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AWARENESS AND ENGAGEMENT WITH ARTIFICIAL INTELLIGENCE TECHNOLOGIES AS PREDICTORS OF UNDERGRADUATES' READINESS IN BUILDING AND WOODWORK TECHNOLOGY FOR CONSTRUCTION PRACTICE IN BENUE STATE

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ABSTRACT

This study investigates the levels of awareness and engagement with Artificial Intelligence (AI) technologies among undergraduate students in building and woodwork technology programmes in Nigeria, and examines their preparedness for professional practice in the construction industry. Employing a quantitative research design, data were collected from 167 students across universities, polytechnics, and colleges of education using a validated 20-item questionnaire (Cronbach's α = 0.78). Descriptive statistics revealed moderate levels of AI awareness ($M_1 = 1.97$, $SD_1 = 0.77$) and engagement ($M_1 = 2.28$, $SD_1 = 0.79$), with polytechnic students demonstrating the highest awareness and university students reporting the greatest engagement. However, students exhibited limited readiness ($M_1 = 2.16$, $SD_1 = 0.85$) to apply AI technologies in real-world construction scenarios. Regression and correlation analyses ($\alpha = 0.05$) indicated a statistically significant positive relationship between AI awareness, engagement, and industry readiness, though the explained variance was modest. The findings underscore critical gaps in current curricular integration of AI applications, such as machine learning and automated systems, within construction-related disciplines. Based on these results, the study recommends targeted interventions, including enhanced AI-focused coursework, practical training initiatives, and faculty development programmes, to bridge the disparity between academic training and industry requirements.

Keywords: Artificial Intelligence, Construction Education, Student Readiness, Nigeria, Vocational Training

INTRODUCTION

The construction industry is undergoing a profound transformation driven by advancements in Artificial Intelligence (AI) technologies. These innovations, including machine learning, computer vision, and predictive analytics, are enhancing efficiency, precision, and safety across all phases of construction projects (Li et al., 2020; Zhong et al., 2019). As the industry evolves, future professionals, particularly building and woodwork technology graduates must acquire competencies in these technologies to meet contemporary workforce demands (Ogunboyo et al., 2019). However, in developing contexts such as Nigeria, a significant disparity persists between the AI skills taught in academic programmes and those required by the construction sector (Li et al., 2020). This study examines this gap by assessing Nigerian students' awareness of, engagement with, and readiness to apply AI technologies in professional practice.

AI in this context refers to narrow AI systems such as machine learning algorithms, automated design tools, and robotics that can perform specialized tasks in construction, such as project scheduling, risk assessment, and quality control (Russell & Norvig, 2016). These technologies differ fundamentally from theoretical concepts like Artificial General Intelligence (AGI) (Bostrom, 2014) or superintelligent AI, which are irrelevant to vocational training. Awareness, defined as students' familiarity with AI concepts and applications remains low in Nigerian institutions. For instance, Ogunboyo et al. (2019) found that while students recognized basic AI terminology, their understanding of its practical uses in construction was superficial. This gap stems from inadequate curriculum coverage of AI (Li et al., 2020), limited access to digital infrastructure (Zhong et al., 2019), and a shortage of faculty expertise (Ogunboyo et al., 2019). Engagement is the degree to which students actively interact with AI tools, which is equally limited within the Nigerian tertiary education system. Fredricks et al. (2004) conceptualized engagement as a multidimensional construct encompassing behavioural (participation), cognitive (investment in learning), and affective (interest) dimensions. In Nigerian institutions, engagement is often constrained by a lack of hands-on training opportunities, despite evidence that practical exposure correlates with workforce readiness (Zhong et al., 2019). Readiness, as conceptualized by Fugate et al. (2004), reflects students' preparedness to apply acquired skills in professional settings. In construction education, this entails proficiency in using AI tools for tasks like Building Information Modelling (BIM) or automated safety monitoring (Zhong et al., 2019). Yet, Nigerian graduates frequently report feeling ill-equipped for these demands, citing minimal exposure to AI during training (Li et al., 2020).

Nigeria's tertiary education system comprises universities, polytechnics, and colleges of education, each with distinct pedagogical emphases. Universities prioritize theoretical instruction in building technology (Akinwale, 2020), while polytechnics focus on technical skills (Olawale & Abiodun, 2019). Colleges of education train vocational instructors but often lack AI resources (Ajayi & Adeoye, 2018). This institutional diversity necessitates tailored interventions to address AI competency gaps. This study, therefore, empirically evaluates the level of AI awareness among building/woodwork technology students across Nigerian institutions, variations in engagement with AI technologies by institution type, and the predictive relationship between awareness, engagement, and industry readiness.

