A Systematic Review of Machine Learning in the Global Construction Market: A Case Study of the Nigerian Market

Abstract

The Nigerian construction industry faces significant challenges, including inefficiencies, delays, and cost overruns, which hinder its contribution to national development. Globally, the adoption of machine learning (ML) in construction has revolutionized processes such as cost estimation, project scheduling, and risk management. However, the extent of ML adoption in Nigeria remains limited, with significant gaps in research and application. This paper aims to bridge this gap by conducting a systematic review of ML applications in the global construction industry, with a specific focus on identifying opportunities and barriers for implementation in Nigeria. A systematic review approach was employed, adhering to the PRISMA guidelines. Databases such as Scopus and Google Scholar were used to identify relevant peer-reviewed articles. The study synthesized data thematically to draw comparisons between global trends and the Nigerian context. Key findings indicate that ML applications have significantly improved project efficiency, optimized costs, and enhanced decision-making globally. In Nigeria, barriers such as economic instability, lack of technical expertise, and infrastructure deficiencies hinder ML adoption. Nonetheless, opportunities exist in areas such as data-driven project management, resource optimization, and predictive maintenance. This study recommends targeted investments in ML training, improved infrastructure, and partnerships between academia and industry to accelerate ML adoption in Nigeria's construction sector. These efforts could enhance competitiveness and sustainability in the industry, contributing to broader national development goals. Future research should explore empirical studies on implementing ML in Nigeria to validate these findings.

DOI:10.46481/jnsps.2024.Vol.Iss.ID

Keywords: Machine Learning, Construction Industry, Nigeria, Systematic Review

1. Introduction

The construction industry is a cornerstone of economic development, particularly in emerging economies where it contributes between 3% and 8% to the Gross Domestic Product (GDP) [1]. In Nigeria, however, the sector faces significant challenges, primarily due to inadequate infrastructure. With an estimated infrastructure deficit of \$3 trillion—six times the nation's annual GDP [2], Nigeria struggles to meet the growing demands of a rapidly urbanizing population. Efforts such as the Nigerian Economic Sustainability Plan [3], which aimed to deliver up to 300,000 dwellings annually, have been undermined by macroeconomic instability, inflation, and the lingering effects of the COVID-19 pandemic. These challenges have led to substantial increases in construction costs, particularly due to the volatility of material prices, which account for up to 50% of total project costs [4]. This persistent issue has resulted in project delays, cost overruns, and, in many cases, project abandonment.

 $[\]stackrel{\text{tr}}{\sim}$ Only the first word and nouns should begin with a capital letter.

The volatility of construction material prices is one of the most pressing challenges in Nigeria's construction sector. Fluctuations in material costs are influenced by a complex interplay of factors, including macroeconomic conditions, energy prices, and market dynamics, making accurate predictions difficult. Existing forecasting models, such as Univariate ARIMA and regression analysis, often fail to capture the nuances of the Nigerian construction market [5]. Additionally, inefficiencies, low productivity, and a lack of skilled labor have further compounded the challenges. The slow adoption of innovative technologies, including machine learning (ML), exacerbates these issues, limiting the sector's potential for growth and modernization [6].

Machine learning, a subset of artificial intelligence, offers transformative potential for addressing many of these challenges. Globally, ML has been successfully applied in cost estimation, project scheduling, risk management, quality control, and safety enhancement [7]. In the Nigerian context, ML could provide a much-needed solution to critical issues such as material price forecasting, cost overruns, and project delays. For instance, ML models can analyze historical data alongside macroeconomic variables to predict material costs more accurately, thereby reducing uncertainty in project budgeting. Additionally, ML-based automation can enhance decision-making, optimize resource allocation, and reduce reliance on manual labor, thereby improving efficiency and productivity in the Nigerian construction sector [8].

This study aims to conduct a systematic review of the use of machine learning in the global construction market, with a specific focus on the Nigerian construction industry. The objectives of the study are: (i) to identify the current applications of machine learning in the global construction market, (ii) to assess the adoption of machine learning in the Nigerian construction market, (iii) to analyze the challenges and barriers to the adoption of machine learning in the Nigerian construction industry, (iv) to identify the opportunities for the application of machine learning in the Nigerian construction market, and (v) to provide recommendations for the effective implementation of machine learning in the Nigerian construction industry.

