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The Role of AI Integration in Building Technology Education for Graduate Employability in Nigeria

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ABSTRACT

The global construction industry is undergoing a profound transformation driven by Construction 4.0, with Artificial Intelligence (AI) emerging as a pivotal technological force. Yet a critical skills gap persists in developing nations such as Nigeria, where the pace of educational curriculum development lags significantly behind industry demands. This study examines the integration of AI into Building Technology education programs in Nigerian universities and its implications for graduate employability. Employing an explanatory sequential mixed-methods design, the quantitative phase administered surveys to 120 final-year students, 40 faculty members across four universities in South-East Nigeria, and 60 construction industry employers, to assess the current level of AI integration and its perceived relationship with employability. A subsequent qualitative phase conducted semi-structured interviews with 12 faculty heads and 12 senior industry managers to identify the institutional barriers constraining AI-driven pedagogy. The study is theoretically anchored in the Construction 4.0 Maturity Model, adapted to evaluate educational program readiness. Findings reveal that Building Technology programs currently operate at a nascent 'Initial/Ad Hoc' stage of digital maturity. Institutional constraints, including inadequate infrastructure, limited faculty expertise, and absence of strategic vision were confirmed as significant predictors of low AI adoption. Employer data further revealed that graduates with AI competencies received significantly higher employability ratings than those with traditional skills alone. These findings provide a data-driven basis for curriculum reform, targeted policy investment, and strategic university-industry collaboration to equip Nigeria's construction workforce for the digital era of construction.

Keywords: construction 4.0, artificial intelligence, building technology education, graduate employability, skills gap, Nigerian universities

INTRODUCTION

The global economic landscape is being reshaped by the Fourth Industrial Revolution (Industry 4.0), a paradigm characterized by the convergence of digital, physical, and biological systems. This transformation has catalyzed disruptive innovation across all productive sectors, with the construction industry being no exception (Zabala-Vargas et al., 2023). The concept of "Construction 4.0" has emerged to describe the application of Industry 4.0 principles within the built environment sector, aiming to overcome long-standing challenges of low productivity, cost overruns, and project delays (Jäkel et al., 2024; Sawhney et al., 2020). For decades, the construction industry has lagged behind manufacturing in productivity growth and digitalization (Barbosa et al., 2017; Okanya et al., 2025). Construction 4.0 technologies, including Building Information Modeling (BIM), the Internet of Things (IoT), robotics, and Artificial Intelligence (AI), present a significant opportunity to enhance efficiency, safety, and sustainability across the entire project lifecycle (Forcael et al., 2020; Toyin & Mewomo, 2023).

Among these transformative technologies, AI is increasingly recognized as a pivotal driver of innovation. AI applications, including machine learning, generative design, and predictive analytics, are proving invaluable for optimizing complex processes such as project scheduling, material selection, cost estimation, and risk mitigation (Abioye et al., 2021; Okonkwo et al., 2025). As the industry shifts towards data-driven decision-making, proficiency in AI tools is emerging as a core professional competency rather than a niche specialization (Pan & Zhang, 2021). Consequently, there is a rising global demand for construction professionals equipped with advanced digital and analytical capabilities (Rane, 2024). This technological shift has, however, created a significant skills gap between the competencies demanded by the modern construction industry and those supplied by traditional higher education programs, a gap that is particularly acute in developing economies (Ogunrinde et al., 2026).

In Nigeria, a nation with a rapidly growing population and substantial infrastructure needs, the construction sector is a crucial driver of economic development (Chukwu & Anaele, 2025; Nwobodo-Anyadiegwu & Okanya, 2026). Yet the industry is constrained by a shortage of skilled labor and a persistent mismatch between graduate competencies and employer expectations (Aliu & Aigbavboa, 2020; Nwakile et al., 2025). Employers consistently report that built environment graduates, while possessing sound theoretical knowledge, lack the practical, digital, and problem-solving skills required for a technology-driven workplace (Ebekozien et al., 2024; Toyin & Mewomo, 2023). One assessment found that a substantial proportion of Nigerian graduates lack foundational digital skills, a deficiency that severely limits their employability and constrains the industry's capacity for innovation (Olagunju et al., 2025).

The onus of bridging this gap falls heavily on higher education institutions. Universities in many parts of Africa, including Nigeria, face significant challenges in adapting to this technological reality, including infrastructural deficits, limited funding, insufficient faculty expertise in emerging technologies, and curricula that have evolved slowly (Guadu et al., 2025). Building Technology education programs, often situated within Vocational and Technical Education faculties, are designed to produce graduates for the construction industry but frequently remain anchored in conventional methodologies, with little formal integration of Construction 4.0 concepts, particularly AI (Nwobodo-Anyadiegwu & Okanya, 2026; Okereke et al., 2024). While the imperative to modernize construction education is globally recognized (Okonkwo et al., 2025), there is a scarcity of empirical research systematically assessing the state of AI integration within specific educational contexts in developing countries (Nnaji & Karakhan, 2020; Ukala & Iheukwumere, 2025).

The challenge facing Building Technology education in developing economies spans multiple interconnected dimensions. A fundamental knowledge gap exists, as existing literature provides limited empirical evidence on how Construction 4.0 maturity manifests in educational settings within resource-constrained contexts (Nwobodo-Anyadiegwu & Okanya, 2026). A practice gap persists between industry-level AI integration and graduate preparation (Okonkwo et al., 2025). A measurement gap also remains: while industry demand for AI skills is documented globally, quantitative evidence of the employability implications of these skills in developing economies is scarce (Aghimien et al., 2018; Nnaji & Karakhan, 2020). This study addresses these interconnected deficits through a focused investigation of Building Technology education in South-East Nigerian universities. By framing the specific challenges of a developing nation within the global context of

Construction 4.0, this paper generates insights that are locally relevant and internationally significant, contributing to the broader discourse on educational transformation in the digital age.

Research Questions

To guide this investigation, the study is structured around the following research questions:

1. What is the current level of AI integration within the Building Technology curriculum in Nigerian universities compared to the global benchmarks of Construction 4.0?

2. What are the significant institutional and infrastructural factors (e.g., power, software access, faculty expertise) that constrain the adoption of AI-driven pedagogy in Nigerian building technology departments?

3. How does proficiency in Artificial Intelligence tools (such as generative design and predictive scheduling) influence the perceived employability of graduates among construction industry employers in Nigeria?

Research Hypotheses

H_1: There is a significant negative correlation between the existing Building Technology curriculum content and the digital skill requirements of the Construction 4.0 era, indicating a substantial curriculum-industry misalignment.

H_2: Institutional constraints (inadequate infrastructure and limited technical support) significantly predict the low adoption rate of AI tools in Nigerian university Building Technology programs.

H_3: There is a significant difference in the employability ratings of graduates with AI competencies compared to those with only traditional Building Technology skills, as perceived by construction industry employers.

LITERATURE REVIEW

The Global Rise of Construction 4.0

The term Construction 4.0 represents the adaptation of Industry 4.0 principles to the architecture, engineering, and construction (AEC) sector. It signifies a paradigm shift from traditional, often fragmented processes to a more integrated, industrialized, and digitized approach to the entire lifecycle of a built asset (Jäkel et al., 2024). The core objective of Construction 4.0 is to leverage digital technologies to achieve comprehensive improvements in productivity, efficiency, quality, safety, and sustainability (Sawhney et al., 2020). Unlike the manufacturing sector, where Industry 4.0 concepts are relatively mature, the construction industry's adoption of these technologies is still in its early stages, with varying degrees of maturity across different regions and organizations (Perrier et al., 2024).

The technological pillars of Construction 4.0 are diverse and interconnected. Building Information Modeling (BIM) is widely regarded as a foundational technology, providing a digital representation of a facility's physical and functional characteristics that serves as a shared knowledge resource for decision-making (Borrmann et al., 2018; Toyin & Mewomo, 2023). Other key technologies include the Internet of Things (IoT) for real-time data collection from sites, robotics and automation for performing repetitive or hazardous tasks, additive manufacturing (3D printing) for creating complex components, and augmented/virtual reality (AR/VR) for visualization and training (Forcael et al., 2020; Toyin & Mewomo, 2023). Central to harnessing the potential of these data-generating technologies is Artificial Intelligence (AI), which provides the analytical power to transform vast amounts of data into predictive insights and automated actions (Pan & Zhang, 2021).

