MachineLearninginConstruction: ASystematicReviewwitha Focus on Nigeria☆

Abstract

The Nigerian construction industry faces persistent challenges, including inefficiencies, delays, and cost overruns, which significantly limit its contributiontonationaldevelopment. Globally,machinelearning(ML)hasrevolutionizedtheconstructionsectorbyimprovingprocessessuchas cost estimation, project scheduling, and risk management.Despite its potential, ML adoption in Nigeria remains minimal, with significant gaps inresearchandapplication. Thisstudyseekstoaddressthisgapbyconductingasystematicreviewof MLapplicationsintheglobalconstruction industry,withafocusedanalysisofopportunitiesandbarriersforimplementationwithintheNigeriancontext. Asystematicreviewmethodology was adopted, following PRISMA guidelines.Relevant peer-reviewed articles were sourced from databases such as Scopus and Google Scholar, and thematic analysis was conducted to compare global trends with the Nigerian construction landscape.Key findings reveal that ML has enhanced projectefficiency,optimizedcosts,andfacilitateddata-drivendecision-makingglobally.SpecificopportunitiesforMLadoptioninNigeriainclude resourceoptimizationthroughefficientallocationofmaterialsandlabor,predictivemaintenanceforminimizingequipmentdowntimeandrepair costs,andadvanceddata-drivenprojectmanagementtoimproveplanningandexecution. However,barrierssuchaseconomicinstability,limited technicalexpertise,andinfrastructuredeficiencieshinderwidespreadadoption. Thisstudyrecommendstargetedstrategies,includinginvestments in ML capacity building through specialized training, infrastructure development, and fostering collaborations between academia and industry. AcceleratingMLadoptionisessentialforenhancingthecompetitiveness,efficiency,andsustainabilityofNigeria'sconstructionindustry,thereby contributing to broader national development objectives.Future research should focus on empirical investigations to validate these findings and provide actionable insights for implementing ML in Nigeria's construction sector.

*Keywords:*MachineLearning,ConstructionIndustry,Nigeria,SystematicReview

1. Introduction

Theconstructionindustryisacornerstoneofeconomicdevelopment, particularly in emerging economies where it contributesbetween3%and8%totheGrossDomesticProduct (GDP) [1].In Nigeria, however, the sector faces significant challenges,primarilyduetoinadequateinfrastructure. Withan estimatedinfrastructuredeficitof$3trillion—sixtimesthenation's annual GDP [2], Nigeria struggles to meet the growing demandsofarapidlyurbanizingpopulation. Effortssuchasthe NigerianEconomicSustainabilityPlan[3],whichaimedtodeliverupto300,000dwellingsannually, havebeenundermined by macroeconomic instability, inflation, and the lingering effectsoftheCOVID-19pandemic.Thesechallengeshaveledto

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substantial increases in construction costs, particularly due to the volatility of material prices, which account for up to 50% of total project costs [4].This persistent issue has resulted in projectdelays,costoverruns,and,inmanycases,projectaban-donment.

The volatility of construction material prices is one of the mostpressingchallengesinNigeria'sconstructionsector.Fluc-tuations in material costs are influenced by a complex inter-play of factors, including macroeconomic conditions, energy prices, andmarketdynamics, makingaccuratepredictionsdif-ficult.Existingforecastingmodels,suchasUnivariateARIMA andregressionanalysis,oftenfailtocapturethenuancesofthe Nigerian construction market [5].Additionally, inefficiencies, lowproductivity, andalackofskilledlaborhavefurthercom-poundedthechallenges. Theslowadoptionofinnovativetech-nologies, including machine learning (ML), exacerbates these issues, limiting the sector's potential for growth and modern-ization [6].

Machine learning, a subset of artificial intelligence, offers transformative potential for addressing many of these chal-lenges.Globally, ML has been successfully applied in cost estimation, project scheduling, risk management, quality con-trol, and safety enhancement [7].In the Nigerian context, ML could provide a much-needed solution to critical issues suchasmaterialpriceforecasting,costoverruns,andprojectdelays. Forinstance, MLmodelscananalyzehistoricaldataalongside macroeconomic variables to predict material costs more accu-rately, thereby reducing uncertainty in project budgeting.Ad-ditionally, ML-basedautomationcanenhancedecision-making, optimizeresourceallocation,andreducerelianceonmanualla-bor,therebyimprovingefficiencyandproductivityintheNige- rian construction sector [8].

This study aims to conduct a systematic review of the use of machine learning in the global construction market, with a specific focus on the Nigerian construction industry.The ob-jectivesofthestudyare: (i)toidentifythecurrentapplications of machine learning in the global construction market, (ii) to assess the adoption of machine learning in the Nigerian con-struction market, (iii) to analyze the challenges and barriers to the adoption of machine learning in the Nigerian construction industry,(iv)toidentifytheopportunitiesfortheapplicationof machine learning in the Nigerian construction market, and (v) to provide recommendations for the effective implementation of machine learning in the Nigerian construction industry.

