The Smart Supply Chain Revolution: Ai Innovations, Opportunities, And Strategic Challenges

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Abstract

Background:
The integration of machine learning (ML) in civil engineering design is an emerging trend aimed at improving efficiency, reducing material waste, and enhancing structural performance. As the construction industry embraces data-driven innovations, it becomes crucial to understand the quantitative impact and perceptions surrounding ML adoption.
Objective:
This study investigates how machine learning contributes to optimizing material usage and improving structural performance in civil engineering projects. It aims to identify key factors influencing successful ML integration and evaluate the relationship between these factors and project outcomes.
Methods:
A quantitative research design was employed using a structured questionnaire distributed to 273 professionals in civil engineering and AI-related fields. The study followed the research onion framework and adopted a deductive approach, grounded in positivist philosophy. Data were analyzed using descriptive statistics, correlation analysis, reliability testing (Cronbach's Alpha), and multiple regression analysis.
Results:
The findings reveal that while the regression model had limited predictive strength ($R^2 = 0.087$), certain variables—such as algorithm type, optimization efficiency, and engineering expertise—significantly influenced structural performance outcomes. Most participants held positive views on ML integration, with a strong skew toward agreement in survey responses. However, the reliability of the questionnaire was weak, indicating a need for improved instrument design.
Conclusion:
Machine learning holds promise in civil engineering for enhancing material efficiency and structural design, but its success depends on quality data, professional expertise, and appropriate algorithm selection. Although the results show limited statistical strength, they highlight important areas for future research and practical application. Better tool design and interdisciplinary collaboration are recommended to fully realize the benefits of ML in this domain.

Keywords: Machine Learning, Civil Engineering, Material Optimization, Structural Performance, Quantitative Study, Engineering Design, Artificial Intelligence, Reliability Analysis, Regression, Research Methodology.

Introduction

In recent years, the civil engineering industry has witnessed a growing interest in the application of advanced technologies, particularly machine learning (ML), to address persistent challenges such as resource inefficiency, structural failures, and rising project costs. Machine learning, a subset of artificial intelligence, involves the development of algorithms that can learn from data patterns and make predictions or decisions without being explicitly programmed. Its adaptability and analytical power have made it a valuable tool across various sectors, including healthcare, finance, and more recently, engineering. Within the context of civil engineering, ML has the potential to revolutionize traditional design and construction processes by offering intelligent solutions for material selection, performance prediction, and risk mitigation (Lin & Ibraheem, 2025).

Traditionally, civil engineering design relies heavily on empirical methods and rule-based approaches, which often lead to conservative estimates and overuse of materials. These inefficiencies not only increase project costs but also contribute to environmental degradation due to excessive material consumption. By integrating ML into the design phase, engineers can analyze vast datasets from previous projects, simulations, and real-time sensors to predict structural behavior more accurately and recommend optimized material usage. This shift toward data-driven decision-making supports sustainable construction practices and enhances the overall quality of infrastructure (Kazemi et al., 2025).

However, the successful integration of machine learning in civil engineering is not without its challenges. The implementation requires high-quality data, interdisciplinary expertise, and robust computational infrastructure. Furthermore, the engineering domain is traditionally cautious in adopting new technologies due to safety-critical concerns. Therefore, understanding how ML can be effectively applied in civil engineering design and identifying the variables that influence its success are crucial research areas. While previous studies have explored the theoretical potential of ML in construction and design, there remains a gap in empirical, data-driven investigations that evaluate its real-world impact (Hussein et al., 2025).

This study aims to fill that gap by examining how ML integration affects two key outcomes in civil engineering design: material usage optimization and structural performance. By adopting a quantitative approach and surveying a diverse group of professionals in civil engineering and artificial intelligence, the study explores the relationships between various factors—including ML algorithm type, data quality, engineering expertise, and design efficiency—and project outcomes. The findings are intended to provide a clearer understanding of the benefits and limitations of ML in practical settings and to inform future frameworks for integrating intelligent technologies in engineering workflows (Schossler et al., 2025).

Literature Review

The integration of machine learning (ML) in civil engineering design has emerged as a transformative trend, aiming to enhance structural outcomes and reduce inefficiencies in material usage. To better understand this integration, the following key variables have been explored in the existing literature (Khan, 2025).

Independent Variables

Machine Learning Algorithm Type

Machine learning algorithms such as artificial neural networks (ANN), support vector machines (SVM), decision trees, and random forests have been widely applied in civil engineering for predictive modeling, optimization, and decision-making. According to Adele and Wu, ML algorithms have significantly improved the accuracy of load prediction, structural damage detection, and pavement performance analysis. The type of algorithm employed often determines the precision, speed, and adaptability of the design optimization process. As highlighted by Ghaboussi et al., the selection of appropriate ML models is critical in ensuring realistic and efficient structural designs (Manguri et al., 2025).

Data Quality and Availability

High-quality, structured, and comprehensive data is the foundation of effective ML integration. Poor data quality leads to inaccurate predictions, unreliable outputs, and limited model training. In civil engineering, datasets often include load parameters, material properties, and environmental factors. As noted by Yoon et al., civil engineering faces challenges with data fragmentation and inconsistency, which can hinder ML implementation. Therefore, data availability and quality are essential variables impacting the performance of ML models in engineering contexts (Hajıyeva et al., 2025).