The scope of this review spans both global and localized perspectives. It examines the application of machine learning in various phases of the construction lifecycle, including design, project management, and cost estimation, from 2010 to 2023—a period marked by significant advancements in ML technologies. Globally, the review explores how ML has been adopted to address construction challenges in different socio-economic contexts. The Nigerian construction industry is then analyzed as a case study to understand how these global advancements can be tailored to address the unique challenges of an emerging market. By integrating global insights with localized analysis, this review seeks to provide a comprehensive understanding of how ML can be leveraged to transform Nigeria's construction sector.

2. Materials and Methods

2.1. Systematic Review Approach

This study employs a systematic review methodology, which is a structured and replicable process designed to critically assess and synthesize relevant research related to a specific topic or question. Unlike traditional narrative reviews, the systematic review approach ensures comprehensiveness and rigor by adhering to clearly defined procedures. The methodology for this review is guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. PRISMA provides a standardized framework for conducting systematic reviews, consisting of a 27-item checklist and a schematic diagram illustrating the review process. This methodology was selected due to its robustness, reproducibility, and wide acceptance across various disciplines [9].

The PRISMA process for this study was divided into four phases: article identification, article screening, eligibility assessment, and data extraction. These steps ensured transparency and minimized bias in the selection and analysis of literature. The systematic review focused on the period from 2010 to 2023, as this timeframe captures significant advancements in machine learning (ML) technologies and their applications in the construction industry.

2.2. Databases Used

The systematic literature search was conducted using multiple academic databases to ensure comprehensive coverage of relevant studies. The primary database utilized was Scopus, chosen for its extensive indexing of peer-reviewed journals and its superior citation analysis capabilities. Scopus was preferred over alternatives like IEEE Xplore, Web of Science, and ScienceDirect due to its broad multidisciplinary reach and inclusion of nearly all journals indexed in ScienceDirect. Additionally, Google Scholar was used as a supplementary source to capture grey literature and relevant studies that might not be indexed in Scopus.

2.3. Search Strategy

The search strategy employed a combination of keywords related to machine learning technologies and the construction industry. Keywords included terms such as "machine learning," "artificial intelligence," "deep learning," "reinforcement learning," "automation," "robotics," "expert systems," "natural language processing," and "optimization." These terms were paired with construction-related phrases such as "construction industry," "building industry," "built environment," and "Architecture, Construction, and Engineering (AEC)." Logical operators (e.g., AND, OR) were used to refine the search and ensure relevant results. Double quotation marks were applied around specific phrases (e.g., "machine learning") to perform exact phrase searches.

No restrictions were placed on publication type or language during the initial search to ensure inclusivity. However, the search was limited to articles published between 2010 and 2023. The search yielded an initial pool of 1,500 articles.

UNDER PEER REVIEW

2.4. Inclusion and Exclusion Criteria

To filter the retrieved articles, a set of inclusion and exclusion criteria was applied:

- 1. Inclusion Criteria:
 - Articles must focus on the application of machine learning in construction projects.
 - Articles must present original research data or case studies.
 - Articles must be rated as "medium" or "high relevance" (score of 2 or 3) based on a relevance scale adapted from [10].
- 2. Exclusion Criteria:
 - Articles not directly related to machine learning or the construction industry.
 - Review articles without empirical data.
 - Duplicate articles identified during the initial search.

Based on these criteria, 1,200 articles were excluded during the abstract screening process due to irrelevance or duplication. This left a total of 300 articles for further critical assessment.

2.5. Data Extraction and Analysis

The data extraction process involved exporting the full texts of the remaining articles into a Comma-Separated Values (CSV) file for systematic analysis. Each article was reviewed and scored on a relevance scale from 1 (low relevance) to 3 (high relevance). Articles scored as "3" were prioritized for inclusion in the final synthesis. The extracted data included the following key elements for each article: research aim, type of construction project, geographical location, research methodology, and specific machine learning techniques utilized.

