Adoption of Artificial Intelligence (AI) on Construction Projects:

An evaluation of the level of awareness and current state in Imo State, Nigeria [1]

Elvis Izuchukwu Nnadozie, Benedict Amade, and Gregory Chimere Enyinna

Abstract

Artificial intelligence (AI), as a prominent digital technology, has made substantial contributions to enhancing company operations, service procedures, and industrial productivity across multiple areas. This study seeks to identify and assess the level of awareness and current implementation of various AI technologies among construction project firms and professionals in Imo state. The investigation was guided by the diffusion of innovation (DOI) theory. The study used a descriptive, exploratory, and survey research design with a purposive sampling strategy to pick a sample of 442 respondents from a population of 932 respondents using Krejcie and Morgan's method for sample size determination. The data collection and survey instrument consist of a well-structured questionnaire and site visits. The acquired data was displayed as frequency distribution tables using descriptive statistical methods from IBM SPSS Statistics version 26.0. The mean item score (MIS) was utilised to analyse the study's major objectives. The study's findings indicate that knowledge and current use of various AI technologies among construction project firms and experts in Imo State are somewhat low. This is due to the fact that respondents' awareness of AI is somewhat low, with computer vision rating highest (MIS=2.75), followed by machine learning (ML) (MIS=2.59). The adoption of AI by the various respondents was also somewhat low. Predictive analytics had the highest adoption rate (MIS=2.72), followed by computer vision (MIS=2.71), machine learning (ML) (MIS=2.64), knowledge-based systems (MIS=2.59), automated planning and scheduling (MIS=2.53), and robotics and automation (MIS=2.44). This study advises that a concerted effort be made to ensure that practitioners in Imo state embrace the usage of applicable AI tools through awareness generation. Given the benefits of AI tools in construction project management, efforts should be directed towards the implementation of ANN and SVM to ensure schedule and cost issues are resolved.

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1. Introduction

AI in construction, sometimes known as "Construction 4.0" or "smart construction," has the potential to revolutionise project delivery. It provides solutions for automating complex tasks, optimising design processes (e.g., generative design), improving on-site safety with predictive analytics and computer vision, improving project scheduling and risk management, tracking progress with drones and sensors, and managing facilities more efficiently (Pan & Zhang, 2021). Studies in developed economies have shown that AI adoption can result in considerable increases in productivity, accuracy, and safety while eliminating waste and cost overruns.

Project management in the construction sector has distinct problems that have a direct impact on project success. These issues stem from variations in location, personnel, equipment, and logistics, as well as economic and cost variables (Nnadozie, 2025; Smith & Wong, 2022). These can raise the level of uncertainty during project planning and implementation, resulting in overspending, project delays, and disagreements among customers, staff, and contractors. Furthermore, traditional project management methods employed by today's construction enterprises rely primarily on project managers' knowledge, while data is collected manually in a variety of non-digital formats via decentralised storage. This results in the use of delayed, faulty, or inadequate information in decision making, jeopardising process improvement. The construction industry faces numerous challenges that have limited its growth and resulted in significantly lower productivity levels than other sectors, such as retail, health care, or manufacturing (Timilsena et al., 2024). The industry allocates approximately 1% of its total budget to technology investments, which is a fraction of what is seen in sectors like financial services and manufacturing. This underinvestment reveals that the construction industry is one of the least digitised in the world, with players widely acknowledging a long-standing culture resistant to change. The purpose of this study is to examine the level of awareness and present condition of AI use in building construction project delivery in Imo state, Nigeria.

2. Literature review

The construction sector is regarded as a major contributor to the global economy, accounting for 13% of global GDP and projected to grow by 85% to $15.5 billion by 2030, with three leading countries - China, the United States, and India - accounting for 57% of global demand (Egwim et al., 2021). AI applications in construction include a wide range of topics, including productivity increase, safety improvements, quality assurance, document management, preconstruction planning, claims and litigation, and site planning. These applications demonstrate AI's versatility and ability to revolutionise construction. AI in construction is a practical tool for analysing and managing the supply of construction materials and skilled labour. Other uses include logic-controlled instruments for tracking logistics and waste generated during construction. Artificial intelligence is also utilised to distribute and transport building materials and products, as well as to combat counterfeit construction products and supplies.

AI was first introduced in the 1950s with the goal of replicating human intelligence using computer systems. Although the field of AI has seen significant fluctuations over the years, primarily due to a mismatch between expectations and available applications (Holzmann & Lechiara, 2022), it appears that current AI technologies are mature enough to provide significant improvements in various aspects of the workplace, including project operational and managerial processes.

The use of AI in construction has risen dramatically, owing to its potential to improve performance and efficiency. While the application of artificial intelligence in construction is still in its early stages, a limited set of construction technology entrepreneurs are gaining attention and market presence for their AI-powered solutions. This momentum is projected to have a significant impact on decision-making processes in construction project management, highlighting the importance of a thorough grasp of AI's possible applications. In this broad realm of building, projects can be divided into five stages. The stages are: commencement, planning, execution, control, and closure. Figure 1 displays a flowchart that explains each stage of the project lifecycle.

