International Journal of Computer Applications Technology and Research
Volume 15–Issue 01, 07 – 15, 2026, ISSN: -2319–8656
DOI:10.7753/IJCATR1501.1002

AI-Driven Predictive Analytics for Resource, Schedule, and Carbon Optimisation in Nigerian Construction and Energy Projects

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Abstract: The Nigerian construction and energy sectors face persistent challenges related to cost overruns, schedule delays, inefficient resource utilisation, and rising carbon emissions. These challenges are exacerbated by fragmented data systems, manual planning practices, and limited adoption of advanced digital tools. This paper explores the application of AI-driven predictive analytics as a strategic solution for optimising resource allocation, project scheduling, and carbon performance in Nigerian construction and energy projects. By leveraging machine learning algorithms, historical project data, real-time sensor inputs, and geospatial information, predictive analytics can forecast material demand, labour productivity, equipment usage, schedule risks, and emissions trajectories with greater accuracy. The study examines how AI-enabled models support proactive decision-making, reduce waste, enhance time efficiency, and align projects with national sustainability and energy transition goals. Particular attention is given to the Nigerian context, including data availability constraints, infrastructural limitations, regulatory considerations, and capacity gaps. The paper argues that integrating predictive analytics into project management and energy planning frameworks can significantly improve project delivery outcomes while supporting low-carbon development pathways. It concludes by highlighting implementation pathways, governance requirements, and policy implications necessary to scale AI-driven optimisation across Nigeria's construction and energy value chains.
Keywords: AI-driven analytics; Predictive modelling; Construction management; Energy projects; Carbon optimisation; Nigeria

1. INTRODUCTION

1.1 Background: Construction and Energy Project Challenges in Nigeria

Nigeria's construction and energy sectors play a critical role in national economic development, infrastructure expansion, and energy security, yet both sectors continue to experience systemic project delivery challenges. Large-scale construction and energy projects are frequently characterised by cost overruns, schedule delays, inefficient use of materials and labour, and suboptimal coordination among stakeholders [1]. These inefficiencies are often linked to fragmented planning processes, limited use of data-driven decision-support tools, and heavy reliance on manual forecasting methods [2].In the construction sector, inaccurate resource estimation and poor schedule control contribute significantly to project delays and budget escalation, particularly in public infrastructure and energy-related construction projects [3].

Similarly, energy projects, including power generation, transmission, oil and gas infrastructure, and renewable energy developments, face uncertainty in demand forecasting, logistics planning, and operational scheduling, leading to productivity losses and financial risk [4].Beyond cost and time performance, the carbon intensity of construction activities and energy infrastructure has emerged as a growing concern. Construction materials such as cement and steel, combined with diesel-powered equipment and inefficient logistics, contribute substantially to greenhouse gas emissions [5]. Energy projects further amplify this challenge through carbon-intensive fuel use, transmission losses, and inefficient operational practices [6]. As Nigeria seeks to balance infrastructure expansion with climate commitments and sustainable development goals, the need for integrated approaches that address resource efficiency, schedule certainty, and carbon reduction has become increasingly urgent [7].

1.2 Emergence of AI-Driven Predictive Analytics in Project Delivery

Globally, artificial intelligence and predictive analytics are transforming project delivery by shifting decision-making from reactive responses to proactive and anticipatory strategies [8]. Predictive analytics leverages historical project data, real-time inputs, and advanced machine learning algorithms to forecast future outcomes related to cost, schedule performance, resource demand, and risk exposure. Unlike traditional deterministic planning tools, AI-driven models can identify complex, non-linear relationships within large datasets and continuously improve prediction accuracy over time [1].In construction and energy projects, AI-enabled predictive analytics supports early identification of schedule slippage, optimisation of labour and equipment deployment, and anticipation of supply chain disruptions [2].

These capabilities enable project managers and planners to intervene before risks materialise, improving overall project performance. Internationally, the adoption of AI in project management is accelerating, supported by advances in cloud computing, building information modelling [BIM], Internet of Things [IoT] sensors, and digital twins [3].While advanced economies have begun integrating these technologies into mainstream project delivery, adoption in developing contexts

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remains uneven, often constrained by data availability, institutional readiness, and governance frameworks [4].

1.3 Research Gap and Problem Statement

Despite the growing global literature on AI applications in construction and energy project management, there is limited empirical and context-specific research focusing on Nigeria. Existing studies tend to concentrate on developed economies or treat African contexts in a highly aggregated manner, overlooking local project dynamics, regulatory environments, and infrastructural constraints [5].

Furthermore, much of the Nigerian literature focuses on individual performance indicators such as cost or time, with limited integration of carbon optimisation into project analytics frameworks [6]. This creates a significant knowledge gap regarding how AI-driven predictive analytics can be effectively adapted to Nigerian construction and energy projects to simultaneously optimise resources, schedules, and carbon performance. Without contextualised frameworks and evidence, decision-makers lack practical guidance on how to deploy these technologies in a manner aligned with national development and sustainability priorities [7].

