

# Evaluating the Application of Machine Learning in Quality Control of Residential Housing Projects in Lagos State, Nigeria

Akanni Prince Oluleye<sup>1\*</sup>; Makinde Olutunji Johnson<sup>2</sup>; Obasa Ayotomide James<sup>3</sup>; Oluwasanya Taiwo<sup>4</sup>

<sup>1,2,4</sup>Department of Building, Federal University of Technology, Akure

<sup>3</sup>Department of Quantity Surveying, Federal University of Technology, Akure

Corresponding Author: Akanni Prince Oluleye<sup>1\*</sup>

Publication Date: 2026/10/01

**Abstract:** Residential building construction in Lagos State, Nigeria, continues to be affected by recurring structural failures and quality non-conformances linked to an overreliance on manual, inconsistently applied quality control (QC) practices and a fragile regulatory enforcement environment. While international evidence increasingly shows that Machine Learning (ML) technologies can substantially improve construction quality monitoring, no empirical study had systematically examined the existing state of QC practice or the level of ML application specifically within the Lagos State residential construction context. This study evaluate the application of Machine Learning in construction quality control within the study area. A quantitative research design was adopted, with a structured questionnaire administered to 376 stratified-randomly sampled construction professionals: architects, civil and structural engineers, quantity surveyors, builders, and building control officers drawn from a sampling frame of 6,402 professionals. Data were analysed using descriptive statistics, Relative Importance Index (RII), and chi-square tests of association. Findings show that visual inspection dominates existing QC practice (91.5% of respondents), followed by standardised checklists (65.7%) and material testing (62.5%), while technology-enabled methods such as BIM, drone inspection, and digital monitoring tools remain used by fewer than 14% of practitioners; regulatory enforcement was rated the least consistently practised QC activity (RII = 54.4%). With respect to Machine Learning, 71.5% of respondents reported limited or no familiarity with ML in construction, and fewer than 8% of ML-familiar respondents had experienced any substantive ML deployment on their projects; chi-square tests confirmed that this awareness deficit does not vary significantly by professional category, experience, or firm size (all  $p > 0.05$ ). Lack of reliable structured data (RII = 78.0%) and ML's restriction to large-scale or foreign-funded projects (RII = 70.2%) were identified as the most significant contextual barriers. The study concludes that quality control in Lagos residential construction remains predominantly manual and reactive, and that Machine Learning adoption is at a very early, sector-wide pre-adoption stage requiring coordinated awareness-building and data infrastructure development before meaningful uptake can occur.

**Keywords:** Quality Control, Machine Learning, Residential Housing, Construction Technology Adoption.

**How to Cite:** Akanni Prince Oluleye; Makinde Olutunji Johnson; Obasa Ayotomide James; Oluwasanya Taiwo (2026) Evaluating the Application of Machine Learning in Quality Control of Residential Housing Projects in Lagos State, Nigeria.

*International Journal of Innovative Science and Research Technology*, 11(9), 2241-2252.

<https://doi.org/10.38124/ijisrt/26sep1183>

## I. INTRODUCTION

The technology and innovative tools accompanying the fourth industrial revolution have transformed the operational efficiency of construction industries worldwide (Akanni et al., 2023). The introduction of Machine Learning into the construction sector has been positioned as a means of improving project quality and outcomes (Akinosho et al., 2020). In Nigeria, the residential housing sector continues to grapple with problems including poor construction practices,

weak project management, and inadequate quality checks (Afolabi et al., 2019). Lagos, as Nigeria's economic nerve centre, presents a particularly important context for examining these problems: the state faces a housing shortage exceeding three million units, alongside growing concern over the quality and safety of existing housing stock (Oluwole & Ibrahim, 2020). Poorly designed buildings and inconsistent quality assurance have made residential construction in Lagos a matter of public safety concern (Osuizugbo & Oyeyipo, 2020).

Quality control in residential housing construction is the process of ensuring that materials, workmanship, and finished buildings meet established standards and regulations (Adeyemi & Ojo, 2021). In Nigeria, the conventional approach to quality assurance has relied on periodic human inspection and testing of materials and workmanship (Okonkwo et al., 2022) an approach vulnerable to human error, inconsistency, and subjectivity. Several studies trace recurring building defects and failures in Lagos back to inadequate quality control during construction (Nwachukwu & Emoh, 2019). The Lagos State Building Control Agency (LASBCA) recorded no fewer than 60 building collapse incidents between 2018 and 2022, many attributed directly to poor material quality, non-adherence to approved structural drawings, and inadequate supervision (LASBCA, 2022). Traditional quality control approaches in Lagos's residential zones remain heavily dependent on manpower and subjective judgement, rendering them susceptible to errors, irregularities, and inconsistent enforcement (Windapo & Rotimi, 2018); site inspectors are frequently constrained by insufficient manpower relative to the number of active construction sites, creating gaps in supervision during which defects such as poor reinforcement, incorrect concrete mix ratios, and substandard masonry can go undetected (Ajayi et al., 2019).

Machine Learning a subset of artificial intelligence that enables computers to learn from data, identify patterns, and support decisions with minimal human intervention (Jordan & Mitchell, 2019) has been applied internationally to defect detection, structural health assessment, predictive maintenance, cost estimation, and schedule optimisation in construction (Chen et al., 2020). Techniques such as convolutional neural networks for visual defect analysis, support vector machines for material classification, and predictive modelling for structural assessment have proven effective at improving the speed, accuracy, and efficiency of quality control in more technologically advanced construction sectors (Cha et al., 2018; Tixier et al., 2019). In China, ML combined with Building Information Modelling has been used to inspect reinforced structures with high accuracy (Zhang et al., 2021); in the United Kingdom, drones have supported defect detection in housing developments (Chen et al., 2020); and in the United States, predictive models have been used to forecast and pre-empt quality problems (Kim et al., 2019).

Despite this growing body of international evidence, the residential housing sector in Lagos State is characterised by a dual structure a formal sector with structured (if imperfectly enforced) quality control, and a substantial informal sector reliant on artisans and small contractors with limited technical oversight (Oduwaye et al., 2020; Obi & Arif, 2021). Existing research on digital technology adoption in the Nigerian construction industry has tended to address the phenomenon broadly (Olawumi & Chan, 2018; Owolabi et al., 2019), without systematically documenting the current state of quality control practice or the specific level of ML awareness and application within Lagos State's residential housing sector. This gap matters because recommendations for policy, technology investment, and training will lack the

contextual grounding needed to be effective without locally-sourced evidence and without it, efforts to introduce digital innovation risk repeating a familiar pattern in the Nigerian construction industry, where systems are purchased but never properly installed, or installed but neglected due to inadequate institutional capacity (Olatunji et al., 2023).

This study therefore sets out to examine the existing quality control practices currently used in residential housing projects in Lagos State, and to appraise the current level and nature of Machine Learning application in construction quality control within the study area providing the empirical baseline needed to inform realistic, context-appropriate strategies for improving construction quality assurance in Lagos State.

### ➤ *Research Hypothesis*

- H<sub>0</sub>: There is no significant relationship between construction professionals' demographic and organisational characteristics (professional category, years of experience, and firm size) and their level of familiarity with, or application of, Machine Learning in quality control of residential housing projects in Lagos State.
- H<sub>1</sub>: There is a significant relationship between construction professionals' demographic and organisational characteristics and their level of familiarity with, or application of, Machine Learning in quality control of residential housing projects in Lagos State.