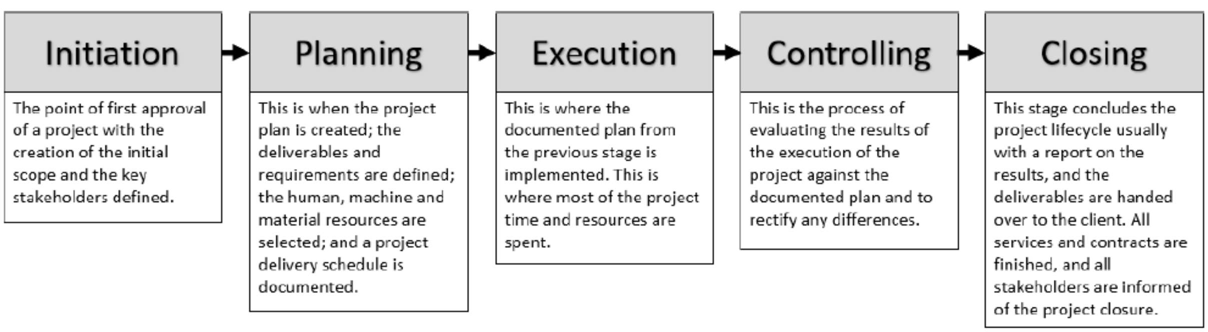

Figure 1: A flowchart of the five stages of the project lifecycle. (Smith & Wong, 2022)

Construction is one of the most complicated and resource-intensive industries, with numerous stakeholders, changeable project settings, and high-risk decision-making processes. Traditional project delivery techniques frequently suffer from inefficiencies like as cost overruns, timetable delays, safety issues, and fragmented communication (Nnadozie, 2025). In response to these ongoing issues, AI has emerged as a disruptive tool for better construction project delivery. AI technologies use large datasets, powerful algorithms, and machine learning models to improve project planning, coordination, and execution over the whole lifecycle.

Taboada et al. (2023) investigated artificial intelligence-enabled project management: a systematic literature review. In this regard, the study conducted a systematic literature analysis to investigate the role of artificial intelligence in emerging project management; applications of AI techniques in the project management performance areas are discussed. The findings indicate that the number of influential publications on artificial intelligence-enabled project management has grown dramatically over the last decade. The findings show that artificial intelligence, specifically machine learning, can be extremely useful in the management of construction and information technology projects; it is especially encouraging for improving planning, measurement, and uncertainty performance domains by providing promising forecasting and decision-making capabilities.

Kineber et al. (2024) conducted research on revolutionising construction: A cutting-edge decision-making methodology for implementing artificial intelligence in sustainable building projects. The study looked at how specific AI drivers influence the adoption of this technology in the construction industry. The research techniques included a thorough review of past studies to identify the key parameters impacting AI adoption in the construction industry. Data was gathered via a well-structured survey of important stakeholders in the building construction industry. The three key constructs of technological devices, advancement, and knowledge were identified from the set of drivers using exploratory factor analysis. According to this research, deploying AI in construction has the potential to improve health and safety while also expediting project completion. To determine how these characteristics, relate to AI adoption in the construction industry, partial least squares structural equation modelling was utilised. The study's findings revealed that the impact of AI installation in the construction industry is quite considerable due to technological advancements and expertise, accounting for approximately 15% of the effects that have been directly observed. The practical implications of AI for policymakers, engineers, and construction stakeholders are numerous, and they give useful insights for tailored strategies targeted at leveraging AI's potential to improve projects, promote sustainability, and raise safety standards.

Salimimoghadam et al. (2025) conducted research on the rise of AI in project management, including a comprehensive analysis of existing opportunities, enablers, and impediments. The study's goal is to critically analyse existing literature in order to identify opportunities, enablers, and impediments to AI adoption, as well as to provide a comprehensive framework for future research and practice. A systematic literature review (SLR) conducted in accordance with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) standards showed three major themes: The Knowledge Ecosystem in Project Management: In the Age of AI, The Meeting of AI and Humanity in Project Management, and Integrating AI into Project Management and Landscaping. The findings show AI's transformative effects on forecasting accuracy, risk mitigation, stakeholder engagement, and safety management, while also addressing problems such as legacy system integration, data quality issues, and change resistance. The study provides significant insights for both researchers and practitioners, assisting in the navigation of adoption barriers, capitalising on enablers, and revealing AI's potential to transform project management techniques across industries.

Fontana (2024) investigated how AI is affecting the building industry: past, present, and future. The study examined the evolution of AI and its present uses in construction, including scheduling, estimating, contract administration, and site safety, showing both benefits and limitations. The study also looked at prospective AI uses over the next five years based on current trends to improve construction and eventually transform industrial processes using technologies such as autonomous drones, digital twins, and AI-enhanced robotics.