1.4 Aim, Objectives, and Scope of the Study

The aim of this study is to examine the role of AI-driven predictive analytics in optimising resource allocation, project scheduling, and carbon performance in Nigerian construction and energy projects. The specific objectives are to analyse the theoretical foundations of predictive analytics, assess its applicability within the Nigerian context, and evaluate its potential to improve efficiency and sustainability outcomes [8]. The scope of the study encompasses major construction and energy project types in Nigeria, with emphasis on planning, execution, and operational phases.

2. CONCEPTUAL AND THEORETICAL FRAMEWORK

2.1 Predictive Analytics and Machine Learning Foundations

Predictive analytics refers to the use of statistical techniques, machine learning algorithms, and data mining methods to analyse historical and real-time data in order to forecast future outcomes [7]. At its core, predictive analytics relies on machine learning models that learn patterns from data and generate probabilistic predictions rather than fixed estimates. Supervised learning techniques, such as regression models, decision trees, and neural networks, are commonly used to predict project cost, duration, and resource demand based on labelled historical datasets [8].Unsupervised learning approaches, including clustering and anomaly detection, support identification of hidden patterns in project performance data, such as recurring causes of delay or inefficiency [9]. Time-series forecasting models are particularly relevant for construction and energy projects, as they enable prediction of resource consumption, productivity trends, and emissions trajectories over the project lifecycle [10]. Optimisation models further extend predictive analytics by recommending optimal decisions, such as resource allocation strategies or schedule adjustments, under defined constraints [11].

2.2 AI in Construction Project Management

In construction project management, AI-driven predictive analytics enhances traditional planning tools by improving accuracy and adaptability. Resource allocation models use historical productivity data, weather conditions, and site constraints to forecast labour and equipment requirements with greater precision [12]. This reduces over-allocation, idle time, and material waste. Predictive schedule models analyse activity sequences, dependencies, and risk factors to estimate the likelihood of delays and identify critical risk points before construction begins [13].AI-based systems also support dynamic re-planning by updating forecasts as new data becomes available during project execution. This capability is particularly valuable in complex Nigerian projects, where external disruptions such as supply chain delays, power shortages, and regulatory changes are common [14]. By embedding predictive analytics into project management workflows, construction firms can move from static baseline schedules to continuously optimised delivery strategies.

2.3 AI Applications in Energy Project Planning and Operations

Energy projects involve long planning horizons, capital-intensive investments, and high exposure to operational risk. AI-driven predictive analytics supports demand forecasting, asset performance prediction, and maintenance scheduling across energy infrastructure systems [15]. In power generation and transmission projects, predictive models can forecast load demand, equipment degradation, and failure risks, enabling more efficient capacity planning and reduced downtime. For oil, gas, and renewable energy projects, AI tools improve logistics planning, drilling or installation schedules, and operational efficiency by integrating geospatial, operational, and environmental data [16]. Within the Nigerian context, predictive analytics offers potential to improve coordination across fragmented energy value chains and reduce inefficiencies that contribute to cost escalation and emissions [17].

2.4 Carbon Optimisation and Digital Sustainability Models

Carbon optimisation involves the systematic reduction of greenhouse gas emissions across project lifecycles through informed design, planning, and operational decisions [7]. Digital sustainability models integrate carbon accounting with predictive analytics to forecast emissions associated with materials, equipment use, transportation, and energy consumption [8]. AI-driven models enable comparison of alternative project scenarios, allowing decision-makers to

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select options that minimise carbon impact while maintaining cost and schedule performance [9].In construction and energy projects, predictive carbon analytics supports early identification of high-emission activities and evaluation of mitigation strategies, such as material substitution, logistics optimisation, and energy efficiency measures [10]. By embedding carbon considerations into predictive planning frameworks, AI-driven analytics aligns project delivery with broader climate and sustainability objectives, providing a theoretical foundation for low-carbon infrastructure development in Nigeria [11].

Figure 1: Conceptual framework linking AI-driven predictive analytics to resource, schedule, and carbon optimisation

3. NIGERIAN CONSTRUCTION AND ENERGY SECTOR CONTEXT

3.1 Overview of the Nigerian Construction Industry

The Nigerian construction industry is a key contributor to national economic growth and infrastructure development, accounting for a significant share of employment and capital expenditure [16]. The sector encompasses public infrastructure projects such as roads, bridges, housing, hospitals, and energy-related facilities, alongside private commercial and residential developments. Project typologies range from small-scale building works to large, complex infrastructure and energy construction projects that involve multiple contractors, consultants, and government agencies [17]. Project delivery models in Nigeria commonly include traditional design–bid–build arrangements, design–build contracts, and public–private partnerships. While design–bid–build remains dominant in public sector projects, design–build and hybrid procurement models are increasingly adopted for energy and industrial projects to improve time and cost certainty [18]. However, these delivery models often rely on static planning tools and deterministic schedules, limiting their ability to respond effectively to uncertainty. Fragmented coordination among stakeholders, weak contract enforcement, and inconsistent data documentation further exacerbate inefficiencies in resource utilisation and schedule control [19].

