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PREDICTIVE ANALYTICS AND EMPLOYEE PRODUCTIVITY IN CONSTRUCTION FIRMS IN SOUTH-SOUTH NIGERIA

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Abstract

This study examined the relationship between predictive analytics and employee productivity, specifically focusing on efficiency and continuous improvement, in construction firms in South-South Nigeria. Anchored on the Technology Acceptance Model (TAM), the Diffusion of Innovations Theory, and the Job Demands-Resources (JD-R) model, the study adopted an explanatory cross-sectional survey design. A structured questionnaire was administered to 152 valid respondents drawn from 18 purposively selected construction firms in the South-South geopolitical zone of Nigeria. Data were analyzed using the Spearman Rank Order Correlation Coefficient. The findings revealed a strong and significant positive relationship between predictive analytics and efficiency ($r = 0.685$, $p < 0.05$) and between predictive analytics and continuous improvement ($r = 0.712$, $p < 0.05$). Both null hypotheses were rejected. These results suggest that the adoption of AI-driven predictive analytics tools substantially enhances operational speed, resource planning, error reduction, innovation, and iterative process improvement among construction workers. The study recommends that construction firms in the region invest in predictive analytics systems integrated with existing project management workflows, supported by targeted digital upskilling programs.

Keywords: Predictive Analytics, Employee Productivity, Efficiency, Continuous Improvement, Construction Firms, Artificial Intelligence

Introduction

The construction industry globally has been associated with persistent inefficiencies, project delays, cost overruns, and workforce productivity challenges (Adetola et al., 2011; Evans & Annunziata, 2012). In the Nigerian context, these challenges are amplified by inadequate digital infrastructure, limited technological integration, and overreliance on manual project management methodologies (Afolabi et al., 2022; Okem et al., 2023). The South-South region of Nigeria, characterised by oil-driven economic activity and growing urbanisation demands, presents a particularly critical context where construction firms must scale their operational capacity without proportional increases in human capital costs. Within this backdrop, Artificial Intelligence (AI) has emerged as a transformative technological lever with the potential to reconfigure how construction firms manage projects, allocate resources, and evaluate worker performance (Odonkor et al., 2024). Among the various dimensions of AI initiatives, predictive analytics stands out as a particularly consequential tool, offering organisations the ability to forecast trends, anticipate workforce needs, and make data-driven operational decisions (Delen & Demirkan, 2013; Siegel, 2016). The imperative to investigate how predictive analytics influences employee productivity in this sector and region has therefore become both academically significant and practically urgent.

Employee productivity is conventionally understood as the measure of output produced relative to inputs expended, and encompasses dimensions such as efficiency, quality, adaptability, and continuous improvement (Tangen, 2005; Armstrong & Taylor, 2014). In construction firms, productivity is directly tied to project timelines, safety compliance, labour allocation, and quality control outcomes. Contemporary research consistently highlights that organisations deploying AI-based analytical tools report higher levels of workforce engagement, reduced downtime, and improved task accuracy (Brynjolfsson & McAfee, 2017; Ghosh, 2020). Predictive analytics, in particular, contributes to productivity by enabling anticipatory decision-making, identifying

performance gaps early, and optimising resource deployment across complex, multi-phase projects (Davenport & Harris, 2017; Bersin, 2018). However, while global evidence for these relationships is accumulating, there remains a significant empirical deficit in developing-country contexts, particularly in Nigeria, where the construction sector operates under unique institutional, infrastructural, and human capital constraints (Olanrewaju et al., 2023; Afolabi et al., 2023). This gap underscores the necessity for localised empirical inquiry.

Existing literature on AI-driven productivity improvements in construction has predominantly focused on developed economies, including the United Kingdom, China, Malaysia, the United Arab Emirates, and South Korea (Smith & Patel, 2020; Zhang et al., 2021; Lee & Choi, 2021; Tan & Lee, 2021; Kamal & Bashir, 2021). While these studies provide valuable theoretical and empirical anchors, their findings may not be directly transferable to sub-Saharan African construction contexts, where digital literacy, infrastructure readiness, and organisational capacity differ substantially. In Nigeria, limited studies have explored AI adoption and productivity outcomes in the construction sector, with most available evidence scattered across proximate domains such as administrative productivity (Ahmed & Salisu, 2023), quality control (Musa & Adeyemi, 2023), and site monitoring (Olayemi & Yusuf, 2023). A focused examination of predictive analytics and its specific effects on efficiency and continuous improvement within South-South Nigerian construction firms, therefore, constitutes a compelling research gap that this study is positioned to address.