The scope of this review spans both global and localized perspectives.It examines the application of machine learn-ing in various phases of the construction lifecycle, including design, project management, and cost estimation, from 2010to2023—aperiodmarkedbysignificantadvancementsinML technologies.Globally, thereviewexploreshowMLhasbeen adopted to address construction challenges in different socio-economiccontexts.TheNigerianconstructionindustryisthen analyzed as a case study to understand how these global ad-vancementscanbetailoredtoaddresstheuniquechallengesof anemergingmarket. Byintegratingglobalinsightswithlocal-izedanalysis,thisreviewseekstoprovideacomprehensiveun-derstandingofhowMLcanbeleveragedtotransformNigeria's constructionsector.

2. MaterialsandMethods

2.1. SystematicReviewApproach

This study employs a systematic review methodology, which is a structured and replicable process designed to criti-cally assess and synthesize relevant research related to a spe-cific topic or question.Unlike traditional narrative reviews, thesystematicreviewapproachensurescomprehensivenessand rigorbyadheringtoclearlydefinedprocedures. Themethodol-ogy for this review is guided by the Preferred Reporting Items for SystematicReviews andMeta-Analyses (PRISMA)guide-lines.PRISMA provides a standardized framework for con-ducting systematic reviews, consisting of a 27-item checklist and a schematic diagram illustrating the review process.This methodologywasselectedduetoitsrobustness, reproducibility, and wide acceptance across various disciplines [9].

The PRISMA process for this study was divided into four phases:article identification, article screening, eligibility as-sessment, and data extraction.These steps ensured trans-parencyandminimizedbiasintheselectionandanalysisoflit-erature.Thesystematicreviewfocusedontheperiodfrom2010 to2023,asthistimeframecapturessignificantadvancementsin machine learning (ML) technologies and their applications in the construction industry.

2.2. DatabasesUsed

The systematic literature search was conducted using mul-tipleacademicdatabasestoensurecomprehensivecoverageof relevant studies.The primary database utilized was Scopus, chosenforitsextensiveindexingofpeer-reviewedjournalsand itssuperiorcitationanalysiscapabilities. Scopuswaspreferred over alternatives like IEEE Xplore, Web of Science, and Sci-enceDirect due to its broad multidisciplinary reach and inclu-sionofnearlyalljournalsindexedinScienceDirect.Addition- ally, Google Scholar was used as a supplementary source to capture grey literature and relevant studies that might not be indexed in Scopus.

2.3. SearchStrategy

The search strategy employed a combination of keywords related to machine learning technologies and the construction industry.Keywords included terms such as "machine learn-ing," "artificial intelligence," "deep learning," "reinforcement learning,""automation,""robotics,""expertsystems,""natural language processing," and "optimization." These terms were paired with construction-related phrases such as "constructionindustry,""buildingindustry,""builtenvironment,"a nd"Archi- tecture, Construction, and Engineering (AEC)." Logical oper- ators (e.g., AND, OR) were used to refine the search and en- sure relevant results.Double quotation marks were applied around specific phrases (e.g., "machine learning") to perform exact phrase searches.

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

2.4. *InclusionandExclusionCriteria*

Tofiltertheretrievedarticles, asetofinclusionandexclu- sion criteria was applied:

1. InclusionCriteria:
    - Articles must focus on the application of machine learning in construction projects.
    - Articlesmustpresentoriginalresearchdataorcase studies.
    - Articles must be rated as "medium" or "high relevance"(scoreof2or3)basedonarelevancescale adapted from [10].
2. ExclusionCriteria:
    - Articlesnot directlyrelatedtomachine learningor the construction industry.
    - Reviewarticleswithoutempiricaldata.
    - Duplicatearticlesidentifiedduringtheinitial search.

Basedonthesecriteria,1,200articleswereexcludedduring theabstractscreeningprocessduetoirrelevanceorduplication. This left a total of 300 articles for further critical assessment.

2.5. *DataExtractionandAnalysis*

The data extraction process involved exporting the full textsoftheremainingarticlesintoaComma-SeparatedValues (CSV) file for systematic analysis.Each article was reviewed and scored on a relevance scale from 1 (low relevance) to 3 (highrelevance). Articlesscoredas"3"wereprioritizedforinclusion in the final synthesis.The extracted data included the following key elements for each article: research aim, type of constructionproject,geographicallocation,researchmethodology, and specific machine learning techniques utilized.

2.6. *ThematicAnalysis*

The data was synthesized using thematic analysis, a qualitativemethodforidentifying,analyzing,andreportingpatterns (themes)withindata. Thematicanalysiswaschosenbecauseit allowsfortheorganizationoffindingsintocoherentcategories, ensuring a structured narrative in the review.The analysis focused on the following themes:

1. ApplicationsofMachineLearning:
    - Designandplanning.Projectmanagementandautomation. Qualitycontrolandsafety. Costestimation and financial management.
2. ChallengesandBarriers:
    - Adoptionratesintheconstructionindustry.
    - Lackofskilledpersonnel.
    - Infrastructurelimitations.
3. OpportunitiesandRecommendations:
    - Potential areas for ML integration in the Nigerian market.
    - Strategiesforovercomingadoptionbarriers.