Artificial Intelligence in the Construction Industry

AI is rapidly moving from a theoretical concept to a practical tool within the construction industry. Its applications span the entire project lifecycle, from planning and design to construction and operations. In the design phase, Generative AI and machine learning algorithms can explore thousands of design options based on predefined constraints (e.g., cost, materials, energy performance), helping architects and engineers identify optimal solutions far more quickly than through manual methods (Tapeh & Naser, 2023). This application is particularly transformative in architectural design education, where it fosters creativity and complex problem-solving (Onatere-Ubrurhe et al., 2025). During construction, AI-powered predictive analytics can forecast project schedules, identify potential delays, and optimize resource allocation. By analyzing historical data and real-time inputs from IoT sensors, AI models can predict the compressive strength of concrete, identify safety hazards on-site, and automate progress monitoring (Abioye et al., 2021; Okonkwo et al., 2025). This shift towards data-driven decision-making promises to mitigate the instability of costs, deadlines, and quality that has long plagued the industry (Jäkel et al., 2024). However, the effective use of these tools requires a workforce proficient in data analysis, programming, and AI principles, skills that are not typically emphasized in traditional construction education (Okanya et al., 2025).

Building Technology Education in Nigerian Universities

In Nigeria, education for the construction industry at the university level is primarily delivered through programs such as Building Technology, Architecture, Civil Engineering, Estate Management, Urban and Regional Planning, Surveying and Geoinformatics, and Quantity Surveying. Programs like Civil Engineering are housed within the Faculty of Engineering, while programs like Building Technology, Architecture, Estate Management, Urban and Regional Planning, Surveying and Geoinformatics, and Quantity Surveying are housed within the Faculty of Environmental Sciences. The "Building Technology Education" program, however, is often housed within the Faculty of Education or Faculty of Vocational and Technical Education (VTE), positioning it as a discipline focused on both technical competence and pedagogical training (Okanya et al., 2019). For instance, at the University of Nigeria, Nsukka (UNN), Building Technology Education is offered as a specialization within the B. Tech in Industrial Technical Education program and is frequently combined with Woodwork Technology (Nwobodo Anyadiegwu & Okanya, 2026). The program's philosophy is geared towards skills acquisition for gainful employment, aiming to produce teachers for technical colleges, polytechnics, universities, as well as self-employed entrepreneurs in the building and woodwork trades (National Universities Commission [NUC], 2023).

An examination of the curricula from several Nigerian universities reveals a strong emphasis on foundational and traditional construction knowledge. The curriculum at UNN, for example, includes courses such as "Building Construction Technology I, II, & III," "Technical Drawing," "Building Science," and "Interior Design and Decoration" (NUC, 2022). Similarly, programs at Michael Okpara University of Agriculture, Umudike (MOUAU) and Alex Ekwueme Federal University, Ndufu-Alike (AE-FUNAI) offer degrees in Building or as part of Industrial Technology Education, focusing on core construction principles (NUC, 2022). While these courses provide a solid theoretical base, they show limited evidence of integrating advanced digital competencies aligned with Construction 4.0. This curricular focus on traditional methods contributes directly to the skills gap observed by industry employers, who increasingly require graduates proficient in modern digital tools (Kalu et al., 2026; Ngalburgi, 2024).

The Employability Skills Gap in Nigeria's Built Environment

The disconnect between academic training and industry needs is a well-documented problem in Nigeria's construction sector. Olagunju et al. (2025) noted that while employers value graduates' theoretical knowledge and willingness to learn, they frequently observe significant deficiencies in practical experience, digital skills, communication, and teamwork. The rapid advancement of technologies like BIM and AI is further widening this gap, as higher education has been slow to adapt (Turkyilmaz et al., 2024). Toyin and Mewomo (2023) reinforce this, noting that employers now actively seek construction management graduates who possess not only academic qualifications but also competencies in innovative technological tools. The Nigerian construction industry itself suffers from a severe shortage of skilled artisans and technicians, a problem exacerbated by a lack of adequate vocational training (Chukwu et al., 2026; Kalu et al., 2026). This skills mismatch has tangible consequences for graduate employability. Youth unemployment in Nigeria is alarmingly high, with a 2022 report indicating that over 53% of young people, including university graduates, were unemployed (Okereke & Okanya, 2024). Employers increasingly state that a degree certificate alone is insufficient; it is the demonstrable skills that open doors. This places immense pressure on universities to reform their curricula to be more practical and industry-relevant, fostering university-industry partnerships and integrating hands-on training with emerging technologies.

Challenges of AI Integration in African Higher Education

The challenge of integrating AI into curricula is not unique to Nigeria but is a continent-wide issue in Africa. While AI offers promising solutions to persistent problems like staff shortages and unequal access to quality education, its implementation is fraught with significant ethical, socio-technical, and infrastructural hurdles (Nwakile et al., 2025). Key challenges include a pronounced digital divide, with unequal access to reliable power, internet connectivity, and necessary hardware and software (Nwibe & Bakare, 2022; Orji & Ogbuanya, 2022).

Furthermore, there is a heavy reliance on AI tools developed in the Global North, which raises concerns about algorithmic bias, data privacy, and cultural relevance. These tools may perpetuate existing inequalities or erase indigenous values and knowledge systems if not adapted with a critical, decolonial lens (Guadu et al., 2025; UNESCO, 2025). Ethical issues such as academic dishonesty, facilitated by generative AI tools like ChatGPT, are a major concern, particularly in institutions with weak digital literacy frameworks and policy gaps (Ogunrinde et al., 2026). Addressing these multifaceted challenges requires a responsible, inclusive, and culturally grounded approach to AI adoption in African higher education, one that prioritizes local ownership, ethical guidelines, and context-sensitive frameworks.

THEORETICAL FRAMEWORK

The Construction 4.0 Maturity Model

To systematically assess the level of AI integration in Building Technology education and benchmark it against industry evolution, this study adopts the Construction 4.0 Maturity Model as its theoretical framework. Maturity models are established tools used to evaluate the capability and readiness of an organization or process within a specific domain by defining a series of progressive evolutionary stages or levels (Fraser et al., 2002; Jäkel et al., 2024). In the context of Industry 4.0 and Construction 4.0, these models serve as a holistic framework for companies to assess their current state of digital transformation, identify areas for improvement, and develop a strategic roadmap for advancement (Heidenwolf & Szabó, 2024). While numerous maturity models exist for domains like BIM and general digitalization, a specific focus on Construction 4.0 is a more recent development, addressing a recognized research gap (Tuma Neto et al., 2022).

Existing models for general digitalization in construction were found to be insufficient for assessing the full spectrum of Construction 4.0 capabilities (Jäkel & Klemt-Albert, 2023). Therefore, recent research has focused on developing comprehensive Construction 4.0 maturity models that encompass the unique characteristics of the industry (Das et al., 2023). For this study, we synthesize a hybrid maturity model based on recent frameworks, such as the Digital Construction Company Maturity Model (DCCMM) proposed by Jäkel et al.

(2024) and similar models focusing on digital transformation in construction (Han et al., 2025; Rane, 2023). This synthesized model is structured around key dimensions and progressive maturity levels, adapted to evaluate an academic program rather than a commercial enterprise.

Dimensions of the Maturity Model

The adapted model for assessing Building Technology programs comprises five core dimensions: (1) Strategy and Leadership: This dimension evaluates the extent to which the university and departmental leadership have a clear vision and strategic plan for integrating Construction 4.0 and AI into the curriculum. It assesses the presence of policies, funding allocation, and leadership commitment to digital transformation. (2) Curriculum and Pedagogy: This is the central dimension, focusing on the content of the curriculum. It assesses the degree to which AI and other Construction 4.0 technologies are explicitly taught, the use of AI-driven pedagogical tools, and the shift from theoretical instruction to project-based, data-driven learning. (3) Technology and Infrastructure: This dimension assesses the availability and accessibility of the necessary technological infrastructure, including computer labs, high-speed internet, specialized software (e.g., generative design tools, predictive modeling platforms), and reliable power supply. (4) People and Competencies: This dimension focuses on the human element, evaluating the digital literacy and AI-specific expertise of faculty members. It also considers the mechanisms for faculty training, professional development, and the digital skills of the students themselves. (5) Industry Collaboration and Ecosystem: This dimension assesses the strength and nature of partnerships between the university and the construction industry. It examines the extent to which the curriculum is informed by industry needs, the availability of internships, and collaborative research projects involving Construction 4.0 technologies.

Maturity Levels

The model defines six progressive maturity levels, adapted from established frameworks (Jäkel et al., 2024), to classify the status of the academic programs:

Level 0: Non-Existent. There is no awareness or recognition of Construction 4.0 or AI within the program. The curriculum is entirely traditional.

Level 1: Initial/Ad Hoc. There is a nascent awareness of digital technologies. Some individual faculty members may introduce basic digital tools on an ad hoc basis, but there is no institutional strategy or formal integration.

