H., Yang, X., Li, J., Guo, R., and Li, H. (2023). AutoRepo: a general framework for multi-modal LLM-based automated construction reporting.

Pu, Y., Liu, Z., and Ng, S. T. (2023). AI-driven construction management: integrating IoT and predictive analytics. *Automation Constr.* 147, 104795.

Reid, G. (2024). What do civil engineers need to know about AI? *Civ. Eng. Mag.* 94 (10), 60–67.

Rong, C., Li, J., Zhou, H., Yang, W., and Cui, J. (2025a). Generative AI: a systematic review of applications in intelligent transportation systems. *Front. Eng. Manag.* 12 (2), 231–242. doi:10.1007/s42524-024-01465-6

Rong, R., Ma, S., Ren, N., Lin, Q., and Jia, N. (2025b). Generative artificial intelligence in intelligent transportation systems: a systematic review of applications. *Front. Eng. Manag.* doi:10.1007/s42524-025-4241-9

Sargiotis, D. (2024). Advancing civil engineering with AI and machine learning: from structural health to sustainable development. *Int. J. Archit. Plan.* 4 (2), 54–81. doi:10.51483/ijarp.4.2.2024.54-81

Sargiotis, D. (2024). Transforming civil engineering with AI and machine learning: innovations, applications, and future directions. *SSRN*. doi:10.2139/ssrn.5021723

Silva, V. P., Carvalho, R. A., Rêgo, J. H. D. S., and Evangelista, F. Jr. (2023). Machine learning-based prediction of the compressive strength of Brazilian concretes: a dual-dataset study. *Materials* 16 (14), 4977. doi:10.3390/ma16144977

Wu, C., Li, X., Guo, Y., Wang, J., Ren, Z., Wang, M., et al. (2022a). Natural language processing for smart construction: current status and future directions. *Automation Constr.* 134, 104059. doi:10.1016/j.autcon.2021.104059

Wu, Z., Zhou, Q., Ding, L., and Li, C. (2022b). Sensation transfer for immersive exoskeleton motor training: implications of haptics and viewpoints. *Automation Constr.* 141, 104411. doi:10.1016/j.autcon.2022.104411

Xu, Y., Zhou, Y., Sekuła, P., and Ding, L. (2021). Machine learning in construction: from shallow to deep learning. *Dev. Built Environ.* 6, 100045. doi:10.1016/j.dibe.2021.100045

Zhang, Z., Zhang, Z., and Xie, X. (2024). Development of AI-based systems for construction safety monitoring: current trends and future prospects. *J. Constr. Eng.* 2024.