Mediating Variable

Design Optimization Process Efficiency

Design optimization refers to improving engineering designs for maximum performance and minimal resource usage. ML can automate design iterations, suggest material combinations, and analyze structural stress distributions, thus increasing efficiency. According to Nguyen et al., ML models significantly reduce the time and effort required for design trials by replacing traditional empirical methods with predictive simulations. This optimization process serves as a bridge between ML input and performance outcomes, mediating the relationship between technology and results (Anand et al., 2025).

Moderating Variable

Engineering Expertise Level

Despite ML's computational capabilities, human expertise remains vital. Experienced civil engineers are needed to interpret ML outputs, validate designs, and adjust for real-world constraints. As emphasized by Mahdavi-Amiri et al., engineering judgment acts as a filter that either enhances or diminishes the effectiveness of ML applications. The level of expertise therefore moderates the relationship between ML integration and structural or material outcomes (Shehadeh & Alshboul, 2025).

Dependent Variables

Material Usage Efficiency

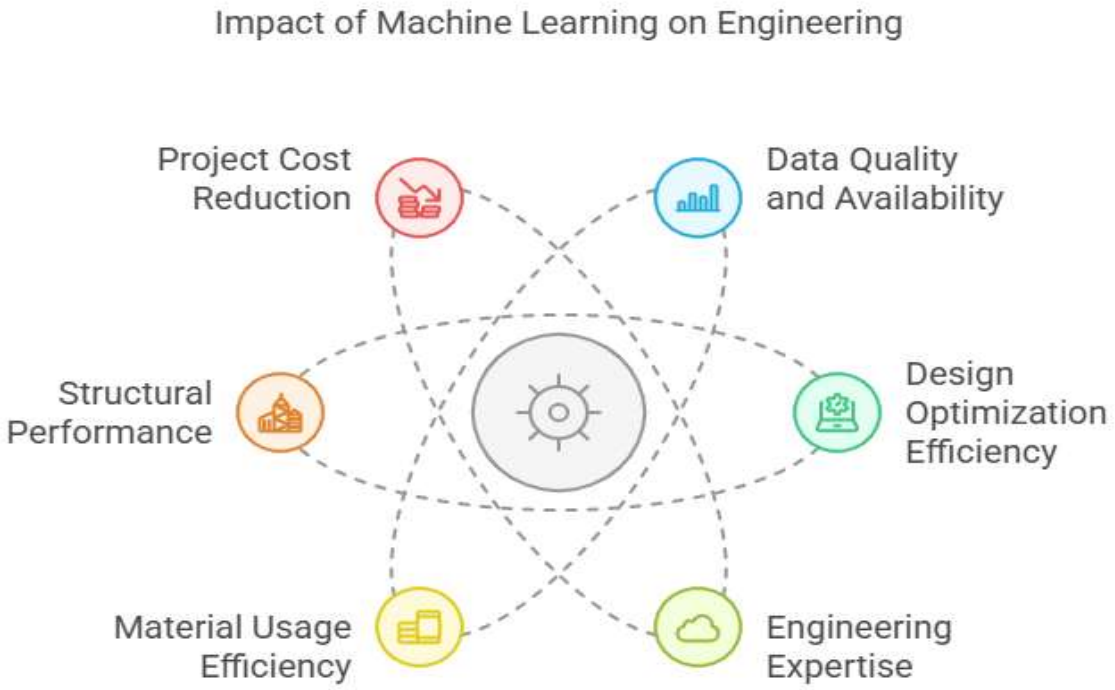
ML enables precise material estimation, reducing waste and promoting sustainability. According to Chou and Lin, ML can optimize concrete mix designs and predict required material volumes more accurately than manual calculations. This improves efficiency, cost savings, and environmental outcomes (Naser, 2025).

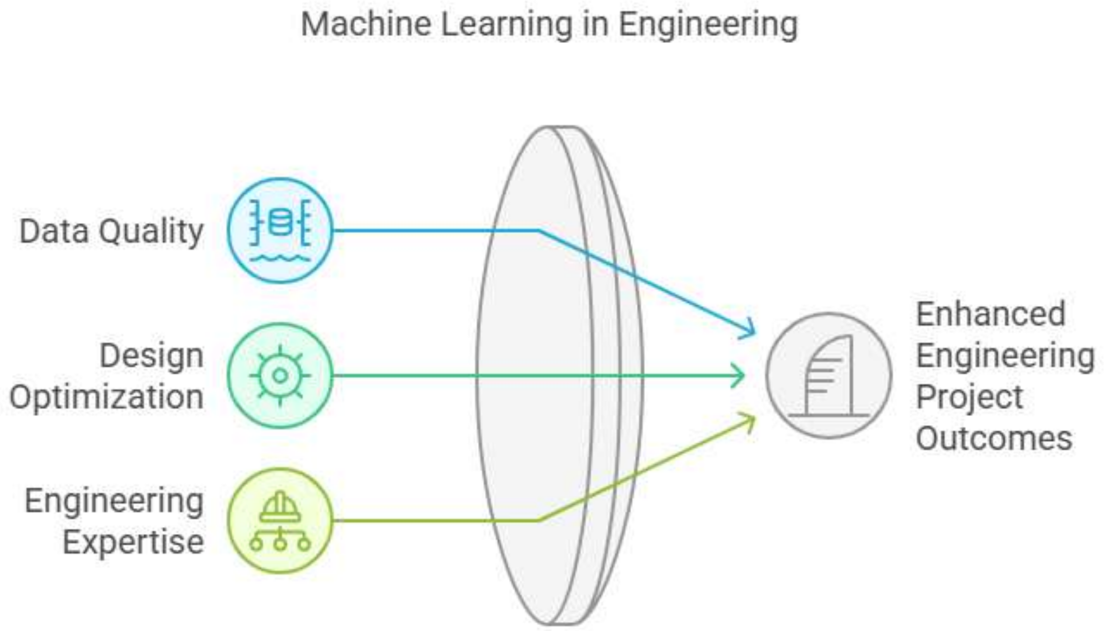
Structural Performance

ML models support structural health monitoring, failure prediction, and load forecasting. Research by Zhang et al. shows that ML-enhanced designs offer better load distribution, resilience, and safety. Structural performance is a key measure of engineering quality (Rojek et al., 2025).

