



Impact of Artificial Intelligence Adoption on Material Wastage in the Construction Industry in Lagos State, Nigeria

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Abstract

Materials constitute one of the most critical resources in construction, accounting for over half of total project costs, which makes effective material management essential. However, the construction industry continues to experience significant material wastage due to heavy reliance on manual and conventional construction processes. In Lagos State, rapid construction growth has intensified inefficiencies in material management, resulting in financial losses, project delays and environmental concerns. This study assesses the impact of AI adoption on material wastage in the construction industry in Lagos State. A quantitative descriptive survey was conducted among 164 construction professionals including architects, engineers, project managers, builders and quantity surveyors using structured questionnaires and stratified random sampling. Data were analysed using SPSS v30, applying descriptive and inferential techniques including Relative Importance Index, Kendall's Tau correlation, regression, and exploratory factor analysis. Results indicate moderate AI awareness but limited practical application. Drones for site monitoring (3.33) and robotic bricklayers (3.11) showed emerging adoption, while security concerns (4.51), lack of understanding (4.49), and cost (4.47) were major barriers. Inferential analysis shows complexity negatively influences adoption (-0.588), while labour efficiency (0.778) and cost reduction (0.774) strongly drive

AI use. The study concludes that AI adoption significantly enhances material management efficiency.

Keywords: Artificial Intelligence, Automation, Construction Industry, Lagos State, Material Wastage, Predictive Analytics.

1. INTRODUCTION

The construction industry faces numerous challenges that have hindered its growth and productivity, especially when compared to more digitized industries. Digitization within the construction sector has been slow, primarily due to a long-standing resistance to change (Adesola, 2023). This lack of digitalization and overreliance on manual processes make project management complex and unnecessarily tedious. Material wastage remains a major challenge in the construction industry, particularly in developing countries such as Nigeria. In Lagos State, where construction activities are expanding rapidly, inefficient material utilization has led to financial losses, project delays, and environmental concerns. Since materials account for over half of total construction costs, even small quantities of waste can significantly affect overall project expenditure (Olanrewaju et al., 2022). While other industries are leveraging automation and data-driven tools, the limited integration of Artificial Intelligence (AI) in Nigeria's construction industry has hindered progress toward sustainability and operational efficiency. The lack of localized empirical evidence underscores the need to assess the practical application of AI in material waste control within the Nigerian construction environment.

Artificial Intelligence (AI) refers to the simulation of human intelligence in machines that are capable of performing tasks such as reasoning, learning, problem-solving and decision-making without explicit human intervention (Russell & Norvig, 2022). In construction management, the Socio-Technical Systems (STS) perspective underscores that the effectiveness of AI implementation relies on harmonizing technical infrastructures (hardware, software, data systems) with social subsystems such as skills, culture, leadership and collaboration (Yu et al., 2021; Wang et al., 2023). A critical aspect of this social subsystem is the level of professional knowledge, as firms that invest in AI literacy and integrate digital competencies into their core operations are better positioned to capture and exploit data insights for continuous improvement. The global construction sector has traditionally lagged behind industries such as manufacturing and finance in artificial intelligence adoption; however, advancements in digital technologies and rising sustainability pressures have recently driven increased implementation of AI solutions (Oesterreich & Teuteberg, 2016; Deloitte, 2022).

Despite the benefits, several recent empirical studies highlight persistent challenges in adopting artificial intelligence within the construction industry (Mossman, 2019 and Abioye et al., 2021).

Many firms remain hesitant to invest in AI due to high implementation costs, limited awareness, and inadequate digital infrastructure (Turner et al., 2022). Cybersecurity concerns and fears of job displacement continue to hinder broader AI acceptance among construction professionals (Oyedele, 2021). The shortage of skilled talent also poses a significant barrier, as the lack of cross-disciplinary expertise combining AI proficiency with construction knowledge remains a major constraint to successful implementation (Ghobakhloo, 2022). Governance and ethical concerns related to AI adoption necessitate clear regulatory frameworks to promote transparency, accountability, and fairness in AI-driven construction processes (Winfield & Jirotko, 2023).