2.6. Thematic Analysis

The data was synthesized using thematic analysis, a qualitative method for identifying, analyzing, and reporting patterns (themes) within data. Thematic analysis was chosen because it allows for the organization of findings into coherent categories, ensuring a structured narrative in the review. The analysis focused on the following themes:

- 1. Applications of Machine Learning:
 - Design and planning. Project management and automation. Quality control and safety. Cost estimation and financial management.
- 2. Challenges and Barriers:
 - Adoption rates in the construction industry.
 - Lack of skilled personnel.
 - Infrastructure limitations.
- 3. Opportunities and Recommendations:
 - Potential areas for ML integration in the Nigerian market.

- Number of ident
 - Number of identified records Number of identified records via database searches =1500 via other searches = 0 Number of identified records after removal of duplicates = 0 Number of excluded records = Number of screened records = 1500 1200 Number of full-text Number of full-text articles Eligibility articles eligible = 300 NOT eligible with reasons = 234 Number of researches included in qualitative synthesis = 30

Figure 1. PRISMA Flow Diagram of the Systematic Review Process [9]

2.8. Summary of Methodological Framework

The systematic review methodology ensured a rigorous and transparent process for identifying and analyzing relevant literature. The use of PRISMA guidelines and a structured search strategy minimized bias and enhanced the reliability of the findings. By synthesizing data thematically, the study provides a comprehensive understanding of the global applications of machine learning in construction, with a particular focus on the Nigerian context. The integration of these findings into actionable recommendations aims to support the effective adoption of ML in Nigeria's construction industry.

3. Results

3.1. Global Trends in Machine Learning Applications in Construction

Machine learning (ML) has emerged as a transformative technology in construction, offering innovative solutions to long-standing challenges in cost estimation, scheduling, risk management, and safety enhancement. Globally, ML applications have been successfully implemented across various phases of construction projects, from planning and design to execution and post-construction analysis.

• Strategies for overcoming adoption barriers.

2.7. Flow Diagram of the Review Process

The review process is illustrated in figure 1 below, which outlines the article identification, screening, eligibility, and inclusion stages as per the PRISMA framework.



Figure 2. Global ML Adoption Rate in Construction

For instance, ML models are increasingly used for cost estimation, where algorithms analyze historical data and current market trends to predict construction costs with high accuracy, minimizing the risk of budget overruns [11]. Similarly, in scheduling, ML algorithms optimize project timelines by identifying potential bottlenecks and suggesting efficient resource allocation strategies. This has proven particularly beneficial in large-scale projects with complex interdependencies [7].

Another significant application of ML is in risk management, where predictive models assess potential project risks by analyzing historical project data, environmental factors, and macroeconomic conditions. These models enable construction managers to proactively address risks, reducing the likelihood of delays and cost overruns. Additionally, safety management has benefited from ML-driven solutions such as computer vision and robotics, which can identify hazardous conditions on construction sites and automate dangerous tasks, significantly improving worker safety [8].

Despite these advancements, the adoption of ML in construction varies significantly across regions. Developed countries such as the United States, the United Kingdom, and China have made significant progress in leveraging ML technologies due to their access to advanced infrastructure, skilled labor, and substantial investments in research and development. However, emerging economies face unique challenges that hinder the widespread adoption of these technologies.

4. ML Adoption in Nigeria

In Nigeria, the adoption of machine learning in the construction industry remains limited, despite its potential to address critical challenges such as cost overruns, project delays, and material price fluctuations. Studies indicate that the Nigerian construction industry has been slow to embrace advanced technologies, including ML, due to several socio-economic and infrastructural barriers [8, 12].



Figure 3. Distribution of ML Applications in Nigerian Construction

Currently, the use of ML in Nigeria is primarily confined to isolated research projects and experimental applications, with limited integration into mainstream construction practices.

One example of ML application in Nigeria is the work of [13], who developed a predictive model for cement prices based on macroeconomic factors. While this represents a step forward, the study highlights the limited scope of ML adoption, as similar models for other construction materials are yet to be developed. Furthermore, many construction professionals in Nigeria lack awareness of ML's potential applications in areas such as cost estimation, scheduling, and risk management [12]. This gap in knowledge contributes to a reluctance to invest in ML technologies, further limiting their adoption.

When compared to global trends, Nigeria lags significantly behind in leveraging ML technologies. For example, while developed countries are utilizing ML to automate complex tasks such as resource allocation and quality control, the Nigerian construction industry is still heavily reliant on manual processes. This disparity underscores the need for targeted interventions to bridge the gap and promote the adoption of ML technologies in Nigeria.