## II. LITERATURE REVIEW

### ➤ *Conceptual Foundations of Construction Quality Control*

Quality control in construction is concerned with ensuring that construction work meets established standards, distinct from quality assurance (which concerns planning to ensure quality) and total quality management (a broader philosophy of continuous improvement) (Olawale & Sun, 2021; Afolabi et al., 2020). In residential housing, quality control typically involves checking material quality, monitoring construction processes, inspecting workmanship, and testing completed work; failure at any stage can lead to structural defects or building failure (Adeyemi et al., 2022). Established management frameworks including the Plan-Do-Check-Act cycle adapted from manufacturing, and the ISO 9001:2015 Quality Management System standard adopted by some Nigerian construction firms provide structured reference points against which quality control practice can be measured (Olawale & Sun, 2021; Ojo & Adeyemi, 2020).

### ➤ *Regulatory and Institutional Framework for Construction Quality in Lagos*

Construction quality in Lagos is governed by a layered framework spanning federal, state, and local regulation. The National Building Code (2019) sets minimum design, materials, and workmanship standards nationally (Federal Ministry of Works and Housing, 2019), while the Lagos State Urban and Regional Planning and Development Law (2019) operationalises these requirements at the state level, mandating building permits, site inspections by LASBCA

officers, and occupancy certificates. The Nigerian Industrial Standards specify material quality requirements, enforced by the Standards Organisation of Nigeria (Okonkwo et al., 2022). However, studies document a persistent gap between regulation and practice: one study found that only 34% of residential construction projects in Lagos had obtained a building permit before commencing work, and fewer than 20% had been inspected by LASBCA during construction (Oduwaye et al., 2020) a lapse that allows poor materials and substandard workmanship to go largely unchecked.

#### ➤ *Existing Quality Control Practices in Residential Housing Projects*

Quality control in Lagos residential construction is dominated by manual inspection and reactive testing. Babatunde et al. (2020) surveyed construction professionals in Lagos and found that routine visual inspection and post-construction material testing were the most frequently applied QC methods, while statistical quality control tools such as control charts were understood but rarely used in practice meaning current QC approaches tend to identify problems only after they occur, rather than preventing them. Olawale and Sun (2020) similarly found that quality control responsibility typically falls to site supervisors, whose effectiveness is undermined by scope creep, missing documentation, and time pressure. Eze et al. (2018) noted that artisans and foremen frequently rely on personal experience to judge quality, particularly on smaller projects lacking a formal QC team.

Formal quality management systems remain rare: Idoro (2018) found that ISO certification was largely confined to large multinational firms, while smaller companies which construct the majority of Lagos housing operated without any structured QMS, a pattern Akinradewo et al. (2020) attributed to certification cost and limited technical skill. Material and structural quality control present particular concerns. Oyewole and Dare (2019) found that concrete quality in low-cost Lagos housing projects often failed to meet specified standards due to cost-cutting and insufficient on-site testing, with laboratory cube testing rarely conducted correctly on small projects. Adenuga (2019), reviewing building collapses in Lagos between 2010 and 2018, found that most were traceable to poor quality control particularly substandard materials and insufficient concrete strength compounded by the absence of real-time quality monitoring capable of catching problems before they escalated.

Non-Destructive Testing (NDT) offers a way of assessing structural quality without damaging the tested element, commonly used to evaluate concrete strength via methods such as the rebound hammer test and Ultrasonic Pulse Velocity (UPV) testing (Malhotra & Carino, 2018; Proceq, 2019). The rebound hammer test is widely used for its portability and low cost but is affected by surface conditions, concrete age, and moisture, producing errors of up to  $\pm 25\%$  relative to destructive strength testing (Trtnik et al., 2019). UPV testing, while more capable of detecting internal voids and honeycombing, is similarly affected by reinforcement, aggregate size, and temperature at the time of testing. In the Lagos context, these limitations are

compounded by inconsistent site-mixed concrete, variable aggregate quality, high humidity, and limited technical training among site personnel (Okonkwo et al., 2022; Nwachukwu & Emoh, 2019).

A broader survey by Obi and Arif (2021), covering 210 Lagos construction professionals, found that visual inspection by site supervisors was cited by 87% of respondents as their primary QC method, followed by periodic material testing (52%) and verification of supplier quality certificates (41%); advanced methods such as NDT and digital quality management systems were reported by fewer than 15% of respondents. Adeyemi et al. (2020) found that the average site engineer in Lagos oversees more than three construction sites simultaneously a workload that limits the depth and consistency of quality checks while Nwachukwu and Emoh (2019) documented 43 building collapses in Lagos between 2016 and 2019, 67% of which were attributed to substandard materials, poor workmanship, or non-adherence to design specifications.

#### ➤ *Current Application of Machine Learning in Construction Quality Control*

Machine Learning has been applied across construction cost estimation, scheduling, safety management, productivity monitoring, and quality control since around 2018 (Akinosho et al., 2020). Within quality control specifically, ML particularly deep learning has been used to assess concrete, steel, and building envelope quality: predicting concrete strength, detecting cracks, classifying material quality from images, detecting weld defects and corrosion severity in steel, and identifying facade cracks and moisture damage in building envelopes (Kim et al., 2019; Chen et al., 2020). Visual defect detection is among the most developed applications. Kim et al. (2019) trained convolutional neural networks (CNNs) on 40,000 annotated images of concrete cracks, achieving 98.4% detection accuracy substantially outperforming human visual inspection. Chen et al. (2020) deployed a drone-mounted CNN defect detection system on a 12-storey building in Hong Kong, reducing inspection time by 62% and identifying defects in otherwise inaccessible areas, though the study also noted that image quality varies with lighting and weather, and that such systems require substantial training data and real-time computing capacity constraints particularly relevant to a context like Lagos, where data and equipment access remain limited (Okonkwo et al., 2022).

Predictive quality management represents a further application. Kim et al. (2019) used gradient boosting to forecast concrete quality defects on South Korean construction projects with 87% accuracy, enabling interventions before defects occurred rather than after. Natural Language Processing has similarly been explored for extracting quality-related information from inspection reports and project documentation (Zhang et al., 2021), though its application in Nigeria remains constrained by incomplete, unformatted, and non-digitised project records (Adekunle et al., 2022). ML application within the Nigerian and African construction context remains at an early stage relative to East Asia, North America, and Europe. Okonkwo et al. (2022)

found that where ML is used in Nigeria, it is concentrated in cost and time prediction, infrastructure health monitoring, and academic research, with no evidence of established use in residential housing quality control attributable to the absence of large construction datasets, limited professional awareness, and the cost of implementation. Adekunle et al. (2022) found that only 11% of Nigerian construction professionals surveyed had direct experience with ML tools, and fewer than 5% had applied ML specifically to quality control. Nonetheless, early applications exist: Afolabi et al. (2020) developed an Artificial Neural Network model that outperformed empirical formulas in predicting concrete strength using locally sourced Nigerian aggregate data, while Adeyemi and Ojo (2021) applied a CNN model to detect surface cracks in Lagos residential buildings, achieving 89% detection precision on locally collected test images evidence that ML can function in the Nigerian context, even as wider adoption remains limited.

#### ➤ *Theoretical Frameworks for Technology Adoption*

Adoption of new technologies in construction is shaped by several established theoretical frameworks. The Technology Acceptance Model (TAM), proposed by Davis (1989), holds that professionals are more likely to adopt a technology when they perceive it as useful and easy to use; Olatunji et al. (2021) found this pattern holds in developing-country contexts, where perceived usefulness is a particularly strong predictor of adoption intent. The Unified Theory of Acceptance and Use of Technology (UTAUT) further identifies social influence and facilitating conditions as important adoption factors, both found to be especially relevant in the Nigerian context (Adekunle & Lawal, 2022). The Diffusion of Innovations (DOI) theory (Rogers, 1962) frames adoption as a function of a technology's relative advantage, compatibility, complexity, trialability, and observability with relative advantage and compatibility identified in the literature as particularly influential in shaping ML adoption in Lagos construction (Okonkwo et al., 2022).