STATEMENT OF THE PROBLEM

Artificial Intelligence (AI) technologies are revolutionizing the construction industry by enhancing efficiency, precision, accuracy, and safety in various construction stages and processes. According to Li et al. (2020), these advancements necessitate that future professionals in the construction industry, including building and woodwork technology undergraduates, possess a substantial level of awareness of AI technologies to meet industry demands after graduation. Despite the significant transformation of the building and woodwork construction industry with AI technologies, such as machine learning, predictive analytics, and automated systems (Zhong et al., 2019), there remains a noticeable gap between the skills taught in academic programmes and the skills required by the construction industry (Li et al., 2020). Current research indicates that the level of awareness of AI technologies among building and woodwork technology undergraduate students is generally low. For instance, Ogunboyo et al. (2019) found that while students are familiar with the basic concepts of AI, their understanding of its specific applications in construction is limited. This gap can be attributed to the insufficient incorporation of AI-related content in curricula (Li et al., 2020), limited access to digital resources (Zhong et al., 2019), and a lack of faculty expertise (Ogunboyo et al., 2019). Furthermore, the level of engagement with AI technologies among students is critical for equipping them with the necessary competencies and readiness to meet the evolving demands of the construction industry (Ogunboyo et al., 2019). Despite the potential benefits of AI technologies in the modern-day construction industry, there is still a lack of empirical data on how the awareness and engagement with these AI tools influence the readiness of building and woodwork technology undergraduates for professional practice. Furthermore, the gap between academic preparation and industry requirements suggests an urgent need to examine the awareness and engagement levels of building and woodwork technology undergraduates regarding AI technologies and their readiness for industry practice.

PURPOSE OF THE STUDY

The general purpose of this study is to examine the relationship between the level of awareness and engagement with AI technologies and the readiness of building/woodwork technology undergraduate students for practice in the construction industry. Specifically, the study sought to:

1. Determine the level of awareness of AI technologies among different groups of building/woodwork technology undergraduate students
2. Determine the level of engagement with AI technologies among different groups of building/woodwork technology undergraduate students
3. Determine how the level of awareness and engagement with AI technologies predict building/woodwork technology undergraduate students' readiness for industry practice

RESEARCH QUESTIONS

1. What is the level of awareness of AI technologies among different group of building and woodwork technology undergraduate students?
2. What is the level of engagement with AI technologies among different group of building and woodwork technology undergraduate students?
3. What is the level of readiness of building and woodwork technology undergraduate students to engage with AI technologies for industry practice?

NULL HYPOTHESES

1. There is no statistically significant impact of the level of awareness of AI technologies on readiness of building/woodwork technology undergraduate students
2. There is no statistically significant impact of the level of engagement of AI technologies on readiness of building/woodwork technology undergraduate students
3. There is no statistically significant relationship between levels of awareness and engagement with AI technologies and building/woodwork technology undergraduate students' readiness for practice in industry.

LITERATURE REVIEW

The integration of Artificial Intelligence (AI) into construction education has revolutionised key aspects of the industry, including design optimisation, safety monitoring, and project management (Li et al., 2020; Zhong et al., 2019). Within academic settings, AI applications encompass emerging technologies such as Building Information Modelling (BIM) systems and machine learning algorithms for structural analysis (Zhong et al., 2019). However, recent studies indicate that construction students in developing nations like Nigeria frequently demonstrate limited exposure to these technologies due to significant curricular gaps and institutional resource constraints (Ogunbayo et al., 2019). Awareness of AI technologies, operationally defined as students' familiarity with both fundamental AI concepts and their practical industry applications, shows considerable variation across Nigeria's tertiary education institutions (Ogunbayo et al., 2019). While empirical data suggests that 62% of surveyed students recognise basic AI terminology, only 23% can adequately describe its specific applications in construction contexts (Ogunbayo et al., 2019). This disparity primarily stems from three interrelated factors: the absence of dedicated AI modules in most curricula, inadequate access to necessary software and hardware infrastructure, and limited faculty expertise in these emerging technological domains (Li et al., 2020; Zhong et al., 2019).

Student engagement with AI technologies, which encompasses both behavioural participation and cognitive investment in learning processes, remains suboptimal throughout Nigerian higher education institutions (Fredricks et al., 2004). This situation principally results from a severe shortage of practical learning opportunities and an overreliance on theoretical instruction methodologies (Akinwale, 2020). As Fredricks et al. (2004) emphasise, meaningful engagement requires not only the active utilisation of AI tools in coursework but also a comprehensive understanding of their underlying algorithmic principles and a clear recognition of their professional relevance. Current research indicates that Nigerian students achieve only partial engagement, with university students demonstrating marginally higher participation rates compared to their polytechnic counterparts, likely attributable to relatively better resource availability in university settings (Ogunbayo et al., 2019).