3.2 Energy Infrastructure Development in Nigeria

Nigeria's energy infrastructure spans power generation and transmission, oil and gas exploration and processing, and an expanding renewable energy sector. Power generation projects include thermal plants, hydropower facilities, and increasingly solar-based installations aimed at improving electricity access and reliability [20]. Transmission and distribution infrastructure development remains critical due to aging assets, technical losses, and capacity constraints. Oil and gas projects continue to dominate capital investment, involving pipelines, processing facilities, and export infrastructure, while renewable energy projects are gaining traction in response to energy access gaps and climate commitments [21].Energy infrastructure projects are capital intensive and exposed to operational, logistical, and regulatory risks. Inadequate planning and inefficient resource allocation often lead to cost escalation and project delays, particularly in remote or environmentally sensitive locations [22]. These challenges highlight the need for advanced planning tools capable of integrating technical, economic, and environmental variables across the project lifecycle.

3.3 Carbon Emissions Profile of Nigerian Infrastructure Projects

Construction and energy infrastructure projects contribute substantially to Nigeria's greenhouse gas emissions through material production, equipment operation, transportation, and energy use [23]. Carbon-intensive materials such as cement and steel are widely used in construction, while diesel-powered machinery and inefficient logistics further increase emissions. Energy projects amplify this profile through fossil fuel-based power generation, gas flaring, and transmission losses. Although Nigeria's per-capita emissions remain relatively low globally, infrastructure-driven emissions are expected to rise as development accelerates [24].This emissions trajectory creates pressure to integrate carbon considerations into infrastructure planning and delivery. However, carbon accounting practices in Nigerian projects are often limited or absent, with environmental assessments typically conducted as compliance exercises rather than integrated decision-support tools. This gap presents an opportunity for predictive analytics to support proactive carbon optimisation alongside traditional performance objectives.

3.4 Digital Maturity and Data Readiness in Nigeria

Digital maturity within Nigeria's construction and energy sectors remains uneven. While large firms and multinational operators increasingly adopt digital tools such as BIM, enterprise resource planning systems, and basic data analytics, many local contractors rely on manual record-keeping and spreadsheet-based planning [16]. Data fragmentation, poor data quality, and limited interoperability across systems constrain the effectiveness of advanced analytics. Additionally, challenges related to skills shortages, inadequate digital infrastructure, and governance frameworks limit widespread adoption of AI-driven solutions [17].Despite these constraints, growing investments in digital infrastructure, cloud services, and smart energy systems indicate increasing readiness for data-driven project management. This evolving landscape provides a foundation for the gradual integration of AI-driven predictive analytics tailored to Nigeria's institutional and infrastructural realities [18].

4. AI-DRIVEN RESOURCE OPTIMISATION MODELS

4.1 Predictive Resource Demand Forecasting

Predictive resource demand forecasting applies machine learning algorithms to estimate future requirements for materials, labour, and equipment based on historical project data and real-time inputs [23]. In construction projects, predictive models analyse variables such as project scope, design specifications, productivity rates, weather conditions, and site constraints to forecast material quantities and delivery schedules. For labour, AI-driven systems predict workforce demand and skill requirements, reducing idle time and labour shortages [24].Equipment utilisation forecasting supports optimal deployment and maintenance planning, minimising downtime and excessive fuel consumption. In Nigerian construction and energy projects, where supply chain disruptions and logistical challenges are common, predictive forecasting improves planning accuracy and reduces uncertainty [25].

4.2 AI-Based Cost and Productivity Modelling

AI-based cost and productivity models extend traditional estimating techniques by incorporating dynamic and probabilistic analysis. Machine learning algorithms identify patterns in cost drivers, productivity trends, and risk factors that are often overlooked in deterministic models [26]. These models continuously update cost forecasts as project conditions change, enabling early identification of budget overruns. Productivity modelling integrates data from site activities, equipment performance, and workforce outputs to assess efficiency in real time. In energy projects, predictive analytics supports optimisation of operational costs by forecasting fuel consumption, maintenance needs, and asset performance [27]. The use of AI-driven cost and productivity modelling enhances financial control and supports evidence-based decision-making throughout the project lifecycle.