Level 2: Defined. The department has begun to formally define digital competencies as learning objectives. Foundational digital skills (e.g., advanced BIM) are integrated into specific courses. AI is recognized as a future requirement, though concrete implementation is absent.

Level 3: Managed. AI concepts are formally introduced in the curriculum, perhaps through an elective or a dedicated module. The institution provides some access to the necessary software and infrastructure. Some faculty members have developed expertise in AI.

Level 4: Integrated. AI and data analytics are embedded across multiple courses. Students engage in projects requiring the use of AI tools for analysis and design. Established partnerships with industry facilitate technology-focused internships and collaborative projects.

Level 5: Optimizing/Innovative. The program is a recognized leader in Construction 4.0 education, actively contributing to research in AI applications for construction. The curriculum is continuously updated based on cutting-edge industry trends, and AI is used both as a subject of study and as a pedagogical tool.

This theoretical framework was instrumental in addressing the research questions. It provided the structure for the survey instrument and interview protocol, allowing for a systematic evaluation of the current status of AI integration (RQ1), a categorized analysis of the barriers within each dimension (RQ2), and a basis for correlating program maturity with the employability outcomes observed in the industry (RQ3). **Figure 1** illustrates the theoretical framework.

METHODOLOGY

Research Design

This study employs an explanatory sequential mixed-methods research design. This two-phase approach is particularly well-suited to address the complexity of the research questions (Creswell & Plano Clark, 2018). The first phase consists of a quantitative investigation to assess the current status of AI integration, its correlation with Construction 4.0 requirements, and its perceived impact on graduate employability. The second, qualitative phase is designed to explain and elaborate on the quantitative findings, providing in-depth insights into the institutional and infrastructural barriers hindering AI adoption (Draucker et al., 2020). The rationale for this design is that quantitative data can identify the 'what' and 'how much' (e.g., the level of integration, the strength of correlations), while the subsequent qualitative data can uncover the 'why' (e.g., the reasons behind the low adoption rates). The point of integration, or "connecting," occurs when the results of the quantitative analysis are used to purposefully select participants for the qualitative phase, ensuring that the interviews can effectively explain unexpected or significant quantitative findings (Draucker et al., 2020).

Area of Study

The study is geographically focused on the South-East geopolitical zone of Nigeria. This region was selected due to its significant concentration of federal universities and its growing economic and infrastructural development, which places increasing demands on the local construction industry. The universities selected for this study are the primary institutions in the region that offer degree programs in Building Technology or closely related fields within Vocational and Technical Education (VTE). These institutions are: University of Nigeria, Nsukka (UNN), Nnamdi Azikiwe University, Awka (UNIZIK), Michael Okpara University of Agriculture, Umudike (MOUAU), and Alex Ekwueme Federal University, Ndufu-Alike, Ikwo (AE-FUNAI). These universities represent a diverse mix of first-generation and newer federal institutions, providing a comprehensive view of the state of Building Technology education in the region.

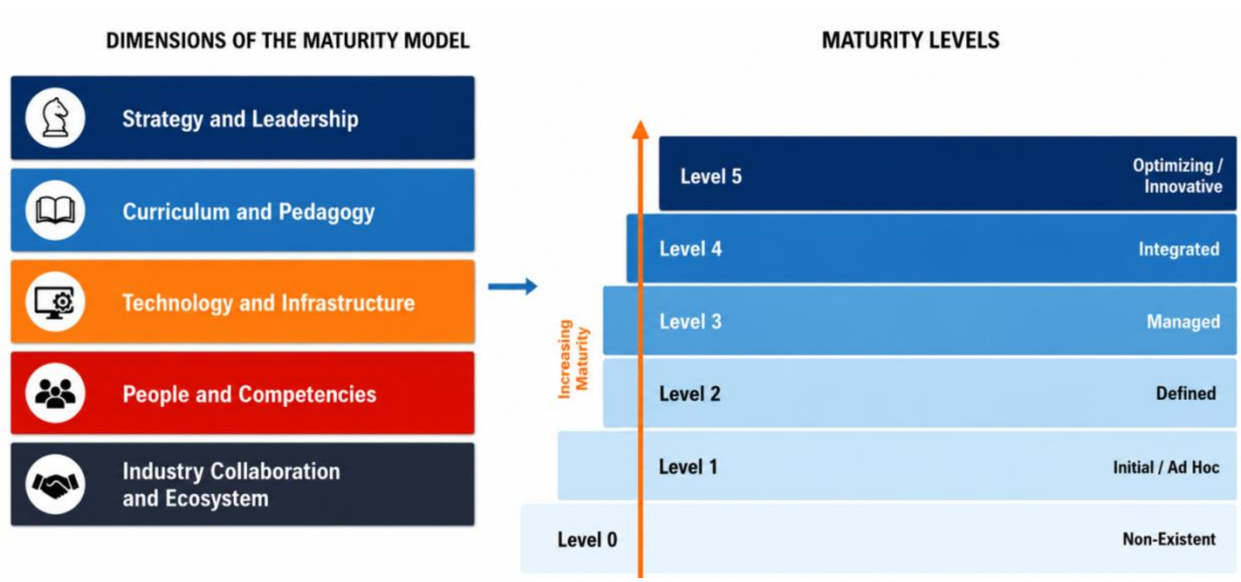

Figure 1. Theoretical Framework

Population and Sampling

The study population comprises three distinct groups: (a) Academic Staff: The lecturers, associate professors, and professors teaching Building Technology Education and related VTE programs at the four selected universities. Their accessible population is 60. (b) Students: All final year undergraduate students enrolled in the Building Technology Education and related VTE programs at the four universities. Their accessible population is 200. Final year students were chosen as they have the most comprehensive exposure to the curriculum. (c) Industry Employers: These include senior level professionals such as Project Managers, CEOs, HR Managers, Site Engineers, in medium to large scale construction companies operating in the major commercial cities of South East Nigeria (Enugu, Awka, Owerri, Umuahia, Abakaliki). Their accessible population was 100 firms. A stratified random sampling technique was employed for the quantitative phase to ensure representation from each university and stakeholder group. The sample size was determined to ensure statistical validity. For the qualitative phase, a purposive sampling strategy was used. Academic department heads and senior industry managers were selected based on their strategic oversight and extensive experience, ensuring rich and insightful data regarding institutional policies and industry expectations. **Table 1** outlines the sample distribution for the quantitative survey. A total of 220 participants were targeted, comprising 40 academic staff, 120 students, and 60 industry employers. Stratified random sampling ensures that each university is proportionately represented within the academic and student groups, while a combination of convenience and snowball sampling was used to reach a sufficient number of industry professionals.

Table 2 shows the purposive sample for the qualitative interviews. A total of 24 in-depth interviews were planned, targeting 12 academic leaders and 12 senior industry managers to provide a deep contextual understanding of the quantitative findings.

Data Collection Instruments

Three primary instruments were developed for this study: ***(a)*** *Curriculum-Industry Alignment Survey (CIAS):* A structured questionnaire designed for academic staff and students. It uses a 5-point Likert scale to measure the current level of AI/Construction 4.0 integration in the curriculum (addressing RQ1) and the perceived importance of these skills. The items were developed based on the dimensions of the Construction 4.0 Maturity Model. *(b) Graduate Employability & Skills Survey (GESS):* A structured questionnaire for industry employers. It assesses satisfaction with graduates' current skill sets, the importance placed on AI-related competencies, and the perceived employability of graduates with versus without these skills (addressing RQ3).

The Relative Importance Index (RII) will be used to rank skills. *(c) Semi-Structured Interview Protocol:* An open-ended question guide for academic leaders and industry managers.

Table 1. Sample distribution for participants

Participant Group	Target Population (Approx.)	Sample Size (n)	Sampling Method
Academic Staff	60	40	Stratified Random
Final-Year Students	200	120	Stratified Random
Industry Employers	100+	60	Convenience & Snowball
Total	360+	220	

Table 2. The purposive sample for the qualitative interviews

Participant Group	Selection Criteria	Sample Size (n)	Sampling Method
Heads of Department / Program Coordinators	Leadership role in curriculum development and implementation	12 (3 from each university)	Purposive
Senior Industry Managers	Minimum 10 years of experience; involvement in graduate recruitment	12	Purposive
Total		24	

The questions are designed to explore the institutional, infrastructural, and pedagogical barriers to AI adoption (addressing RQ2) and to elicit detailed narratives about the skills gap and potential solutions. The protocol was developed based on the Consolidated Framework for Implementation Research (CFIR) to ensure a comprehensive exploration of barriers and facilitators (Szeszulski et al., 2025). The instruments were validated through a pilot test with a small group of non-participating academics and industry professionals to ensure clarity, relevance, and reliability. The reliability of the survey scales was assessed using Cronbach's alpha, with a target coefficient of > 0.70.