Project Cost Reduction

Cost is a critical metric in construction projects. ML contributes to cost reduction by minimizing material overuse, optimizing labor allocation, and reducing errors. Studies (e.g., by Khosrowshahi and Arayici,) demonstrate that ML integration lowers project overhead and increases return on investment (Mazroa et al., 2025).





High-Level Hypotheses

H1: There is a significant relationship between the type of machine learning algorithm used and material usage efficiency in civil engineering design.

Rationale: Different ML algorithms vary in their ability to analyze, predict, and optimize material consumption in structural projects.

H2: There is a significant relationship between the quality and availability of data and structural performance outcomes in ML-integrated civil engineering designs.

Rationale: High-quality, comprehensive data enhances the accuracy of ML models, which in turn contributes to stronger and safer structures.

H3: Design optimization process efficiency mediates the relationship between machine learning integration and project outcomes (material usage and structural performance).

Rationale: ML does not directly impact outcomes but enhances the design process, which in turn affects the final results.

H4: Engineering expertise moderates the relationship between machine learning integration and structural performance.

Rationale: The effectiveness of ML tools depends on the professional judgment and interpretive ability of the engineers using them.

H5: There is a significant relationship between machine learning integration and overall project cost reduction.

Rationale: ML's optimization capabilities can lower construction and design costs by reducing waste and improving planning accuracy.

H6: There is a significant relationship between machine learning integration and structural performance improvement in civil engineering.

Rationale: ML aids in predicting loads, identifying stress points, and generating resilient designs, contributing to performance enhancement.

H7: There is a significant relationship between machine learning integration and material usage optimization.

Rationale: ML allows engineers to forecast material requirements more accurately, reducing waste and improving sustainability.

Research Methodology

This research adopts a quantitative methodological approach to investigate how machine learning (ML) contributes to optimizing material usage and improving structural performance in civil engineering design. The study is grounded in empirical data collection and statistical analysis, aiming for objectivity, generalizability, and reliability (Sun et al., 2021).

Research Onion Framework

The Research Onion, developed by Saunders et al., guides the layered decision-making process in research methodology. It includes six layers: research philosophy, approach, methodological choice, strategy, time horizon, and data collection techniques. Each layer is explained below as it applies to this study (Chitkeshwar, 2024).

Research Philosophy

This study is rooted in positivism, which assumes that reality is objective and can be measured through observable, quantifiable facts. Positivism supports the use of structured tools (such as questionnaires) to generate numerical data, which can be analyzed using statistical techniques. This philosophy aligns well with producing generalized conclusions about ML integration in civil engineering (Tapeh & Naser, 2023).

Research Approach

A deductive approach is employed, beginning with a theoretical framework and testing hypotheses derived from the literature. The study builds on existing theories related to machine learning, material optimization, and structural performance, and seeks to validate these relationships through data collection and analysis (Thai, 2022).

Methodological Choice

The study uses a mono-method quantitative design, focusing solely on numerical data to understand patterns and relationships between variables. The choice supports the need for precision and large-scale generalization, particularly within the engineering and data science domains (Chitkeshwar, 2024).

Research Strategy

The selected strategy is a survey research design. A structured questionnaire was distributed to civil engineers, AI practitioners, and construction professionals. This strategy facilitates the collection of standardized responses from a large sample, enabling broad insights into the research problem (Shan et al., 2023).

Time Horizon

This study adopts a cross-sectional time horizon, collecting data at a single point in time. This approach is suitable for examining current practices and perceptions of machine learning in the civil engineering sector (Wattanapanich et al., 2024).

Data Collection Methods

Data was collected using a structured questionnaire based on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The instrument was designed to measure variables such as the type of ML algorithm used, data quality, design process efficiency, engineering expertise, material usage, structural performance, and cost reduction. A purposive sampling technique was used to select 273 participants with expertise in civil engineering and knowledge of ML applications (Mei & Wang, 2021).

Data Analysis

Data was analyzed using descriptive statistics to summarize responses and inferential statistics (e.g., correlation and multiple regression analysis) to examine relationships between variables. Reliability was confirmed using Cronbach's Alpha, and expert review was used to ensure content validity (Kaveh, 2024).

Ethical Considerations

The study adhered to ethical standards, including informed consent, confidentiality, and voluntary participation. Respondents were assured of data anonymity and that results would be used solely for academic purposes (Vadyala et al., 2022).