Artificial Intelligence (AI) has emerged as a transformative tool in minimizing material waste by enabling data-driven forecasting, enhanced inventory management, and automated procurement decisions (Li & Wang, 2022). Research indicates that AI-enabled waste management systems can reduce material wastage by 15–25% and increase recycling rates by 20–30% compared to traditional methods. AI-based models can analyze historical data on material usage across previous projects to predict optimal procurement quantities, reducing both surplus and shortages (Rahman et al., 2023). AI technologies such as robotic arms and automated sorting machines can separate recyclable materials from mixed construction waste, improving recovery rates and reducing landfill disposal. Ultimately, studying the impact of artificial intelligence in controlling material management is essential for improving economic outcomes, enhancing operational efficiency, and fulfilling social responsibility obligations within the construction industry. This is achieved by examining the levels of construction professionals' knowledge on the adoption of artificial intelligence in material management, identifying the barriers to the adoption of artificial intelligence in material management on construction sites in Lagos State and assessing the impact of artificial intelligence adoption on material wastage on construction sites.

2. LITERATURE REVIEW

Globally, the construction industry encompasses a wide range of activities including residential, commercial, industrial, and infrastructural projects (Ofori 2015). However, the industry continues to face persistent challenges such as low productivity, fragmented project execution, poor material management, and a slow pace of technological adoption (Bahr & Laszig, 2021). AI's influence in the construction sector is growing rapidly; applications such as predictive analytics, robotics, machine learning, and computer vision are transforming planning, scheduling, design, and quality assurance. Material waste in construction continues to pose a major challenge to project performance, environmental sustainability, and cost efficiency. Wastage often results from design errors, poor logistics, frequent project changes,

mishandling of materials, and inaccurate quantity estimation (Zhang et al., 2021). Artificial Intelligence (AI) has emerged as a transformative tool in minimizing material waste by enabling data-driven forecasting, enhanced inventory management, and automated procurement decisions (Li & Wang, 2022).

The application of AI in waste management extends beyond simple monitoring to active decision-making and automation. Machine learning algorithms analyze patterns in waste generation to forecast future waste volumes, enabling better procurement planning and storage management (Chen & Lu, 2019). Tools like smart bins and robotic sorting units identify, classify, and sort materials with high accuracy, increasing recycling efficiency (Noiki et al., 2021; Rooney, 2021).

Everett Rogers' Diffusion of Innovation Theory describes how innovations, like AI, spread through a social system over time. The theory categorizes adopters into innovators, early adopters, early majority, late majority, and laggards. This theory is particularly relevant when evaluating construction professionals' willingness to adopt new AI-driven methods. The Resource-Based View (RBV) theory emphasizes that a firm's internal resources and capabilities form the foundation of its sustainable competitive advantage (Barney et al., 2021). Within the context of the construction industry, Artificial Intelligence (AI) technologies have increasingly been recognized as strategic resources that satisfy the VRIN criteria (valuable, rare, inimitable, and non-substitutable) when appropriately developed and deployed (Hosseini et al., 2023; Ghosh et al., 2022). Socio-Technical Systems Theory suggests that AI adoption succeeds only when technical tools are implemented in harmony with human skill sets, organizational culture, leadership, and collaboration (Yu et al., 2021; Wang et al., 2023).