Data Analysis

The data analysis proceeded in two stages, corresponding to the mixed-methods design. *(a) Quantitative Analysis:* Data from the surveys were analyzed using IBM SPSS Statistics (Version 23). *(b) Descriptive Statistics:* Frequencies, means, and standard deviations were used to summarize the demographic data and the current status of AI integration (RQ1). *(c) Correlation Analysis:* Pearson correlation was used to test the relationship between the existing curriculum content and the industry's required digital skills (H_{01}). *(d) Regression Analysis:* Multiple regression analysis was conducted to determine if institutional constraints (as measured in the survey) significantly predict the low adoption rate of AI tools (H_{02}). *(e) T-Test/ANOVA:* An independent samples t-test or ANOVA was used to compare the employability ratings of graduates with and without AI skills, as perceived by employers (H_{03}). *(f) Qualitative Analysis:* The audio-recorded interviews were transcribed verbatim. Thematic analysis was employed to identify, analyze, and report patterns (themes) within the data. The process involved*: (1)* Familiarization with the data, (2) Generating initial codes, (3) Searching for themes based on the coded data, (4) Reviewing and refining themes, (5) Defining and naming themes, and (6) Producing the report, using illustrative quotes to substantiate the analysis. The qualitative findings were integrated with the quantitative results in the discussion section to provide a comprehensive explanation of the research problem.

Ethical Considerations

Ethical approval for this study was obtained from the research ethics committees of the participating universities. All participants were provided with a detailed information sheet explaining the purpose of the study, the voluntary nature of their participation, and their right to withdraw at any time without penalty. Written informed consent was obtained from all participants before data collection. To ensure confidentiality and anonymity, all personal identifiers were removed from the data, and participants were assigned pseudonyms in the reporting of qualitative findings.

All figures in this manuscript were produced by the authors. **Figure 1** is an author-constructed schematic diagram illustrating the dimensions and levels of the adapted Construction 4.0 Maturity Model described in the Theoretical Framework. **Figure 2** was generated programmatically in Python (Matplotlib) directly from the barrier intensity dataset summarized in **Table 5**. The plotted values, axis intervals, and scale markings were checked against the source data to confirm accuracy.

RESULTS

RQ1: Current level of AI integration within the Building Technology curriculum

To address the first research question, data from the Curriculum-Industry Alignment Survey (CIAS) administered to students and academic staff were analyzed. The maturity level of the programs was assessed against the adapted Construction 4.0 Maturity Model. **Table 3** shows that the overall maturity of Building

Technology programs in the studied universities is at 'Level 1: Initial/Ad Hoc', with a mean score of 1.97. This indicates that while there is some awareness of digital technologies, integration is not systematic. The 'Technology and Infrastructure' dimension scored the lowest (1.65), suggesting a critical lack of necessary hardware and software. 'Industry Collaboration' scored highest (2.30), indicating that some foundational links with industry exist, even if not focused on high-level technology.

Hypothesis Testing for H_{01}

Reliability of Measurement Instruments

Prior to the main hypothesis testing, the internal consistency of the survey scales was assessed using Cronbach's alpha. **Table 4a** presents the reliability coefficients for each subscale of the Curriculum-Industry Alignment Survey (CIAS) and the Graduate Employability and Skills Survey (GESS). As shown in **Table 4a**, all subscales and overall Cronbach's alpha coefficients exceeded the a priori threshold of .70, ranging from .791 (CIAS – People and Competencies) to .863 (CIAS – Technology and Infrastructure). The values indicate satisfactory to good internal consistency across all measurement instruments (Nunnally & Bernstein, 1994; George & Mallery, 2003), thereby supporting the reliability of the quantitative data used to test the study's hypotheses. No subscale fell below the acceptable threshold, and no remedial action was required.

To formally test the null hypothesis (H_{01}) that there is no significant correlation between the existing Building Technology curriculum content and the digital skill requirements of the Construction 4.0 era, a Pearson correlation analysis was conducted. Curriculum content was operationalized through student and staff ratings of current course coverage, while industry requirements were measured through employer ratings of skill importance. The results, presented in the revised **Table 4b** below, show a very weak positive correlation ($r = .152$) between current curriculum content and the skills required by industry. This correlation did not reach statistical significance at the conventional $\alpha = .05$ level ($p = .089$). Therefore, we fail to reject the null hypothesis H_{01}.

Table 3. Status of AI Integration in Building Technology Curriculum

Maturity Dimension	Mean Score (1-5 Scale*)	Standard Deviation	Assessed Maturity Level
Strategy and Leadership	1.85	0.75	Level 1 (Initial/Ad Hoc)
Curriculum and Pedagogy	2.10	0.88	Level 1 (Initial/Ad Hoc)
Technology and Infrastructure	1.65	0.81	Level 0 (Non-Existent) / Level 1 (Initial)
People and Competencies (Faculty)	1.95	0.92	Level 1 (Initial/Ad Hoc)
Industry Collaboration	2.30	0.79	Level 2 (Defined)
Overall Maturity Score	1.97	0.83	Level 1 (Initial/Ad Hoc)

*Scale: 1=Non-Existent, 2=Initial, 3=Defined, 4=Integrated, 5=Optimizing

Table 4a. Cronbach's Alpha Reliability Coefficients for Survey Subscales

Instrument / Subscale	No. of Items	Cronbach's α	Interpretation
CIAS – Strategy and Leadership	8	.813	Good
CIAS – Curriculum and Pedagogy	10	.847	Good
CIAS – Technology and Infrastructure	9	.863	Good
CIAS – People and Competencies	8	.791	Acceptable
CIAS – Industry Collaboration	7	.804	Good
CIAS – Overall Scale	42	.847	Good
GESS – Overall Scale	18	.823	Good

Note. CIAS = Curriculum-Industry Alignment Survey; GESS = Graduate Employability and Skills Survey. Interpretation follows George and Mallery's (2003) guidelines: $\alpha > .90$ = Excellent; .80–.89 = Good; .70–.79 = Acceptable; .60–.69 = Questionable.

Table 4b. Pearson correlation analysis – Curriculum Content and Industry Skill Requirements

Variable	Statistic	Industry Skill Requirements
Curriculum Content Coverage	Pearson Correlation *(r)*	.152
	Sig. (2-tailed) *(p)*	.089
	N	220

The non-significant result in **Table 4b** indicates that the data do not provide sufficient statistical evidence to confirm or deny a linear relationship between curriculum content coverage and industry skill requirements at the specified level of statistical power. This finding should be interpreted with care: a failure to reject H_{01} does not confirm that the curriculum is aligned with industry needs; rather, it means the study lacked sufficient statistical evidence to quantify the magnitude of any such misalignment through this particular correlational measure alone. It is important to note that the weak positive direction of $r = .152$ is consistent with prior theoretical expectations of minimal alignment, but this directionality cannot be relied upon as confirmatory evidence, given the non-significance of the result.

The practical evidence for curriculum-industry misalignment is more robustly established through the convergence of findings from the qualitative phase and the maturity benchmarking data. The overall maturity score of 1.97 (Level 1: Initial/Ad Hoc, **Table 3**) and the rich qualitative narratives presented under RQ2 collectively and compellingly indicate a substantial gap between what is taught and what the industry requires. Considered together, this multi-method evidence suggests a meaningful misalignment, though the Pearson correlation alone does not provide quantitative confirmation thereof.

RQ2: Barriers to AI Adoption

The qualitative interviews with 12 academic leaders yielded rich and layered data on the institutional, infrastructural, and strategic barriers to AI integration in Building Technology programs. Thematic analysis identified five primary themes, mapped against the dimensions of the Construction 4.0 Maturity Model and summarized in **Table 5**. **Figure 2** provides a graphical representation of the mean barrier intensity scores, rated on a scale from 1 (Not a Barrier) to 5 (Severe Barrier) by the academic informants. All five barrier categories were rated above 3.5 on this scale, with 'Institutional and Infrastructural Deficits' recording the highest mean intensity score (4.72), followed by 'Lack of Strategic Vision' (4.58) and 'Human Capacity and Resistance to Change' (4.43). The scale in **Figure 2** ranges evenly from 1 to 5, with increments of 0.5, ensuring a consistent and interpretable visual representation.