Hashimzai and Mohammadi (2024) conducted a thorough literature assessment of emerging trends and problems in project management to investigate the integration of AI. The study's goal is to investigate new trends, key uses, and problems of AI in project management, as well as assess its impact on risk management, resource allocation, and decision-making in complicated projects. The study uses a systematic literature review (SLR) technique based on the PRISMA protocol to analyse peer-reviewed papers from the MDPI, IEEE, Science Direct, and Emerald databases published between 2018 and 2024. Keywords combined with Boolean operators were utilised to filter relevant studies, resulting in a balanced and focused selection of high-quality papers. The findings demonstrate AI's ability to proactively identify hazards, adapt to dynamic project contexts, and optimise resource allocation, hence improving decision-making efficiency and project outcomes. However, implementation costs and opposition to organisational change remain significant impediments. The consequences indicate that, while AI considerably improves project management, overcoming these issues is critical for wider use and scalability. This study finds that AI is a game changer in project management, providing insight into emerging patterns and significant obstacles. Future research should concentrate on creating scalable, cost-effective AI solutions to remove adoption barriers, hence broadening the benefits of AI integration across industries.

Panagopoulou (2025) conducted research on using AI in construction: prospects and obstacles. The study aimed to investigate the applications, challenges, and benefits of this implementation in the construction industry. Based on substantial literature study and qualitative research conducted through semi-structured interviews with industry specialists. The study looks into how AI redefines the construction project lifecycle, from planning and design to execution. AI applications such as generative design, predictive analytics, and machine learning are being used by businesses to increase efficiency, safety, sustainability, and cost management. The study focusses on upcoming technologies such as autonomous cars, robotics, and real-time data platforms, which improve on-site operations and resource planning. Furthermore, case examples demonstrate how industry leaders such as Skanka and Obayashi Corporation are using AI for environmental assessments, safety improvements, and geotechnical diagnostics.

Despite the benefits presented by AI, a number of hurdles are impeding its implementation. Significant impediments include high initial expenses, integration challenges, workers' lack of digital literacy, and organisational opposition. Concerns concerning data dependability, algorithm bias, ethical governance, and infrastructure deficiencies also hamper adoption. Nonetheless, the results indicate an optimistic outlook for AI's future in building. Professionals see AI as a core infrastructure component rather than an optional tool. The study emphasises the importance of cross-disciplinary collaboration, ongoing training, ethical monitoring, and leadership commitment in ensuring inclusive and effective AI integration. This study adds to the developing debate on AI in construction by offering a grounded, human-centered examination of both its revolutionary potential and the practical challenges it encounters. It emphasises the significance of balancing technological innovation with strategic, social, and ethical considerations to promote a resilient, data-driven, and sustainable construction industry.

2.1 Theoretical review

Numerous theoretical frameworks have been established and introduced to understand the adoption of new technology, addressing both individual and organizational contexts (Felemban et al., 2024).

2.1.1 Diffusion of innovation (DOI) theory

Diffusion of Innovation E.M. Rogers' theory, introduced in 1962, explains how an idea or product gathers momentum and diffuses (or spreads) over time within a certain population or social system (Monga et al., 2024). The theory aims to highlight the key aspects involved in the spread of innovation, such as the innovation itself, communication channels, time, and context (Figure 2). According to Rogers (2003), individuals or groups involved in adoption regard new ideas, practices, and objects as innovations. The extent to which a person adopts creative approaches before their colleagues determines their level of innovativeness (Alka'awneh et al., 2025; Nnadozie, 2025). Rogers (2003) established five groups through which adopters move: innovators, early adopters, early majority, late majority, and laggards.

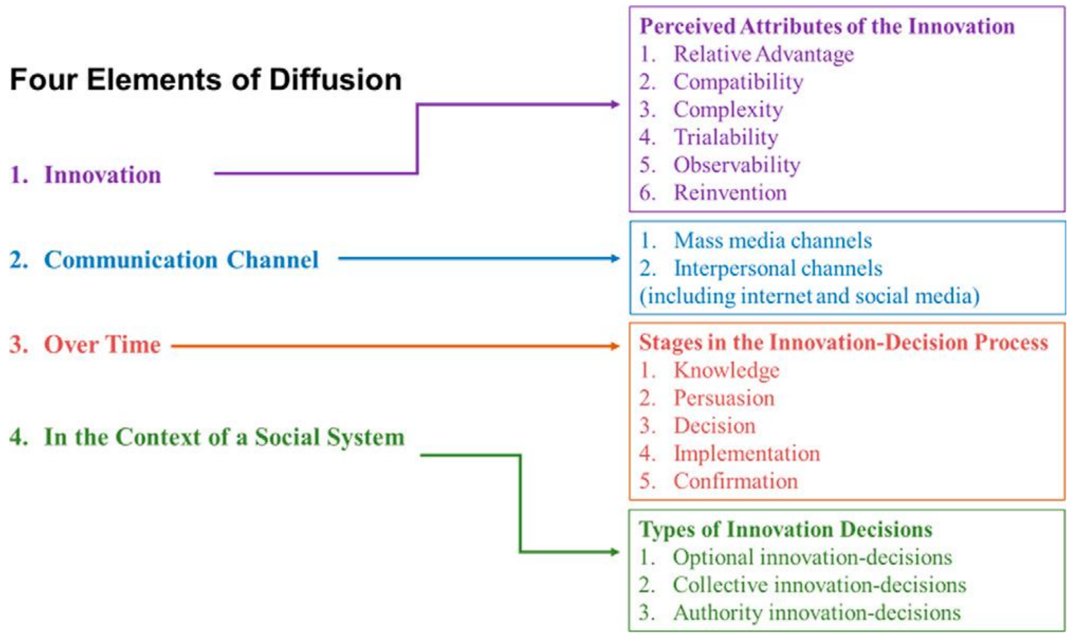

Figure 2.: Four key components of Diffusion of Innovation Theory (Monga et al., 2024).