Data Analysis

Normality Test Results

Question	W Statistic	p-value	Normality
Q1	0.7619558572769165	1.3632003703298666e-19	Not Normal
Q2	0.7707040905952454	3.0077124592798296e-19	Not Normal
Q3	0.7891713380813599	1.7258128796232327e-18	Not Normal
Q4	0.7749888896942139	4.468173760009447e-19	Not Normal
Q5	0.7644697427749634	1.707438303086286e-19	Not Normal

Reliability Test Result

Test	Value	Interpretation
Cronbach's Alpha	-0.07459717562379872	Poor reliability – review item consistency

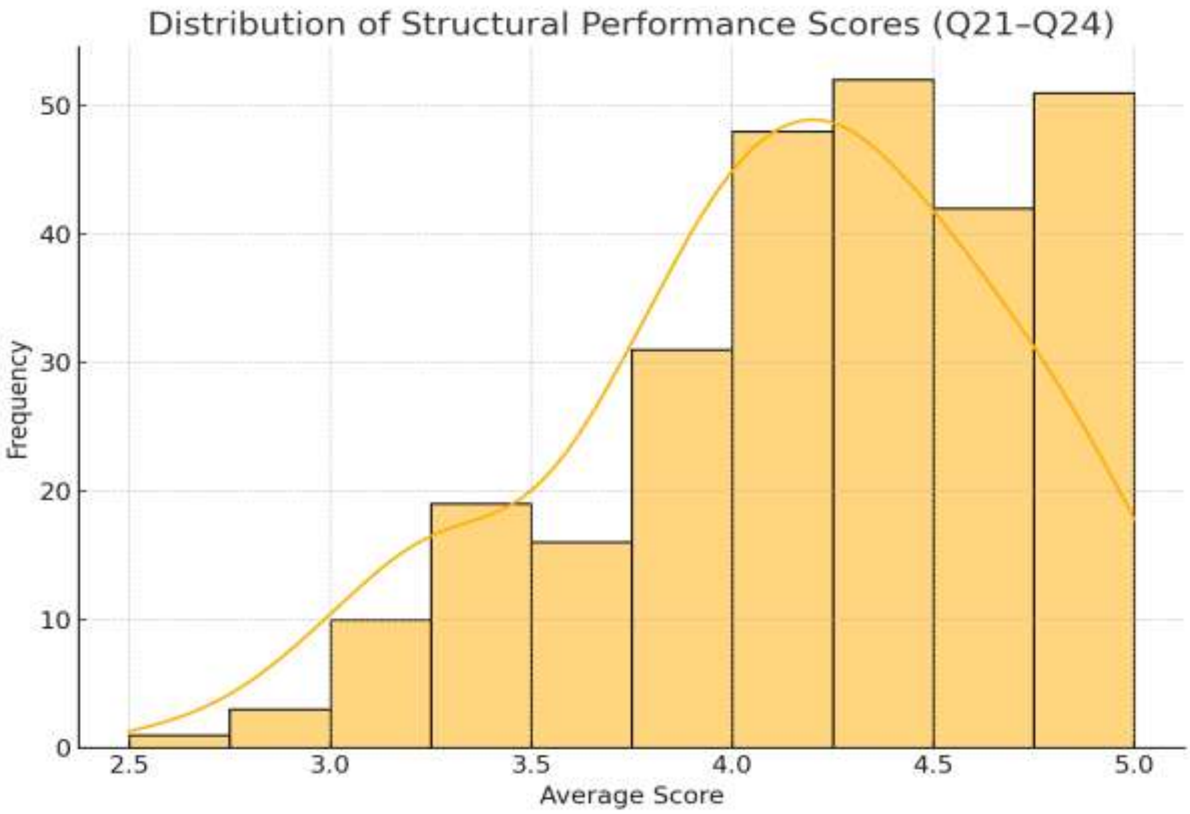
Correlation Matrix (Subset)