4.3 Waste Reduction and Efficiency Gains

One of the most significant benefits of AI-driven resource optimisation is waste reduction. Predictive analytics minimises over-ordering of materials, reduces rework through improved planning accuracy, and optimises logistics routes to lower fuel use and emissions [28]. In construction projects, AI-supported planning reduces material waste and improves on-site coordination. In energy projects, predictive maintenance and operational optimisation reduce energy losses and unplanned outages. These efficiency gains translate into cost savings, schedule reliability, and lower environmental impact, aligning project delivery with sustainability objectives [29].

Table 1: Comparison of Traditional vs AI-Driven Resource Planning Approaches

Dimension	Traditional Planning	AI-Driven Predictive Planning
Resource estimation	Static, experience-based	Data-driven and adaptive
Schedule integration	Limited	Fully integrated and dynamic
Waste management	Reactive	Proactive and predictive
Cost control	Periodic	Continuous and real-time
Carbon considerations	Minimal	Embedded in optimisation models

Overall, AI-driven resource optimisation models offer a transformative approach to managing the complexity of Nigerian construction and energy projects by improving efficiency, reducing waste, and supporting sustainable infrastructure delivery [30]

5. SCHEDULE OPTIMISATION AND RISK PREDICTION

5.1 Schedule Delay Drivers in Nigerian Projects

Schedule delays remain a persistent challenge in Nigerian construction and energy projects, undermining cost efficiency, investor confidence, and service delivery outcomes [29]. Common delay drivers include inaccurate baseline schedules, poor coordination among contractors and consultants, late design changes, and weak risk anticipation mechanisms. External factors such as supply chain disruptions, inflation-driven material shortages, adverse weather conditions, and regulatory approvals further compound schedule uncertainty [30]. In energy projects, delays are frequently associated with equipment importation bottlenecks, logistics constraints in remote locations, grid integration challenges, and security-related disruptions [31].Traditional scheduling approaches in Nigeria typically rely on deterministic critical path methods and static progress tracking, which assume stable conditions and linear task relationships. These methods often fail to capture dynamic interactions among activities or the cumulative impact of multiple risk factors over time. As a result, schedule risks are identified late, when corrective actions are costly or ineffective. Addressing these systemic weaknesses requires predictive approaches capable of anticipating delay risks before they materialise [32].

5.2 Machine Learning Models for Schedule Forecasting

Machine learning models enhance schedule forecasting by analysing historical project data to identify patterns associated with delay occurrence and duration. Supervised learning techniques, including regression models, random forests, and neural networks, are commonly used to predict activity durations and overall project completion timelines based on variables such as project size, complexity, resource availability, and environmental conditions [33]. These models generate probabilistic forecasts rather than single-point estimates, allowing project teams to assess the likelihood of schedule slippage under different scenarios.Time-series models are particularly effective for monitoring schedule performance during execution, as they detect deviations from planned progress and forecast future delays based on observed trends. Classification models further support risk prediction by categorising activities or work packages according to their delay risk levels, enabling targeted interventions [34]. In energy projects, predictive analytics can forecast commissioning delays, maintenance downtime, and operational disruptions by integrating technical and operational data. The adaptive learning capability of machine learning models allows forecasts to improve continuously as new data becomes available, making them well suited to the volatile conditions characteristic of Nigerian projects [35].

5.3 Integration with BIM, IoT, and Project Management Tools

The effectiveness of AI-driven schedule optimisation is significantly enhanced through integration with digital project management technologies. Building Information Modelling provides a structured data environment that links schedule information with design and quantity data, enabling more accurate activity sequencing and progress tracking [36]. When combined with predictive analytics, BIM-based schedules can be dynamically updated to reflect changing site conditions and risk forecasts.Internet of Things sensors contribute real-time data on equipment usage, environmental conditions, and site productivity, feeding predictive models with high-frequency inputs that improve forecast accuracy. For energy projects, IoT-enabled monitoring of assets and infrastructure supports predictive maintenance scheduling and reduces unplanned downtime. Integration with project management platforms allows predictive insights to be embedded directly into planning and reporting workflows, facilitating timely decision-making by project managers and stakeholders [29]. In the Nigerian context, phased integration strategies are often required due to uneven digital maturity, but even partial integration can deliver meaningful improvements in schedule visibility and control [30].

5.4 Impacts on Time Certainty and Project Performance

AI-driven schedule optimisation and risk prediction have significant implications for time certainty and overall project performance. By identifying high-risk activities early and forecasting potential delays, predictive analytics enables proactive mitigation measures such as resource reallocation, re sequencing of tasks, and contingency planning [31]. Improved time certainty enhances cost control by reducing claims, penalties, and financing costs associated with delays. For energy projects, reliable schedules support timely capacity delivery and operational readiness, contributing to energy security and service reliability.Predictive scheduling also improves stakeholder communication by providing transparent, data-driven insights into schedule risks and expected outcomes. This transparency supports more effective coordination among contractors, regulators, and financiers, reducing disputes and improving governance outcomes [32]. Over time, the accumulation of predictive performance data contributes to organisational learning, enabling continuous improvement in planning accuracy and delivery capability. In the Nigerian construction and energy sectors, widespread adoption of AI-driven schedule optimisation has the potential to transform project delivery culture from reactive problem-solving to anticipatory, performance-oriented management, delivering long-term benefits for infrastructure development and sustainability objectives [33].