A diverse range of cultural and disciplinary environments contribute to the DOI hypothesis, while adoption outcomes are directly influenced by participant characteristics and how they make decisions regarding new innovations (Alka'awneh et al., 2025). DOI describes how technology spreads through certain channels when members of social systems receive it for specific timeframes. According to Nnadozie (2025), client perceptions and technology requirements have a significant impact on the rate of innovation diffusion. In technical settings, the five main components are relative advantage, complexity, compatibility, trialability, and observability (Rogers, 1995).

The rate of adoption specifies the relative time that individuals accept the invention. The distinction between adoption and diffusion is perhaps best explained in an essay by Ghoshal and Bartlett in 1988. Adoption refers to the phases that an individual or organisation goes through between hearing about an innovation and adopting it. Meanwhile, the diffusion idea focusses on the spread of information and can thus be defined as adoption across numerous units. The rate of adoption stated here is a time-based function of the number of units in the diffusion network that have adopted the innovation. Rogers has observed substantial relationships between this process and the five qualities of an innovation outlined above. Innovativeness is a time-dependent concept that categorises individuals or groups of adopters based on how early they adopt new ideas. This is depicted as an S-shaped cumulative adoption curve, which has been widely utilised in modelling. Looking at the rate of this cumulative S-curve yields a conventional bell curve.

Figure 3 depicts a bell curve that is used to define five categories or personas that characterise how early an individual or other unit of adopters is in the adoption process (Stenberg and Nilsson, 2020). The following categories are listed in chronological order, with innovators being the first to adopt: early adopters, early majority, late majority, and laggards. Each of these categories is assigned specific characteristics that can be used to explain, predict, and strategise the adoption process.

The innovation-decision process involves a single individual or small group conceptualising the adoption process as a decision maker (Rogers 2003). It is defined as the mental process that begins when a decision-making role learns about a new invention and ends with the final confirmation of an adoption or rejection decision (Rogers 2015). This method indicates that distinct sets of knowledge are learnt at different stages of the mental process. The uncertainties that drive the demand for information will alter depending on whether this process is prior to a choice to adopt or reject, or if the process is in the implementation phase.

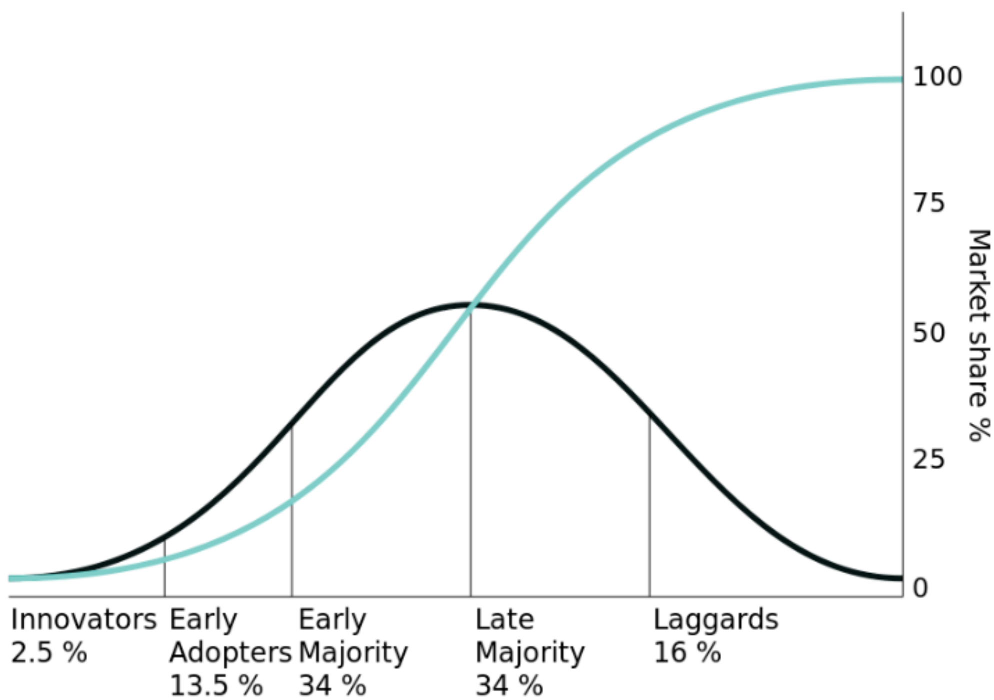

Figure 3: Innovativeness based on Rogers

One universal drawback of the DOI theory is that it fails to take into account environmental factors that influence operational business performance, including regulatory requirements and market-level competition. Figure 3 depicts the DOI.

The theory of innovation diffusion seeks to study the elements that influence dispersion and whether innovations are shared or accepted at the individual or organisational level (Xue & Chen, 2024). The acceptance of new technology at the individual level to the diffusion of innovation at the collective level is the key to the successful completion of the acceptance of new technology in organisations, and the value of technological innovation is fully realised when it is effectively transferred, distributed, and prompts a response among innovation agents.

