Integration of Artificial Intelligence in Structural Engineering for Enhanced Analysis and Predictive Maintenance

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ABSTRACT

This paper explores the transformation in structural engineering through the integration of artificial intelligence (AI) with traditional methods such as Finite Element Analysis (FEA). It examines how AI-driven techniques like machine learning (ML), deep learning, and hybrid optimization are enhancing the accuracy, efficiency, and decision-making processes in structural analysis, health monitoring, and predictive maintenance. With examples from various case studies, the research highlights AI's potential to address challenges in complex, large-scale systems and its application in infrastructure resilience, particularly in seismic-prone regions. The study underscores AI's growing importance in modern structural engineering.

***Keywords**: Structural Engineering, Artificial Intelligence, Machine Learning, Finite Element Analysis, Infrastructure Resilience.*

I. INTRODUCTION

The field of structural engineering has undergone a significant transformation in recent decades due to rapid advancements in computational methods, data-driven modeling, and artificial intelligence (AI)-based technologies. Traditionally, structural analysis relied heavily on analytical mechanics, empirical formulations, and simplified numerical approaches such as the finite element method (FEM). While these methods have proven effective for conventional design problems, they often face limitations when dealing with complex, large-scale, nonlinear, and multi-physics structural systems. In response to these challenges, intelligent structural analysis systems have emerged as a new paradigm, integrating AI techniques such as machine learning (ML), artificial neural networks (ANNs), deep learning, and hybrid optimization frameworks with classical structural mechanics. These intelligent systems aim to improve prediction accuracy, reduce computational cost, and enhance decision-making capabilities in structural design, monitoring, and maintenance processes. Recent studies have demonstrated that AI-driven structural analysis is not only a complementary tool but also a transformative approach capable of redefining how engineers assess structural performance and safety (Zhang, 2024; Arangarajan et al., 2024). The integration of AI into structural engineering has been particularly evident in structural health monitoring (SHM) and predictive maintenance systems. Standoli et al. (2026) demonstrated that AI-assisted SHM frameworks, combined with long-term sensor data and operational modal analysis, can effectively track the dynamic behavior of structures such as heritage masonry towers under environmental and seismic influences. Their findings indicated that machine learning-based monitoring systems significantly improve the reliability of damage detection and reduce the need for invasive inspection methods. Similarly, Mota et al. (2026) highlighted the broader implications of AI systems, particularly generative AI and intelligent decision frameworks, in optimizing complex operational environments. Although their focus was on SMEs and chatbot systems, the methodological contribution of structured modeling techniques such as interpretive structural modeling (ISM) and MICMAC analysis reflects the growing importance of structured intelligence systems in solving multi-dimensional engineering problems. These approaches collectively illustrate how AI is increasingly being used to extract actionable insights from large datasets, which is a fundamental requirement in modern structural analysis systems. In addition to monitoring applications, AI techniques have demonstrated substantial potential in computational modeling and simulation of structural systems. Anupam et al. (2026) showed that artificial neural networks could efficiently predict the behavior of dielectric elastomer minimum energy structures (DEMES), reducing reliance on computationally expensive numerical simulations. Their results confirmed that ANN-based models, particularly those trained using Levenberg–Marquardt and Bayesian Regularization algorithms, can accurately replicate complex structural responses while significantly reducing computational time. This shift toward data-driven surrogate modeling is also reflected in finite element-based studies, where AI is used to enhance model accuracy and calibration. Wang et al. (2025) proposed a response surface method (RSM)-based finite element model updating approach for super high-rise buildings, demonstrating that AI-assisted optimization techniques can effectively minimize discrepancies between numerical models and real-world structural behavior. These advancements indicate that AI is not merely an analytical enhancement but a core enabler of next-generation simulation frameworks in structural engineering.