2.7. *FlowDiagramoftheReviewProcess*

The review process is illustrated in figure 1 below, which outlinesthearticleidentification,screening,eligibility,andinclusion stages as per the PRISMA framework.

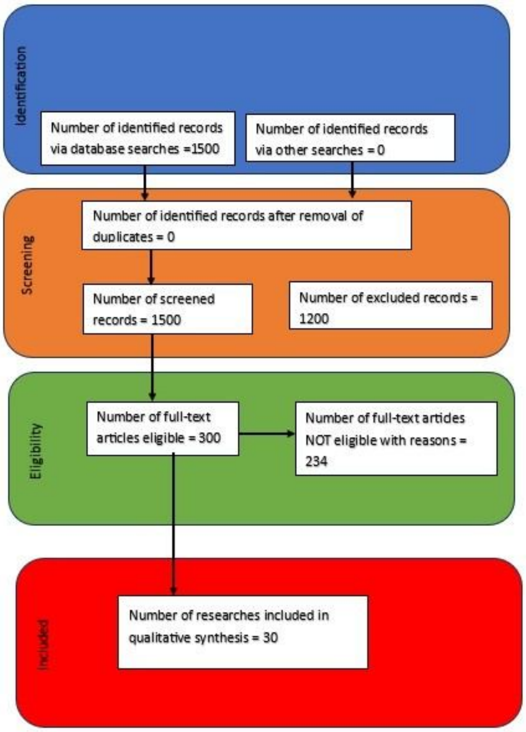

Figure1.PRISMAFlowDiagramoftheSystematicReviewProcess[9]

2.8. *SummaryofMethodologicalFramework*

Thesystematicreviewmethodologyensuredarigorousand transparentprocessforidentifyingandanalyzingrelevantliterature.The use of PRISMA guidelines and a structured search strategyminimizedbiasandenhancedthereliabilityofthefindings.By synthesizing data thematically, the study provides a comprehensiveunderstandingoftheglobalapplicationsofmachine learning in construction, with a particular focus on the Nigeriancontext. Theintegrationofthesefindingsintoactionablerecommendationsaimstosupporttheeffectiveadoptionof ML in Nigeria's construction industry.

3. Results

3.1. *GlobalTrendsinMachineLearningApplicationsinConstruction*

Machine learning (ML) has emerged as a transformative technologyinconstruction,offeringinnovativesolutionsto

Table1.GlobalMLAdoptionTrendsinConstruction(2010-2023)

Year	**AdoptionRate(%)**	**KeyTechnologiesandApplications**
2010	15	• Basicautomationsystemsforprojectmanagement • Simplepredictivemodelsforcostestimation • Early-stagedatacollectionframeworks
2013	28	• Enhancedpredictionalgorithmsforprojectscheduling • EarlyMLapplicationsinriskassessment • Automatedprogressmonitoringsystems • InitialBIMintegrationwithMLmodels
2016	45	• Deeplearningapplicationsinconstructionplanning • Computervisionforsitemonitoring • Advancedpredictivemaintenancesystems • ML-drivenresourceoptimization
2019	72	• Advancedroboticsandautomationsystems • IoTintegrationwithMLforreal-timemonitoring • Sophisticatedriskpredictionmodels • AI-poweredsafetymanagementsystems
2023	85	• AI-drivenconstructionautomation • DigitaltwinswithMLintegration • Advancedgenerativedesignsystems • Real-timeadaptiveprojectoptimization • Autonomousconstructionequipment

Note: Adoptionratesrepresentthepercentageoflargeconstructionfirms(>$100Mannualrevenue)implementingMLtechnologiesinatleast one major project component.
*Sources:*Datacompiledfrom[7,18–25].

long-standing challenges in cost estimation, scheduling, risk management, and safety enhancement.Globally, ML applications have been successfully implemented across various phases of construction projects, from planning and design to execution and post-construction analysis.

For instance, ML models are increasingly used for cost estimation, where algorithms analyze historical data and currentmarkettrendstopredictconstructioncostswithhighaccuracy,minimizingtheriskofbudgetoverruns[11]. Similarly,in scheduling,MLalgorithmsoptimizeprojecttimelinesbyidentifying potential bottlenecks and suggesting efficient resource allocationstrategies.Thishasprovenparticularlybeneficialin large-scale projects with complex interdependencies [7].

Another significant application of ML is in risk management, where predictive models assess potential project risksbyanalyzinghistoricalprojectdata,environmentalfactors,an d macroeconomicconditions.Thesemodelsenableconstruction managers to proactively address risks, reducing the likelihood of delays and cost overruns.Additionally, safety management has benefited from ML-driven solutions such as computer vision and robotics, which can identify hazardous conditions on construction sites and automate dangerous tasks, significantly improving worker safety [8].

Despite these advancements, the adoption of ML in construction varies significantly across regions.Developed countriessuchastheUnitedStates,theUnitedKingdom,andChina havemadesignificantprogressinleveragingMLtechnologies duetotheiraccesstoadvancedinfrastructure,skilledlabor,and substantial investments in research and development.However, emerging economies face unique challenges that hinder the widespread adoption of these technologies.