Research indicates that AI-enabled waste management systems can reduce material wastage by 15–25% and increase recycling rates by 20–30% compared to traditional methods (McKinsey & Company, 2024). AI-based models can analyze historical data on material usage across previous projects to predict optimal procurement quantities, reducing both surplus and shortages (Rahman et al., 2023). Despite the benefits, several recent empirical studies highlight persistent challenges. Many firms remain hesitant to invest in AI due to high implementation costs, limited awareness, and inadequate digital infrastructure (Turner et al., 2022). Cybersecurity concerns and fears of job displacement continue to hinder broader AI acceptance among construction professionals (Oyedele, 2021). In Nigeria, the construction industry faces challenges in material management, resulting in wastage, cost overruns, and reduced efficiency. Although artificial intelligence (AI) can improve efficiency and reduce wastage, its adoption in construction material management remains limited. Existing studies focus mainly on efficiency and organizational readiness, with little attention to AI's role in controlling material wastage (Adebayo & Ogunlana, 2025; Ajayi, 2023; Olatunji & Adebayo,

2024). Consequently, empirical evidence is lacking on professionals' AI knowledge, adoption barriers, and its impact on material wastage control.

3. METHODOLOGY

A quantitative research design was adopted for this study. This approach allows for the systematic collection of numerical data to evaluate construction professionals' knowledge, identify barriers, and assess the influence of AI technologies on controlling material wastage. The research method utilized a structured questionnaire to obtain standardized responses that can be easily compared and statistically analyzed. According to Kumar and Rani (2022), a structured questionnaire allows researchers to gather standardized responses that can be easily compared and statistically analyzed. Similarly, Osei and Boateng (2023) emphasized that well-structured questionnaires improve response accuracy and reduce interviewer bias. The target population comprises construction professionals, including Quantity Surveyors, Project Managers, Architects, Civil Engineers, and Builders, who are directly involved in material planning, procurement, and site execution. To maintain a focused and manageable scope, the research population was limited to 267 professionals. A stratified random sampling technique was adopted for this study to ensure adequate representation of the various professional categories involved in construction activities within Lagos State. Stratified sampling was considered appropriate because it allows the population to be divided into subgroups (strata) based on professional roles. Based on the calculation, a sample size of 160 respondents was determined to be adequate and statistically representative. A total of 164 questionnaires were distributed and successfully retrieved, representing a 100% response rate. A questionnaire was employed as the primary data collection instrument. It was divided into three (3) main sections: **Section A:** Demographic and professional information such as designation, years of experience, and firm type. **Section B:** Information related to the level of AI adoption and its impact on procurement, inventory control, and resource optimization. **Section C:** Challenges, benefits, and future prospects of AI adoption. The questionnaire was administered using a combination of physical (hand-delivery) and electronic (Google Forms and emails) methods. Descriptive and inferential statistical techniques were employed using SPSS (Version 30) to analyse the data. The questionnaire was reviewed by experts in construction management and research methodology to ensure content validity and clarity of questions. Reliability testing was conducted using Cronbach's Alpha to examine internal consistency. A Cronbach's Alpha value of **0.70** or higher indicates an acceptable reliability level.

4. FINDINGS AND DATA ANALYSIS

To assess the impact of construction professional knowledge on the adoption of AI for material management.

From Table 1, the results indicate that Drones for site monitoring and inspection recorded the highest mean score ($M = 3.33$), suggesting it is currently the most impactful AI application perceived by respondents. This is followed by Robotic bricklayers ($M = 3.11$) and Material tracking and digital management ($M = 3.09$). Conversely, AI tools such as waste-sorting robots ($M = 1.81$) and smart bin systems ($M = 2.06$) recorded lower mean values, indicating they are in early adoption stages in the Nigerian context. The high ranking of drones for site monitoring is consistent with the findings of Ibrahim and Zhao (2022) and Zhang and Liu (2024), which suggest that firms in developing economies prioritize AI tools that offer immediate improvements in operational efficiency and site oversight. The moderate impact attributed to material tracking and digital management aligns with the Socio-Technical Systems (STS) perspective, where the effectiveness of technical tools depends heavily on the harmonizing of technical infrastructures with social subsystems such as professional skills and organizational culture (Wang et al., 2023). The relatively lower mean scores for automated sorting systems and waste-sorting robots suggest a gap in specialized knowledge and technical infrastructure required to support these niche applications, while AI has emerged as a transformative tool in minimizing material waste, its effectiveness is often constrained by the level of professional literacy and the availability of localized data to drive AI-based models.