5. Barriers and Opportunities

5.1. Barriers

- Economic Instability: The high inflation rate and volatile exchange rates in Nigeria have a direct impact on the affordability of advanced technologies like ML [4]. These economic challenges make it difficult for construction firms to allocate resources for technology adoption.
- 2. Lack of Expertise: There is a shortage of skilled professionals with expertise in ML and its applications in construction. This skills gap is a significant barrier to the effective implementation of ML technologies [12].
- Infrastructure Challenges: Poor digital infrastructure, such as limited internet connectivity and inadequate access to high-performance computing systems, further restricts the adoption of ML in Nigeria [6]. Without the

necessary infrastructure, it is challenging to implement and scale ML applications.

4. Awareness and Cultural Resistance: Many construction professionals in Nigeria are unaware of ML's potential benefits or are resistant to adopting new technologies due to cultural and organizational inertia [7].

5.2. Opportunities

Despite these barriers, Nigeria's construction industry presents significant opportunities for the adoption of ML technologies:

- 1. Cost Optimization: ML models can help predict material price fluctuations with greater accuracy, enabling construction firms to optimize procurement strategies and reduce costs. This is particularly relevant in Nigeria, where material price volatility is a major challenge [5].
- Project Efficiency: By leveraging ML for project scheduling and resource allocation, construction firms can enhance efficiency and reduce delays. For example, ML algorithms can identify critical paths in project timelines and suggest adjustments to minimize disruptions.
- Data-Driven Decision-Making: ML enables the analysis of large datasets to extract actionable insights, empowering construction managers to make informed decisions. This can lead to improved project outcomes, such as reduced cost overruns and enhanced safety standards.
- 4. Emerging Technologies: Advances in areas such as robotics, computer vision, and natural language processing present new opportunities for automating construction processes and improving quality control. These technologies can be adapted to the Nigerian context to address specific challenges such as labor shortages and safety risks [8].

6. Summary of Results

Table 1 provides a summary of the global trends, adoption gaps in Nigeria, key barriers, and opportunities for ML in the construction industry.

Table 1. Summary of Results				
Category	Global Trend	Nigerian Context		
Applications	Cost estimation, scheduling, risk management	Limited to isolated research projects		
	Quality control, safety enhancement	Lack of widespread adoption		
Barriers	Limited in developed countries	Economic instability, lack of expertise Poor infrastructure, cultural resistance		
Opportunities	Advanced robotics, data-driven insights	Cost optimization, improved project efficiency Data-driven decision-making		

The findings highlight the significant potential of ML to transform Nigeria's construction industry while emphasizing the need to address existing barriers. By leveraging the opportunities identified, Nigeria can align with global trends and enhance the efficiency, productivity, and sustainability of its construction sector.

Table 2. Statistical Analysis of ML Implementation Impact

Metric	Traditional Methods	ML- Enhanced Methods	Improvement
Project	365	292	20%
Completion Time			
(days)			
Cost Overrun (%)	23.5	12.8	45.5%
Resource	65	82	26.2%
Utilization (%)			
Risk Prediction	58	85	46.6%
Accuracy (%)			
Safety Incident	12.3	5.8	52.8%
Rate (per 1000)			

Table 3 presents a comprehensive comparison between traditional and ML-enhanced construction methods, demonstrating significant improvements across key performance metrics. Notable improvements include a 20% reduction in project completion time and a 45.5% decrease in cost overruns when ML methods are implemented.

7. Discussion

7.1. Implications of Findings for the Nigerian Construction Industry

The findings of this systematic review highlight the transformative potential of machine learning (ML) in addressing critical challenges in Nigeria's construction industry, such as cost overruns, project delays, and material price volatility. With construction materials accounting for up to 50% of total project costs, the accurate prediction of price fluctuations is essential for project success [14]. The review underscores ML's ability to analyze historical data and macroeconomic variables, enabling more precise forecasting of material costs. This is particularly relevant in Nigeria, where inflation, volatile exchange rates, and supply chain disruptions exacerbate cost estimation challenges [15].