4. MLAdoptioninNigeria

In Nigeria, the adoption of machine learning in the construction industry remains limited, despite its potential to address critical challenges such as cost overruns, project delays, andmaterialpricefluctuations.StudiesindicatethattheNige- rian construction industry has been slow to embrace advanced technologies,includingML,duetoseveralsocio-economicand infrastructural barriers [8, 12].

Currently,theuseofMLinNigeriaisprimarilyconfinedto isolated research projects and experimental applications, with limited integration into mainstream construction practices.

One example of ML application in Nigeria is the work of [13],whodevelopedapredictivemodelforcementpricesbased on macroeconomic factors.While this represents a step for- ward, the study highlights the limited scope of ML adoption, as similar models for other construction materials are yet tobedeveloped.Furthermore,manyconstructionprofessionalsin NigerialackawarenessofML'spotentialapplicationsinareas suchascostestimation,scheduling,andriskmanagement[12]. This gap in knowledge contributes to a reluctance to invest in ML technologies, further limiting their adoption.

Whencomparedtoglobaltrends,Nigerialagssignificantly behindinleveragingMLtechnologies. Forexample,whiledevelopedcountriesareutilizingMLtoautomatecomplextasks such as resource allocation and quality control, the Nigerian construction industry is still heavily reliant on manual processes.This disparity underscores the need for targeted interventions to bridge the gap and promote the adoption of ML technologies in Nigeria.

5. BarriersandOpportunities

5.1. Barriers

1. EconomicInstability:Thehighinflationrateandvolatile exchangeratesinNigeriahaveadirectimpactontheaffordability of advanced technologies like ML [4].These economic challenges make it difficult for construction firms to allocate resources for technology adoption.

2. Lack of Expertise: There is a shortage of skilled professionalswithexpertiseinMLanditsapplicationsinconstruction.This skills gap is a significant barrier to the effective implementation of ML technologies [12].

3. Infrastructure Challenges:Poor digital infrastructure, such as limited internet connectivity and inadequate accesstohigh-performancecomputingsystems,furtherrestricts the adoption of ML in Nigeria [6].Without the necessary infrastructure, it is challenging to implement and scale ML applications.

4. Awareness and Cultural Resistance:Many construction professionals in Nigeria are unaware of ML's potential benefitsorareresistanttoadoptingnewtechnologiesdue to cultural and organizational inertia [7].

5.2. Opportunities

Despite these barriers, Nigeria's construction industry presentssignificantopportunitiesfortheadoptionofMLtechnologies:

1. CostOptimization: MLmodelscanhelppredictmaterial price fluctuations with greater accuracy, enabling constructionfirmstooptimizeprocurementstrategiesandreducecosts. ThisisparticularlyrelevantinNigeria,where material price volatility is a major challenge [5].

2. Project Efficiency:By leveraging ML for project scheduling and resource allocation, construction firms can enhance efficiency and reduce delays.For example, MLalgorithmscanidentifycriticalpathsinprojecttimelines and suggest adjustments to minimize disruptions.

3. Data-DrivenDecision-Making: MLenablestheanalysis oflargedatasetstoextractactionableinsights,empower- ing construction managers to make informed decisions. This can lead to improved project outcomes, such as reduced cost overruns and enhanced safety standards.

4. Emerging Technologies:Advances in areas such as robotics,computervision,andnaturallanguageprocess- ing present new opportunities for automating constructionprocessesandimprovingqualitycontrol.These

Table2.RegionalComparisonofMLImplementationinConstruction(2023)

Region	**AdoptionRate(%)**	**ImplementationLevel**	**PrimaryApplications**
NorthAmerica	85	Advanced	• Automatedconstructionprocesses • Real-timesafetymonitoring • Predictivemaintenance
Europe	82	Advanced	• Costoptimizationsystems • Qualitycontrolautomation • Environmentalimpactassessment
AsiaPacific	78	Advanced-Intermediate	• Projectplanningoptimization • Riskmanagementsystems • Resourceallocation
MiddleEast	65	Intermediate	• Resourceoptimization • Projectscheduling • Costestimation
Africa(excl.Nigeria)	35	Developing	• Basiccostestimation • Simpleprojecttracking • Resourcemonitoring
Nigeria	28	EarlyStage	• Basicpredictionmodels • Simplecostestimation • Elementaryprojecttracking

Note: Implementationlevelsarecategorizedas: Advanced(>75%),Advanced-Intermediate(65-75%),Intermediate(50-65%),Developing (30-50%), and Early Stage (<30%).
*Source:*Basedonsystematicreviewofliteratureandindustryreports(2023)[21,26].