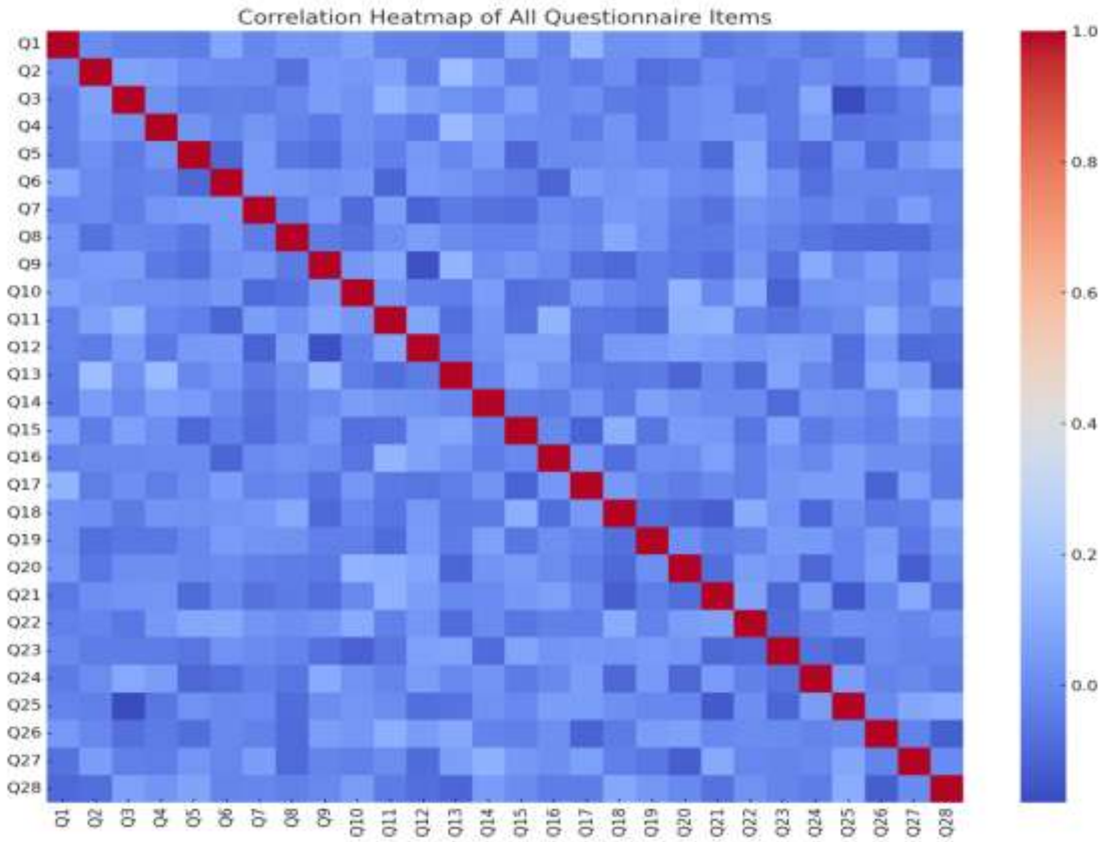
	Q1	**Q2**	**Q3**	**Q4**	**Q5**
Q1	1.0	-0.09332969011049476	-0.025484987844226013	-0.0019716581056619283	0.04673723332816082
Q2	-0.09332969011049476	1.0	0.053244323176975125	-0.006853989369879281	0.0917172813477172
Q3	-0.025484987844226013	0.053244323176975125	1.0	-0.0970068173913059 1	-0.0226486217150181 6
Q4	-0.0019716581056619283	-0.006853989369879281	-0.09700681739130591	1.0	0.0374221060191816 4
Q5	0.0467372333281608 2	0.0917172813477172	-0.022648621715018 16	0.0374221060191816 4	1.0