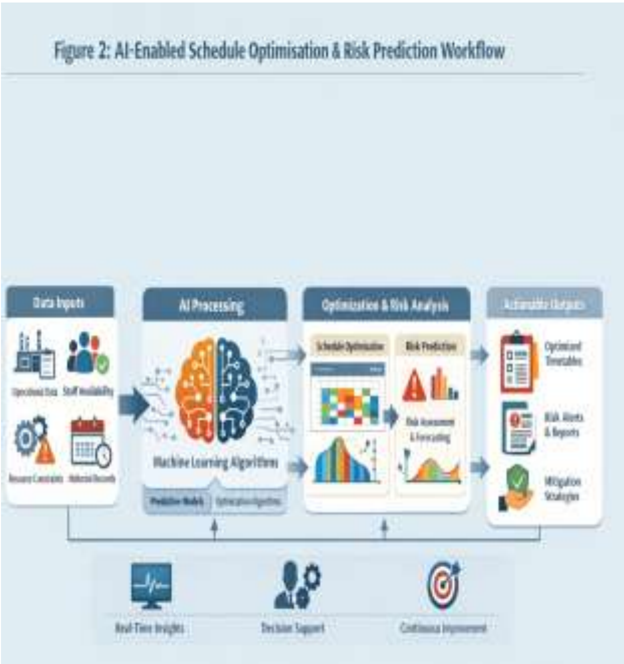

Figure 2: AI-enabled schedule optimisation and risk prediction workflow

6. CARBON OPTIMISATION THROUGH PREDICTIVE ANALYTICS

6.1 Carbon Hotspots in Construction and Energy Projects

Carbon emissions in construction and energy projects arise from multiple sources across the project lifecycle, with significant concentrations in material production, equipment operation, transportation, and energy consumption [35]. In construction projects, high-emission materials such as cement, steel, and asphalt constitute major carbon hotspots due to their energy-intensive manufacturing processes. On-site activities involving diesel-powered machinery and generators further increase emissions, particularly in contexts where grid electricity supply is unreliable [36].Energy projects introduce additional carbon hotspots through fossil fuel-based power generation, gas flaring, transmission losses, and inefficient operational practices. In Nigeria, these emissions are exacerbated by aging infrastructure, long-distance logistics, and limited adoption of energy-efficient technologies [37]. Identifying and quantifying these hotspots is a prerequisite for effective carbon optimisation, yet traditional project planning tools often treat emissions as secondary considerations rather than core performance metrics.

6.2 Predictive Emissions Modelling

Predictive emissions modelling applies AI-driven analytics to forecast carbon emissions associated with project activities before and during execution. By integrating historical emissions data, material quantities, logistics routes, equipment usage, and energy consumption patterns, machine learning models can estimate emissions trajectories with greater accuracy than static carbon accounting methods [38]. Material-related emissions models predict the carbon impact of alternative design and procurement choices, enabling comparison of low-carbon materials and construction techniques. Logistics-focused models forecast emissions from transportation based on routing, vehicle types, and fuel consumption, supporting optimisation of delivery schedules and supply chains. Energy use models analyse projected power demand, fuel usage, and operational efficiency to estimate emissions from construction sites and energy facilities. These predictive capabilities allow project teams to anticipate emissions outcomes under different scenarios and identify high-impact mitigation opportunities early in the project lifecycle [39].

6.3 AI-Supported Low-Carbon Decision-Making

AI-supported decision-making transforms carbon optimisation from a compliance-driven activity into an integrated planning function. Predictive analytics enables scenario analysis that evaluates trade-offs between cost, schedule, and carbon performance, supporting balanced decision-making aligned with sustainability objectives [40]. For example, AI models can assess whether schedule acceleration through additional equipment use would increase emissions beyond acceptable thresholds, or whether alternative sequencing could achieve time savings with lower carbon impact. In construction projects, predictive analytics supports low-carbon design optimisation, just-in-time material delivery, and reduced rework. In energy projects, AI-driven optimisation enhances fuel efficiency, reduces transmission losses, and supports predictive maintenance strategies that lower emissions over asset lifecycles. By embedding carbon metrics into predictive planning tools, decision-makers gain continuous visibility into emissions performance rather than relying on retrospective reporting [41].