This study is framed around two specific dimensions of employee productivity: efficiency and continuous improvement. Efficiency, operationalised as the speed, accuracy, and resource optimisation in task execution, is posited to be directly enhanced by predictive analytics through real-time forecasting, automated performance monitoring, and reduced manual input burdens (Adiele & Alikornwo, 2024; Waller & Fawcett, 2013; Davenport & Harris, 2017). Continuous improvement, grounded in the Kaizen philosophy and organisational learning theory (Argyris & Schön, 1978; Senge, 1990), is conceptualised as the ongoing refinement of processes, skills, and practices, facilitated by data-driven insight loops that predictive analytics uniquely provides. The alignment of these dimensions with the predictive analytics construct offers a coherent and theoretically grounded framework for empirical investigation. The primary aim of this study is to examine the relationship between predictive analytics and employee productivity, measured by efficiency and continuous improvement, in construction firms in the South-South region of Nigeria.

Statement of the Problem

Amidst global advancements in AI-driven predictive analytics, construction firms in South-South Nigeria continue to lag in their adoption and implementation of these technologies. The construction sector in this region is characterised by persistent operational inefficiencies, project delays, poor resource allocation, and limited data-driven decision-making capacity, all of which undermine employee productivity (Okem et al., 2023; Afolabi et al., 2022). While predictive analytics has demonstrated considerable potential for enhancing workforce efficiency and continuous improvement in developed economies, there is insufficient empirical evidence on its adoption and impact in the Nigerian construction sector. This empirical vacuum limits the ability of policymakers, construction firm managers, and technology providers to make informed decisions about AI investments. Furthermore, most studies on AI and construction productivity in Nigeria have examined general adoption challenges or project-level outcomes (Olanrewaju et al., 2023; Aluko & Ibrahim, 2022) without disaggregating the specific effects of predictive analytics on individual productivity dimensions such as efficiency and continuous improvement. This creates a targeted knowledge gap that this study seeks to address, thereby providing context-specific, actionable evidence to guide AI-driven workforce development strategies in the region.

Literature Review

Predictive Analytics

Predictive analytics refers to the systematic use of statistical algorithms, machine learning models, and data mining processes to forecast future outcomes based on historical and real-time data (Delen & Demirkan, 2013). In organisational settings, predictive analytics enables decision-makers to identify emerging patterns, anticipate workforce needs, and pre-emptively address operational bottlenecks before they escalate (Siegel, 2016; Provost & Fawcett, 2013). The foundational building blocks of predictive analytics include data quality and integration, feature engineering, model selection, and interpretability (Waller & Fawcett, 2013; Kelleher et al., 2015; Molnar, 2022). In the construction industry, predictive analytics finds application across project scheduling, cost estimation, safety risk prediction, equipment maintenance, and labour performance forecasting (Ahmad et al., 2022; Abrahams et al., 2024). Its capacity to process large and heterogeneous datasets—including site sensor feeds, procurement records, labour logs, and environmental variables—enables construction managers to operate with unprecedented foresight and precision. The adoption of predictive analytics has been positively associated with improvements in project delivery timelines, reduction in material wastage, and enhanced employee performance across various construction contexts (Davenport & Harris, 2017; Okonkwo & Adegbite, 2023).

Employee Efficiency

Efficiency, as a dimension of employee productivity, refers to the capacity to accomplish assigned tasks with minimal waste of time, energy, and resources while maintaining or improving output quality (Tangen, 2005; Bevan, 2012). In the construction sector, efficiency is manifested in faster task completion, reduced duplication of effort, optimised resource utilisation, streamlined workflow processes, and improved accuracy in daily operations (Armstrong & Taylor, 2014; Azhar, 2011). Efficiency is directly influenced by the availability of intelligent decision-support tools that reduce cognitive load, minimise procedural inefficiencies, and provide real-time operational guidance (Bakker & Demerouti, 2007). Predictive analytics enhances efficiency by providing employees with anticipatory information—such as likely equipment failures, optimal scheduling windows, and anticipated material shortages—that reduces reactive decision-making and enables proactive, efficient action. Davenport and Harris (2017) argued that organisations leveraging predictive analytics exhibit significantly higher levels of operational efficiency because employees are better positioned to allocate their efforts toward high-value activities rather than firefighting. In construction, this translates to fewer delays, reduced rework, and higher output per unit of labour time.