Table 1: Descriptive Statistics of Impact of adoption of AI

Impact of adoption of AI	Mean		Std. Deviation	Variance
	Statistic	Std. Error	Statistic	Statistic
Smart bin systems	2.0610	.06627	.84864	.720
Waste sorting robots	1.8110	.07110	.91054	.829
Sensor-based waste monitoring system	1.8720	.07088	.90774	.824
Automated haul trucks	1.9817	.07210	.92327	.852
Dumpster renter	1.9693	.07608	.97134	.943
TrashBot	2.0488	.08105	1.03796	1.077
Robotic demolition system	1.9259	.06926	.88153	.777
Lifecycle analysis tools	1.8160	.08313	1.06132	1.126
Recycling optimization	1.9085	.08013	1.02613	1.053
Smart inventory management	2.1062	.07760	.98157	.963
Drones for site monitoring	3.3313	.07127	.90986	.828
Material tracking and management	3.0920	.07477	.95458	.911
Automated sorting system	2.1779	.07780	.99331	.987
IoT sensors	2.0247	.08488	1.08032	1.167
Energy management system	2.5000	.08045	1.03022	1.061
Robotic bricklayers	3.1104	.07929	1.01231	1.025

The results indicate that Technological advancement recorded the highest mean score ($M = 4.47$), suggesting it is currently the most significant driver perceived by respondents. This is followed by Improved project planning/scheduling ($M = 4.42$) and Cost savings ($M = 4.37$). These findings suggest that the primary motivation for AI adoption is the desire for enhanced productivity and operational efficiency. The high ranking of technological advancement as a driver is consistent with the findings of Zhang and Liu (2024), which suggest that firms are increasingly adopting AI to stay competitive in a rapidly evolving digital landscape. Similarly, the focus on cost savings and improved project planning aligns with the Resource-Based View (RBV), where AI is seen as a strategic resource that enables firms to optimize resource allocation and minimize waste (Barney et al., 2021). The relatively lower mean score for environmental sustainability ($M = 3.98$) suggests that while it is an important consideration, it may not be the primary driver for AI adoption in the Nigerian construction industry compared to more immediate economic and operational benefits. This finding is supported by Anuoluwapo and Muhammed (2021), who noted that while there is growing awareness of sustainability, its integration into construction practices remains a secondary priority for many firms.

Table 2: Key drivers that influence AI adoption in material management



Driver behind the adoption of AI	Mean		Std. Deviation	Variance
	Statistic	Std. Error	Statistic	Statistic
Environmental sustainability	3.9817	.04615	.59106	.349
Increasing complexity of construction projects	4.0427	.06885	.88165	.777
Need for efficiency and cost reduction	4.2195	.05741	.73517	.540
Regulatory compliance	4.2547	.05994	.76059	.578
Labour efficiency	4.1111	.05675	.72232	.522
Supply chain optimization	3.4756	.06383	.81738	.668
Design optimisation	3.4356	.06338	.80918	.655
Automated quality control	4.0617	.07205	.91700	.841

Material reuse and recycling	3.7485	.06761	.86312	.745
Improved supplier management	4.0183	.06266	.80239	.644
Cost savings	4.3780	.05421	.69424	.482
Waste sorting and recycling	3.6951	.06831	.87486	.765
Enhanced reporting and compliance	4.1534	.06251	.79801	.637
Data driven decision making	4.2683	.05197	.66552	.443
Technological advancement	4.4785	.05729	.73146	.535
Improved project planning and scheduling	4.4294	.05705	.72834	.530
Improved accuracy in material estimation and procurement	4.3497	.05808	.74148	.550

To evaluate the barriers involved in the adoption of AI for material management in the construction industry