6.4 Alignment with Nigeria's Climate and Energy Transition Goals

Nigeria has articulated climate and energy transition objectives through national policies aimed at reducing emissions intensity while expanding infrastructure and energy access [35]. AI-driven predictive analytics aligns with these goals by enabling data-driven pathways to low-carbon development without constraining economic growth. Predictive carbon optimisation supports more efficient use of resources, reduces waste, and enhances the viability of renewable and low-carbon energy projects. In the Nigerian context, where development needs are substantial, predictive analytics provides a pragmatic approach to integrating climate considerations into mainstream project delivery, supporting both national and international sustainability commitments [36].

Table 2: AI Applications for Carbon Reduction Across Project Phases

Project Phase	AI Application	Carbon Reduction Mechanism
Design	Predictive material selection	Lower embodied carbon
Planning	Logistics and schedule optimisation	Reduced transport emissions
Construction	Equipment usage forecasting	Lower fuel consumption
Operation	Predictive maintenance	Improved energy efficiency
Decommissioning	Lifecycle emissions modelling	Reduced end-of-life impacts

7. IMPLEMENTATION CHALLENGES, GOVERNANCE, AND POLICY IMPLICATIONS

7.1 Data Availability, Quality, and Interoperability Challenges

Effective deployment of AI-driven predictive analytics depends on the availability of high-quality, interoperable data. In Nigeria, construction and energy project data are often fragmented across organisations and stored in incompatible formats, limiting their analytical value [40]. Incomplete historical records, inconsistent data standards, and limited real-time data collection constrain model accuracy and scalability. Addressing these challenges requires investment in data governance frameworks, standardised data protocols, and digital infrastructure that supports secure data sharing across project stakeholders [41].

7.2 Skills, Capacity, and Institutional Readiness

Skills shortages represent a major barrier to AI adoption in Nigerian construction and energy sectors. Limited availability of data scientists, digital engineers, and AI-literate project managers restricts the effective use of predictive analytics tools [42]. Institutional resistance to change, combined with limited awareness of AI benefits, further slows adoption. Capacity-building initiatives, targeted training programmes, and partnerships with academic and technology institutions are essential to build the human capital required for AI-enabled project delivery [43].

7.3 Ethical, Legal, and Governance Considerations

The use of AI in project decision-making raises ethical and governance concerns related to data privacy, algorithmic transparency, and accountability. Predictive models may embed biases present in historical data, leading to skewed outcomes if not properly governed [44]. Clear governance structures are needed to define responsibility for AI-driven decisions, ensure explainability of predictive outputs, and protect sensitive project and operational data. In regulated sectors such as energy and public infrastructure, governance frameworks must align AI deployment with existing legal and procurement requirements [45].

7.4 Policy and Regulatory Implications for Nigeria

Policy support is critical for scaling AI-driven predictive analytics across Nigerian construction and energy projects. Governments can play a catalytic role by promoting digital standards, incentivising low-carbon project delivery, and integrating AI-enabled analytics into public procurement and infrastructure planning frameworks [40]. Regulatory clarity on data use, digital tools, and carbon reporting can reduce uncertainty and encourage private sector investment. By aligning policy, governance, and capacity development, Nigeria can harness AI-driven predictive analytics to improve project performance while advancing sustainable and low-carbon infrastructure development [41].

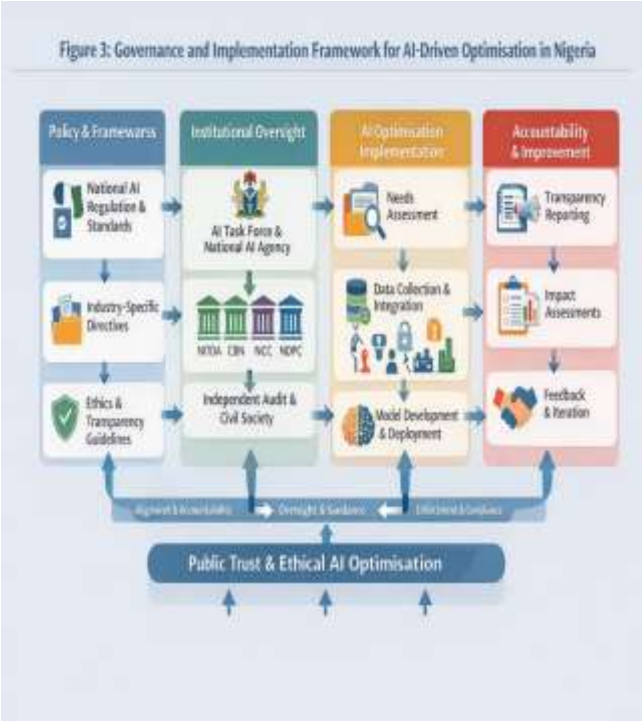

Figure 3: Governance and implementation framework for AI-driven optimisation in Nigeria

8. CONCLUSION

This study has examined the role of AI-driven predictive analytics in optimising resource allocation, project scheduling, and carbon performance within Nigerian construction and energy projects. The analysis demonstrates that predictive analytics offers a transformative shift from reactive, experience-based planning to proactive, data-driven decision-making. By integrating machine learning models with project management processes, organisations can improve forecasting accuracy, reduce waste, enhance schedule certainty, and embed carbon considerations into core project delivery functions. The Nigerian context, characterised by project complexity, data fragmentation, and infrastructure constraints, highlights both the urgency and the potential value of adopting predictive analytics as a strategic enabler of efficient and sustainable infrastructure development.