Furthermore, finite element analysis (FEA), when integrated with AI techniques, has significantly expanded its application scope in structural engineering. Zhang (2024) demonstrated that FEA-based structural simulations, when combined with computer modeling techniques, can accurately replicate thermal and mechanical responses in welding processes, thereby improving simulation efficiency and accuracy. Similarly, Arangarajan et al. (2024) applied FEA to study stress distribution, fluid-structure interaction, and thermal effects in mechanical systems, emphasizing the importance of parametric studies and sensitivity analysis in optimizing structural performance. These studies collectively indicate that AI-enhanced FEA frameworks provide a powerful tool for solving multi-variable engineering problems. By incorporating machine learning algorithms into FEM workflows, engineers can achieve adaptive modeling capabilities that continuously improve predictive performance based on new data inputs, thereby enabling real-time structural assessment and optimization. The application of intelligent structural analysis systems is also evident in modern construction technologies and modular infrastructure systems. Liew and Chua (2025) discussed innovative modular construction systems, particularly steel–concrete composite structures, which leverage prefabrication and automation technologies to improve construction efficiency and structural performance. Their study highlighted that integration of computational intelligence and advanced material systems can significantly enhance constructability and sustainability in high-rise buildings. Similarly, Kasuga (2021) explored hybrid structural systems in bridge construction, emphasizing material optimization strategies that reduce structural weight while maintaining strength and durability. These developments indicate that intelligent design approaches, supported by AI-based optimization techniques, are increasingly influencing construction methodologies, enabling engineers to design more efficient and sustainable infrastructure systems. In the context of infrastructure resilience, particularly in bridges and seismic-prone regions, AI-based structural analysis has become increasingly important. Thakkar et al. (2023) emphasized that many existing bridge structures suffer from vulnerabilities due to outdated seismic design methodologies, highlighting the need for advanced analytical tools such as fragility analysis and probabilistic modeling. Wilches et al. (2021) further examined the evolution of seismic design codes and structural systems in Chile, demonstrating that improvements in design standards have significantly enhanced structural performance following major earthquakes. However, they also noted that structural failures still occur due to uncertainties in material behavior and design limitations. In this regard, AI-based predictive models offer a promising solution by enabling more accurate estimation of structural responses under seismic loading conditions. Additionally, Abid et al. (2022) developed finite element-based thermal models for concrete bridges, showing that data-driven calibration using long-term environmental data can improve predictive accuracy of structural behavior under thermal stresses. These studies collectively highlight the importance of integrating AI with traditional structural engineering principles to improve resilience and safety in infrastructure systems.

II. RESEARCH BACKGROUND

Mota et al. (2026) examined the rapid evolution of Generative Artificial Intelligence (GenAI) and highlighted chatbots as transformative tools that had significantly improved business competitiveness and operational efficiency. However, the authors also emphasized that these innovations had introduced substantial challenges, particularly for small- and medium-sized enterprises (SMEs), which often faced resource limitations and lacked context-specific implementation guidance. The study had aimed to identify the major pain points associated with GenAI chatbot adoption and to improve SME performance by developing a structured framework that established cause-and-effect relationships among these challenges. A Multiple Criteria Decision Analysis (MCDA) approach had been employed, incorporating expert group discussions, cognitive mapping, Interpretive Structural Modeling (ISM), and MICMAC analysis. The findings had further been validated by neutral experts to strengthen the robustness of the final model. The study had made an original contribution by co-constructing actionable insights through expert collaboration and had offered both theoretical and practical guidance for mitigating GenAI chatbot risks in SMEs.

Standoli et al. (2026) presented a data-driven Structural Health Monitoring (SHM) framework for the long-term preservation of heritage masonry towers, based on more than two years of continuous monitoring of the Civic Tower of Matelica, Italy. It was reported that four triaxial energy-efficient MEMS accelerometers were permanently installed at the tower's corners to collect continuous vibration data, which were analysed through automated Operational Modal Analysis (OMA) and machine learning techniques. The study highlighted that the integrated AI-assisted approach enabled the tracking and predictive modelling of the tower's dynamic behaviour under environmental and seismic effects, especially after the 2016–2017 seismic sequence, while environmental influences were also accounted for to improve the reliability of structural assessment. It was further observed that the framework helped in assessing structural health, minimizing invasive inspections, avoiding unnecessary interventions, and extending the service life of the structure. The findings suggested that AI-assisted SHM could significantly improve the resilience, sustainability, and preservation of historic masonry towers, while also offering a replicable model for cultural heritage conservation.

Anupam et al. (2026) examined dielectric elastomer minimum energy structures (DEMES), which had attracted considerable attention due to their capability to switch between multiple equilibrium states. The authors explained that these structures were formed when a pre-stretched elastomer film adhered to an inextensible frame and attained equilibrium through energy minimization. It was reported that conventional approaches for analyzing DEMES mechanics, including numerical, theoretical, and experimental methods, had often been labor-intensive and time-consuming. To address this limitation, the study introduced the use of artificial neural network (ANN) techniques for efficiently predicting the behavior of DEMES-based actuators. Using the Levenberg–Marquardt and Bayesian Regularization algorithms, the performance of two prototypes, namely the four-arm gripper and the flapping-wing actuator, was predicted. The findings indicated that the ANN-based approach had shown excellent agreement with numerical results while substantially reducing computational time. The study concluded that ANN techniques had offered a fast and reliable tool for the parametric evaluation, design, and analysis of DEMES structures.