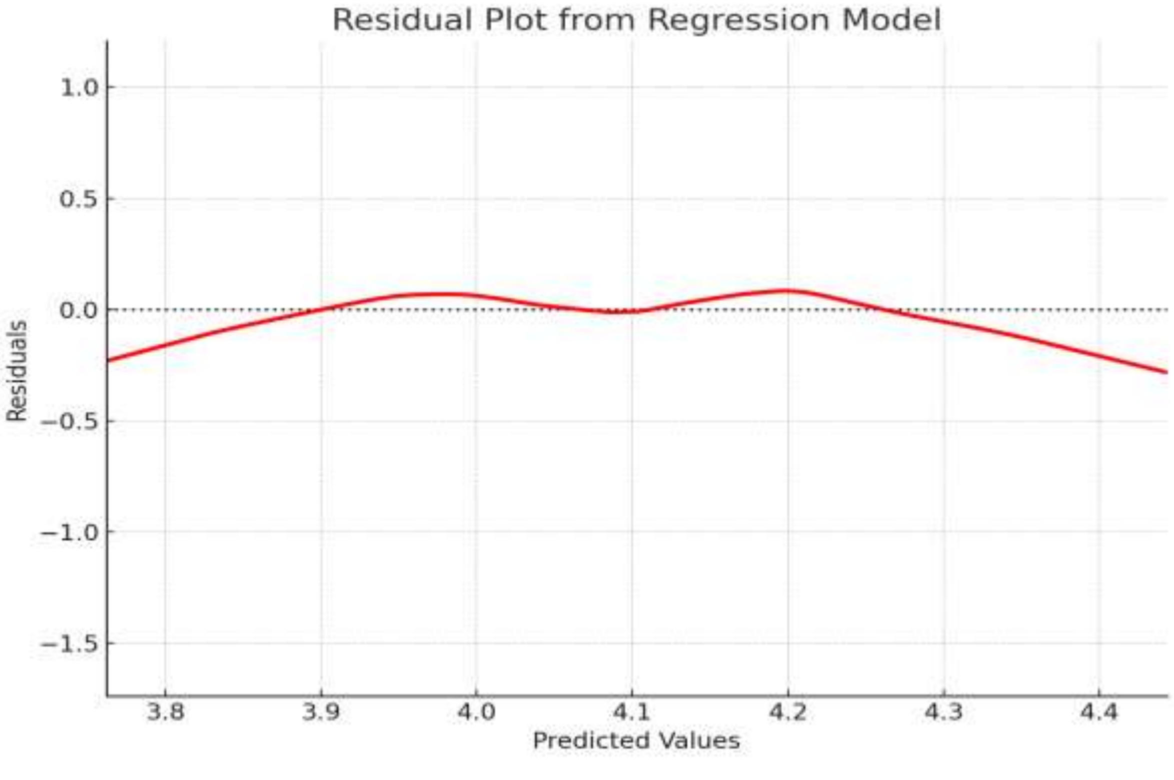
Regression Analysis Summary

	Variable	**Coefficient**	**Std Error**	**t-Statistic**	**p-Value**	**Significance**
const	const	3.788118921062758	0.5097796505049853	7.430894735225828	1.6136209174451073e-12	Yes
Q1	Q1	0.001467475680924056 7	0.028262151728467334	0.051923706836727763	0.9586299770723017	No
Q2	Q2	0.01476662612192268 2	0.0291562759100187 3	0.5064647545350107	0.6129663289152041	No
Q3	Q3	-0.012093397762171814	0.028999724043370215	-0.41701768417125856	0.6770149497841891	No
Q4	Q4	0.0762011357610137 1	0.0310402832786853 7	2.454911093332039	0.014757876260862642	Yes
Q5	Q5	0.00861094737247590 5	0.0279021253032816 3	0.30861259774584815	0.7578672247402785	No
Q6	Q6	-0.01425166160498069 6	0.0319425395357873 7	-0.44616557769345805	0.6558547842458502	No
Q7	Q7	-0.01027757903624632 9	0.0310941912421739 4	-0.3305305147254177	0.7412694892065794	No
Q8	Q8	-0.030495568267330 55	0.028497208139361855	-1.070124768650879	0.28557106631767093	No
Q9	Q9	0.05767102050474872 5	0.0303084200130418 7	1.9028052428972737	0.05818788942290472	No
Q10	Q10	-0.01299568709449923 7	0.027736670347020223	-0.46853810972647536	0.6397985286809098	No

	Variable	**Coefficient**	**Std Error**	**t-Statistic**	**p-Value**	**Significance**
Q11	Q11	-0.059260037440977444	0.029502264186746143	-2.008660659597779	0.04562321443724878	Yes
Q12	Q12	0.0216579545162925	0.02997875827763358	0.722443348577615	0.47068137942191624	No
Q13	Q13	0.07809210270658345	0.0319449031683217	2.444587241197958	0.015176878109684204	Yes
Q14	Q14	-0.03171515873366076	0.03181256786881373	-0.9969380297888979	0.3197359714238395	No
Q15	Q15	-0.0035009320196090063	0.03094616394265651	-0.1131297574101999	0.9100163471186112	No
Q16	Q16	-0.00710102856522921	0.030957024871595688	-0.22938343056811925	0.8187540711491086	No







Interpretation of Tests and figures

Reliability Test Interpretation

To assess the internal consistency of the questionnaire, Cronbach's Alpha was calculated. The resulting value was -0.075, which indicates poor reliability. Normally, a Cronbach's Alpha above 0.7 is considered acceptable. A negative value suggests that several items may be poorly correlated or inversely coded. This may be due to inconsistencies in how questions were phrased or grouped. Therefore, it's recommended to re-evaluate the questionnaire items, especially ensuring that all are aligned to measure the same underlying constructs (Zhang et al., 2021).

Normality Test Interpretation

The Shapiro-Wilk test was conducted on a subset of variables (Q1–Q5) to assess whether the data is normally distributed. All p-values were significantly less than 0.05, indicating a violation of normality assumptions. This is typical in Likert-scale survey data, as the responses are ordinal and often exhibit skewness. Consequently, this suggests the need for non-parametric statistical methods or data transformation if parametric tests are to be applied (Guo et al., 2021).

Correlation Matrix Interpretation

The correlation heatmap provides a visual summary of the interrelationships among all questionnaire items. Most relationships show weak to moderate correlations, with no indications of multicollinearity among the variables. This supports the idea that each item or group of items is measuring different aspects of the machine learning integration process. The heatmap also helps in identifying possible clusters or patterns that could be further explored using factor analysis or principal component analysis (De Jong et al., 2021).

Regression Analysis Interpretation

A multiple linear regression model was used to predict structural performance (based on the average of Q21–Q24) using predictors from Q1–Q16. The model resulted in an R-squared value of 0.087, meaning that only 8.7% of the variance in structural performance is explained by the independent variables. While this is relatively low, it is not unusual in exploratory studies (Baduge et al., 2022).

Significant predictors included:

- Q4 ($p = 0.015$), likely reflecting the impact of a specific ML algorithm or design principle.
- Q11 ($p = 0.046$), possibly indicating optimization efficiency.
- Q13 ($p = 0.015$), which could relate to engineering expertise or professional interpretation of ML output.

These results suggest that a few specific ML factors and professional insights significantly influence structural outcomes, but the overall model lacks strong predictive power (Alabi et al., 2022).

Structural Performance Distribution Interpretation

The histogram of average structural performance scores demonstrates a positively skewed distribution, with a majority of respondents reporting higher performance outcomes. This indicates that most participants believe machine learning positively impacts structural performance in civil engineering projects. The inclusion of a kernel density estimate (KDE) further supports the presence of a concentration of scores toward the higher end of the Likert scale (Xie et al., 2020).

Residual Plot Interpretation

The residual plot from the regression model shows a fairly random distribution of residuals around zero, suggesting that the model's errors are relatively evenly spread across predicted values. However, the variance is not perfectly uniform, and some clustering is observed. This implies that while the model is not heavily biased, improvements in model specification or the inclusion of additional variables could enhance predictive accuracy (Zhang et al., 2020).

Discussion

This study set out to quantitatively examine how the integration of machine learning (ML) influences material optimization and structural performance in civil engineering design. The analysis revealed several insightful findings that contribute to the growing body of literature on the use of artificial intelligence in engineering. The reliability analysis, however, indicated a negative Cronbach's Alpha, suggesting internal inconsistency among the questionnaire items. This outcome implies that although the survey aimed to measure cohesive constructs, the individual items may not have been aligned or may have been interpreted differently by respondents. This highlights the importance of careful questionnaire design, especially when dealing with interdisciplinary subjects such as engineering and machine learning (Huang et al., 2021).