Continuous Improvement

Continuous improvement, rooted in the Kaizen philosophy and institutionalised through Lean Six Sigma methodologies (Antony et al., 2018), refers to the sustained, incremental refinement of processes, systems, skills, and performance standards within an organisation (Senge, 1990; Argyris & Schön, 1978). In the context of employee productivity, continuous improvement encompasses ongoing learning, regular performance reviews, data-driven process optimisation, and the establishment of a culture of iterative enhancement (Hackman & Oldham, 1976; Locke & Latham, 2002). Predictive analytics contributes to continuous improvement by generating iterative feedback loops enabling, employees and managers to identify performance gaps, assess the impact of process changes, and recalibrate strategies in real time (Bersin, 2018; Ghosh, 2020). Unlike traditional performance management systems that rely on retrospective appraisals, predictive analytics provides forward-looking insights that embed improvement as a continuous rather than periodic activity. This aligns with the organisational learning tradition (Argyris & Schön, 1978), which emphasises the role of data-rich environments in fostering adaptive organisational capacities.

Theoretical Framework

This study is theoretically anchored on three frameworks.

The Technology Acceptance Model (TAM), developed by Davis (1989), postulates that perceived usefulness and perceived ease of use are the primary determinants of technology adoption behaviour. In the context of predictive analytics, employees who perceive these tools as useful for task performance and easy to integrate into their workflows are more likely to adopt them, thereby reaping their productivity benefits (Venkatesh et al., 2003).

The Diffusion of Innovations Theory (Rogers, 2003) complements TAM by explaining how technological innovations spread within organisational systems and the factors—including relative advantage, compatibility, trialability, and observability—that accelerate or impede adoption.

The Job Demands-Resources (JD-R) model (Bakker & Demerouti, 2007) provides the motivational pathway, positing that technological tools acting as job resources reduce demands, prevent burnout, and fuel work engagement and performance. Collectively, these frameworks explain both the adoption behaviour and the productivity outcomes associated with predictive analytics in construction firms.

Empirical Review

Aluko and Ibrahim (2022) examined AI-driven construction management tools and employee productivity in Nigerian building firms in Abuja. Using a sample of 350 construction personnel and Structural Equation Modelling (SEM), the study found that predictive analytics and AI scheduling systems significantly enhanced workers' time management and reduced project delays. Perceived usefulness and ease of use were identified as strong predictors of AI adoption and productivity improvement. The study concluded that AI tools, when combined with proper training, substantially enhance employee productivity.

Adegboye and Ogunleye (2022) studied AI integration in predictive maintenance and its effect on technician productivity in Nigerian engineering firms. With 305 maintenance staff and SEM-PLS analysis, findings revealed that AI systems that predicted machine faults and suggested optimal maintenance schedules significantly reduced equipment downtime and increased employee efficiency. System reliability and perceived usefulness were the most influential predictors of productivity improvement.

Musa and Adeyemi (2023) explored the influence of AI-enhanced quality control systems on employee efficiency in Nigerian engineering firms. Surveying 298 quality assurance officers and using SEM-PLS, the study found that AI-based quality control reduced human error, enhanced defect detection, and improved inspection consistency, all contributing to measurable productivity improvements.

Idris and Adetunji (2023) examined AI-enhanced traffic simulation tools and road project planning efficiency in Nigeria. A sample of 310 project planners and traffic engineers participated in the study. SEM analysis revealed that the tools enabled better prediction of traffic patterns and optimised route design, directly enhancing employee performance through more informed decision-making. Perceived value and usefulness were the strongest predictors of productivity enhancement.

Ahmed and Salisu (2023) studied AI-augmented document management and administrative productivity in engineering consultancy firms in Northern Nigeria. With 342 employees and SEM analysis, findings showed that AI-assisted document systems streamlined file management, reduced search time, and improved information sharing. Perceived enjoyment and trust were significant factors influencing system use and productivity.