Liew and Chua (2025) discussed advancements in modular construction, focusing on steel and concrete modular systems, as well as an innovative lightweight and long-span steel–concrete composite approach. They highlighted the constructability, strength, and robustness of these systems, noting that steel modular systems utilized lightweight properties for rapid assembly and structural integrity through corner support systems, whereas concrete modular systems emphasized durability and fire resistance via composite structural wall systems. The authors proposed a lightweight steel–concrete composite system that combined the advantages of both materials, providing extended spans, durability, flexibility, and ease of assembly. They described robust fast-joining techniques and a lightweight steel fibre-reinforced slim floor system that enabled expedited installation and global stability. The study also indicated that the integration of automation and prefabrication techniques could transform construction practices by improving productivity, efficiency, and quality. Finally, they suggested directions for further research to develop more sustainable and efficient building solutions capable of addressing site installation challenges.

Wang et al. (2025) proposed a finite element model updating method for super high-rise buildings based on the response surface method (RSM) to accurately represent their dynamic characteristics and enhance simulation accuracy. They considered a 120 m super high-rise building as the study object and initially developed a refined finite element model, identifying the elastic modulus and density of the main concrete and steel components as parameters for updating. A significance analysis was performed on 16 parameters, including E1–E8 and D1–D8, along with the first ten natural frequencies, from which six parameters were ultimately selected. A sample set of updating parameters was generated using central composite design (CCD) and applied to the finite element model. Response surface equations for the first ten natural frequencies were obtained through quadratic polynomial fitting, and a genetic algorithm was employed to determine the optimal solution of the objective function. The case study results showed that errors in the first ten natural frequencies of the updated model remained within 5%, demonstrating that the model accurately reflected the building's current condition and provided a basis for structural health monitoring, damage detection, and reliability assessment.

Zhang (2024) highlighted that advancements in computer and Internet technology had reached a peak of innovation, with applications becoming increasingly widespread. The study emphasized that computer simulation technology had emerged as a key direction in recent years, capable of significantly influencing daily life. The author examined the role of finite element analysis (FEA) in structural analysis by employing ANSYS-based FEA combined with structural analysis methods and validating the approach through computer-simulated welding thermal cycle examples. The results indicated that the simulated temperature curves closely matched experimentally measured curves, with the absolute error initially increasing to a maximum around 11 seconds before rapidly declining and gradually stabilizing near 180–200 °C. The study suggested that such computer simulations could accurately model welding temperature fields and offered valuable insights for welding research. Furthermore, the integration of FEA with structural analysis reportedly reduced simulation runtime by an average of 3.58 minutes and improved overall efficiency by 21.81%, demonstrating that FEA could optimize structural analysis, enhance accuracy, and expand the practical applications of computer simulation technology.

Arangarajan et al. (2024) investigated the domain of structural analysis and finite element methods in mechanical design, employing a multifaceted approach to comprehensively examine the mechanical behaviour of building structures. They applied Finite Element Analysis (FEA) to study a steel structure under various loading conditions, identifying stress distributions critical for structural optimization. The research further focused on Fluid-Structure Interaction (FSI), exploring the complex interplay between fluid forces and structural responses, and proposed implications for offshore construction. Thermal simulations of composite materials were conducted to provide insights into temperature-induced stresses, guiding material selection and design modifications in extreme thermal environments. Sensitivity analyses and parametric studies were performed to systematically evaluate the effects of design parameters on structural performance, supporting optimization efforts. Validation against experimental data was reported to enhance the reliability and accuracy of the numerical simulations.

Thakkar et al. (2023) highlighted that bridges played a crucial role in modern transportation infrastructure by providing convenient and efficient connectivity, yet they were vulnerable to forces that could cause substantial damage, particularly during seismic events. They observed that a country's economy depended heavily on its bridge network, while many older bridges constructed before 1970 exhibited signs of deterioration influenced by climate change and other factors. The authors noted that seismic design codes at the time of construction lacked sufficient guidance for ensuring ductility and capacity, resulting in deficient structures. Their study reviewed existing literature on the seismic behaviour of bridges and the analytical approaches employed to evaluate performance, emphasizing the factors affecting different bridge types. They aimed to establish a theoretical basis for selecting suitable analysis methods, focusing on retrofitting, pre-earthquake planning, and loss assessment. Additionally, they elaborated on seismic design philosophies, analytical methodologies, and the development of fragility curves, including their application to retrofitted bridges.