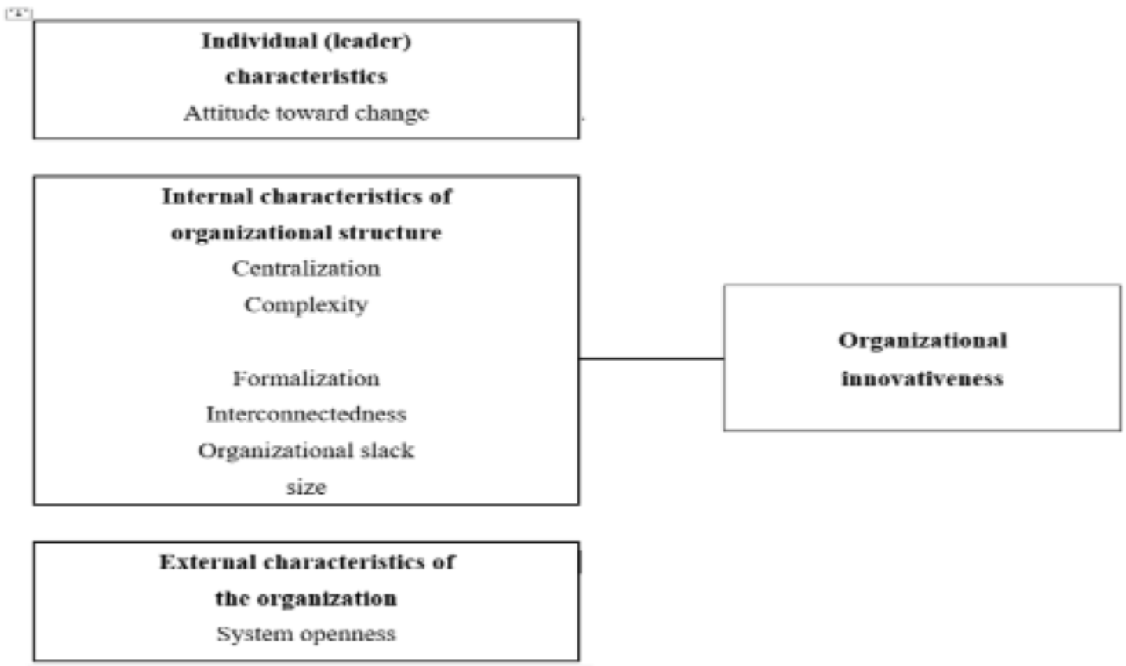

Figure 4: Diffusion of Innovations Theory (DOI) (Rogers, 1995)

3. Methodology

This study deployed the use of quantitative methods to achieve the research objectives; a quantitative approach was employed as the major methodology. The method involves a survey research of construction industry practitioners, to collect opinions as well as empirical data regarding the research objectives. The choice for this design is that the design it provides an in-depth investigation of an individual, group, institution of phenomenon (Mugenda & Mugenda, 2003). The quantitative approach (survey research) enabled the researcher to obtain qualitative information whose qualitative results were used to draw or make generalizations based on measurements and testing of results on the issues bordering on quality management systems on road construction projects (Aleper, 2015). This study adopted a descriptive survey research design. A descriptive survey design is appropriate as it allows for the collection of quantitative data from a sample of a population to describe the attitudes, opinions, behaviours, or characteristics of that population systematically and accurately (Creswell & Creswell, 2018). The goal is to provide a snapshot of the current state of AI adoption in Imo State's construction industry.

Furthermore, the study incorporated qualitative data through semi-structured interviews to provide depth, context, and richer explanation to the quantitative findings. This mixed-methods approach is chosen because while the survey quantified the levels of awareness, adoption, and perceived impact, the interviews helped to elucidate the underlying reasons for the challenges and explore potential solutions in greater detail (Saunders, Lewis, & Thornhill, 2019). The primary emphasis, however, remains on the quantitative component, making this an embedded mixed-methods design.

The targeted population for this study was limited to practitioners registered with Ministry of Works in Imo state and operating within the Three geopolitical zones of the state. The state was chosen because of proximity and the high number of road construction projects which give a true reflection of state of and number of on-going construction projects in the state. The study covered 932 registered professionals within Imo state. In order to help achieve a good representative from a large population, the researcher took into consideration the factors that influence and has much to do with AI and the targeted respondents. Details of the population are displayed in table 1.

Table 1: Population of the professionals

S/N	Professionals	Population
1	Project manager	73
2	Building technology/site supervisor	125
3	Other (Please specify)	118
4	Architect	115
5	Quantity surveyor	176
6	Client representative	43
7	Mechanical/electrical engineer	160
8	Civil/structural engineer	122
	Total	**932**

Selecting the intended sample is a critical component of any research; unambiguous identification and misidentification of the targeted sample have both advantages and disadvantages. However, surveying the entire population to address research questions is impractical due to the high expense and difficulty in obtaining research variables (Kojo, 2014). A sample size can relate to a subset of a population (Aleper, 2015), and a purposeful sampling strategy was used in this investigation. In this study, a sample of 442 practitioners or respondents were determined and selected for the study using the Krejcie & Morgan technique of sample size determination. See the appendix for the table. This "guide for sample determination" is given in table 2 below.