The paper contributes to knowledge by providing a context-specific framework that links AI-driven predictive analytics with resource, schedule, and carbon optimisation in developing economy settings. Unlike existing studies that focus on isolated performance metrics or advanced economies, this research advances an integrated perspective that aligns project efficiency with sustainability objectives. It also extends theoretical discussions on digital project management by incorporating carbon optimisation as a co-equal performance dimension alongside cost and time.

From a practical standpoint, the findings underscore the strategic importance of digital readiness, data governance, and capacity development in enabling effective AI adoption. For Nigerian construction and energy stakeholders, predictive analytics presents an opportunity to improve project delivery reliability, strengthen investor confidence, and support national development priorities. Strategically, widespread adoption can enhance infrastructure resilience, accelerate energy transition efforts, and position Nigeria to leverage digital innovation in achieving long-term economic growth and low-carbon development pathways.

9. REFERENCE

1. Flyvbjerg B. Survival of the unfittest: why the worst infrastructure gets built—and what we can do about it. Oxford Rev Econ Policy. 2009;25[3]:344–367.
2. Eze Dan-Ekeh. DEVELOPING ENTERPRISE-SCALE MARKET EXPANSION STRATEGIES COMBINING TECHNICAL PROBLEM-SOLVING AND EXECUTIVE-LEVEL NEGOTIATIONS TO SECURE TRANSFORMATIVE INTERNATIONAL ENERGY PARTNERSHIPS. International Journal Of Engineering Technology Research & Management (IJETRM). 2018Dec21;02(12):165–77.
3. B. F. Kayode *et al.*, "Temporal-Spatial Attention Network (TSAN) for DoS Attack Detection in Network Traffic," *2025 10th International Conference on Machine Learning Technologies (ICMLT)*, Helsinki, Finland, 2025, pp. 413-426, doi: 10.1109/ICMLT65785.2025.11193363
4. Odunola BK, Solomon WC, Mohammed SU, Sa'ad A, Nyoungue AC, Leontine NN. Optimizing biogas production through co-digestion of cow dung and chicken droppings. *AIP Conf Proc.* 2025;3321:040001. doi:10.1063/5.0289631.
5. Udeh NC. *Building sustainable SME banking strategies that expand market access, boost client retention, and support economic inclusion*. International Journal of Financial Management and Economics. 2018;1(1):126-135. doi:10.33545/26179210.2018.v1.i1.674.
6. Otoko J. Microelectronics cleanroom design: precision fabrication for semiconductor innovation, AI, and national security in the U.S. tech sector. Int Res J Mod Eng Technol Sci. 2025;7(2)
7. Ogunyemi FM, Owolabi IO, Busari IO, Olakunle TJ. Carbon accounting for ESG leadership: innovating sustainability practices in emerging markets. *Int J Multidiscip Res Sci Eng Technol*. 2023;6(11):3279. doi:10.15680/IJMRSET.2023.0611014
8. Damilola Olofintuyi. ADVANCING ABIOTIC STRESS TOLERANCE IN CROPS THROUGH PRECISION GENETIC ENGINEERING AND MOLECULAR BREEDING TOOLS. International Journal Of Engineering Technology Research & Management (IJETRM). 2024Dec21;08(12):611–23.
9. Nwenekama Charles-Udeh. Leveraging financial innovation and stakeholder alignment to execute high-impact growth strategies across diverse market environments. Int J Res Finance Manage 2019;2(2):138-146. DOI: 10.33545/26175754.2019.v2.i2a.617
10. Kolawole Oloke. Designing AI-first financial inclusion platforms using low-latency cloud services for emerging markets. Int J Res Finance Manage 2025;8(2):992-1002. DOI: 10.33545/26175754.2025.v8.i2k.636
11. Eze Dan-Ekeh. Engineering high-value commercialization frameworks integrating technical innovation with strategic sales leadership to drive multimillion-dollar growth in global energy markets. World J Adv Res Rev. 2019;4(2):256-268. doi:10.30574/wjarr.2019.4.2.0152
12. Akinbode RD. *The Need for Exercise Prescription for Bariatric Patients* (Master's thesis, Lamar University-Beaumont).
13. Adegoke SO, Chiamaka OT. Global tariff shocks and U.S. agriculture: causal machine learning approaches to competitiveness and market share forecasting. *Int J Res Publ Rev*. 2025;6(4):16173–16188. doi:10.55248/gengpi.6.0425.16109
14. Nosakhare VO, Kayode B, Akerele S, et al. Machine Learning in Cybersecurity: A Multi-Industry Case Study Analysis for Enhanced Threat Detection and Response. *J Artif Intell Mach Learn & Data Sci*. 2025;3(2):2684-2691. DOI: doi.org/10.51219/JAIMLD/Victor-Oriakhi-Nosakhare/568
15. Feyisayo Michael Ogunyemi. Green financing mechanisms for closing the trillion-dollar climate investment gap: A multi-stakeholder framework integrating public policy, private capital, and carbon accounting standards. Int J Res Finance Manage 2020;3(2):99-108. DOI: 10.33545/26175754.2020.v3.i2a.6091 citation
16. Robert Adeniyi Aderinmola. "Toward a Behavioural Intelligence Framework for Financial Stability: A National Model for Mitigating Systemic Risk in the United States Economy." Volume. 10 Issue.10, October-2025 International Journal of Innovative Science and Research Technology (IJISRT)2350-2358 https://doi.org/10.38124/ijisrt/25oct978
17. Olanrewaju A, Anavhe J. Project delivery challenges in the Nigerian construction industry. J Eng Des Technol. 2015;13[2]:252–276.
18. World Bank. Nigeria infrastructure diagnostics update. Washington DC: World Bank; 2018.
19. Hammond G, Jones C. Inventory of carbon and energy: ICE v2.0. Bath: University of Bath; 2011.
20. Intergovernmental Panel on Climate Change. Climate change 2014: mitigation of climate change. Cambridge: Cambridge University Press; 2014.
21. Oladele AK, Solomon WC, Muhammad SU. Optimization of process variables in the production of biodiesel from Jatropha–Neem hybrid feedstock mixture. *International Journal of Advances in*