#### ➤ *Empirical Review and Identified Gaps*

Empirical work on quality control in Lagos residential construction has established the dominance of manual, reactive practices. Babatunde et al. (2020) confirmed visual inspection and post-construction testing as the most-used QC methods, but did not examine digital or ML-based alternatives. Olawale and Sun (2020, 2021) documented reliance on supervisor competence and identified common defects (wall cracking cited by 78% of respondents, rising damp by 67%, roof leakage by 62%), without evaluating technological interventions. Idoro (2018) established limited ISO 9001 uptake among SMEs but did not assess the cost-effectiveness of alternative QMS approaches. Adenuga (2019) linked building collapses to poor structural QC and absent real-time monitoring but offered no framework for implementing such monitoring. On the technical side, Malhotra and Carino (2018) and Trtnik et al. (2019) established the accuracy characteristics and limitations of conventional NDT methods without considering ML integration or tropical/local-context applicability, while Hannachi and Guetteche (2020) demonstrated ANN-based

improvement in concrete strength prediction outside the Lagos/Nigeria context. Obi and Arif (2021) offered the most direct evidence on QC method prevalence in Lagos but did not investigate ML adoption readiness or digital infrastructure among respondents.

On the ML application side, Akinosho et al. (2020) established that deep learning models (CNN, RNN) dominate international construction ML applications, but found scarce empirical evidence specific to residential quality control in Nigeria, with the absence of large labelled datasets flagged as a major barrier. Kim et al. (2019) and Chen et al. (2020) demonstrated strong ML performance in high-income country settings with established data infrastructure conditions not directly transferable to Lagos. Zhang et al. (2021) showed ML-based defect detection outperforming human inspection generally, but noted NLP applicability in Nigeria is restricted by low levels of record digitisation. Okonkwo et al. (2022) confirmed that fewer than 15% of Lagos-based construction companies maintain digitised QC logs, and identified the shortage of ML professionals and implementation cost as key barriers, though without experimental validation of ML models or a phased implementation framework. Adekunle et al. (2022) established very low rates of hands-on ML experience among Nigerian professionals and identified social influence and management support as significant adoption predictors, but did not measure actual quality outcomes. Afolabi et al. (2020) and Adeyemi and Ojo (2021) provided pilot-level evidence that ML models can be trained on Nigerian data with promising accuracy, but both studies were limited in sample size and lacked integration into a broader QC process.

Across this literature, a consistent gap emerges: while individual studies document either the state of conventional QC practice or isolated pilot applications of ML in Nigeria, no study has systematically and jointly examined existing QC practice and the current level of ML awareness and application specifically within Lagos State's residential housing sector, across the full range of relevant professional categories. This study addresses that gap by empirically documenting both dimensions concurrently, generating the baseline evidence needed to design realistic, sector-appropriate pathways toward ML-supported quality control in Lagos.

### III. RESEARCH METHODOLOGY

#### ➤ *Research Design*

The study adopted a quantitative, cross-sectional research design, appropriate for generating statistical evidence on the prevalence and patterns of existing QC practice and ML application among Lagos construction professionals at a single point in time (Saunders et al., 2019). The design combined descriptive and explanatory objectives, describing the current state of practice while identifying factors associated with observed patterns.

#### ➤ *Study Area*

The study was conducted in Lagos State, Nigeria, focusing on areas with concentrated residential construction

activity, including Lagos Island, Victoria Island, Ikeja, Lekki, Ajah, and Epe.

#### ➤ *Population of the Study*

The target population comprised construction professionals engaged in residential housing development and quality control across Lagos State, drawn from the membership of relevant professional bodies: the Nigerian Institute of Building (NIOB), the Council for the Regulation of Engineering in Nigeria (COREN), the Nigerian Society of Engineers (NSE), the Nigerian Institute of Quantity Surveyors (NIQS), the Nigerian Institute of Architects (NIA) Lagos State chapters and the Lagos State Building Control Agency (LASBCA). The sampling frame totalled 6,402 professionals, comprising architects (465), quantity surveyors (780), builders (662), civil/structural engineers (4,300), and building control officers (195).

#### ➤ *Sampling Technique and Sample Size*

A stratified random sampling technique was used, with the population stratified by professional category and simple random sampling applied within each stratum. Sample size was determined using the Taro Yamane (1967) formula at a 0.05 precision level, yielding a required sample of 376 respondents, proportionally allocated as: architects (32), quantity surveyors (40), builders (35), civil/structural engineers (245), and building control officers (24).

#### ➤ *Data Collection Instrument and Method*

A structured questionnaire, adapted from validated technology adoption instruments (Akinola & Balogun, 2023) and developed in line with Aghimien et al. (2020), was administered. The instrument combined closed-ended questions, Likert-scale items, and restricted open-ended items. Data collection combined direct face-to-face distribution at professional body meetings, industry events, and site offices, and indirect distribution via online forms shared through professional body email lists and WhatsApp groups, with a cover letter explaining the study's purpose and confidentiality, followed by two rounds of follow-up at two-week intervals.

#### ➤ *Method of Data Analysis*

Data were analysed using the Statistical Package for Social Sciences (SPSS). For the objectives addressed in this study, descriptive statistics (frequency, percentage, mean score, standard deviation) and Relative Importance Index (RII) were used to examine existing QC practices, while descriptive statistics, cross-tabulation, and chi-square tests of association were used to appraise the current application of Machine Learning and test for associations with professional category, experience, and firm characteristics.

#### ➤ *Reliability and Validity*

Content validity was ensured through expert review of the questionnaire by construction management researchers prior to distribution, supported by a pilot study.

#### ➤ *Ethical Considerations*

Ethical clearance was obtained prior to data collection. Participation was voluntary, with respondents informed of their right to withdraw at any stage; personal identifiers were stored separately from research data, and reporting was limited to anonymised statistical summaries (Creswell & Creswell, 2018).

### IV. DATA ANALYSIS AND PRESENTATION

#### ➤ *Pilot Study*

A pilot study was conducted with ten construction professionals not included in the main sample, drawn to reflect the diversity of professional backgrounds in the main study. Feedback led to the rewording of three items and a change in response-scale labelling in one section from an agreement scale to a frequency scale. Reliability testing of the pilot data via Cronbach's Alpha returned acceptable values across all relevant scales ( $\alpha > 0.70$ ).

#### ➤ *Response Rate and Demographic Profile*

A total of 376 questionnaires were distributed using stratified random sampling; all 376 were returned complete, representing a 100% response rate attributable to structured, in-person administration. Respondents were predominantly male (84.8%) and concentrated in the 25–44 age range (63.3% combined). The sample was well educated, with 44.4% holding a Bachelor's degree and 21.5% a Master's degree. Civil/structural engineers formed the largest professional category (65.2%), reflecting their proportion in the sampling frame, followed by quantity surveyors (10.6%), builders (9.3%), architects (8.5%), and building control officers (6.4%). Most respondents (30.9%) had 10–14 years of professional experience. Site supervision/quality inspection and design review/structural specification were jointly the most common primary responsibilities (32.4% each). The Lekki/Ajah corridor was the most frequently cited primary area of operation (32.2%), consistent with the area's concentration of active high-density residential construction. In terms of firm size, 36.2% of respondents worked in small enterprises (11–50 staff) and 30.1% in micro enterprises (10 or fewer staff), while 39.1% reported an annual project budget between ₦50 million and ₦200 million indicating that the sector is dominated by small-to-medium-scale operations.