Table 2: Population and sample size of the professionals

S/N	Professionals	Population	Sample size
1	Project manager	73	31
2	Building technology/site supervisor	125	50
3	Other (Please specify)	118	46
4	Architect	115	40
5	Quantity surveyor	176	54
6	Client representative	43	21
7	Mechanical/electrical engineer	160	113
8	Civil/structural engineer	122	92
	Total	**932**	**447**

Table 2 displays the category, study population, sample size, and sampling method employed. The table shows a sample size of 447 respondents. To guarantee that meaningful data were collected, the research instrument (i.e. questionnaire) used in this study was carefully constructed and evaluated in a pilot study, followed by minor adjustments to produce a well-validated survey instrument. All statements were mostly based on findings from the literature review. The survey's questions were classed as "closed-ended" or "open-ended" because the majority of them asked for opinions or subjective measurements. Such questions were formatted according to the "Likert" rating scale. For example, 5 equals extremely agree, 4 equals agree, 3 equals neutral, 2 equals disagree, and 1 equals severely disagree. The number of points in a Likert rating scale can be adjusted as needed, allowing for the use of various anchors (e.g., very important to very trivial) (Nnadozie, 2025). The questionnaire distribution began in June 2024, with the questionnaire collection process beginning in July 2025 and ending in September 2025. The questionnaires were collected directly from the respondents.

All of the pilot questionnaire respondents, some of whom were also participated in the discussions, [agreed with the proposed research topic, and none indicated difficulty in responding to the questionnaire, while also expressing support and willingness to participate in future surveys.

The comments from the preliminary studies helped to finalise the format of the major questionnaire and lay the groundwork for the main survey. The questionnaire was distributed to respondents and was utilised for the purposes of the research as defined by the objectives. According to the results of the pilot survey, more respondents chose to get the questionnaire by hand delivery rather than electronically. In regard to a postal questionnaire. According to Willar (2012), some of the drawbacks of this technique include a low response rate and a lack of chance to explain and urge respondents to answer all questions.

According to Kojo (2014), the data collection strategies for any research are secondary and primary data. Because of the nature of this study, which focused on the impact of AI implementation on construction project delivery in Imo state, data was gathered through face-to-face semi-structured interviews and a questionnaire survey. Questionnaires were distributed to principal contractors, subcontractors, and the client's project managers, all of whom were expected to complete them. The questionnaires are distributed to contracting organisations with the goal of covering the entire spectrum of management, including top, middle, and lower levels, as well as those directly involved in quality management. The questionnaires' objective is to reveal the genuine challenges with AI deployment throughout the delivery of a major infrastructure project.

Data analysis is the process of creating reports that provide meaning to the data acquired (Mohamed, 2023). Data was cleaned first, then entered into SPSS version 25.0 for analysis. Because the data is primarily quantitative, descriptive and inferential analysis were utilised in data analysis. The descriptive analysis involves calculating frequencies, percentages, means, and standard deviations. In order to fulfil the study's purpose of identifying and evaluating the level of awareness and current state of adoption of various AI technologies among construction project firms and professionals in Imo State, a mean item score (MIS) was utilised. MIS was used to calculate mean values for the variables (Nasila & Cloete, 2018).

3.1 Results

This aspect focused on data analysis, interpretation, and presenting of the results. The study sampled 447 respondents from a target population of 932 to obtain data on AI applications and construction project delivery in Imo State, Nigeria. The questionnaire return rate findings are provided in table 3 below.

Table 3: Population of respondents after the retrieval of questionnaire

S/N	Professionals	Population	Sample size	Retrieved samples	Samples analyzed
1	Project manager	73	31	28	27
2	Building technology/site supervisor	125	50	49	48
3	Other (Please specify)	118	46	46	44
4	Architect	115	40	39	37
5	Quantity surveyor	176	54	52	51
6	Client representative	43	21	20	19
7	Mechanical/electrical engineer	160	113	110	110
8	Civil/structural engineer	122	92	90	90
	Total	**932**	**447**	**434**	**426**

According to the study, 426 of 447 targeted respondents completed and returned the questionnaire, accounting for 95.3%. This is commendable in the sense that a reasonable and above-50 percent response rate was attributed to the data collection technique, in which the researcher enlisted the help of other friends and well-wishers to administer the questionnaires. The response rate was high, and the sample represented the population accurately.

The study targeted practitioners from various building construction projects in Imo state, Nigeria, with a specific focus on all of the experts listed in table 3 above. The first section of the questionnaire looked into the results about the practitioners' demographic characteristics. They include the institution where they worked, how long practitioners have been in the industry, the respondents' level of education, and their position within the organisation. Table 4 shows details of the demographic response.