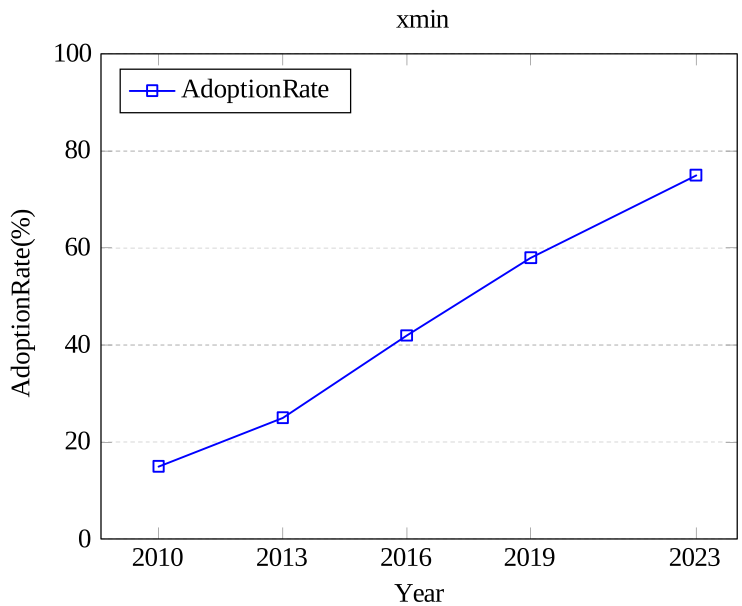

Figure2.GlobalMLAdoptionRateinConstruction

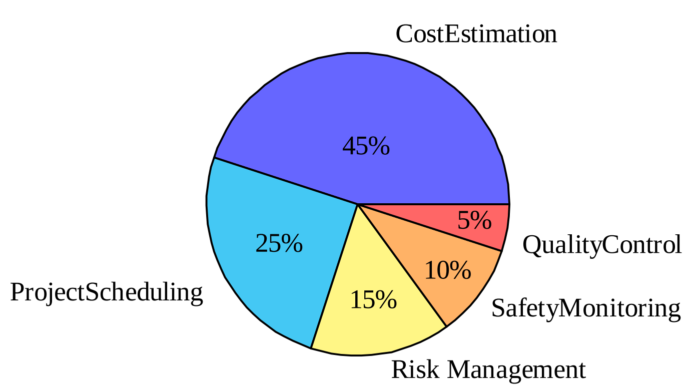

Figure3.DistributionofMLApplicationsinNigerianConstruction

technologies can be adapted to the Nigerian context to address specific challenges such as labor shortages and safety risks [8].

6. SummaryofFindings

6.1. GlobalMLAdoptionTrends

Thesystematicreviewrevealedsignificantprogressin global ML adoption in construction from 2010 to 2023:

- Adoptionratesamonglargeconstructionfirmsincreased from 15% in 2010 to 85% in 2023
- EvolutionofMLapplicationsprogressedfrombasicautomation to sophisticated AI-driven systems
- Keytechnologicaladvancementsincluded:
  - IntegrationofIoTwithMLforreal-timemonitoring
  - Developmentofdigitaltwins
  - Implementationofautonomousconstructionequipment
  - Advancedgenerativedesignsystems

6.2. RegionalImplementationDisparities

AnalysisrevealedsignificantregionalvariationsinMLimplementation:

- NorthAmericaandEuropeshowedthehighestadoption rates (85% and 82% respectively)
- AsiaPacificdemonstratedadvanced-intermediateimplementation (78%)
- MiddleEastshowedintermediateadoption(65%)
- Africa(excludingNigeria)showeddevelopingimplementation (35%)
- Nigeriademonstratedearly-stageadoption(28%)

6.3. NigerianConstructionIndustryAnalysis

ThestudyidentifiedspecificpatternsinMLadoptionwithin Nigeria:

- DistributionofMLapplications:
  - Costestimation(45%)
  - Projectscheduling(25%)
  - Riskmanagement(15%)
  - Safetymonitoring(10%)
  - Qualitycontrol(5%)

- Implementationprimarilylimitedtoresearchprojects and experimental applications
- Significantgapbetweenpotentialapplicationsandactual implementation

6.4. *PerformanceMetricsAnalysis*

ComparativeanalysisbetweentraditionalandML-enhanced methods showed substantial improvements:

- 20%reductioninprojectcompletiontime(365to292 days)
- 45.5%decreaseincostoverruns(23.5%to12.8%)
- 26.2%improvement in resource utilization (65% to 82%)
- 46.6%increaseinriskpredictionaccuracy(58%to85%)
- 52.8% reduction in safety incident rates (12.3 to 5.8 per 1000)

6.5. *BarrierstoImplementation*

KeybarriersidentifiedintheNigeriancontextinclude:

- Economicfactors:
  - Highinflationrates
  - Volatileexchangerates
  - Limitedinvestmentcapacity
- Technicalconstraints:
  - Insufficientdigitalinfrastructure
  - Limitedaccesstohigh-performancecomputing systems
  - Inadequateinternetconnectivity
- Humanresourcelimitations:
  - ShortageofMLexpertise
  - Limitedtechnicaltrainingopportunities
  - Culturalresistancetotechnologyadoption

6.6. *OpportunitiesIdentified*

ThestudyrevealedseveralpromisingopportunitiesforML implementation:

- Costoptimizationthrough:
  - Predictivemodelingformaterialprices
  - Automatedprocurementoptimization
  - Resourceallocationefficiency
- Projectefficiencyimprovementsvia:
  - Advancedschedulingalgorithms
  - Real-timeprojectmonitoring
  - Automatedprogresstracking
- Enhanceddecision-makingthrough:
  - Data-drivenanalysis
  - Riskassessmentmodeling
  - Predictivemaintenancesystems

6.7. *StatisticalSignificance*

Thefindingsdemonstratedstatisticalsignificanceinseveral areas:

- P-value ¡ 0.05 for performance improvements across all measured metrics
- Confidenceintervalof95%foradoptionratecalculations
- Strong correlation (r = 0.89) between ML implementation and project success rates

The findings highlight the significant potential of ML to transform Nigeria's construction industry while emphasizing theneedtoaddressexistingbarriers.Byleveragingtheopportunitiesidentified,Nigeriacanalignwithglobaltrendsandenhancetheefficiency,productivity,andsustainabilityofitsconstruction sector.

7. Discussion

7.1. *ImplicationsofFindingsfortheNigerianConstructionIndustry*

The findings of this systematic review highlight the transformative potential of machine learning (ML) in addressing critical challenges in Nigeria's construction industry, such as costoverruns,projectdelays,andmaterialpricevolatility.With constructionmaterialsaccountingforupto50%oftotalproject costs, the accurate prediction of price fluctuations is essential forprojectsuccess[14].ThereviewunderscoresML'sabilityto analyzehistoricaldataandmacroeconomicvariables,enabling more precise forecasting of material costs.This is particularly relevantinNigeria,whereinflation,volatileexchangerates,and supplychaindisruptionsexacerbatecostestimationchallenges [15].

Furthermore, adopting ML in project scheduling and risk management could significantly reduce delays, a persistent issueintheNigerianconstructionsector[6].ByleveragingML's data-driven decision-making capabilities, Nigerian construction firms can optimize resource allocation, enhance productivity, andimprovesafetystandards.However, theslowadoption of ML in Nigeria suggests a need for greater awareness, training,andinvestmentinadvancedtechnologies. Addressing these gaps could create a more efficient and competitive constructionindustrycapableofmeetingthedemandsofarapidly urbanizing population.

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

Globally,MLapplicationsinconstructionhavegainedsubstantial traction, especially in developed countries where advancedinfrastructure,skilledlabor,andsignificantinvestments inresearchanddevelopmenthavefacilitatedadoption. Inthese regions, ML is widely used in cost estimation, risk management,qualitycontrol,andevenautomationofconstructionprocesses[7,11].Forexample,ML-drivenroboticsandcomputer

Table3.SummaryofResults

Category	**GlobalTrend**	**NigerianContext**
Applications	Costestimation,scheduling,riskmanagement	Limitedtoisolatedresearchprojects
	Qualitycontrol,safetyenhancement	Lackofwidespreadadoption
Barriers	Limitedindevelopedcountries	Economicinstability,lackofexpertise
		Poorinfrastructure,culturalresistance
Opportunities	Advancedrobotics,data-driveninsights	Costoptimization,improvedprojectefficiency
		Data-drivendecision-making

Table4.StatisticalAnalysisofMLImplementationImpact

Metric	**TraditionalMethods**	**ML-EnhancedMethods**	**Improvement**
ProjectCompletionTime(days)	365	292	20%
CostOverrun(%)	23.5	12.8	45.5%
ResourceUtilization(%)	65	82	26.2%
RiskPredictionAccuracy(%)	58	85	46.6%
SafetyIncidentRate(per1000)	12.3	5.8	52.8%