Table 5. The key barriers identified from the qualitative data

Main Theme	Sub-themes	Illustrative Quote
1. Institutional and Infrastructural Deficits	Chronic underfunding and poor power supply	"*How can we talk about AI when we can't guarantee power for a 3-hour practical? The generators are old, and fuel is expensive. We are struggling with the basics*." (HOD_A)
2. Lack of access to software and modern labs	Inadequate Infrastructure	"*Specialized software for generative design or simulation is subscription-based and costs thousands of dollars. The university budget cannot cover this. Our students are still learning with outdated CAD versions*." (HOD_C)
3. Human Capacity and Resistance to Change	Shortage of faculty with AI expertise	"*Most of us were trained in the traditional way. We are experts in concrete technology, not machine learning. We need training for the trainers, but there are no opportunities*." (HOD_B)
4.Bureaucratic curriculum review process	Policy Deficiencies	"*To introduce a new course, it takes years to get it through the university senate. The process is slow and rigid. By the time a course on AI is approved, the technology has already moved on*." (HOD_D)
5. Lack of Strategic Vision	Absence of a digital transformation strategy	"*There is no top-down push for this. It's not a university priority. Construction 4.0 is just a buzzword to the administration; there is no concrete policy or roadmap for us to follow*." (HOD_A)

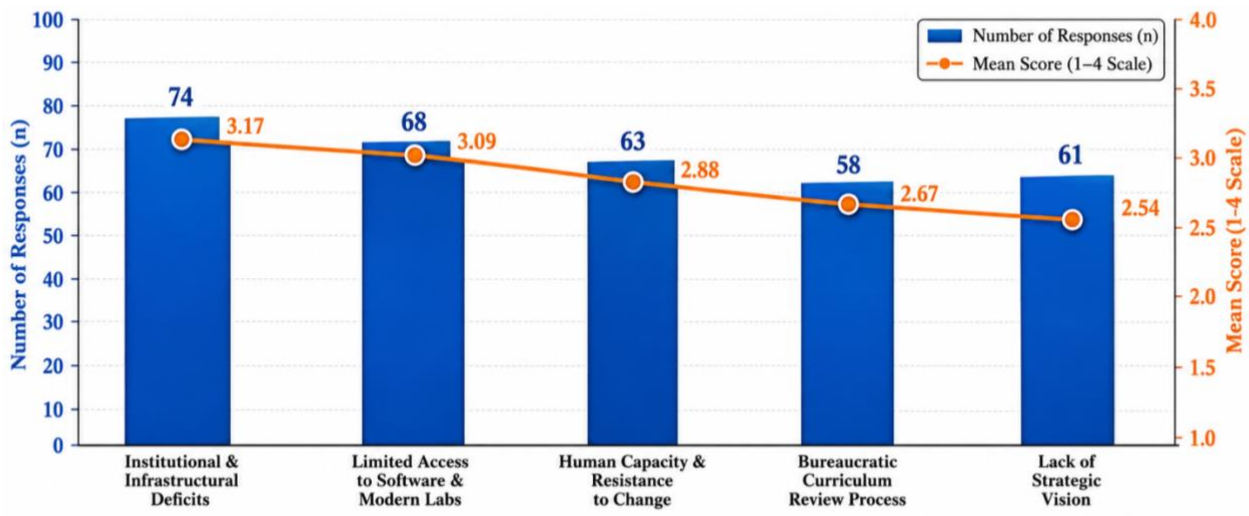

Figure 2. Barriers to AI Adoption

The 'Bureaucratic Curriculum Review Process' (4.21) and 'Lack of Access to Software and Modern Labs' (4.18) also registered high intensity levels, reinforcing the conclusion that barriers to AI integration are pervasive, structural, and deeply embedded in the institutional environment of Nigerian universities. The findings strongly point to a combination of severe infrastructural limitations, a critical gap in faculty skills, and a lack of strategic direction from university leadership as the primary factors constraining the adoption of AI-driven pedagogy.

Hypothesis Testing for H_{02}

The multiple regression analysis (**Table 6**) results remain substantively unchanged. The model was statistically significant ($F(2, 157) = 54.89$, $p < .001$) and accounted for 41.2% of the variance in AI adoption rate ($R^2 = .412$). Both predictors—Infrastructure Score ($\beta = -0.515$, $p < .001$) and Technical Support Score ($\beta = -0.231$, $p = .017$)—were significant negative predictors of AI adoption rate. Consequently, the null hypothesis H_{02} is rejected, and the research hypothesis H_2 is supported: institutional constraints significantly predict the low rate of AI integration in Nigerian Building Technology programs.

Data from the Graduate Employability & Skills Survey (GESS) completed by 60 industry employers, were analyzed. Employers were asked to rate the employability of two graduate profiles: one with traditional skills and one with added AI competencies. **Table 7** shows a statistically significant difference in the mean employability ratings between the two profiles ($t(59) = -8.914$, $p < .001$). Graduates with AI competencies received a significantly higher mean rating ($M = 8.15$) compared to those with only traditional skills ($M = 5.85$). This indicates that industry employers place a high value on AI skills.

Table 6. Multiple Regression Analysis

Model	Unstandardized B	Std. Error	Standardized Beta	t	Sig.
(Constant)	3.451	0.211		16.355	.000
Infrastructure Score	−0.482	0.095	−0.515	−5.073	.000
Technical Support Score	−0.213	0.088	−0.231	−2.420	.017

Model Summary: $R^2 = .412$, $F(2, 157) = 54.89$, $p < .001$

Table 7. Employability Ratings

Graduate Profile	N	Mean Rating (out of 10)	Std. Deviation	t-value	Sig. (2-tailed)
Traditional Skills	60	5.85	1.25	−8.914	.000
AI Competencies	60	8.15	0.95		

Influence of AI Proficiency on Graduate Employability

Hypothesis Testing for H_{03}

For H_{03}, the independent samples t-test (**Table 7**) yielded a statistically significant difference in mean employability ratings between graduates with traditional skills ($M = 5.85$, $SD = 1.25$) and those with AI competencies ($M = 8.15$, $SD = 0.95$), $t(59) = -8.914$, $p < .001$. The null hypothesis H_{03} is therefore rejected, and H_3 is supported: industry employers perceive a significant employability advantage for graduates with AI competencies.

Summary of Major Findings

1. The current level of AI integration in Building Technology programs across South-East Nigerian universities is at an 'Initial/Ad Hoc' maturity stage (Overall Mean = 1.97), indicating a significant gap when benchmarked against global Construction 4.0 standards.

2. The Pearson correlation between current curriculum content and industry digital skill requirements was positive but weak ($r = .152$) and did not reach statistical significance ($p = .089$). Consequently, H_{01} was not rejected. While this result does not statistically confirm the magnitude of curriculum-industry misalignment, convergent evidence from the qualitative findings and maturity benchmarking points to a meaningful gap between academic preparation and industry expectations.

3. Institutional and infrastructural constraints, including chronic underfunding, inadequate power and internet infrastructure, limited access to AI-capable software, and a shortage of faculty expertise, were confirmed as significant predictors of low AI integration, supporting H_2 (H_{02} rejected).

4. Nigerian construction industry employers perceive graduates with AI competencies as significantly more employable than those with traditional skills alone ($M = 8.15$ vs. $M = 5.85$, $p < .001$), supporting H_3 (H_{03} rejected) and indicating a clear market premium for advanced digital capabilities.

DISCUSSION

The Chasm between Academia and Industry 4.0

The finding that Building Technology programs in South-East Nigeria operate at an 'Initial/Ad Hoc' maturity level (Overall Mean = 1.97) provides a quantified diagnosis of a problem long discussed in qualitative and theoretical terms. This aligns with global observations that the construction sector, and by extension its educational pipeline, lags significantly behind other industries in digitalization (Barbosa et al., 2017; Nwibe & Ogbuanya, 2024). The present study localizes this global trend, demonstrating that Nigerian universities are not merely lagging but are at the very nascent stages of this transformation.

The Pearson correlation analysis (**Table 4b**) yielded a non-significant result ($r = .152$, $p = .089$), meaning that H_{01} could not be rejected at the $\alpha = .05$ level. This result does not statistically confirm the presence or magnitude of a curriculum-industry alignment gap; rather, it indicates that the study's correlational evidence alone is inconclusive in this regard. Taken in isolation, the non-significant correlation would suggest insufficient evidence to quantify the relationship between curriculum content and industry requirements. However, when considered alongside the qualitative findings and the maturity benchmarking results, a compelling convergent picture emerges. The pervasive 'Initial/Ad Hoc' maturity profile across all five dimensions of the Construction 4.0 Maturity Model, combined with the rich thematic evidence from academic leaders describing curricula rooted in pre-digital methodologies, provides robust multi-method grounds for concluding that a substantial curriculum-industry gap exists. This interpretation is consistent with findings reported by Nwakile et al. (2025)

and Toyin and Mewomo (2023) regarding the mismatch between graduate competencies and employer expectations in Nigeria's built environment sector. The highest maturity score in 'Industry Collaboration' (2.30) suggests that while nominal channels with industry exist, typically through student internships, these are not strategically leveraged to translate industry's technological expectations back into curriculum design.