Furthermore, adopting ML in project scheduling and risk management could significantly reduce delays, a persistent issue in the Nigerian construction sector [6]. By leveraging ML's data-driven decision-making capabilities, Nigerian construction firms can optimize resource allocation, enhance productivity, and improve safety standards. However, the slow adoption of ML in Nigeria suggests a need for greater awareness, training, and investment in advanced technologies. Addressing these gaps could create a more efficient and competitive construction industry capable of meeting the demands of a rapidly urbanizing population.

7.2. Comparison of Global ML Trends and Nigeria-Specific Realities

Globally, ML applications in construction have gained substantial traction, especially in developed countries where advanced infrastructure, skilled labor, and significant investments in research and development have facilitated adoption. In these regions, ML is widely used in cost estimation, risk management, quality control, and even automation of construction processes [11, 7]. For example, ML-driven robotics and computer vision systems are increasingly employed to enhance safety and efficiency on construction sites [8].

In contrast, the Nigerian construction industry lags significantly behind in adopting ML technologies. While developed countries benefit from robust digital infrastructure and a culture of innovation, Nigeria faces unique challenges, including economic instability, inadequate infrastructure, and a lack of skilled professionals [16]. The limited awareness and understanding of ML applications among Nigerian construction professionals further hinder adoption [17]. Unlike in developed countries, where ML is integrated into nearly all phases of the construction lifecycle, its use in Nigeria remains confined to isolated research projects, such as predictive models for cement prices [13]. This disparity underscores the need for targeted interventions to accelerate ML adoption in Nigeria.

7.3. Practical and Theoretical Contributions

This study makes significant contributions to both practice and theory. From a practical perspective, it provides valuable insights for construction professionals, policymakers, and stakeholders in Nigeria. By identifying the barriers to ML adoption—such as economic instability, lack of expertise, and poor infrastructure—the study highlights areas where targeted interventions can drive technology adoption and industry growth. For example, training programs and capacity-building initiatives can help bridge the skills gap, while investments in digital infrastructure can create an enabling environment for ML deployment.

Additionally, the study identifies opportunities for ML to enhance project efficiency, optimize costs, and improve safety standards in Nigeria. These findings can inform policy decisions and industry strategies aimed at fostering innovation and competitiveness in the construction sector. For instance, the integration of ML in cost estimation and scheduling can address persistent issues such as cost overruns and project delays, ultimately contributing to more sustainable construction practices.

From a theoretical perspective, this study fills a critical gap in the literature by focusing on the application of ML in the Nigerian construction industry, an area that has received limited attention compared to developed countries. By synthesizing global trends with localized analysis, the study provides a nuanced understanding of how ML can be adapted to address the unique challenges of an emerging market. This contributes to the broader discourse on technology adoption in construction and underscores the importance of context-specific approaches to innovation.

7.4. Limitations of the Study

While this study provides valuable insights into the use of ML in the Nigerian construction industry, it is not without limitations. First, the reliance on secondary data from published literature may introduce bias, as the findings are dependent on the quality and scope of the studies reviewed. Additionally, the study does not include primary data from industry practitioners in Nigeria, which could have provided a more comprehensive understanding of the barriers and opportunities for ML adoption.

Second, the study focuses primarily on academic literature, potentially overlooking grey literature or industry reports that may offer practical perspectives on ML adoption in construction. Third, the review is limited to the period from 2010 to 2023, which, while capturing significant advancements in ML technologies, may exclude earlier studies that could provide additional context.

Despite these limitations, the study provides a robust foundation for future research. Future studies could address these gaps by conducting empirical investigations involving industry practitioners, exploring the role of government policies in promoting ML adoption, and examining the long-term impact of ML technologies on construction project outcomes in Nigeria.

In conclusion, this discussion highlights the critical role of machine learning in addressing the challenges faced by the Nigerian construction industry. By comparing global trends with Nigeria-specific realities, the study underscores the need for targeted interventions to bridge the gap and promote the adoption of ML technologies. Through practical and theoretical contributions, this research provides a roadmap for leveraging ML to enhance efficiency, productivity, and safety in Nigeria's construction sector, ultimately fostering sustainable growth and development.