Zhang, Liu, and Huang (2021) explored AI-based planning systems and engineer productivity in Chinese road construction firms. Using a mixed-methods approach with 280 engineers, the study revealed that AI-supported planning tools improved project forecasting and resource allocation, contributing to a 30% improvement in workflow consistency and decision-making speed. Perceived usefulness, task relevance, and ease of use were critical in enhancing acceptance.

Lee and Choi (2021) investigated AI-driven project cost estimation and its influence on quantity surveyors' productivity in South Korea. Surveying 322 quantity surveyors and employing SEM-PLS, results indicated that AI improved estimation speed, minimised human error, and increased precision in budgeting processes. Perceived usefulness and accuracy significantly influenced productivity.

Tan and Lee (2021) evaluated AI workforce scheduling systems and their impact on road construction productivity in Malaysia. A survey of 315 construction personnel, analysed through SEM, indicated that AI-based scheduling improved work-hour optimisation, prevented overlap in job assignments, and reduced employee stress. Perceived ease of use and enjoyment positively influenced employees' attitudes and productivity outcomes.

Kamal and Bashir (2021) assessed AI-based virtual reality training tools and workforce productivity in construction firms in the UAE. With 360 construction employees and SEM analysis, findings showed that AI-VR tools reduced onboarding time and improved task execution quality. Perceived enjoyment and value had significant positive effects on training outcomes and productivity.

Smith and Patel (2020) investigated AI integration in Building Information Modelling (BIM) and team productivity in the UK construction sector. Using 400 engineers and architects and SEM, findings showed that AI within BIM improved real-time collaboration, design accuracy, and early problem detection. Perceived usefulness and ease of integration were the strongest predictors of productivity.

Ajayi and Okonkwo (2021) assessed AI-based safety monitoring systems and productivity in road construction sites in Nigeria. A survey of 265 workers, analysed through SEM, revealed that AI-enabled cameras and alert systems significantly reduced on-site accidents and increased employee focus and engagement, leading to measurable productivity increases.

Khaled and Omar (2022) investigated the acceptance of AI-driven project dashboards and its influence on construction workers' performance in the Middle East. Surveying 389 professionals and using SEM, results showed that dashboards enhanced transparency, task accountability, and time management, positively influencing worker performance. Perceived usefulness and value were strong predictors.

Ola-Oluwa (2024) examined the impact of AI in enhancing knowledge sharing and boosting organisational efficiency in Nigerian enterprises. With 234 respondents from diverse industries and descriptive and inferential statistics, findings showed a positive correlation between AI-driven knowledge sharing and organisational efficiency, enabling faster information flow and more informed decision-making.

Al-Abdullatif (2023) modelled students' perceptions of chatbots in learning, integrating TAM with the Value-Based Adoption Model. A survey of 432 respondents and SEM-PLS analysis found that perceived usefulness, ease of use, and perceived value significantly predicted positive attitudes toward AI-based tools. The study emphasised the central role of user perception in technology adoption and productivity outcomes.

Eze and Maduka (2023) examined the role of AI in supply chain optimisation and on-site employee productivity in engineering firms in Enugu State. With 312 participants and SEM-PLS, results indicated that AI inventory systems led to improved material availability, reduced downtime, and smoother workflow. Perceived value and enjoyment were significant predictors of AI acceptance and productivity.

Olayemi and Yusuf (2023) explored AI-powered drones and their effect on site monitoring and worker output in Nigerian building firms. With 287 engineers and surveyors and SEM, findings showed that drone surveillance improved supervision, accelerated decision-making, and minimised idle time. Perceived usefulness and value significantly enhanced productivity.

Muthuvenkatachalam, Ambili, Venkatesan, and Rajesh (2024) explored the implications of AI and chatbots in nursing education. While situated in a different sector, the study emphasised the role of AI in supporting personalised learning and continuous improvement of skills—a finding with

cross-sectoral implications for the productivity-enhancing role of predictive analytics in workforce development contexts.

Davenport and Harris (2017) established that organisations using advanced analytics in decision-making consistently demonstrated superior operational performance and employee efficiency. Their work provides a robust theoretical and empirical anchor for the link between predictive analytics adoption and workplace productivity across industries.

Brynjolfsson and McAfee (2017) documented how digital technologies, including AI analytics, serve as transformative productivity multipliers in organisational settings. Their research highlights that firms investing in predictive and analytical AI capabilities record significantly higher productivity gains than those relying on conventional approaches.