Abid et al. (2022, March) aimed to introduce a simplified flexible design model for thermal actions in concrete bridge superstructures, and they conducted both experimental and finite element analyses to achieve this. They reported that concrete temperature, solar radiation, air temperature, and wind speed were recorded from an experimental concrete box-girder segment over a full one-year cycle and were utilized in the study. A thermal finite element model was then developed and verified, which was subsequently employed for parametric analyses. They also used the verified model along with long-term climate data from 1960 to 2013 for 10 cities in Turkey to propose thermal action design models and procedures. Furthermore, they presented positive and negative vertical temperature gradient models based on the top surface maximum temperature gradient, linked to the region's solar radiation history, and suggested simplified correlations and design procedures to estimate the maximum and minimum mean temperatures of concrete bridges.

Kasuga (2021) examined hybrid structures, emphasizing two primary objectives: reducing the weight of concrete structures through technological integration and clarifying structural functions by combining different materials. The study illustrated the first objective with lightweight bridges, noting that various hybrid bridge types, such as corrugated steel web, hybrid truss, and composite girder types, had been constructed. However, it was highlighted that steel components necessitated ongoing maintenance throughout the structure's lifespan. To address this, Kasuga described the development of the butterfly web bridge, which combined conventional concrete with high-strength fibre-reinforced concrete. The precast web panels, shaped like butterfly wings and reinforced only in tension areas with prestressing steel, achieved a thickness of 15 cm, while other concrete members were cast-in-place, resulting in a 15–20 % weight reduction compared with conventional concrete box girders. The second objective was exemplified by the hybrid stay cable anchorage system in cable-stayed and extradosed bridge towers, where steel resisted horizontal tensile forces and concrete absorbed vertical compressive forces. Kasuga reported that laboratory experiments had been conducted to confirm the structural behaviour of these evolving systems and traced the evolution of stay cable anchorage technologies from the 2000s to more cost-effective solutions in the 2010s.

Wilches et al. (2021) examined the historical evolution of seismic design codes and structural systems for bridges in Chile, a country with a long history of strong seismicity. They indicated that Chile had continually upgraded its seismic design standards, particularly after major earthquakes, yet recent seismic events had still caused extensive damage to highway bridges, including deck collapses, large transverse residual displacements, yielding and failure of shear keys, and unseating of main girders. Much of this vulnerability was attributed to construction deficiencies and insufficient detailing guidelines in earlier design codes. Following the 2010 Maule earthquake, they reported that new structural design criteria were introduced, notably the inclusion of a site coefficient for seismic force estimation in shear keys, seismic bars, and diaphragms. The authors traced Chilean earthquake history and bridge construction practices, described the main failure modes observed during the Maule event, and compared Chilean bridge seismic codes with Japanese and U.S. standards, concluding that Chilean design and construction practices had progressively evolved toward more conservative approaches to enhance structural performance and reliability.

III. KEY FINDINGS FROM STUDY

Author & Year	Title	Methodology	Key Findings	Relevance to Intelligent Structural Analysis Systems
Mota et al. (2026)	Generative AI chatbot impacts on SMEs	MCDA, ISM, MICMAC, expert validation	Identified key barriers and structured cause–effect relationships in AI adoption	Shows structured AI decision frameworks applicable to engineering systems
Standoli et al. (2026)	AI-based SHM of heritage masonry towers	Sensor-based monitoring, OMA, ML models	AI improved predictive monitoring and reduced invasive inspections	Demonstrates AI-driven structural health monitoring systems
Anupam et al. (2026)	ANN-based DEMES analysis	ANN (Levenberg–Marquardt, Bayesian Regularization)	ANN accurately predicted structural behavior with reduced computation time	Shows ANN effectiveness in structural response prediction
Liew & Chua (2025)	Modular construction systems	Conceptual + structural analysis	Steel–concrete composites improved efficiency, strength, and constructability	Supports AI-enabled modular structural optimization concepts
Wang et al. (2025)	FEM model updating using RSM	Finite element modeling + RSM + GA optimization	Updated model reduced frequency error to within 5%	Demonstrates AI-based model calibration in structural systems
Zhang (2024)	FEA in structural simulation	Numerical simulation (ANSYS-based)	Improved accuracy and reduced computational time in structural simulations	Highlights integration of computational intelligence in FEA
Arangarajan et al. (2024)	FEA & mechanical simulation	FEA, FSI, thermal analysis, sensitivity study	Enhanced optimization and reliability of structural behavior prediction	Supports AI-assisted multi-physics structural modeling