The Exploratory Factor Analysis (EFA) identified three primary thematic barriers. Factor 1 (Operational and Security Barriers), specifically lack of regulatory compliance (0.875), aligns with Winfield and Jirotko (2023), who emphasized that the absence of clear legal frameworks creates uncertainty, hindering the transition to AI-driven processes. Factor 2 (Technology Awareness and Readiness Barriers), featuring resistance to change (0.812) and lack of understanding (0.784), confirms the Diffusion of Innovation (DOI) Theory perspective, where the industry's conservative nature acts as a significant bottleneck (Chui, 2017). This is further supported by Ghobakhloo (2022), who noted that a shortage of cross-disciplinary expertise remains a major constraint. Finally, Factor 3 (Technical and Supply Chain Barriers), led by AI system complexity (0.892), reinforces the findings of Turner et al. (2022) regarding the difficulty of integrating complex digital infrastructure. Table 3, present the barriers affecting AI

Table 3 shows that several critical barriers significantly affect AI adoption in material management practices.



Barriers affecting the AI	Mean		Std. Deviation	Variance
	Statistic	Std. Error	Statistic	Statistic

The lack of understanding of AI technology	4.2500	.05428	.69507	.483
Security	4.2561	.05906	.75634	.572
The complexity of AI	4.2683	.05999	.76821	.590
Resistance to change by site personnel's and management	4.2683	.05744	.73558	.541
Restricted access to complex AI models	4.1585	.05397	.69122	.478
Regulatory compliance	4.3436	.06053	.77284	.597
Insufficient awareness about AI technology	4.2160	.05519	.70243	.493
Limited visibility and tracking	4.2500	.06016	.77043	.594
Technology availability	4.4472	.05280	.66989	.449
Limited awareness and sustainability practice	4.3049	.05762	.73791	.545
Supply chain disruption	3.7485	.07299	.93190	.868
Quality control	4.5061	.05898	.75532	.571

Correlation Analysis

From Table 3, the results of the Kendall Tau-b correlation demonstrate that there is a significant positive relationship between most AI applications and effective material management. Specifically, Drones for site monitoring recorded a high correlation coefficient. These findings are consistent with the literature by Li and Wang (2022), which highlights that AI-enabled waste management systems can reduce material wastage by 15–25%. However, a notable exception was TrashBot, which exhibited a moderately discordant relationship). This negative correlation suggests that the current implementation or perception of this specific technology in the Lagos construction context does not yield the expected improvements in material management. This aligns with the challenges identified by Turner et al. (2022) regarding the mismatch between certain high-tech tools and existing site infrastructures in developing economies. To facilitate the interpretation of these components, a Varimax rotation was performed. This process clarified the relationship between variables, grouping

them into distinct, meaningful categories based on their factor loadings. The grouping of the variables according to the various components is displayed in Table 4.

Table 4: The grouping of the variables according to the various components

Component s	Variables	Factors
1.	Operational and security barrier	Lack of security Lack of regulatory compliance Poor quality control
2.	Technology awareness and readiness barrier	The lack of understanding of AI technology Resistance to change by site personnel and management Restricted access to complex AI models Insufficient awareness about AI technology
3.	Technical and supply chain barrier	The complexity of AI Supply chain disruption

Root Cause Analysis (Fishbone Diagram)

Root Cause Analysis (RCA), specifically utilizing the Ishikawa Diagram (or Fishbone Diagram), was employed to visually structure and analyze the relationship between the final identified barriers (the causes) and the ultimate problem (the effect). This technique provides a clear, hierarchical representation of the key factors hindering the full adoption of Artificial Intelligence in material management within the construction industry in Lagos State.