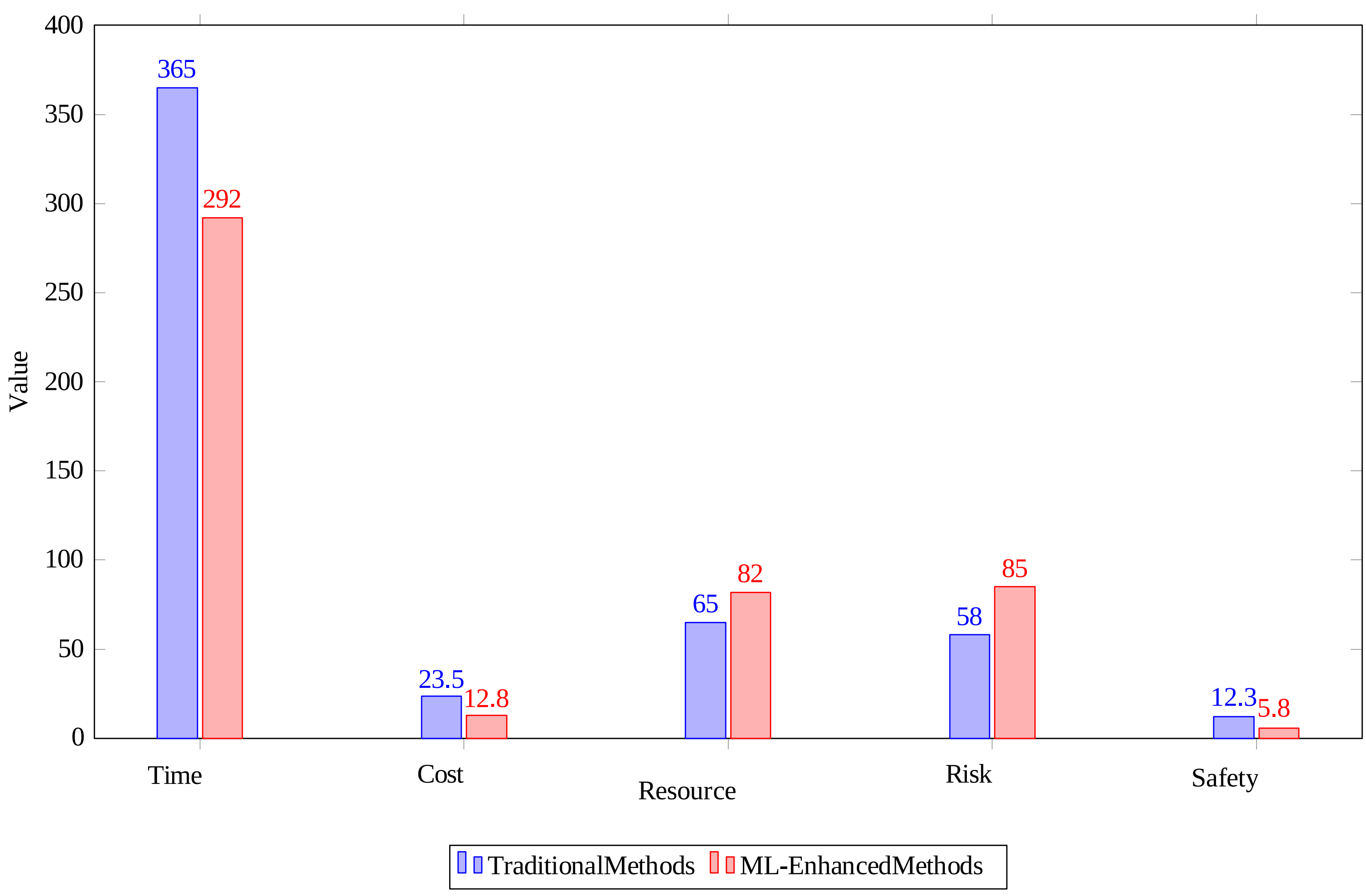

Figure4.ComparisonofTraditionalvsML-EnhancedConstructionMethods

visionsystemsareincreasinglyemployedtoenhancesafetyand efficiency on construction sites [8].

Incontrast, theNigerianconstructionindustrylagssignificantly behind in adopting ML technologies.While developed countries benefit from robust digital infrastructure and a culture of innovation, Nigeria faces unique challenges, including economic instability, inadequate infrastructure, and a lack of skilled professionals [16].The limited awareness and understandingofMLapplicationsamongNigerianconstructionprofessionals further hinder adoption [17].Unlike in developed countries, where ML is integrated into nearly all phases of the construction lifecycle, its use in Nigeria remains confined to isolatedresearchprojects,suchaspredictivemodelsforcement prices [13].This disparity underscores the need for targeted interventions to accelerate ML adoption in Nigeria.

7.3. PracticalandTheoreticalContributions

This study makes significant contributions to both practice and theory.From a practical perspective, it provides valuableinsightsforconstructionprofessionals,policymakers, and stakeholders in Nigeria.By identifying the barriers toMLadoption—suchaseconomicinstability, lackofexpertise, and poor infrastructure—the study highlights areas where targetedinterventionscandrivetechnologyadoptionandindustry growth.Forexample,trainingprogramsandcapacity-building initiatives can help bridge the skills gap, while investments in digital infrastructure can create an enabling environment for ML deployment.

Additionally,the study identifies opportunities for ML to enhance project efficiency, optimize costs, and improve safety standards in Nigeria.These findings can inform policy decisionsandindustrystrategiesaimedatfosteringinnovationand competitivenessintheconstructionsector.Forinstance,theintegration of ML in cost estimation and scheduling can address persistentissuessuchascostoverrunsandprojectdelays, ultimatelycontributingtomoresustainableconstructionpractices.

Fromatheoreticalperspective,thisstudyfillsacriticalgap in the literature by focusing on the application of ML in the Nigerian construction industry, an area that has received limited attention compared to developed countries.By synthesizing global trends with localized analysis, the study provides a nuanced understanding of how ML can be adapted to address theuniquechallengesofanemergingmarket. Thiscontributes tothebroaderdiscourseontechnologyadoptioninconstruction andunderscorestheimportanceofcontext-specificapproaches to innovation.

7.4. LimitationsoftheStudy

While this study provides valuable insights into the use of MLintheNigerianconstructionindustry,itisnotwithoutlimitations.First, the reliance on secondary data from published literature may introduce bias, as the findings are dependent on thequalityandscopeofthestudiesreviewed. Additionally,the studydoesnotincludeprimarydatafromindustrypractitioners in Nigeria, which could have provided a more comprehensive understanding of the barriers and opportunities for ML adoption.