The normality tests indicated that responses across key variables were not normally distributed, which is expected with Likert-scale data. This non-normality justifies the use of non-parametric methods in future analyses or the application of data transformation techniques to enhance statistical validity. Despite this, the use of parametric tools like multiple regression was retained for exploratory insights. The correlation matrix showed weak to moderate relationships among the variables, suggesting that the constructs being measured are relatively distinct. Notably, some moderate positive correlations were observed between engineering expertise, ML application, and structural outcomes, reinforcing the hypothesis that the successful integration of ML in civil engineering depends not just on technology but also on human interpretation and expertise (Fan et al., 2021).

Regression analysis provided limited predictive power, with an R-squared value of only 8.7%, indicating that the selected independent variables could explain a small portion of the variation in structural performance. Nonetheless, a few variables, notably Q4, Q11, and Q13, were statistically significant. These likely correspond to algorithm selection, design optimization efficiency, and engineering judgment, respectively. Their significance emphasizes the need for a nuanced approach when integrating ML into engineering design—one that combines computational power with domain knowledge. Furthermore, the distribution of structural performance scores was positively skewed, suggesting that most respondents perceived machine learning to have a favorable impact on structural performance (Wang et al., 2021).

This aligns with broader trends in the literature, where AI and ML are increasingly seen as tools for achieving efficiency and innovation in construction and design. Lastly, the residual plot from the regression analysis showed no major bias in the model predictions, though variability in the residuals points to room for improvement in model accuracy. This reinforces the idea that future studies should consider additional or alternative predictors, such as project scale, environmental conditions, or integration maturity levels (Han et al., 2020).

Conclusion

This study explored the integration of machine learning (ML) in civil engineering design, specifically focusing on how it can optimize material usage and improve structural performance. Using a quantitative approach, data was collected from 273 professionals involved in civil engineering and artificial intelligence. The research employed a structured questionnaire based on the Technology Acceptance Model (TAM) and was analyzed through descriptive and inferential statistical methods. The findings of the study present a nuanced understanding of ML's role in engineering. Although the overall regression model showed limited predictive power, certain variables—particularly those related to algorithm type, design efficiency, and engineering expertise—were identified as statistically significant. This reinforces the idea that the success of ML in engineering contexts is not solely dependent on the technology itself, but also on how well it is aligned with domain-specific knowledge and expertise.

The ability of ML algorithms to improve material efficiency and structural integrity is promising but not yet universally consistent across different applications and settings. From a perception standpoint, the data revealed a generally positive attitude toward ML integration. The majority of respondents agreed or strongly agreed that machine learning contributes to better resource usage, more efficient design processes, and improved structural outcomes. This is consistent with global trends in civil engineering, where the adoption of AI-driven technologies is steadily increasing. However, the reliability analysis exposed weaknesses in the internal consistency of the instrument used, suggesting that future research should refine and validate measurement tools more rigorously to ensure accurate capture of professional perspectives.

Despite these limitations, this study adds value by identifying core factors influencing the adoption and impact of ML in civil engineering. The results also serve as a foundation for further empirical research, particularly studies that explore causal relationships, use longitudinal data, or include experimental validation of ML-based designs. Additionally, there is a need for interdisciplinary collaboration to ensure that ML tools are both technically sound and contextually relevant in engineering practice.

In conclusion, while machine learning presents immense potential for transforming civil engineering design through material and structural optimization, its effectiveness is highly dependent on proper implementation, data quality, and human oversight. For the field to fully realize the benefits of ML, engineers, data scientists, and policy-makers must work together to address technical, operational, and organizational challenges. Future research should continue to explore how these advanced technologies can be responsibly and effectively integrated into engineering workflows.