Institutional Paralysis: The Root of Stagnation

The qualitative and quantitative results converge powerfully on the reasons for this stagnation. The barriers identified are not minor hurdles but systemic, structural deficiencies. The regression analysis (H_{02}) confirmed that infrastructural and support deficits are significant predictors of low AI adoption, a finding echoed in the poignant interview quotes from academic leaders. The complaint about the inability to guarantee power for a single practical session (HOD_A) starkly illustrates the challenge of implementing a technology as demanding as AI. This resonates with broader studies on AI adoption in African higher education, which consistently highlight the digital divide and infrastructural deficits as primary obstacles (Guadu et al., 2025; Okanya et al., 2025). Beyond physical infrastructure, the 'human infrastructure' is equally lacking. The shortage of faculty with AI expertise (HOD_B) is a critical bottleneck. This creates a vicious cycle: without trained faculty, AI cannot be taught, and without teaching it, a new generation of potential academics with these skills is not produced. This finding supports the argument by Okonkwo et al. (2025) that reforming construction education requires a focus on faculty development. Furthermore, the institutional inertia, characterized by slow, bureaucratic curriculum review processes (HOD_D) and a lack of strategic vision from university leadership (HOD_A), suggests a state of 'institutional paralysis'. This is not merely a failure of a single department but a systemic issue, where the university as a whole has not prioritized digital transformation in a meaningful way, a challenge also noted in broader analyses of African higher education (Muhammad & Bulama, 2024).

The Clear Mandate from the Market: Digital Skills and Employability

In stark contrast to the slow pace of academic change, the message from the industry is unequivocal. The significantly higher employability rating for graduates with AI competencies (M=8.15 vs. M=5.85) provides a clear market signal. This finding (rejecting H_{03}) directly quantifies the 'employability gap' discussed by Olagunju et al. (2025). Employers are not just vaguely asking for 'digital skills'; they are placing a tangible premium on specific, high-level competencies related to AI and data analysis. This aligns with global trends where data-driven decision-making is becoming a core expectation for construction professionals (Okonkwo et al., 2025; Rane, 2023). This result serves as both a warning and an opportunity. The warning is for students and universities: a traditional Building Technology degree is rapidly losing its currency in the job market. The opportunity is that there is a clear pathway to enhanced employability. Graduates who can acquire these skills, whether through formal curriculum changes or self-directed learning, will have a distinct competitive advantage. This finding should serve as a powerful catalyst for change, providing academic departments with the evidence needed to argue for resource allocation and curriculum reform. It refutes any notion that Construction 4.0 is a distant, irrelevant concept for the Nigerian context; the market is already demanding its skills.

Implications for the Theoretical Framework

Applying the Construction 4.0 Maturity Model to an academic context proved to be a highly effective analytical tool. It allowed for a structured diagnosis of the programs' weaknesses across multiple dimensions, moving beyond a simple analysis of curriculum content. The model highlighted that a low maturity in 'Curriculum and Pedagogy' is not an isolated issue but is deeply interconnected with deficiencies in 'Strategy,' 'Technology,' and 'People.' This holistic perspective is crucial for developing effective interventions. Any attempt to reform the curriculum without simultaneously addressing the infrastructural and faculty competency gaps is bound to fail. The framework, therefore, serves not only as an assessment tool but also as a strategic roadmap, suggesting that progress must be made across all dimensions in a coordinated manner to achieve a higher level of maturity.

CONCLUSION

This study provides compelling empirical evidence of a critical and widening gap between Building Technology education in Nigerian universities and the demands of the Construction 4.0 era. The research demonstrates that these programs are at a nascent stage of digital maturity, largely disconnected from the technological realities of the modern construction industry. This misalignment is primarily driven by severe institutional and infrastructural barriers, including inadequate funding, a lack of essential technology, and a deficit in faculty expertise, all compounded by a lack of strategic vision at the university leadership level. Despite this academic stagnation, the Nigerian construction industry has clearly signaled its demand for a digitally proficient workforce, placing a significant premium on graduates with AI and data analytics competencies. The traditional building technology degree, in its current form, is becoming insufficient for ensuring graduate employability in a data-driven world.

The findings of this research serve as an urgent call to action for all stakeholders. For universities, it is a mandate to move beyond ad hoc efforts and embrace a strategic, holistic approach to digital transformation. For policymakers, it highlights the need for targeted investment in educational infrastructure and faculty development. For the industry, it underscores the importance of moving from passive collaboration to active partnership in shaping the future workforce. Bridging the Construction 4.0 skills gap is not merely an academic exercise; it is an economic imperative for Nigeria, essential for enhancing the productivity of its construction sector, improving graduate employment outcomes, and securing the nation's competitiveness in the global digital economy.

RECOMMENDATIONS

Based on the findings, the following recommendations are proposed:

For University Administration and Policymakers

1. Develop a National Strategy for Digital Education in the Built Environment: Government bodies, in collaboration with regulatory agencies like the National Universities Commission (NUC), should develop and fund a national strategy to modernize built environment education, with a specific focus on integrating Construction 4.0 technologies.

2. Targeted Infrastructure Investment: A special intervention fund should be created to equip universities with the necessary infrastructure, including reliable power, high-speed internet, and dedicated labs with up-to-date software for BIM, data analytics, and AI.

3. Faculty Development Programs: Implement a "train-the-trainer" model, sponsoring faculty for advanced degrees, certifications, and industry placements in technology-focused areas. This is crucial for building the internal capacity to teach these new skills.

4. Flexible Curriculum Review Policies: The NUC and university senates should streamline the curriculum review process to allow for more rapid and agile updates, enabling programs to keep pace with technological change.

For Academic Departments

1. Curriculum Overhaul: Departments should immediately begin a phased overhaul of the curriculum, integrating digital skills at all levels. This should start with making BIM mandatory and then introducing modules on data analytics, IoT, and AI applications in construction.

2. Forge Strategic Industry Partnerships: Move beyond traditional internship placements to create deep, strategic partnerships with tech-forward construction firms. This could involve co-developing courses, hosting guest lectures from industry experts, and establishing joint research projects.

3. Embrace Project-Based Learning: Shift pedagogy from theory-based lectures to hands-on, project-based learning where students use digital tools to solve real-world construction problems.

For the Construction Industry

1. Invest in Academia: Companies should actively invest in the educational pipeline by sponsoring labs, providing software licenses, and funding faculty research in areas relevant to their technological needs.

2. Provide Quality Internships and Apprenticeships: Offer structured, technology-focused internship programs that provide students with meaningful, hands-on experience with Construction 4.0 tools and processes.

LIMITATIONS AND FUTURE RESEARCH

This study, while comprehensive in scope, is subject to several limitations that should be considered when interpreting its findings.

1. Geographically, the study's focus on four federal universities in the South-East geopolitical zone of Nigeria means that the findings may not be fully generalizable to all regions of the country, though it is probable that comparable challenges obtain in other zones given Nigeria's shared national educational infrastructure. Future research should expand the geographical scope to include universities in other geopolitical zones, as well as private and state-owned institutions, to provide a more nationally representative picture.

2. Regarding the industry employer sample, a particular limitation warrants explicit discussion. The employer group (n = 60) was recruited through convenience and snowball sampling, methods that, while commonly employed when a definitive sampling frame is unavailable (Etikan et al., 2015), may introduce selection bias. Specifically, employers who volunteered to participate may be those with greater pre-existing engagement with universities or with stronger views on graduate skill deficiencies. This sampling bias could potentially inflate the magnitude of the perceived employability premium reported for AI-competent graduates. Future studies should employ probability sampling from a registered database of construction firms to improve the representativeness of the employer sample and the generalizability of employability ratings. The demographic spread of the sample across multiple major cities in South-East Nigeria (Enugu, Awka, Owerri, Umuahia, Abakaliki) offers partial mitigation of this limitation.

3. The study also relied on employers' perceived employability ratings rather than objective longitudinal employment or salary data. Future research employing longitudinal designs that track the actual career trajectories, employment rates, and earnings of graduates with and without AI competencies would provide more direct and generalizable evidence of the market value of these skills. A comparative study across different built environment disciplines (Building Technology, Civil Engineering, Architecture, and Quantity Surveying) could also yield valuable insights into how different professions are adapting to the digital shift.