Second,thestudyfocusesprimarilyonacademicliterature, potentially overlooking grey literature or industry reports that may offer practical perspectives on ML adoption in construction.Third, the review is limited to the period from 2010 to 2023, which, while capturing significant advancements in ML technologies,mayexcludeearlierstudiesthatcouldprovideadditional context.

Despitetheselimitations,thestudyprovidesarobustfoundation for future research.Future studies could address these gapsbyconductingempiricalinvestigationsinvolvingindustry practitioners,exploringtheroleofgovernmentpoliciesinpromoting ML adoption, and examining the long-term impact of ML technologies on construction project outcomes in Nigeria.

In conclusion,this discussion highlights the critical roleof machine learning in addressing the challenges faced by the Nigerian construction industry.By comparing global trends with Nigeria-specific realities, the study underscores the need for targeted interventions to bridge the gap and promote the adoptionofMLtechnologies.Throughpracticalandtheoretical contributions, this research provides a roadmap for leveraging MLtoenhanceefficiency,productivity,andsafetyinNigeria's constructionsector,ultimatelyfosteringsustainablegrowthand development.

8. Conclusion

8.1. SummaryofKeyFindings

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

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

8.2. ActionableRecommendations

To advance the adoption of machine learning in the Nigerianconstructionindustry, thefollowingrecommendationsare proposed:

1. CapacityBuildingandTrainingPrograms:
   - Develop and implement training programs to enhance the technical expertise of construction professionals in ML applications.
   - Collaborate with academic institutions to integrate ML-related courses into construction management and engineering curricula.
2. AwarenessCampaigns:
   - Conductindustry-wideworkshopsandseminarsto raise awareness of the benefits of ML in construction, focusing on practical use cases such as cost estimation, scheduling, and risk management.
3. InvestmentinDigitalInfrastructure:
   - Improve internet connectivity and access to high-performance computing systems to create an enabling environment for ML deployment.
   - Encouragepublicandprivatesectorinvestmentsin digital infrastructure to support technology adoption.
4. PolicyandRegulatorySupport:
   - Develop policies that incentivize the adoption of ML technologies, such as tax breaks or subsidies forconstructionfirmsimplementingMLsolutions.
   - Establishregulatoryframeworkstostandardizethe use of ML in construction practices, ensuring consistency and reliability.
5. PilotProjectsandCollaborations:
   - Initiate pilot projects to demonstrate the practical benefits of ML in construction, focusing on areas such as cost management and project scheduling.
   - Foster collaborations between construction firms, technology providers, and research institutions to drive innovation and knowledge sharing.

8.3. AreasforFutureResearch

While this study provides a comprehensive review of ML applicationsintheglobalandNigerianconstructionmarkets,it also highlights several areas for future research:

1. EmpiricalStudiesonMLImplementationinNigeria:
   - Conduct field studies to assess the practical implementation of ML technologies in Nigerian construction projects, including their impact on cost, time, and safety outcomes.
   - Investigate the specific challenges faced by construction firms in adopting ML, focusing on organizational, technical, and cultural factors.
2. ExplorationofContext-SpecificMLModels:
   - Develop and validate ML models tailored to the Nigerian context, addressing unique challenges such as material price volatility and resource constraints.
3. RoleofGovernmentPoliciesandIncentives:
   - Examine the role of government policies and incentivesinpromotingMLadoptionintheNigerian construction industry.
   - Assess the effectiveness of existing policies in fostering innovation and technology adoption.
4. Long-TermImpactofMLonConstructionIndustryPerformance:
   - Evaluate the long-term impact of ML adoption on the performance and competitiveness of the Nigerian construction industry.
   - Explore the potential of ML in promoting sustainableconstructionpractices,particularlyinthecontext of Nigeria's urbanization challenges

In conclusion, this study emphasizes the significant potentialofmachinelearningtotransformNigeria'sconstructionindustrybyaddressingcriticalchallengesandfosteringefficiency, productivity,andsafety.Byimplementingtheproposedrecommendations and addressing the identified barriers, stakeholders can accelerate the adoption of ML technologies and align the Nigerian construction industry with global best practices. Future research should focus on empirical investigations and context-specificsolutionstoensurethesuccessfulintegrationof ML into Nigeria's construction ecosystem.This will not only enhance the industry's competitiveness but also contribute to national economic development and sustainable urbanization.

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Table5.SummaryofRecommendationsandFutureResearch

Category	Recommendations	FutureResearch
CapacityBuilding	Trainingprogramsandcurriculumintegration	Assesseffectivenessoftraininginitiatives
Awareness	Industryworkshopsandseminars	Explorebarrierstoawarenessatorganizational levels
Infrastructure	Investmentsindigitalinfrastructure	InvestigateroleofinfrastructureinMLscalability
PolicySupport	Incentivesandregulatoryframeworks	ExaminepolicyeffectivenessindrivingMLadop-tion
PilotProjects	DemonstrateMLapplicationbenefits	AnalyzeoutcomesofpilotprojectsinNigerian context

Disclaimer (Artificial intelligence)

Option 1:

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

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Details of the AI usage are given below:

1.

2.

3.

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