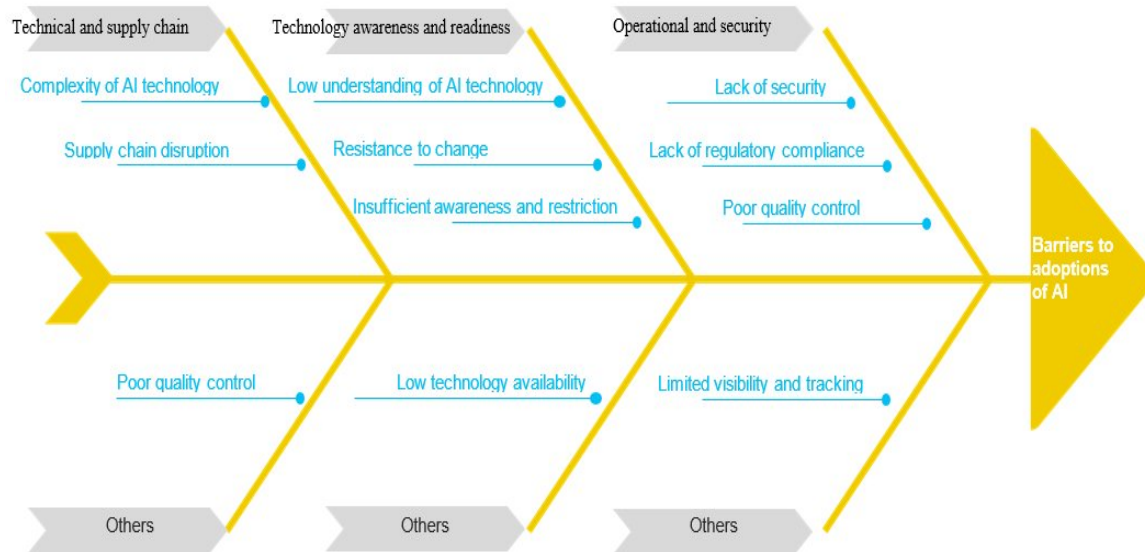


Figure 1: The fish bone diagram for barriers affecting AI adoption

The Root Cause Analysis (Fishbone/Ishikawa Diagram) provides a structured framework for understanding why Artificial Intelligence (AI) adoption remains limited despite its potential, directly linking the identified systemic barriers to the achievement of the research objectives:

Objective 1: The Root Cause Analysis identifies "Technology awareness and readiness" as a core thematic component, directly supporting the assessment of professional knowledge by pinpointing the lack of understanding of AI technology as a fundamental cause for limited practical implementation. This finding confirms that while professionals have moderate awareness, targeted educational interventions are required to fix this foundational knowledge deficit.

Objective 2: The diagram fulfills this objective by categorizing statistical findings into three systemic bones: Operational and Security Barriers (security risks and regulatory gaps), Technology Awareness and Readiness (resistance to change and model access), and Technical and Supply Chain Barriers (AI complexity and logistical disruptions).

Objective 3: the Root Cause Analysis identifies the specific areas where technical failures or systemic risks prevent the realization of AI's positive impact on waste reduction and procurement accuracy. The diagram suggests that the "significant positive impact" of high-performing tools like drones and robotic bricklayers can only be fully realized if the industry strategically mitigates the identified root causes, such as operational risk and data governance gaps.

5. CONCLUSION

The study concludes that AI adoption has a moderate but transformative impact on material management. Drones for site monitoring and material tracking platforms are perceived as the most effective tools currently in use. However, niche waste-management technologies like automated sorting robots have yet to make a significant impact due to their early stage of adoption and the technical infrastructure required for their operation.

It is concluded that the transition towards AI is primarily driven by the pursuit of technological advancement, improved project scheduling, and substantial cost savings. While environmental sustainability is recognized as a benefit, it is not the primary factor influencing the decision-making process of construction firms in Lagos State.

The study concludes that the full-scale integration of AI is hindered by a complex set of barriers. Key among these are operational and security concerns, specifically the lack of clear regulatory compliance and the high cost of initial investment. Additionally, the industry faces a "readiness gap" characterized by internal resistance to change and a shortage of personnel with cross-disciplinary expertise in both construction and AI.



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