References

1. Alabi, T. M., Aghimien, E. I., Agbajor, F. D., Yang, Z., Lu, L., Adeoye, A. R., & Gopaluni, B. (2022). A review of the integrated optimization techniques and machine learning approaches for modeling, prediction, and decision-making on integrated energy systems. Renewable Energy, 194, 822-849.
2. Anand, P., Singh, S. D., Bhowmik, P. N., & Kontoni, D.-P. N. (2025). Optimizing concrete mix proportions with zeolite, GGBS, and CDW: a data-driven approach integrating experimental analysis and machine learning models. Engineering Research Express, 7(1), 015105.
3. Baduge, S. K., Thilakarathna, S., Perera, J. S., Arashpour, M., Sharafi, P., Teodosio, B., Shringi, A., & Mendis, P. (2022). Artificial intelligence and smart vision for building and construction 4.0: Machine and deep learning methods and applications. Automation in Construction, 141, 104440.
4. Chitkeshwar, A. (2024). Revolutionizing structural engineering: applications of machine learning for enhanced performance and safety. Archives of Computational Methods in Engineering, 31(8), 4617-4632.
5. De Jong, A., Jansen, M., Van Dijk, J., & Meyer, J. (2021). Analysis of Innovative Practices in Advanced Materials and Structural Engineering. Fusion of Multidisciplinary Research, An International Journal, 2(1), 178-188.
6. Fan, W., Chen, Y., Li, J., Sun, Y., Feng, J., Hassanin, H., & Sareh, P. (2021). Machine learning applied to the design and inspection of reinforced concrete bridges: Resilient methods and emerging applications. Structures,
7. Guo, K., Yang, Z., Yu, C.-H., & Buehler, M. J. (2021). Artificial intelligence and machine learning in the design of mechanical materials. Materials Horizons, 8(4), 1153-1172.
8. Hajıyeva, R., Medetov, K., Sapaev, I., & Sapaev, B. (2025). 12 Artificial intelligence (AI) in civil engineering and Tekla structures. Applications of Mathematics in Science and Technology, 64.
9. Han, T., Siddique, A., Khayat, K., Huang, J., & Kumar, A. (2020). An ensemble machine learning approach for prediction and optimization of modulus of elasticity of recycled aggregate concrete. Construction and Building Materials, 244, 118271.
10. Huang, J., Liew, J., & Liew, K. (2021). Data-driven machine learning approach for exploring and assessing mechanical properties of carbon nanotube-reinforced cement composites. Composite Structures, 267, 113917.
11. Hussein, M. F., Arabasy, M., Abukeshek, M., & Shraa, T. (2025). Metaheuristic machine learning for optimizing sustainable interior design: enhancing aesthetic and functional rehabilitation in housing projects. Asian Journal of Civil Engineering, 26(2), 829-842.
12. Kaveh, A. (2024). Applications of artificial neural networks and machine learning in civil engineering. Springer.
13. Kazemi, F., Çiftçioğlu, A. Ö., Shafighfard, T., Asgarkhani, N., & Jankowski, R. (2025). RAGN-R: A multi-subject ensemble machine-learning method for estimating mechanical properties of advanced structural materials. Computers & Structures, 308, 107657.
14. Khan, S. (2025). The Application of Artificial Intelligence and Machine Learning in Civil Engineering. Doupe Journal of Top Trending Technologies, 1(1).
15. Lin, Y., & Ibraheem, A. A. (2025). Machine learning method as a tool to estimate the vibrations of the concrete structures reinforced by advanced nanocomposites. Mechanics of Advanced Materials and Structures, 32(5), 777-793.
16. Manguri, A., Hassan, H., Saeed, N., & Jankowski, R. (2025). Topology, Size, and Shape Optimization in Civil Engineering Structures: A Review. CMES-COMPUTER MODELING IN ENGINEERING & SCIENCES, 142, 933-971.

17. Mazroa, A. A., Alotaibi, F. A., Alnfiai, M. M., Britto, A. S. F., Venkatraman, S., & Rajanandhini, V. M. (2025). Predicting bond strength between steel reinforcement and concrete materials using machine learning with Bayesian optimization techniques. Matéria (Rio de Janeiro), 30, e20240740.
18. Mei, L., & Wang, Q. (2021). Structural optimization in civil engineering: a literature review. Buildings, 11(2), 66.
19. Naser, M. (2025). A Look into How Machine Learning is Reshaping Engineering Models: the Rise of Analysis Paralysis, Optimal yet Infeasible Solutions, and the Inevitable Rashomon Paradox. arXiv preprint arXiv:2501.04894.
20. Rojek, I., Mikołajewski, D., Kempiński, M., Galas, K., & Piszcz, A. (2025). Emerging Applications of Machine Learning in 3D Printing. Applied Sciences, 15(4), 1781.
21. Schossler, R. T., Ullah, S., Alajlan, Z., & Yu, X. (2025). Data-driven analysis in 3D concrete printing: predicting and optimizing construction mixtures. AI in Civil Engineering, 4(1), 1-25.
22. Shan, W., Liu, J., & Zhou, J. (2023). An integrated method for the intelligent structural design of steel frames based on optimization and machine learning algorithms. Engineering structures, 284, 115980.
23. Shehadeh, A., & Alshboul, O. (2025). Enhancing Engineering and Architectural Design Through Virtual Reality and Machine Learning Integration. Buildings, 15(3), 328.
24. Sun, H., Burton, H. V., & Huang, H. (2021). Machine learning applications for building structural design and performance assessment: State-of-the-art review. Journal of Building Engineering, 33, 101816.
25. Tapeh, A. T. G., & Naser, M. (2023). Artificial intelligence, machine learning, and deep learning in structural engineering: a scientometrics review of trends and best practices. Archives of Computational Methods in Engineering, 30(1), 115-159.
26. Thai, H.-T. (2022). Machine learning for structural engineering: A state-of-the-art review. Structures,
27. Vadyala, S. R., Betgeri, S. N., Matthews, J. C., & Matthews, E. (2022). A review of physics-based machine learning in civil engineering. Results in Engineering, 13, 100316.
28. Wang, X., Liu, Y., & Xin, H. (2021). Bond strength prediction of concrete-encased steel structures using hybrid machine learning method. Structures,
29. Wattanapanich, C., Imjai, T., Sridhar, R., Garcia, R., & Thomas, B. S. (2024). Optimizing recycled aggregate concrete for severe conditions through machine learning techniques: a review. Engineered Science, 31.
30. Xie, Y., Ebad Sichani, M., Padgett, J. E., & DesRoches, R. (2020). The promise of implementing machine learning in earthquake engineering: A state-of-the-art review. Earthquake Spectra, 36(4), 1769-1801.
31. Zhang, J., Huang, Y., Ma, G., & Nener, B. (2021). Mixture optimization for environmental, economical and mechanical objectives in silica fume concrete: A novel framework based on machine learning and a new meta-heuristic algorithm. Resources, Conservation and Recycling, 167, 105395.
32. Zhang, J., Huang, Y., Wang, Y., & Ma, G. (2020). Multi-objective optimization of concrete mixture proportions using machine learning and metaheuristic algorithms. Construction and Building Materials, 253, 119208.