Table 4: Demographic profile of practitioners

Demographic Variable	Category	Frequency	Percentage (%)
Professional Discipline	Project/Construction Management	153	35.9
	Civil/Structural Engineering	119	27.9
	Architecture	64	15.0
	Quantity Surveying	55	12.9
	Mechanical/Electrical Engineering	35	8.2
Years of Experience	Less than 5 years	98	23.0
	5 - 10 years	170	39.9
	11 - 15 years	98	23.0
	16 years and above	60	14.1
Nature of Organization	Contracting Firm	210	49.3
	Consulting Firm	149	35.0
	Government/Public Client	47	11.0
	Private Client/Developer	20	4.7
Organization Size	Small (< 50 employees)	255	59.9

Demographic Variable	Category	Frequency	Percentage (%)
	Medium (50 - 200 employees)	128	30.0
	Large (> 200 employees)	43	10.1

The high response rate and distribution across major professions ensure that the findings accurately reflect the core stakeholders in Imo State's construction sector. The high amount of responses from Project Management and Engineering (63.8%) is understandable given their role in driving technological adoption on construction sites. The experience profile demonstrates that the majority (77%) have more than 5 years of experience, which lends credence to their statements about project delivery implications. The high representation from small and medium-sized enterprises (SMEs), constituting 89.9% of the sample, is a critical characteristic of the Nigerian construction sector, particularly in Imo state, and is highly relevant for understanding the context of AI adoption, as SMEs face unique resource constraints.

3.2 Level of awareness and current state of adoption of various AI technologies

The mean item score (MIS) was used in this study to identify and assess the level of awareness and current use of various AI technologies among construction project firms and professionals in Imo State. The table below displays the details of the analysis.

Table 5: Awareness levels of AI on construction projects

Descriptive Statistics											
	N	Range	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis		Rank
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error	
Machine learning (ML)	426	4.00	1.00	5.00	2.5892	1.60229	.355	.118	-1.495	.236	3rd
Computer vision	426	4.00	1.00	5.00	2.7465	1.61363	.140	.118	-1.637	.236	1st
Natural Language Processing (NLP)	426	4.00	1.00	5.00	2.4695	1.40596	.356	.118	-1.328	.236	6th
Robotics and automation	426	4.00	1.00	5.00	2.5775	1.51226	.216	.118	-1.565	.236	4th
Predictive Analytics	426	4.00	1.00	5.00	2.6808	1.71676	.262	.118	-1.697	.236	2nd
Optimization	426	4.00	1.00	5.00	2.1761	1.28685	.980	.118	-.244	.236	7th
Automated planning and scheduling	426	4.00	1.00	5.00	2.5563	1.49284	.349	.118	-1.367	.236	5th
Knowledge-based Systems	426	4.00	1.00	5.00	2.1761	1.31935	.889	.118	-.436	.236	7th
Evolutionary algorithms	426	4.00	1.00	5.00	2.1197	1.35551	.938	.118	-.379	.236	9th

The statistics reported in table 5 above show that the respondents' awareness of AI is somewhat low. Computer vision had the highest awareness score of 2.75, followed by predictive analytics, which had a score of 2.68 and was rated second. While the results suggest that Machine learning (ML) has the next MIS of 2.59 and is ranked third. Robotics and automation ranked fourth, with a MIS of 2.58. Automated planning and scheduling was placed seventh, with a MIS of 2.56. Natural Language Processing (NLP) was rated sixth, with a MIS of 2.47. Optimisation and knowledge-based systems were rated ninth, with MIS of 2.17 each. While evolutionary algorithms with a MIS of 2.12 were rated seventh.

Table 6: Adoption levels of AI on construction projects

Descriptive Statistics											
	N	Range	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis		Rank
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error	
Machine learning (ML)	426	4.00	1.00	5.00	2.6432	1.47270	.330	.118	-1.359	.236	3rd
Computer vision	426	4.00	1.00	5.00	2.7113	1.61281	.172	.118	-1.624	.236	2nd
Natural Language Processing (NLP)	426	4.00	1.00	5.00	2.3897	1.51953	.624	.118	-1.122	.236	7th
Robotics and automation	426	4.00	1.00	5.00	2.4437	1.59052	.507	.118	-1.380	.236	6th
Predictive Analytics	426	4.00	1.00	5.00	2.7230	1.75788	.247	.118	-1.747	.236	1st
Optimization	426	4.00	1.00	5.00	2.3192	1.30391	.608	.118	-.981	.236	8th
Automated planning and scheduling	426	4.00	1.00	5.00	2.5329	1.52164	.338	.118	-1.466	.236	5th
Knowledge-based Systems	426	4.00	1.00	5.00	2.5915	1.37279	.156	.118	-1.400	.236	4th
Evolutionary algorithms	426	4.00	1.00	5.00	2.3028	1.28698	.372	.118	-1.388	.236	9th
Valid N (listwise)	426										

The statistics reported in table 6 above show that AI adoption levels among the respective respondents are somewhat low. Predictive analytics had the highest adoption rate, with a MIS of 2.72; computer vision came in second, with a MIS of 2.71. While the results suggest that Machine learning (ML) has the next MIS of 2.64 and is ranked third. Knowledge-based Systems were ranked fourth, with a MIS of 2.59. Automated planning and scheduling, with a MIS of 2.53, was ranked fifth. Robotics and automation were rated sixth, with a MIS of 2.44. Natural Language Processing (NLP) was placed eighth, with a MIS of 2.39. While optimisation with a MIS of 2.32 was ranked eighth. Finally, evolutionary algorithms were rated tenth, with a MIS of 2.31.