#### ➤ *Existing Quality Control Practices in Residential Housing Projects in Lagos State*

Table 1 Quality Control Practices — Frequency and Descriptive Statistics

| Practice                | Count | Percent (%) |
|-------------------------|-------|-------------|
| Visual inspection       | 344   | 91.5        |
| Standardised checklists | 247   | 65.7        |
| Material testing        | 235   | 62.5        |
| Third-party audits      | 100   | 26.6        |
| BIM                     | 51    | 13.6        |
| Drone inspection        | 29    | 7.7         |

|                             |    |     |
|-----------------------------|----|-----|
| Digital monitoring tools    | 29 | 7.7 |
| Statistical Process Control | 10 | 2.7 |

*Multiple Responses Allowed; N = 376 Respondents; Most Respondents (83.8%) Used Between 2 and 4 Practices Simultaneously, with 3 Practices Being the Modal Response (37.0%).*

Visual inspection by site supervisors was the most universally adopted QC method (91.5%), followed by standardised checklists (65.7%) and material testing (62.5%). Technology-enabled methods were markedly under-utilised: BIM (13.6%), drone-based inspection (7.7%), digital/software monitoring tools (7.7%), and Statistical

Process Control (2.7%). These findings confirm continued heavy reliance on traditional, labour-intensive QC methods, consistent with Olawale and Sun's (2015) observation of underdeveloped technology use for construction monitoring in sub-Saharan Africa.

Table 2 Frequency of QC Practice Application — RII Analysis

| Statement                               | Mean  | Std Dev | RII   | RII (%) | Rank |
|-----------------------------------------|-------|---------|-------|---------|------|
| QC failures as a contributor to defects | 3.457 | 1.107   | 0.691 | 69.1    | 1    |
| Skilled manpower availability           | 3.309 | 1.136   | 0.662 | 66.2    | 2    |
| Early defect detection                  | 3.205 | 1.060   | 0.641 | 64.1    | 3    |
| Systematic documentation                | 2.976 | 1.104   | 0.595 | 59.5    | 4    |
| Documented quality standards            | 2.971 | 1.135   | 0.594 | 59.4    | 5    |
| Integrated quality control              | 2.941 | 1.079   | 0.588 | 58.8    | 6    |
| Regulatory enforcement                  | 2.718 | 1.155   | 0.544 | 54.4    | 7    |

Recognition of QC failures as a major contributor to building defects ranked highest (RII = 69.1%), reflecting strong professional acknowledgement of the stakes involved consistent with Nwachukwu and Emoh's (2019) finding that substandard construction and lack of QC control drive Lagos building collapse rates. Regulatory enforcement ranked lowest (RII = 54.4%), reinforcing continued doubts about the

effectiveness of statutory building control oversight. Notably, all seven statements scored below the 0.70 RII threshold, indicating that no QC dimension examined was rated as occurring frequently or consistently revealing a systemic gap between the formal expectation of quality management and its practical, on-site implementation.

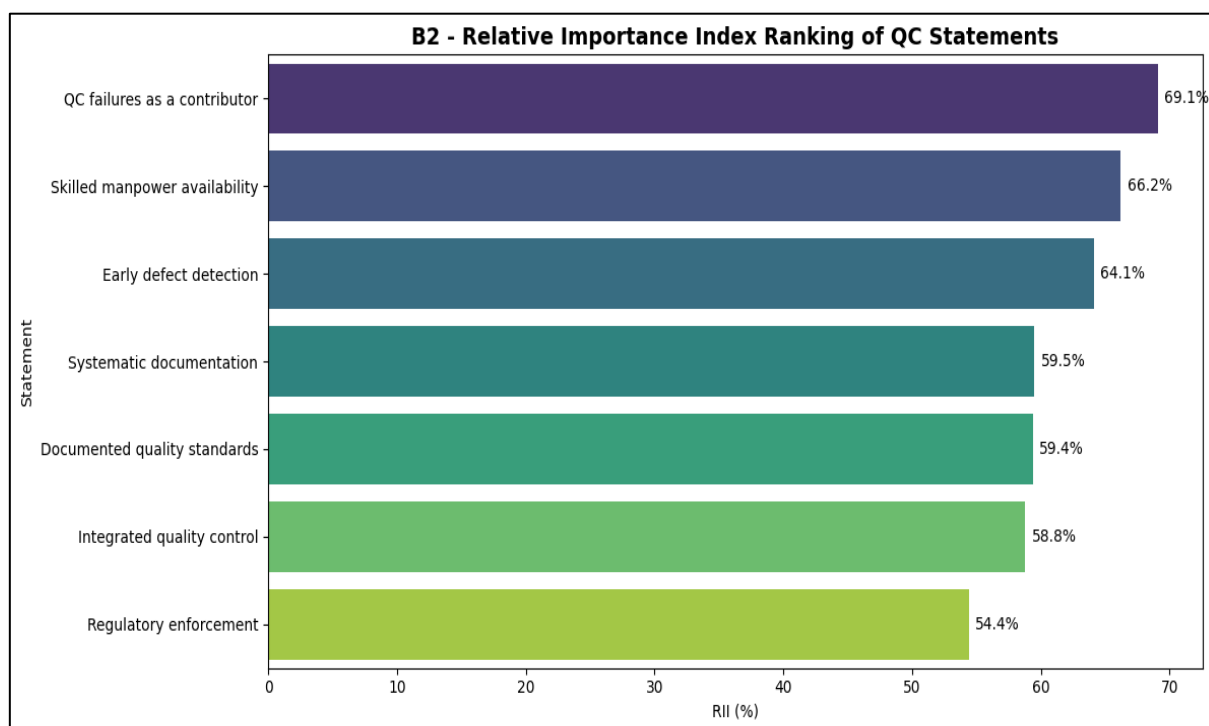


Fig 1 Relative Importance Index Ranking of QC Statement

The RII values for all seven statements fell below 0.70, indicating that none of the QC practices were rated as occurring frequently or consistently. This pattern reveals a systemic gap between the formal expectation of quality

management and its practical implementation on residential construction sites in Lagos State, a finding that aligns with the broader literature on construction quality deficits in Nigerian housing development. (Afolarin, 2013).

➤ *Current Application of Machine Learning in Construction Quality Control*

Table 3 ML Familiarity Level

| Familiarity Level   | Count | Percentage |
|---------------------|-------|------------|
| Slightly familiar   | 147   | 39.1       |
| Not familiar at all | 122   | 32.4       |
| Somewhat familiar   | 79    | 21.0       |
| Very familiar       | 28    | 7.4        |

Combined, 71.5% of respondents reported limited or no familiarity with ML in the construction context, consistent with Adekunle et al.'s (2022) finding of limited AI awareness among Nigerian construction professionals generally.