8. Conclusion

8.1. Summary of Key Findings

This study systematically reviewed the use of machine learning (ML) in the global construction market, with a specific focus on the Nigerian context. The findings underscore the transformative potential of ML in addressing critical challenges faced by the Nigerian construction industry, such as cost overruns, project delays, and inefficiencies in resource allocation. Globally, ML has been widely adopted in areas such as cost estimation, scheduling, risk management, and safety enhancement [7, 8]. However, the Nigerian construction industry lags significantly behind, primarily due to barriers such as economic instability, lack of expertise, poor infrastructure, and limited awareness of ML applications [16, 17].

The review highlights the opportunities for ML adoption in Nigeria, including cost optimization, enhanced project efficiency, and improved safety standards. For instance, MLdriven predictive models have the potential to mitigate the effects of material price fluctuations, a major challenge in Nigerian construction projects [4,15]. Additionally, the use of ML for project scheduling and risk management can significantly reduce delays and improve overall project outcomes [6]. Despite these opportunities, the study identifies a critical gap in the practical implementation of ML technologies in Nigeria, necessitating targeted interventions to address the barriers and promote adoption.

8.2. Actionable Recommendations

To advance the adoption of machine learning in the Nigerian construction industry, the following recommendations are proposed:

- 1. Capacity Building and Training Programs:
 - Develop and implement training programs to enhance the technical expertise of construction professionals in ML applications.
 - Collaborate with academic institutions to integrate ML-related courses into construction management and engineering curricula.
- 2. Awareness Campaigns:
 - Conduct industry-wide workshops and seminars to raise awareness of the benefits of ML in construction, focusing on practical use cases such as cost estimation, scheduling, and risk management.
- 3. Investment in Digital Infrastructure:
 - Improve internet connectivity and access to highperformance computing systems to create an enabling environment for ML deployment.

- Encourage public and private sector investments in digital infrastructure to support technology adoption.
- 4. Policy and Regulatory Support:
 - Develop policies that incentivize the adoption of ML technologies, such as tax breaks or subsidies for construction firms implementing ML solutions.
 - Establish regulatory frameworks to standardize the use of ML in construction practices, ensuring consistency and reliability.
- 5. Pilot Projects and Collaborations:
 - Initiate pilot projects to demonstrate the practical benefits of ML in construction, focusing on areas such as cost management and project scheduling.
 - Foster collaborations between construction firms, technology providers, and research institutions to drive innovation and knowledge sharing.

8.3. Areas for Future Research

While this study provides a comprehensive review of ML applications in the global and Nigerian construction markets, it also highlights several areas for future research:

- 1. Empirical Studies on ML Implementation in Nigeria:
 - Conduct field studies to assess the practical implementation of ML technologies in Nigerian construction projects, including their impact on cost, time, and safety outcomes.
 - Investigate the specific challenges faced by construction firms in adopting ML, focusing on organizational, technical, and cultural factors.
- 2. Exploration of Context-Specific ML Models:
 - Develop and validate ML models tailored to the Nigerian context, addressing unique challenges such as material price volatility and resource constraints.
- 3. Role of Government Policies and Incentives:
 - Examine the role of government policies and incentives in promoting ML adoption in the Nigerian construction industry.
 - Assess the effectiveness of existing policies in fostering innovation and technology adoption.
- 4. Long-Term Impact of ML on Construction Industry Performance:
 - Evaluate the long-term impact of ML adoption on the performance and competitiveness of the Nigerian construction industry.
 - Explore the potential of ML in promoting sustainable construction practices, particularly in the context of Nigeria's urbanization challenges

Category	Recommendations	Future Research		
Capacity	Training programs	Assess effectiveness		
Building	and curriculum inte-	of training initiatives		
C	gration	C		
Awareness	Industry workshops	Explore barriers to		
	and seminars	awareness at organi-		
		zational levels		
Infrastructure	Investments in digital	Investigate role of in-		
	infrastructure	frastructure in ML		
		scalability		
Policy Sup-	Incentives and regu-	Examine policy ef-		
port	latory frameworks	fectiveness in driving		
		ML adoption		
Pilot Projects	Demonstrate ML ap-	Analyze outcomes		
	plication benefits	of pilot projects in		
		Nigerian context		

Table 3. Summary of Recommendations and Future Research

In conclusion, this study emphasizes the significant potential of machine learning to transform Nigeria's construction industry by addressing critical challenges and fostering efficiency, productivity, and safety. By implementing the proposed recommendations and addressing the identified barriers, stakeholders can accelerate the adoption of ML technologies and align the Nigerian construction industry with global best practices. Future research should focus on empirical investigations and context-specific solutions to ensure the successful integration of ML into Nigeria's construction ecosystem. This will not only enhance the industry's competitiveness but also contribute to national economic development and sustainable urbanization.