4. Finally, the non-significant result for H_{01} points to a potential power limitation; future studies with larger, probability-based samples may be better positioned to detect the nature and magnitude of any linear relationship between curriculum content and industry skill requirements.

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All authors reviewed the results and approved the final version of the manuscript

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Ethical statement: The researcher obtained ethical permission to carry out this research from the research ethics committees in line with the Declaration of Helsinki. Ethical approval was obtained from the University of Nigeria Nsukka Research Ethics Committee with reference number: UNN/REC/2023/022. The participants were provided with informed consent forms to fill out and sign accordingly. In order to ensure participants' privacy, we made sure that a succinct, straightforward explanation of the study's goals, objectives, and any hazards was provided. Moreover, it was adequately stressed that their participation or involvement in the research was completely voluntary and that individuals were free to leave at any moment. The researcher equally ensured participants' confidentiality by making sure that participants' personal information was kept private. This means that none of the participants' personal information was made public but rather presented using pseudonyms.

AI statement: During the preparation of this manuscript, the authors used ChatGPT-Pro solely to assist with language editing and formatting consistency. The tool was not used to generate research ideas, design the study, collect or analyze data, interpret results, or construct scholarly arguments; these were developed entirely by the authors. All AI-assisted text was reviewed and edited by the authors; ethical considerations and accuracy checks were applied throughout, and the authors take full responsibility for the final content of this publication.

Data sharing statement: The dataset analyzed during the study is available from the lead or corresponding author upon reasonable request.

REFERENCES

Abioye, S. O., Oyedele, L. O., Akanbi, L., Ajayi, A., Delgado, J. M. D., Bilal, M., Akinade, O. O., & Ahmed, A. (2021). Artificial intelligence in the construction industry: A review of present status, opportunities and future challenges. *Journal of Building Engineering*, *44*, Article 103299. https://doi.org/10.1016/j.jobe.2021.103299

Aghimien, D. O., Aigbavboa, C. O., Oke, A. E., & Koloko, N. (2018). Digitalisation in construction industry: Construction professionals' perspective. *Proceedings of International Structural Engineering and Construction, 5*(2), 1-6. https://doi.org/10.14455/ISEC.res.2018.90

Aliu, J., & Aigbavboa, C. O. (2020). Employers' perception of employability skills among built environment graduates. *Journal of Engineering, Design and Technology, 18*(4), 847-864. https://doi.org/10.1108/JEDT 06 2019 0162

Barbosa, F., Woetzel, J., Mischke, J., Ribeirinho, M. J., Sridhar, M., Parsons, M., Bertram, N., & Brown, S. (2017, February 27). *Reinventing construction through a productivity revolution*. McKinsey Global Institute. https://www.mckinsey.com/capabilities/operations/our-insights/reinventing-construction-through-a-productivity-revolution

Borrmann, A., König, M., Koch, C., & Beetz, J. (Eds.). (2018). *Building information modeling: Technology foundations and industry practice*. Springer. https://doi.org/10.1007/978-3-319-92862-3

Chukwu, D. U., & Anaele, E. O. (2025). Understanding sustainability consciousness and construction sustainable behaviours of preservice teachers of Building Technology Education programme: The moderating role of subjective norms. *Discover Education*, *4*, Article 476. https://doi.org/10.1007/s44217-025-00829-4

Chukwu, D. U., Omeh, C. B., & Ayanwale, M. A. (2026). Predicting sustainable behaviours on building construction sites in Nigeria using the value-belief-norm theory. *Discover Sustainability, 7, Article 255*. https://doi.org/10.1007/s43621-026-02606-1

Creswell, J. W., & Plano Clark, V. L. (2018). *Designing and conducting mixed methods research* (3rd ed.). Sage Publications. https://collegepublishing.sagepub.com/products/designing-and-conducting-mixed-methods-research-3-241842

Das, P., Perera, S., Senaratne, S., & Osei-Kyei, R. (2023). Paving the way for industry 4.0 maturity of construction enterprises: A state of the art review. *Engineering, Construction and Architectural Management*, *30*(10), 4665–4694. https://doi.org/10.1108/ECAM-11-2021-1001

Draucker, C. B., Rawl, S. M., Vode, E., & Carter-Harris, L. (2020). Integration through connecting in explanatory sequential mixed method studies. *Western Journal of Nursing Research*, *42*(12), 1137–1147. https://doi.org/10.1177/0193945920914647

Ebekozien, A., Aigbavboa, C. O., & Samsurijan, M. S. (2024). Appraising alternative building technologies adoption in low-cost housing provision to achieving Sustainable Development Goal 11. *Engineering, Construction and Architectural Management*, *31*(13), 41–58. https://doi.org/10.1108/ECAM-06-2023-0538

Etikan, I., Musa, S. A., & Alkassim, R. S. (2015). Comparison of convenience sampling and purposive sampling. *American Journal of Theoretical and Applied Statistics*, *5*(1), 1–4. https://doi.org/10.11648/j.ajtas.20160501.11

Forcael, E., Ferrari, I., Opazo-Vega, A., & Pulido-Arcas, J. A. (2020). Construction 4.0: A literature review. Sustainability, 12 (22), Article 9755. https://doi.org/10.3390/su12229755

Fraser, P., Moultrie, J., & Gregory, M. (2002). The use of maturity models/grids as a tool in assessing product development capability. In *Proceedings of the 2002 IEEE International Engineering Management Conference (IEMC 2002)* (pp. 244–249). IEEE. https://doi.org/10.1109/IEMC.2002.1038431

George, D., & Mallery, P. (2003). *SPSS for Windows step by step: A simple guide and reference* (4th ed.). Allyn & Bacon.

Guadu, A., Dibekulu, D., & Menberu, A. W. (2025). Artificial intelligence in African higher education: Uses, misuses, and ethical dilemmas. *Advances in Artificial Intelligence and Machine Learning*, *5*(3), 4196–4221. https://doi.org/10.54364/AAIML.2025.53234

Han, Y., Du, H., & Zhao, C. (2025). Development of a digital transformation maturity model for the construction industry. *Engineering, Construction and Architectural Management*, *32*(7), 4384–4412. https://doi.org/10.1108/ECAM-10-2023-1009

Heidenwolf, O., & Szabó, I. (2024). Justification of Construction 4.0 maturity model with a case study of a data-driven façade company. In *Proceedings of the 41st International Symposium on Automation and Robotics in Construction (ISARC 2024)* (pp. 1272-1279). International Association for Automation and Robotics in Construction. https://doi.org/10.22260/isarc2024/0164

Jäkel, J.-I., & Klemt-Albert, K. (2023). Construction 4.0 maturity tool with ontology development methodology for organisations. In *Proceedings of the 2023 Creative Construction Conference (CCC)* (pp. 272–281). https://doi.org/10.3311/CCC2023-033

Jäkel, J.-I., Fischerkeller, F., Oberhoff, T., & Klemt-Albert, K. (2024). Development of a maturity model for the digital transformation of companies in the context of construction industry 4.0. *Journal of Information Technology in Construction*, *29*, 778–809. https://doi.org/10.36680/j.itcon.2024.034

Kalu, Y. O., Odoh, C. E., Kalu, S. U., Ukoji, C. K., Okorie, S. A. (2026). The virtual constructor: AI-powered simulation for enhancing experiential learning in building technology education. *International Journal of Research and Innovation in Social Science, 10*(26), 2636-2643. https://doi.org/10.47772/IJRISS.2026.1026EDU0215

Muhammad, S. Y., & Bulama, K. H. (2024). Technical skills required for enhancing the employability of building technology education undergraduates in degree awarding institutions in North-East Nigeria. *International Journal of Multidisciplinary Research in Science, Technology and Innovation*, *2*(1), 1–12. https://www.ijmrsti.com/2024/03/09/technical-skills-required-for-enhancing-the-employability-of-building-technology-education-undergraduates-in-degree-awarding-institutions-in-north-east-nigeria/

National Universities Commission. (2023). *Core curriculum and minimum academic standards for Nigerian universities (CCMAS)*. https://shorturl.at/LQ9oX

Ngalburgi, S. A. (2024). Challenges of practical skills acquisition among building trade students of federal polytechnics in North Eastern Nigeria. *International Journal of Innovative Research in Technology, Basic and Applied Sciences, 7(*1), 55 74. https://internationalpolicybrief.org/wp-content/uploads/2024/04/ARTICLE-7.pdf

Nnaji, C., & Karakhan, A. A. (2020). Technologies for safety and health management in construction: Current use, implementation benefits and limitations, and adoption barriers. *Journal of Building Engineering, 29*, Article 101212. https://doi.org/10.1016/j.jobe.2020.101212

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill.