Table 4 Status of ML Adoption

| Status                            | Count | Percentage |
|-----------------------------------|-------|------------|
| No, not yet adopted               | 157   | 41.8       |
| I am not aware                    | 67    | 17.8       |
| In pilot/experimental stages only | 18    | 4.8        |
| Yes, on a few projects            | 8     | 2.1        |
| Yes, extensively                  | 4     | 1.1        |

Among the 254 respondents who had some familiarity with ML, the prevailing status was overwhelmingly non-adoption (41.8%), with only 1.1% reporting extensive use. Fewer than 8% of ML-familiar respondents had experienced any substantive ML deployment on their projects. Computer

vision/image-based defect detection was the most frequently encountered ML tool (10.1%), followed by predictive analytics (7.7%) and sensor-based monitoring (3.7%); NLP, drone-based ML imagery analysis, and digital twins remained rarely encountered (under 4% each).

Table 5 RII Ranking of Perceptions of the Current ML Landscape

| Statement                                    | Mean  | RII   | RII (%) | Rank |
|----------------------------------------------|-------|-------|---------|------|
| Lack of quality data is a barrier            | 3.898 | 0.780 | 78.0    | 1    |
| Growing interest in ML adoption              | 3.535 | 0.707 | 70.7    | 2    |
| ML limited to large-scale projects           | 3.508 | 0.702 | 70.2    | 3    |
| Government projects leading ML adoption      | 3.098 | 0.620 | 62.0    | 4    |
| Awareness about ML in construction QC exists | 2.756 | 0.551 | 55.1    | 5    |
| Professional bodies promoting ML adoption    | 2.496 | 0.499 | 49.9    | 6    |
| Infrastructure supports ML implementation    | 2.465 | 0.493 | 49.3    | 7    |

The absence of reliable, structured data was the most widely acknowledged barrier to ML adoption (RII = 78.0%), while current technical infrastructure's ability to support ML deployment scored lowest (RII = 49.3%), alongside limited institutional advocacy from professional bodies (RII = 49.9%).

➤ *Chi-Square Tests of Association*

ML Familiarity by Professional Category and Experience.

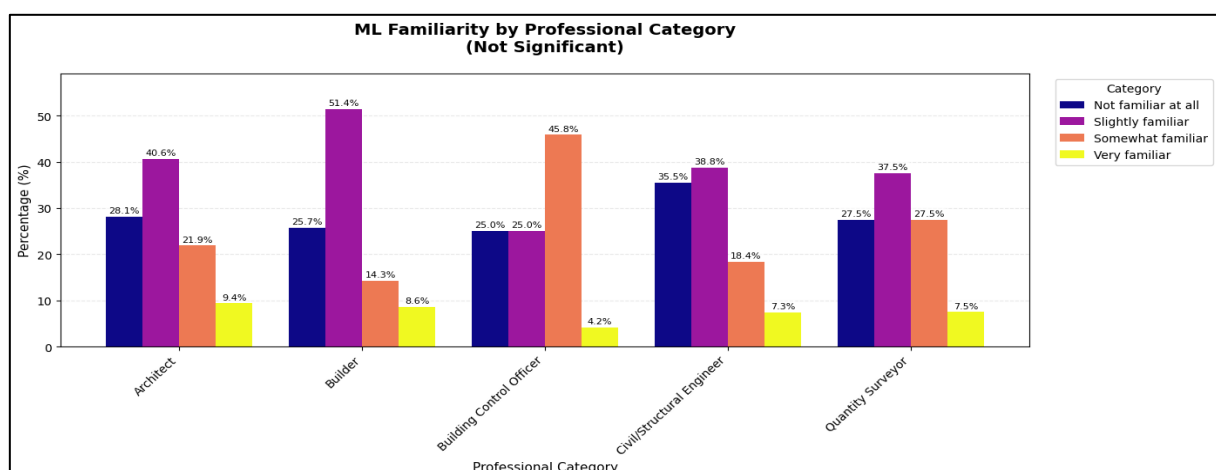


Fig 2 Levels of Familiarity of ML Across Professional Categories ( $\chi^2 = 14.72$ ,  $df = 12$ ,  $p = 0.257$ )

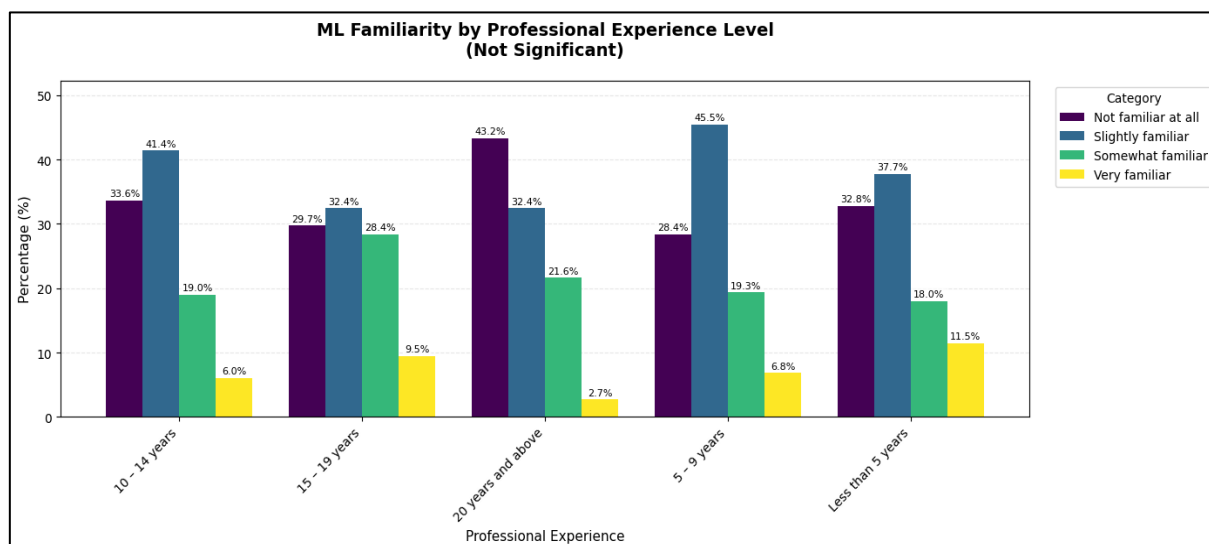


Fig 3 Levels of Familiarity of ML Across Professional Experience ( $\chi^2 = 10.08$ ,  $df = 12$ ,  $p = 0.6088$ )

Cross-tabulation of ML familiarity against professional category showed broadly similar distributions across all five categories, with civil/structural engineers reporting a somewhat higher proportion of "not familiar at all" responses (35.1%). The chi-square test confirmed no statistically significant association between professional category and ML familiarity ( $\chi^2 = 14.72$ ,  $df = 12$ ,  $p = 0.257$ ). Similarly, cross-tabulating ML familiarity against years of professional experience showed a consistent pattern across experience levels, with "slightly familiar" and "not familiar at all" together comprising over 60% of responses in every group; the chi-square test was again non-significant ( $\chi^2 = 10.08$ ,  $df = 12$ ,  $p = 0.609$ ). ML adoption status by experience showed

non-adoption rates ranging from 58.4% to 66.7% across all experience bands, with no meaningful relationship between years of experience and adoption depth. These results confirm that the ML awareness and adoption deficit in Lagos residential construction is a structural, sector-wide characteristic rather than a feature specific to any professional category, experience level, or firm size supporting acceptance of the null hypothesis ( $H_0$ ) that no significant relationship exists between these demographic/organisational characteristics and ML familiarity or application.