Scientific Research and Engineering. 2024 Sep;10(9):18. doi:10.31695/IJASRE.2024.9.2.

22. Assaf SA, Al-Hejji S. Causes of delay in large construction projects. Int J Proj Manag. 2006;24[4]:349–357.
23. Olawale YA, Sun M. Cost and time control of construction projects. J Proj Manag. 2010;28[5]:509–526.
24. Williams T. Assessing and moving on from the dominant project management discourse. Int J Proj Manag. 2005;23[7]:497–508.
25. Chou JS, Pham AD. Smart artificial firefly algorithm-based optimization. Autom Constr. 2013;31:46–59.
26. Zhao X, Hwang BG, Yu G. Identifying critical delay factors. J Constr Eng Manag. 2013;139[4]:04013003.
27. Intergovernmental Panel on Climate Change. Climate change 2021: mitigation of climate change. Cambridge: Cambridge University Press; 2022.
28. Gielen D, Boshell F, Saygin D. The role of renewable energy in the global energy transformation. Energy Strategy Rev. 2019;24:38–50.
29. Love PED, Sing CP, Wang X. Overruns in transportation infrastructure projects. Struct Infrastruct Eng. 2013;9[2]:141–159.
30. United Nations. Transforming our world: the 2030 Agenda for Sustainable Development. New York: UN; 2015.
31. Wamba SF, Gunasekaran A, Akter S, Ren S, Dubey R, Childe SJ. Big data analytics and firm performance. Int J Prod Econ. 2017;191:88–103.
32. Hastie T, Tibshirani R, Friedman J. The elements of statistical learning. 2nd ed. New York: Springer; 2009.
33. Ivanov D, Dolgui A, Sokolov B. The impact of digital technology on supply chain resilience. Int J Prod Res. 2019;57[23]:829–846.
34. Kim GH, Shin JH, Kim S, Shin Y. Comparison of construction cost estimating models. J Constr Eng Manag. 2004;130[4]:534–542.
35. Box GEP, Jenkins GM, Reinsel GC. Time series analysis: forecasting and control. 4th ed. Hoboken: Wiley; 2008.
36. Deb K. Multi-objective optimization using evolutionary algorithms. Chichester: Wiley; 2001.
37. Cheng MY, Cao MT. Accurately predicting labor productivity using neural networks. Autom Constr. 2014;43:1–9.
38. Kim SY, Kim GH. Delay risk prediction in construction projects. KSCE J Civ Eng. 2016;20[1]:19–29.
39. Aibinu AA, Jagboro GO. The effects of construction delays on project delivery in Nigeria. Int J Proj Manag. 2002;20[8]:593–599.
40. Hong T, Fan C. A review of energy forecasting techniques. Energy Procedia. 2016;105:233–238.
41. International Energy Agency. World energy outlook 2021. Paris: IEA; 2021.
42. Nigerian Bureau of Statistics. Construction sector report Q4 2020. Abuja: NBS; 2021.
43. Olatunji OA. Building information modelling adoption in Nigeria. J Eng Des Technol. 2011;9[3]:294–311.