Thakkar et al. (2023)	Bridge fragility analysis	Literature review + seismic assessment models	Identified vulnerabilities in bridge seismic performance	Shows need for AI-based predictive bridge safety systems
Abid et al. (2022)	Thermal effects in concrete bridges	Experimental + FEM + climate modeling	Developed temperature gradient-based design models	Supports AI-enhanced environmental structural prediction
Kasuga (2021)	Hybrid bridge structures	Experimental + structural design review	Hybrid systems reduced weight and improved performance	Indicates AI potential in material-structure optimization
Wilches et al. (2021)	Seismic design evolution in bridges	Historical + comparative code analysis	Improved seismic codes reduced but did not eliminate failures	Emphasizes need for AI-based seismic risk prediction

IV. CONCLUSION

The reviewed literature clearly indicated that intelligent structural analysis systems powered by artificial intelligence (AI) techniques have significantly transformed the field of structural engineering by enhancing prediction accuracy, computational efficiency, and decision-making capabilities. Traditional structural analysis methods such as finite element analysis (FEA), while highly reliable, often face limitations in handling complex, nonlinear, and large-scale structural problems. The integration of AI techniques, including machine learning, artificial neural networks (ANN), response surface methods, and hybrid optimization algorithms, has provided a powerful alternative for addressing these challenges. Studies such as those by Standoli et al. (2026) and Anupam et al. (2026) demonstrated that AI-based models can effectively improve structural health monitoring and predict complex structural behaviors with reduced computational cost. Similarly, Wang et al. (2025) and Zhang (2024) highlighted that AI-assisted finite element model updating and simulation techniques significantly enhance structural accuracy and reliability. Furthermore, research in modular construction, seismic analysis, and hybrid structural systems has shown that AI integration supports optimization of materials, improves structural resilience, and enables better risk assessment under dynamic loading conditions. The evolution of bridge engineering studies by Thakkar et al. (2023) and Wilches et al. (2021) further emphasized the importance of predictive modeling in reducing structural failures and improving seismic design standards. Overall, the literature confirmed that AI-driven structural analysis systems are not only improving existing engineering practices but are also reshaping the future of structural design, monitoring, and maintenance. These systems enable real-time data processing, adaptive learning, and predictive diagnostics, which collectively contribute to safer, more efficient, and more sustainable infrastructure development. Therefore, the integration of AI techniques into structural engineering represents a major advancement that bridges the gap between traditional mechanics-based approaches and modern intelligent computational frameworks, ultimately supporting the development of next-generation smart structural systems.

V. FUTURE SCOPE

- **Integration of Advanced AI and Deep Learning Models:** Future research can focus on the development of deep neural networks, reinforcement learning, and hybrid AI models to improve the accuracy and adaptability of structural analysis systems for complex and nonlinear structures.
- **Real-Time Structural Health Monitoring Systems:** The incorporation of IoT sensors with AI algorithms can enable continuous real-time monitoring of buildings, bridges, and critical infrastructure, allowing early detection of damage and predictive maintenance strategies.

- **Digital Twin Technology in Structural Engineering:** The development of digital twins of infrastructure systems can provide real-time virtual replicas of physical structures, enabling simulation, monitoring, and optimization under varying environmental and loading conditions.
- **AI-Based Seismic Risk Assessment and Disaster Mitigation:** Future studies can focus on integrating AI with probabilistic seismic models to enhance earthquake prediction, fragility analysis, and structural retrofitting strategies for improved resilience.
- **Automation in Finite Element Modeling and Optimization:** AI can be further used to automate mesh generation, parameter selection, and model calibration in finite element analysis, reducing human intervention and improving computational efficiency.
- **Sustainable and Smart Infrastructure Design:** Research can explore AI-driven optimization of sustainable materials, energy-efficient structures, and eco-friendly construction practices to support green building initiatives.
- **Big Data Analytics in Structural Engineering:** The use of large-scale structural datasets combined with machine learning can improve pattern recognition, failure prediction, and long-term performance evaluation of infrastructure systems.
- **Integration with Building Information Modeling (BIM):** Combining AI with BIM platforms can enhance design coordination, construction planning, and lifecycle management of structural systems.
- **Edge Computing and Cloud-Based Structural Analysis:** Future systems may utilize cloud computing and edge AI to process structural data faster and enable decentralized decision-making in smart infrastructure networks.
- **Human–AI Collaborative Engineering Systems:** Development of interactive AI tools that assist engineers in decision-making while preserving human expertise will be a key direction for practical implementation in structural engineering.

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