#### ➤ Potential Benefits of ML Adoption

Table 6 Descriptive Statistics of Benefits Items

| Benefit                           | Mean  | Std Dev | Rank |
|-----------------------------------|-------|---------|------|
| Early defect detection            | 4.255 | 0.835   | 1    |
| Data-driven decisions             | 4.141 | 0.935   | 2    |
| Rework cost reduction             | 4.069 | 0.933   | 3    |
| Accuracy and consistency          | 4.045 | 0.961   | 4    |
| Time and cost savings             | 3.992 | 1.003   | 5    |
| Detect non-compliant materials    | 3.875 | 1.065   | 6    |
| Documentation and audit trails    | 3.771 | 1.139   | 7    |
| Reduce human judgment bias        | 3.761 | 1.155   | 8    |
| Error prevention and incidents    | 3.750 | 1.101   | 9    |
| Code compliance verification      | 3.745 | 1.058   | 10   |
| Predictive maintenance capability | 3.697 | 1.175   | 11   |
| Investor confidence               | 3.609 | 1.188   | 12   |
| Supply chain quality              | 3.585 | 1.131   | 13   |
| Knowledge transfer and training   | 3.439 | 1.185   | 14   |

Table 6 show the mean scores with standard deviations of the 14 listed possible benefits. Early detection of defects was the top priority ( $M = 4.23$ ,  $SD = 0.85$ ), which means that the professionals consider the ability to promptly identify construction non-conformances as the first and foremost benefit of ML-based quality control. This is supported with technical evidence by Dung and Anh (2019), who pointed out that deep convolutional neural networks can reach F1 scores higher than 0.92 for concrete crack detection, which is a level

of performance significantly superior to human inspectors that have been trained. Besides that, data-driven decision-making ( $M = 4.13$ ,  $SD = 0.88$ ) and accuracy and consistency in inspections ( $M = 4.14$ ,  $SD = 0.87$ ) were not much behind, collectively highlighting the strength of algorithmic reliability in quality assurance, which is a quality going beyond subjective judgments. A lower mean score concerning the knowledge transfer and capacity building ( $M = 3.26$ ,  $SD = 1.10$ ) may imply that the long-term structural

results are thought to be less attractive in comparison to the direct operational benefits of ML application. The overall mean score for all 14 benefit items is 3.84, suggesting that the group generally considers ML adoption as quite beneficial for quality control of residential construction.

#### ➤ Multiple Regression Analysis

The multiple regression analyses involved a sample of 376 respondents and seven predictors: firm size, familiarity with ML, benefits composite, risks composite, professional category, professional experience, barriers composite.

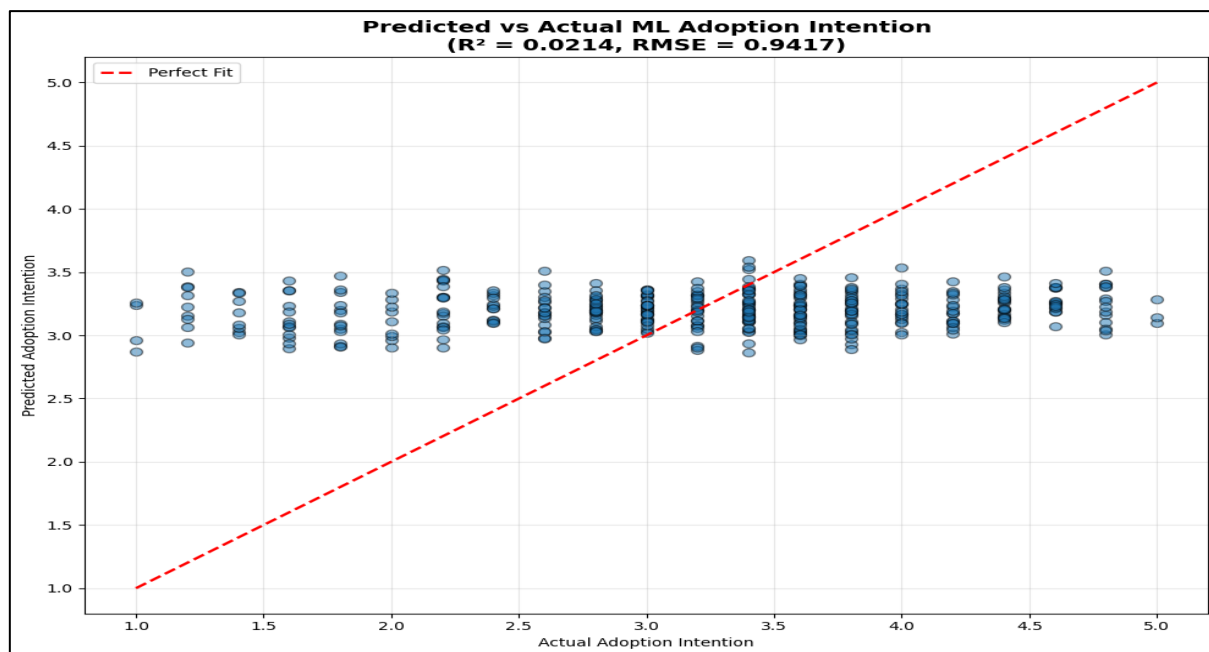


Fig 4 Predicted Versus Actual ML Adoption Intention

The model achieved a very low R-squared of 0.0214 and an adjusted R-squared of 0.0028, meaning that the seven predictors only explained 2.1% of the variance in adoption intention, with the RMSE value of 0.9417 indicating low accuracy of the model prediction, suggesting that the measured variables are not enough to explain the real predictors of this context. The largest positive coefficient was Benefits (Composite) ( $\beta = 0.055$ ), while the largest negative

coefficients were for Professional Experience ( $\beta = -0.103$ ) and ML Familiarity ( $\beta = -0.046$ ); all coefficients were negligibly small and not significant, and Pearson correlations confirmed no significant relationship between adoption intention and benefits ( $r = 0.056$ ,  $p = 0.275$ ), risks ( $r = -0.041$ ,  $p = 0.425$ ), or barriers ( $r = -0.001$ ,  $p = 0.992$ ). The close fit between the two plots visually confirms the model's shortcomings:

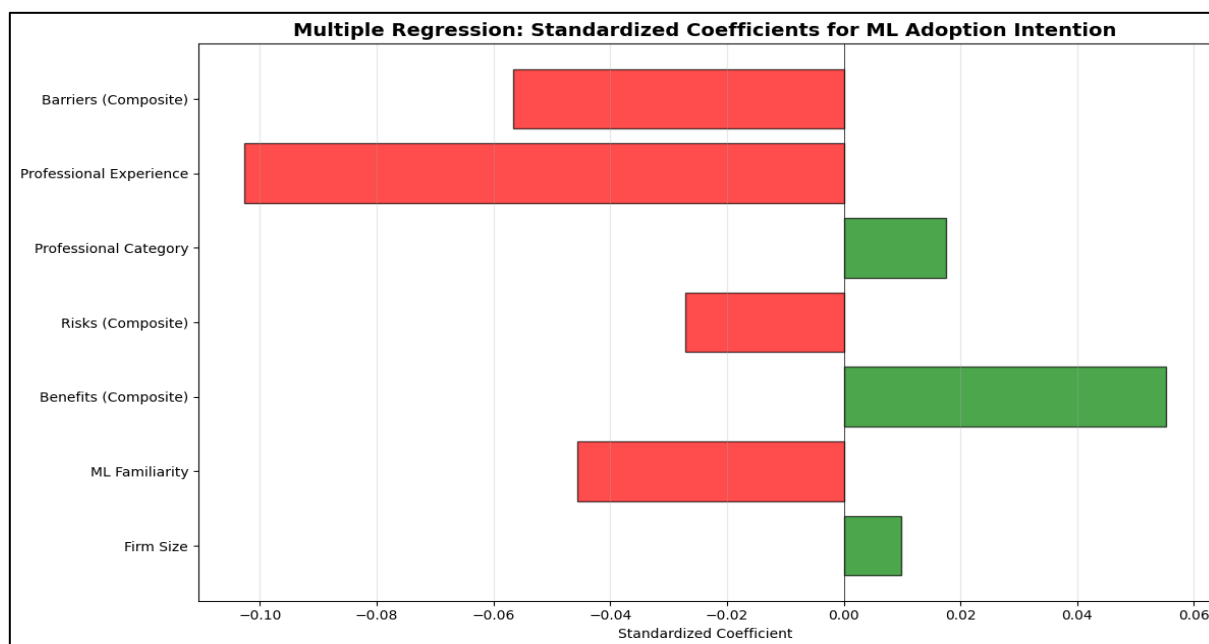


Fig 5 Multiple Regression: Standardized Coefficients for ML Adoption Intention

Predicted values are tightly grouped around 2.9–3.5, even as the actual adoption intention scores vary over the entire 1–5 range. This means that the model is not discriminating and in essence predicts a near constant mean response across the entire range of scores. The results of this study indicate that intention to adopt ML in the construction of residential buildings in Nigeria is not adequately explained by the perceived benefits, barriers, risks, level of experience, and professional role factors independent of each other, suggesting that the unmeasured contextual factors such as organisational culture, project requirements, client demand, and government policy signals may be more significant factors to be investigated.

## V. DISCUSSION OF FINDINGS

The dominance of visual inspection (91.5%) and standardised checklists (65.7%) as QC methods confirms Obi and Arif's (2021) characterisation of Nigerian construction as labour-intensive with human-supervised quality assurance as the norm. The finding that regulatory enforcement was the least consistently practised QC dimension (RII = 54.4%) is consistent with the pattern of weak regulatory follow-through documented by Oduwaye et al. (2020) and helps explain the continued incidence of building collapse linked to unchecked substandard construction (Adeyemi et al., 2022). The finding that 71.5% of respondents have limited or no ML familiarity aligns with the broadly low level of AI awareness reported across the Nigerian construction sector (Obi & Arif, 2021; Adekunle et al., 2022), though it contrasts with somewhat more advanced awareness levels reported in South African and Ghanaian contexts (Simpeh et al., 2022). The non-significant chi-square results across professional category, experience, and firm size, unlike more mature technology-adoption environments where awareness typically correlates with seniority or firm scale, suggest that ML awareness-building interventions in Lagos must be deployed simultaneously across all professional bodies and organisational scales, rather than targeted narrowly at any single segment, to be effective. The regression analysis confirmed that firm size, familiarity with ML, benefits composite, risks composite, professional category, professional experience, and barriers composite are the seven predictors of adoption intention, together explaining 2.1% of its variance. This is consistent with the Technology Acceptance Model (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003), both of which identify perceived utility and contextual enablement as the primary drivers of adoption. The finding that Professional Experience exert the negative influence ( $\beta = -0.103$ ) and structural capacity barriers exert negative influence ( $\beta = -0.01$ ) underscores the need for simultaneous investment in skills development, digital infrastructure, and need data governance — conditions that no single firm or professional can create unilaterally, necessitating sector-wide policy intervention, while composite benefit ( $\beta = 0.06$ ) exert the top positive influence on adoption.

## VI. CONCLUSION AND RECOMMENDATIONS

### ➤ Conclusion

The study concludes that quality control practice in Lagos State residential housing construction remains predominantly traditional, manual, and inconsistently applied. Visual inspection by site supervisors remains the cornerstone of QC activity, while technology-enabled methods are employed by fewer than 14% of practitioners. Crucially, no QC dimension examined achieved an RII above 0.70, and regulatory enforcement the mechanism intended to guarantee baseline compliance ranked lowest of all dimensions assessed, pointing to a fundamental governance gap underlying recurring quality failures in the sector.

The study further concludes that the application of Machine Learning in residential construction quality control in Lagos State is at a very early, predominantly pre-adoption stage, with awareness uniformly low across all professional categories, experience levels, and firm sizes. This uniformity rather than awareness varying meaningfully by professional segment indicates that the ML knowledge deficit is a structural, sector-wide characteristic. The absence of reliable, structured construction data and the concentration of existing ML use in large-scale or foreign-funded projects were identified as the most significant contextual barriers to wider diffusion. Also good internal consistency for all four measurement scales ( $\alpha = 0.89 - 0.95$ ). The most important benefit of ML was early detection of defects, and the top barriers were the lack of skilled professionals and high implementation cost. The multiple regression indicated that the perceived benefits, barriers, and ML familiarity were the main factors influencing the adoption intention ( $R^2 = 0.02$ ).

### ➤ Recommendations

Based on the findings, it is recommended that professional bodies (COREN, NIOB, NIA, NSE, NIQS) integrate foundational Machine Learning literacy into Continuing Professional Development programmes, designed for practitioners with no prior ML background and delivered uniformly across all professional categories and experience levels, given that awareness gaps do not concentrate in any single segment. Regulatory bodies, particularly LASBCA, should strengthen consistency in construction site inspection and enforcement, given that this dimension of QC practice was rated weakest by practising professionals. To address the data barrier most widely identified by respondents, government and industry stakeholders should work toward standardising and digitising quality control documentation including inspection logs, material test certificates, and NDT records as a foundational step toward building the structured datasets that future ML applications will require. Finally, given that current ML use is concentrated in large-scale or foreign-funded projects, targeted pilot programmes involving small and medium-sized construction firms which dominate the Lagos residential sector should be prioritised to ensure that ML-driven quality improvements do not bypass the segment of the market where quality failures are most acute.