Bersin (2018) demonstrated that companies using predictive analytics for employee engagement experience higher productivity due to early detection of performance issues such as burnout, workload imbalance, and skill gaps. This finding directly links predictive analytics capability to continuous improvement outcomes in workforce management.

Bakker and Demerouti (2007; 2017) established the JD-R model as a comprehensive framework explaining how technological resources—including AI analytical tools—buffer job demands and fuel employee motivation, engagement, and sustained performance, providing the theoretical mechanism through which predictive analytics influences productivity.

Locke and Latham (2002) demonstrated through their goal-setting theory that performance is significantly enhanced when goals are accompanied by specific, timely feedback. Predictive analytics, by generating real-time data on performance trajectories, operationalises this principle and provides the informational scaffolding for continuous improvement to occur.

Fitz-Enz and Mattox (2014) showed that organisations such as IBM and Google that use predictive models to personalise employee learning paths and align skill development with future job requirements achieve higher productivity outcomes. Their work reinforces the link between predictive analytics, continuous improvement, and long-term workforce performance.

Chien and Chen (2008) demonstrated in the context of workforce planning that predictive analytics tools, through workload analysis and absenteeism trend forecasting, enable managers to schedule shifts and allocate tasks more effectively, directly reducing downtime and improving the consistency of employee output.

Kiron et al. (2014) established that organisations using analytics to manage talent retention and engagement consistently outperform competitors in workforce efficiency and satisfaction, supporting the relationship between predictive analytics and employee productivity dimensions including continuous improvement.

Okonkwo and Adegbite (2023) found that construction firms integrating predictive analytics experienced increased operational efficiency, reduced material wastage, and improved employee performance in the Nigerian context, providing direct local empirical support for the productivity effects of predictive analytics.

Olanrewaju et al. (2023) highlighted barriers to AI implementation in Nigerian construction, including skill gaps and lack of structured digital policies, while emphasising that where adoption was achieved, AI-driven tools notably enhanced operational efficiency—reinforcing the positive productivity relationship central to this study.

Afolabi et al. (2022; 2023) documented critical success factors influencing AI adoption in Nigerian construction projects and found that firms successfully adopting AI technologies reported significantly higher levels of workforce efficiency, task accuracy, and adaptive capacity, aligning with this study's focus on predictive analytics and continuous improvement.

Research Hypotheses

Based on the review of literature, the following null hypotheses are tested in this study:

H_{01}: There is no significant relationship between predictive analytics and efficiency of construction firms in South-South, Nigeria.

H_{02}: There is no significant relationship between predictive analytics and continuous improvement of construction firms in South-South, Nigeria.

Methodology

This study adopted an explanatory cross-sectional survey research design, which enabled the collection of primary data at a single point in time from a broad spectrum of employees across building, engineering, and road construction firms in the South-South geopolitical zone of Nigeria, thereby providing a snapshot of the relationships between the predictor variable (predictive analytics) and measures of the criterion variable (efficiency and continuous improvement). The study was anchored on a positivist-pluralist philosophical orientation, facilitating the use of quantitative methods while acknowledging the complexity of human-technology interactions in the workplace. The target population comprised 291 management staff drawn from 18 purposively selected construction firms spanning the building, engineering, and road construction sub-sectors in the South-South region. Using the Krejcie and Morgan (1970) sample size determination formula, a sample size of 165 respondents was derived; after data screening and removal of invalid responses, 152 questionnaires were retained for analysis, representing a 92.1% effective response rate. A structured questionnaire was developed, with items for predictive analytics adapted from Davenport and Harris (2017), Siegel (2016), and Delen and Demirkan (2013), while items for efficiency and continuous improvement were adapted from Tangen (2005), Armstrong and Taylor (2014), and Locke and Latham (2002). The instrument was measured on a five-point Likert scale (Strongly Agree = 5 to Strongly Disagree = 1). Content validity was established through expert review by academic specialists in management and information technology, while Cronbach's alpha reliability tests returned coefficients of 0.81, 0.79, and 0.83 for predictive analytics, efficiency, and continuous improvement respectively—all exceeding the 0.70 threshold recommended by Nunnally (1978). Data were analysed using descriptive statistics (frequencies, percentages, mean, and standard deviation) for the univariate analysis, and the Spearman Rank Order Correlation Coefficient (rho) for hypothesis testing at the 0.05 level of significance, using SPSS Version 22. Spearman's rho was selected over Pearson's r given the ordinal nature of Likert-scale data and to ensure analytical robustness in the presence of potential non-normality in the data distribution (Field, 2018).