3.3 Discussions

Our findings show a large fairly low awareness-adoption gap across all AI technologies, which is a frequent phenomenon in developing nations' construction sectors (Pan & Zhang, 2021). Computer vision (MIS=2.75) and predictive analytics (MIS=2.68) have the highest awareness, most likely because of their clear, understandable applications in safety monitoring and cost control, both of which are pressing concerns in Nigeria, particularly in Imo state. The findings of this study accord with those of Pavankumar et al. (2023), who believe that computer vision is primarily utilised to conduct visual activities for two major purposes: inspection and monitoring in order to accomplish intelligent management in the construction project management domain.

However, the adoption levels are quite moderate and universally low. Predictive analytics (including AI analytics) had the highest adoption rate (MIS=2.72), which can be attributed to their low cost, ease of implementation for progress monitoring and topographic mapping, and high visibility of results. This is consistent with Bock (2015), who stated that technologies that provide quick, tangible benefits with a moderate investment are embraced first. This was followed by computer vision (MIS = 2.71), which scored second highest. The findings of this study support Adeloye et al. (2023), who stated that computer vision tries to imitate the human visual system by allowing machines to grasp and interpret digital images and movies. It entails taking photos, processing them with algorithms, and analysing them to aid decision-making in a variety of building jobs. This scenario is similar to how BIM works in construction project management.

The extremely low usage of evolutionary algorithms (MIS=2.12; 2.31) for both awareness and adoption suggests that the sector is still in its early phases of digitalisation. These technologies necessitate a strong digital culture, including widespread BIM adoption, which is currently in its early stages in Imo State and throughout Nigeria (Ezeokoli et al., 2021). The poor scores indicate the significant capital expenditure required and the view that it is unsuited for Nigeria's labour-intensive, cost-sensitive industry.

4. Conclusions and recommendation

The survey found that construction professionals in Imo State have a modest level of awareness and usage of AI technologies. This is due to the fact that respondents' awareness of AI is somewhat low, with computer vision rating highest (MIS=2.75), followed by machine learning (ML) (MIS=2.59). While AI adoption rates were somewhat low among the responders. Predictive analytics had the highest adoption rate (MIS=2.72), followed by computer vision (MIS=2.71), machine learning (ML) (MIS=2.64), knowledge-based systems (MIS=2.59), automated planning and scheduling (MIS=2.53), and robotics and automation (MIS=2.44).

This study suggests raising awareness about AI and emerging technologies in construction through academic conferences and other channels. Annual professional association conferences can also be fertile ground for lobbying for the adoption of AI technology and their application in construction project delivery. There are numerous future and exciting opportunities for the use of AI in the delivery of building projects in the twenty-first century. GA and ANN should be promoted because of their responsibilities in resolving issues with project cost estimation and scheduling.

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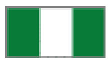
About the Authors

Elvis Izuchukwu Nnadozie, B.Sc

Federal University of Technology
Owerri, Nigeria



Elvis Izuchukwu Nnadozie, B. Sc is a Builder and construction project professional with experience in Site supervision and project management. He holds a Bachelor of Science (B. Sc) of Second Class-Lower degree in Building from the Abia State University, Uturu and currently an M.Sc candidate in Project Management Technology from the Federal University of Technology, Owerri. Elvis has just defended his M.Sc thesis and is currently awaiting its approval. He can be reached via email: elvisizuchi@gmail.com.

Benedict Amade, PhD

Federal University of Technology
Owerri, Nigeria

Dr. Benedict Amade is a Chartered Project Manager by Profession and a Probationer (Member) of Nigerian Institute of Quantity Surveyors (NIQS). He read and obtained a PhD (Doctor of Philosophy) Degree in Project Management Technology from the Federal University of Technology, Owerri, Nigeria. He is a member of the Project Management Institute (PMI) U.S.A. Chairman, Research and Academic Matters, Association of Practicing Professional Project Managers of Nigeria (APPPMON) and a Fellow of Tertiary Education Trust Fund Alliance for Innovative Research (TETFAIR), and presently the Deputy Director, Centre for Research Innovation and Development (CRID) and a Senior Lecturer in the Department of Project Management Technology all at the Federal University of Technology, Owerri, Nigeria where he has been lecturing for the past 15 years. His areas of research interest include construction project management, computer-based project management, construction supply chain management and information technology on construction projects. He has authored over 65 scientific publications in international refereed journals indexed in Scopus, Web of Science, Scimago etc. He has presented quality papers at international conferences both home and abroad. He is actively involved in other consultancy works. He can be reached at https://orcid.org/0000-0003-3368-5432; benedictamade@yahoo.com; benedictamade@futo.edu.ng; benedictamade2@gmail.com.

Gregory Chimere Enyinna, PhD

Federal University of Technology
Owerri, Nigeria

Dr. Gregory Chimere Enyinna is a Reader at the Department of Project Management Technology, and Currently the Head of Department, Project Management Technology, Federal University of Technology, Owerri. He studied B.Sc. in Geography and Planning and an M.Sc. in Environmental Management from Abia State University. He studied his Ph.D in Germany. He is a Fellow of Institute of Management Consulting and the Institute of Policy Management Developers. He is a Resource Person at the World Bank Centre of Excellence in the Federal University of Technology, Owerri.

He can be reached at pycongregco@gmail.com