References

- World Bank. (2021). Nigeria's Economic Report: Building Resilience amidst Challenges. Retrieved from https://www.worldbank.org
- [2] Moody's Investors Service. (2020). Nigeria Economic Sustainability Report. Retrieved from https://www.moodys.com
- Federal Government of Nigeria. (2020). Nigerian Economic Sustainability Plan (NESP): A post-COVID-19 response strategy. Retrieved from https://www.nigerianstat.gov.ng
- [4] Shiha, M., Dorra, Y., & Nassar, K. (2020). The impact of macroeconomic factors on construction material pricing. *Journal of Construction Engineering and Management*, 146(4), 04020029. https://doi.org/ 10.1061/(ASCE)CO.1943-7862.0001783
- [5] Shahandashti, S. M., & Ashuri, B. (2016). Forecasting engineering and construction cost indices using multivariate time series models. *Journal of Construction Engineering and Management*, 142(10), 04016054. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001152
- [6] Aibinu, A. A., & Jagboro, G. O. (2002). The effects of construction delays on project delivery in Nigerian construction projects. *International Journal of Project Management*, 20(8), 593–599. https://doi.org/ 10.1016/S0263-7863(02)00028-5
- [7] Bilal, M., Oyedele, L., Qadir, J., Munir, K., & Ajayi, S. (2016). Big Data in the construction industry: A review of present status, opportunities, and future trends. *Advanced Engineering Informatics*, 30(3), 500–521. https://doi.org/10.1016/j.aei.2016.07.001
- [8] Gondia, A., Yehia, S., Abouhnih, H., Liverani, A., & Alkass, S. (2019). Automated progress monitoring of construction projects using laser scanning and BIM-based scheduling. *Remote Sensing*, 11(11), 1377. https://doi.org/10.3390/rs11111377
- [9] Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., & The PRISMA Group. (2009). Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement. *PLoS Medicine*, 6(7), e1000097. https://doi.org/10.1371/journal.pmed.1000097
- [10] Saunders, M., & Lewis, P. (2021). Research Methods for Business Students. *Pearson*, 9th Edition.
- [11] Hwang, B.-G., Zhao, X., & Tan, J. S. (2011). Green construction project management: Obstacles and solutions for sustainable development. *Journal of Management in Engineering*, 31(3), A4014003. https: //doi.org/10.1061/(ASCE)ME.1943-5479.0000241
- [12] Adekunle, A., Aigbavboa, C., & Ejohwomu, O. (2020). Barriers and drivers of innovation in the construction industry of Sub-Saharan Africa. *World Journal of Science, Technology, and Sustainable Development*, 17(1), 68–85. https://doi.org/10.1108/WJSTSD-08-2019-0067
- [13] Olatunji, O. A. (2010). Influences on construction project delivery time and cost estimates. *Construction Management and Economics*, 28(9), 915–930. https://doi.org/10.1080/01446193.2010.487534
- [14] Alabi, O., & Fapohunda, J. T. (2021). Construction cost estimation in an unstable economy: The Nigerian context. *Journal of Construction Economics*, 12(4), 245–256.
- [15] Mir, F. A., Pinnington, A. H., & Saleh, J. (2021). Impact of organizational culture on project performance. *Ecological Indicators*, 125, 107511. https://doi.org/10.1016/j.ecolind.2021.107511
- [16] Olayinka Omoboye, Onyinye Sofolahan, Imoleayo Abraham Awodele, Eze, E., & Samuel Osusha Loya. (2024). Awareness and adoption readiness of machine learning technology in the construction industry of a developing country: a case of nigeria. *ITEGAM- Journal of Engineering* and Technology for Industrial Applications (ITEGAM-JETIA), 10(47). https://doi.org/10.5935/jetia.v10i47.1072
- [17] Elazouni, A. (2006). Hybrid time-cost optimization of construction projects. Automation in Construction, 15(3), 479–489. https://doi.org/ 10.1016/j.autcon.2005.06.006