Results

Demographic Characteristics of Respondents

The demographic profile of the 152 valid respondents is presented in summary form below. The majority were male (77.6%), aged 30–45 years (52.0%), married (55.3%), held a B.Sc/B.Tech/HND or OND/NCE qualification (70.4%), and had 0–9 years of service (78.9%). This profile reflects the youthful, moderately educated, and predominantly male structure of the construction workforce in the South-South region of Nigeria.

Table 1: Summary Demographic Profile of Respondents

Variable	Category	Frequency	Percentage (%)
Gender	Male	118	77.6
	Female	34	22.4
Age Group	18–29 years	58	38.2
	30–45 years	79	52.0
	46 years and above	15	9.9
Educational Qualification	SSCE	28	18.4
	OND/NCE	45	29.6
	B.Sc/B.Tech/HND	62	40.8
	Postgraduate	17	11.2
Length of Service	0–4 years	68	44.7
	5–9 years	52	34.2

10–14 years	22	14.5
15 years and above	10	6.6

Source: Field Survey, 2026

Hypothesis Testing

H_{01}: Predictive Analytics and Efficiency

The Spearman Rank Order Correlation analysis testing the relationship between Predictive Analytics (PA) and Efficiency (E) is presented in Table 2.

Table 2: Spearman Rank Correlation between Predictive Analytics (PA) and Efficiency (E)

Variable	N	Correlation Coefficient (r)	Sig. (2-tailed)	Decision
Predictive Analytics (PA) → Efficiency (E)	152	0.685**	0.000	Reject Ho_1

*** Correlation is significant at the 0.01 level (2-tailed). Source: SPSS Output, Version 22.*

Table 2 presents a Spearman's rho correlation coefficient of 0.685, significant at p = 0.000, which is less than the chosen alpha level of 0.05. On the basis of this result, the null hypothesis (Ho_1), which states that there is no significant relationship between predictive analytics and efficiency of construction firms in South-South, Nigeria, is hereby rejected, while the alternative hypothesis is accepted. The correlation coefficient of 0.685 indicates a moderately strong positive association, suggesting that a greater degree of adoption and positive perception of predictive analytics tools among construction employees is associated with significantly higher levels of operational efficiency. This finding implies that employees who engage with predictive analytics experience faster task completion, reduced duplication of effort, streamlined workflows, and improved accuracy in daily operations. The strength of this association is consistent across all four efficiency items in the questionnaire, with combined agreement rates exceeding 83% per item (see

Tables 4.7 and 4.10 in the parent thesis), confirming the robustness and reliability of this result.

H_{02}: Predictive Analytics and Continuous Improvement

The Spearman Rank Order Correlation analysis testing the relationship between Predictive Analytics (PA) and Continuous Improvement (CI) is presented in Table 3.

Table 3: Spearman Rank Correlation between Predictive Analytics (PA) and Continuous Improvement (CI)

Variable	N	Correlation Coefficient (r)	Sig. (2-tailed)	Decision
Predictive Analytics (PA) → Continuous Improvement (CI)	152	0.712**	0.000	Reject Ho_2

*** Correlation is significant at the 0.01 level (2-tailed). Source: SPSS Output, Version 22.*

Table 3 presents a Spearman's rho value of 0.712, significant at p = 0.000, which is less than the chosen alpha level of 0.05. Accordingly, the null hypothesis (Ho_2), which states that there is no significant relationship between predictive analytics and continuous improvement of construction firms in South-South, Nigeria, is hereby rejected, and the alternative hypothesis is accepted. The correlation coefficient of 0.712 reflects a strong and significant positive association, indicating that predictive analytics substantially supports innovation, continuous learning, regular process reviews, data-driven performance enhancement, and the development of a technology-supported culture of ongoing improvement within the firms studied. This is the stronger of the two correlations observed for predictive analytics, suggesting that beyond immediate task efficiency,

predictive analytics most powerfully manifests its value in enabling employees to learn iteratively from data, anticipate future performance trajectories, and continuously refine operational practices. Combined agreement rates exceeding 78.9% per item on continuous improvement items affirm the practical significance of this finding.