Nwakile, T. C., Ugwuoke, C. U., Okadi, A., Ali, C. C., Nnadi, H. S., Ikehi, M., Ekwueme, S. U., Okanya, V. A., Eya, C. C., & Emeka, O. (2025). Retrospective assessment of academic and psychological readiness of final-year technical and vocational education students in Nigeria after the 2022 ASUU strike. *Discover Education*, *4*, Article 409. https://doi.org/10.1007/s44217-025-00893-w

Nwibe, K. J., & Bakare, J. (2022). Self-efficacy belief and entrepreneurial intention of electrical/electronics technology education students in South-Eastern Nigerian universities: A moderated mediation analyses. *Journal of Global Entrepreneurship Research*, *12*, 131-141. https://doi.org/10.1007/s40497-022-00318-0

Nwibe, K. J., & Ogbuanya, T. C. (2024). Emotional intelligence and entrepreneurial intention among university undergraduates in Nigeria: Exploring the mediating roles of self-efficacy domains. *Journal of Innovation and Entrepreneurship*, *13*, Article 13. https://doi.org/10.1186/s13731-024-00367-7

Nwobodo-Anyadiegwu, E. N., & Okanya, V. A. (2026). Impact of student-centred learning on motivation and learning outcomes among engineering and building technology students in a Nigerian university. *Discover Education*, *5*, Article 135. https://doi.org/10.1007/s44217-026-01231-4

Ogunrinde, O., Idrissi Gartoumi, K., Osuizugbo, I. C., Hatamleh, M. T., & Oyeyipo, O. (2026). Construction 4.0 technologies for advancing quality management processes. *Engineering, Construction and Architectural Management*, *33*(9), 7395-7414. https://doi.org/10.1108/ECAM-01-2025-0007

Okanya, A. V., Asogwa, J. O., & Vincent, D. A. (2025). Enhancing graduate employability through the introduction of artificial intelligence in building technology education in Nigerian universities. *Vocational and Technical Education Journal*, *5*(1), 183–197. https://votej.com.ng/index.php/votej/article/view/39

Okanya, V. A., Chukwu, D. U., & Ojo, S. A. (2019). Strategies to promote improved construction practices in building construction industry: A case study of building contractors in Nsukka LGA of Enugu State. *International Journal of Vocational Education and Training Research*, *5*(2), 53–58. https://doi.org/10.11648/j.ijvetr.20190502.13

Okereke, G. K., & Okanya, V. A. (2024). Achieving sustainable housing for low and middle-income earners. In M. Noguchi (Ed.), *Prefabricated construction for sustainability and mass customization* (pp. 1–17). IntechOpen. https://doi.org/10.5772/intechopen.111870

Okereke, G. K., Okanya, V. A., Okereke, J., Umar, L., Yakubu, A., Ezugwu, C., & Kontei, E. (2024). Perception of building technology lecturers on the adoption of wearable technologies for worker safety in Nigeria's building construction sector. *Global Journal of Information Technology: Emerging Technologies*, *14*(2), 79–88. https://doi.org/10.18844/gjit.v14i2.9591

Okonkwo, C., Lan, R., Awolusi, I., & Cai, J. (2025). Integrating artificial intelligence into construction education: Assessing the impact on students' perception of knowledge, confidence, and relevance to career. Proceedings of the 2025 ASEE Gulf Southwest Annual Conference. Proceedings of the 2025 ASEE Gulf-Southwest Annual Conference The University of Texas at Arlington, Arlington, TX. https://peer.asee.org/integrating-artificial-intelligence-into-construction-education-assessing-the-impact-on-students-perception-of-knowledge-confidence-and-relevance-to-career

Olagunju, A. R., Kayode, I. A., & Olagunju, M. I. (2025). Factors influencing the employability of built environment graduates in Nigeria's construction sector. *International Journal of Builders in Academia*, *1*(1), 102–1115. http://www.ijba.org.ng/index.php/ijba/article/download/58/11

Onatere-Ubrurhe, J. O., Chinyio, E., & Georgakis, P. (2025). Enhancing building technology education through the integration of virtual reality. *International Journal of Education, Learning and Development*, *13*(1), 65–84. https://doi.org/10.37745/ijeld.2013/vol13n16584

Orji, C. T., & Ogbuanya, T. C. (2022). Mediating roles of ability beliefs and intrinsic motivation in PBL and engagement in practical skills relations among electrical/electronic education undergraduate. *Innovations in Education and Teaching International*, *59*(3), 326–336. https://doi.org/10.1080/14703297.2020.1813188

Pan, Y., & Zhang, L. (2021). Roles of artificial intelligence in construction engineering and management: A critical review and future trends. *Automation in Construction*, *122*, Article 103517. https://doi.org/10.1016/j.autcon.2020.103517

Perrier, N., Bled, A., Bourgault, M., Cousin, N., Danjou, C., Pellerin, R., & Roland, T. (2024). Construction 4.0: A comparative analysis of research and practice. *Journal of Information Technology in Construction*, *29*, 16–39. https://doi.org/10.36680/j.itcon.2024.002

Rane, N. L. (2023) Integrating building information modelling (BIM) and artificial intelligence (AI) for smart construction schedule, cost, quality, and safety management: Challenges and opportunities. *SSRN*. http://dx.doi.org/10.2139/ssrn.4616055

Rane, N. L. (2024). Roles and challenges of ChatGPT and similar generative artificial intelligence in architectural engineering. *International Journal of Artificial Intelligence and Machine Learning, 4*(1), 22-47. https://doi.org/10.2139/ssrn.4607767

Sawhney, A., Riley, M., & Irizarry, J. (Eds.). (2020). *Construction 4.0: An innovation platform for the built environment*. Routledge. https://doi.org/10.1201/9780429398100

Szeszulski, J., Schaefers, A., de Mello, G. D., Gardner, J., George, A., MacMillan Uribe, A. L., Rethorst, C. D., Seguin Fowler, R., & Xin, L. (2025). Design and methodology of a cluster randomized factorial trial to optimize implementation strategies for the Healthy School Recognized Campus initiative. *Frontiers in Public Health, 13*, Article 1652485. https://doi.org/10.3389/fpubh.2025.1652485

Tapeh, A. T. G., & Naser, M. Z. (2023). Artificial intelligence, machine learning, and deep learning in structural engineering: A scientometrics review of trends and best practices. *Archives of Computational Methods in Engineering*, *30*(1), 115–159. https://doi.org/10.1007/s11831-022-09793-w

Toyin, J. O., & Mewomo, M. C. (2023). An investigation of barriers to the application of building information modelling in Nigeria. *Journal of Engineering, Design and Technology*, *21*(2), 442-468. https://doi.org/10.1108/JEDT-10-2021-0594

Toyin, J. O., & Mewomo, M. C. (2023). Assessing the innovative skills and competencies required of construction management graduates. *Organization, Technology and Management in Construction*, *15*(1), 90–106. https://doi.org/10.2478/otmcj-2023-0002

Tuma Neto, A. A., & Araujo de Souza Junior, A. (2022). Industry 4.0 innovations in construction: Proposal of a maturity model. *International Journal for Innovation Education and Research, 10*(9), 418-436. https://doi.org/10.31686/ijier.vol10.iss9.3892

Turkyilmaz, A. H., Polat, G., & Gurkan, A. (2024). Application of Construction 4.0 technologies: Empirical findings from the Turkish construction industry. *Journal of Information Technology in Construction*, *29*, 179–197. https://doi.org/10.36680/j.itcon.2024.009

Ukala, C. C., & Iheukwumere, S. C. (2025). Integrating artificial intelligence (AI) in technical and vocational education and training in public (TVET) institutions in Abia State, Nigeria: Bridging skills gaps for future workforce. *International Journal of Scientific Research in Education*, *18*(1), 35–43. https://www.ijsre.com.ng/assets/vol.18-ukala-iheukwumere.pdf

UNESCO. (2025, July 20). *The cultural cost of AI in Africa's education systems*. https://www.unesco.org/en/articles/cultural-cost-ai-africas-education-systems

Zabala-Vargas, S., Jaimes-Quintanilla, M., & Jimenez-Barrera, M.H. (2023). Big data, data science, and artificial intelligence for project management in the architecture, engineering, and construction industry: A systematic review. *Buildings*, *13*(12), Article 2944. https://doi.org/10.3390/buildings13122944