## REFERENCES

- [1]. Adekunle, S. A., Ejohwomu, O. A., & Ilori, O. M. (2022). Barriers to the adoption of digital technologies in the Nigerian construction industry: A qualitative analysis. *Construction Innovation*, 22(3), 512–530.
- [2]. Adenuga, O. A. (2019). Causes of building collapse in Nigeria: A review of incidents in Lagos State. *African Journal of Environmental Science and Technology*, 13(7), 245–258. <https://doi.org/10.5897/AJEST2019.2685>
- [3]. Adeyemi, A. Y., & Ojo, A. S. (2021). Quality management practices and building defects in Lagos residential construction: Empirical evidence and policy implications. *Journal of Construction in Developing Countries*, 26(1), 45–67.
- [4]. Adeyemi, A. Y., Ojo, A. S., & Adegoke, B. F. (2022). Building collapse incidence, causal factors, and regulatory responses in Lagos State, Nigeria: A mixed-methods assessment. *Journal of Construction in Developing Countries*, 27(1), 61–84.
- [5]. Afolabi, A., Ojelabi, R., Fagbenle, O., Mosaku, T., & Amusan, L. (2019). Construction industry challenges and sustainable development in Nigeria: Stakeholder perspectives. *International Journal of Construction Management*, 19(6), 499–510.
- [6]. Afolabi, A., Ojelabi, R., Fagbenle, O., & Amusan, L. (2020). Emerging technology adoption readiness in Nigerian construction: An industry-wide assessment. *International Journal of Construction Management*, 20(5), 441–453.
- [7]. Aghimien, D., Aigbavboa, C., Oke, A., Thwala, W., & Moripe, K. (2020). Mapping out research focus for robotics and automation research in construction-related studies. *Journal of Engineering, Design and Technology*, 18(5), 1063–1079.
- [8]. Ajayi, S. O., Oyedele, L. O., Akinade, O. O., Bilal, M., Owolabi, H. A., & Alaka, H. A. (2019). Waste effectiveness of the construction industry: Understanding the impediments and requisites for improvements. *Resources, Conservation and Recycling*, 102, 101–112.
- [9]. Akinosho, T. D., Oyedele, L. O., Bilal, M., Ajayi, A. O., Delgado, M. D., Akinade, O. O., & Ahmed, A. A. (2020). Deep learning in the construction industry: A review of present status and future innovations. *Journal of Building Engineering*, 32, Article 101827.
- [10]. Akinradewo, O., Aigbavboa, C., Edwards, D., Thwala, W., & Akinradewo, O. (2020). Acceptance of ISO 9001 quality management system in the Nigerian construction industry. *Journal of Engineering, Design and Technology*, 18(6), 1599–1614.
- [11]. Babatunde, S. O., Ekundayo, D., & Babalola, O. (2020). Quality management practices in building projects in Lagos: An empirical assessment. *International Journal of Construction Management*, 20(4), 381–392.
- [12]. Cha, Y., Choi, W., & Büyüköztürk, O. (2018). Deep learning-based crack damage detection using convolutional neural networks. *Computer-Aided Civil and Infrastructure Engineering*, 32(5), 361–378.
- [13]. Chen, J., Fang, Y., & Chi, H. L. (2020). Automated visual inspection of building surfaces using unmanned aerial vehicles and deep learning: A review. *Automation in Construction*, 120, Article 103346.
- [14]. Creswell, J. W., & Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). SAGE Publications.
- [15]. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340.
- [16]. Eze, E. C., Ugulu, R. A., & Tengan, C. (2018). Rework and abortive works causative factors affecting building construction projects in Lagos, Nigeria. *World Journal of Engineering and Technology*, 6(4), 851–872.
- [17]. Federal Ministry of Works and Housing. (2019). *National Building Code of Nigeria* (Revised ed.). Federal Government of Nigeria.
- [18]. Hannachi, S., & Guetteche, M. N. (2020). Combined method for assessing concrete compressive strength using Schmidt rebound hammer and ultrasonic pulse velocity. *Construction and Building Materials*, 234, Article 117371.
- [19]. Idoro, G. I. (2018). Influence of quality management system certification on the performance of construction projects in Nigeria. *Journal of Civil Engineering and Management*, 24(3), 1–16.
- [20]. Jordan, M. I., & Mitchell, T. M. (2019). Machine learning: Trends, perspectives, and prospects. *Science*, 349(6245), 255–260.
- [21]. Kim, H., Ahn, C. R., & Kim, H. (2019). Proactive quality control using machine learning for construction defect prediction: A case study. *Journal of Computing in Civil Engineering*, 33(4), 04019018.
- [22]. Lagos State Building Control Agency. (2022). *Annual report on building collapse incidents in Lagos State 2018–2022*. LASBCA.
- [23]. Malhotra, V. M., & Carino, N. J. (2018). *Handbook on nondestructive testing of concrete* (2nd ed.). CRC Press.
- [24]. Nwachukwu, C. C., & Emoh, F. I. (2019). Determinants of building collapse in Nigeria: Causes, effects, and remedies. *American Journal of Civil Engineering and Architecture*, 7(1), 24–34. <https://doi.org/10.12691/ajcea-7-1-4>
- [25]. Obi, L. I., & Arif, M. (2021). Skill gaps and technological readiness in the Nigerian construction sector: Implications for Industry 4.0 adoption. *Engineering, Construction and Architectural Management*, 28(9), 2583–2607.
- [26]. Oduwaye, L., Badejo, B., & Adebayo, A. (2020). Housing development and urban growth management in metropolitan Lagos. *Journal of Land Use, Mobility and Environment*, 13(2), 143–161.
- [27]. Ojo, S., & Adeyemi, A. (2020). ISO 9001 and construction quality management in Nigeria. *Journal of Construction Management*, 15(2), 88–101.
- [28]. Okonkwo, E., Anumba, C. J., & Ugwu, O. O. (2022). Machine learning applications in construction: A systematic review of the Nigerian literature. *Built Environment Project and Asset Management*, 12(1), 78–97.

- [29]. Olatunji, O. A., Oluwaseun, M. A., & Alabi, R. T. (2021). Technology acceptance and digital construction in emerging economies: A study of Lagos construction firms. *Technological Forecasting and Social Change*, 170, Article 120914.
- [30]. Olatunji, S. O., Aghimien, D. O., Oke, A. E., & Aigbavboa, C. O. (2023). Institutionalising digital technology for construction project management in Nigeria: Critical success factors. *Engineering, Construction and Architectural Management*, 30(1), 34–52.
- [31]. Olawale, Y., & Sun, M. (2020). Construction project control in Nigeria: Practitioners' perspective on methods used and perceived effectiveness. *Journal of Construction in Developing Countries*, 25(1), 1–26.
- [32]. Olawumi, T. O., & Chan, D. W. M. (2018). A scientometric review of global research on sustainability and sustainable development. *Journal of Cleaner Production*, 183, 231–250.
- [33]. Oluwole, D. A., & Ibrahim, A. D. (2020). Housing deficit and urban sustainability in Lagos megacity: Policy interventions and market responses. *Habitat International*, 98, Article 102143.
- [34]. Osuizugbo, I. C., & Oyeyipo, O. (2020). Obstacles to the adoption of Building Information Modelling (BIM) in Nigeria's construction industry. *International Journal of Construction Management*, 22(14), 2817–2830.
- [35]. Owolabi, J. D., Amusan, L. M., Oloke, C. O., Olusanya, O., Tunji-Olayemi, P., Owolabi, D., Peter, J., & Omuh, I. (2019). Causes and effects of building failure and collapse in Nigeria. *American Journal of Engineering Research*, 3(10), 74–82.
- [36]. Oyewole, M. O., & Dare, O. O. (2019). Assessment of concrete quality in low-cost housing construction in Lagos State, Nigeria. *Journal of Engineering Research*, 24(1), 1–10.
- [37]. Rogers, E. M. (1962). *Diffusion of innovations*. Free Press.
- [38]. Saunders, M., Lewis, P., & Thornhill, A. (2019). *Research methods for business students* (8th ed.). Pearson Education.
- [39]. Simpeh, F., Amoah, C., & Kwasi, B. (2022). Assessment of measures for improving the digital construction skills capacity of the Ghanaian construction industry. *Journal of Engineering, Design and Technology*, 20(2), 408–428.
- [40]. Tixier, A. J.-P., Hallowell, M. R., Rajagopalan, B., & Bowman, D. (2019). Application of machine learning to construction injury prediction. *Automation in Construction*, 69, 102–114.
- [41]. Trtnik, G., Kavcic, F., & Turk, G. (2019). Prediction of concrete strength using ultrasonic velocity and artificial neural networks. *Ultrasonics*, 49(1), 53–60.
- [42]. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view1. *MIS quarterly*, 27(3), 425–478.
- [43]. Windapo, A. O., & Rotimi, J. O. B. (2018). Contemporary issues in building collapse and its implications for sustainable development. *Buildings*, 2(4), 283–299.
- [44]. Yamane, T. (1967). *Statistics: An introductory analysis* (2nd ed.). Harper and Row.
- [45]. Zhang, Y., Yuen, K. V., & Liu, Z. (2021). Automated crack detection in reinforced concrete structures using convolutional neural networks and building information modeling integration. *Computer-Aided Civil and Infrastructure Engineering*, 36(2), 199–218.