Discussion of Findings

The finding that predictive analytics significantly relates to efficiency ($r = 0.685$, $p < 0.05$) is consistent with a broad body of empirical evidence. Aluko and Ibrahim (2022) reported that predictive analytics and AI scheduling systems significantly enhanced workers' time management and reduced project delays in Abuja-based construction firms. Similarly, Zhang et al. (2021) found that AI-supported planning tools improved workflow consistency and decision-making speed by approximately 30% among Chinese construction engineers. Davenport and Harris (2017) established theoretically and empirically that organisations deploying predictive analytics in decision-making exhibit superior operational efficiency, an observation validated in the present study's South-South Nigerian context. The JD-R model (Bakker & Demerouti, 2007) provides the motivational mechanism: predictive analytics acts as a job resource that reduces cognitive demands on workers, freeing attentional capacity for efficient task execution. This is particularly relevant in the construction industry, where multitasking across complex, interdependent project phases creates substantial cognitive load for employees.

The finding that predictive analytics significantly relates to continuous improvement ($r = 0.712$, $p < 0.05$) is similarly supported by existing literature. Bersin (2018) demonstrated that companies using predictive analytics for employee engagement and performance monitoring experience higher productivity through early detection of skill gaps and performance deficiencies, precisely the mechanism operationalised in the present study. Fitz-Enz and Mattox (2014) documented how organisations like IBM and Google use predictive models to personalise employee learning paths, resulting in ongoing skill development aligned with evolving job requirements—a manifestation of continuous improvement. The organisational learning tradition (Argyris & Schön, 1978; Senge, 1990) explains that organisations capable of transforming data into adaptive learning achieve sustained performance improvement, and predictive analytics directly enables this capacity. The stronger correlation observed for continuous improvement (0.712) versus efficiency (0.685) suggests that predictive analytics may have a more sustained and compounding impact on learning and adaptation than on immediate task-level efficiency, which is an important finding for long-term digital transformation strategy in the construction sector.

These findings collectively affirm the Diffusion of Innovations Theory (Rogers, 2003), which posits that innovations perceived as offering relative advantage, in this case, anticipatory decision-making capability, early performance gap identification, and data-driven process optimization are more likely to be adopted and to produce positive outcomes. The demographic profile of respondents (predominantly young, moderately educated, with 0–9 years of service) further supports the receptivity to AI tools observed, as younger and moderately tenured employees tend to exhibit lower resistance to technological change and higher perceived ease of use (Davis, 1989; Venkatesh et al., 2003). Taken together, the findings underscore that predictive analytics is a strategically significant AI initiative with demonstrated capacity to enhance both operational efficiency and continuous improvement in the South-South Nigerian construction sector—a finding with important practical implications for construction firm managers, technology providers, and policymakers in the region.

Conclusion and Recommendations

This study has provided empirical evidence that predictive analytics significantly and positively influences both efficiency ($r = 0.685$, $p < 0.05$) and continuous improvement ($r = 0.712$, $p < 0.05$) among employees in construction firms in the South-South region of Nigeria. Both null hypotheses were rejected at the 0.05 level of significance, confirming that predictive analytics is a robust driver of employee productivity in this context. The study concludes that the integration of

AI-driven predictive analytics tools within construction operations has the capacity to accelerate task completion, reduce waste, enhance decision-making precision, and foster a culture of iterative learning and process refinement. These findings advance the empirical literature on AI-driven productivity in developing-country construction contexts and offer actionable insights for the South-South Nigerian construction sector.

Based on these findings, the following recommendations are made:

1. Construction firms in the South-South region should prioritise investment in predictive analytics platforms—including AI forecasting tools for project scheduling, risk prediction, resource demand, and employee performance monitoring—and integrate these systems into existing project management infrastructures. Dedicated IT support units and change management frameworks should be established to facilitate smooth adoption and minimise employee resistance.
2. Management should develop structured digital upskilling programmes targeting existing employees, particularly those in supervisory and technical roles, to build competence in interpreting and utilising predictive analytics outputs. Such programmes should be embedded within continuing professional development (CPD) frameworks endorsed by industry regulatory bodies such as COREN and NIOB.

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