The critical concept of professional readiness, defined as students' capacity to effectively apply AI competencies in real-world construction practice, presents substantial challenges within the Nigerian educational context (Fugate et al., 2004). Recent graduate surveys reveal that approximately 78% of respondents feel inadequately prepared for AI-dependent roles in the construction industry, primarily citing insufficient practical training experiences and a pronounced disconnect between academic content and contemporary industry requirements (Li et al., 2020; Ogunbayo et al., 2019). This study's theoretical framework integrates two established models: Fredricks et al.'s (2004) engagement theory, which establishes the relationship between active participation and skill acquisition, and Fugate et al.'s (2004) employability model, which conceptualises professional readiness as a function of developed competencies. The synthesis of these frameworks suggests that both awareness and engagement collectively serve as predictors of workforce readiness - a causal relationship that this research aims to empirically validate through rigorous quantitative analysis.

While existing studies has established the growing importance of AI applications in construction education, several significant research gaps remain unaddressed (Li et al., 2020). Few studies have systematically compared AI competency development across different types of tertiary institutions, adequately accounted for Nigeria's unique infrastructural challenges such as unreliable power supply and limited internet access, or implemented longitudinal methodologies to track skill progression over time (Ogunbayo et al., 2019). This study directly addresses these gaps through its comprehensive examination of diverse student populations across multiple institution types, while simultaneously proposing contextually appropriate interventions designed to bridge the growing divide between academic training and industry demands in Nigeria's rapidly evolving construction sector (Akinwale, 2020). The findings will make substantive contributions to ongoing international discussions regarding effective technology integration in vocational education, particularly in resource-constrained environments characteristic of many developing nations (Zhong et al., 2019).

METHODOLOGY

This study employed a quantitative research design to investigate the relationship between Artificial Intelligence (AI) awareness, engagement, and professional readiness among building and woodwork technology students in ertiary institutions in Benue State. The research adopted a cross-sectional survey methodology, targeting the entire population of 167 final-year undergraduate students enrolled in building and woodwork technology programmes across eight tertiary institutions in Benue State, comprising universities (n = 58), polytechnics (n = 72), and colleges of education (n = 37). The comprehensive population approach was justified by the relatively small and accessible cohort size, as well as the need for complete representation across different institution types (Creswell & Creswell, 2018). Data collection was conducted using the researcher-developed Awareness, Engagement with AI Technologies and Readiness for Practice (AEAIT-RFP) questionnaire, which consisted of 20 items across four key sections: demographic information (3 items), AI awareness (5 items), AI engagement (6 items), and industry readiness (6 items). The instrument employed a 4-point Likert scale to minimise neutral responses and elicit clear attitudinal positions (Dörnyei, 2007). Rigorous validation procedures were implemented, including expert review by three construction technology education specialists and a pilot study with 30 students, which established strong internal consistency with Cronbach's alpha coefficients exceeding 0.70 for all subscales (Tavakol & Dennick, 2011) Standardised administration protocols were followed, with questionnaires distributed during scheduled class sessions by researchers and three trained assistants, yielding an exceptional 98.8% response rate (165 completed questionnaires from 167 distributed). This high participation rate effectively mitigated concerns about non-response bias (Groves et al., 2009). The analytical approach incorporated both descriptive and inferential statistical techniques, SPSS version 26 software to compute means and standard deviations for the research questions. Regression analysis assessed predictive relationships between variables, with effect sizes calculated and interpreted according to established conventions (Cohen, 1988).

RESULTS

Research Question One

What is the level of awareness of AI technologies among different group of building/woodwork technology undergraduate students?

Table 1: Mean response and standard deviation scores among different group of building and woodwork technology undergraduate students on AI technologies awareness (N = 165)

S/N	Awareness Indicators	M_1	SD_1	M_2	SD_2	M_3	SD_3	M_t	SD_t
1	I am aware of AI technologies	2.43	0.77	2.20	0.56	2.30	0.90	2.31	0.74
2	I have a good understanding of AI technologies relevant to the construction industry.	1.60	0.78	2.37	0.76	2.00	0.45	1.99	0.66
3	I learned about AI technologies through coursework.	1.45	0.97	2.40	0.67	1.42	0.72	1.76	0.79
4	I am familiar with specific AI applications in construction (e.g., machine learning, predictive analytics)	1.78	0.89	1.89	0.88	1.84	0.84	1.84	0.87
		1.78	**0.80**	**2.22**	**0.77**	**1.92**	**0.73**	**1.97**	**0.77**

Key: M_1 = Mean of University students, SD_1 = Standard deviation of university students, M_2 = Mean of Polytechnic students, SD_2 = Standard deviation of Polytechnic students, M_3 = Mean of College of education students, SD_3 = Standard deviation of college of education students

Table 1 shows a moderate overall awareness of AI technologies among building and woodwork technology students (M_t = 1.97), with polytechnic students demonstrating the highest awareness (M_2 = 2.22) and university students the lowest (M_1 = 1.78). The lowest mean score (1.76) for learning AI through coursework revealed a significant gap in curriculum integration across institutions. Moderate variability (SD_t = 0.77) indicates consistent but varied perceptions, with greater differences in familiarity with specific AI applications (SD_t = 0.87). These findings underscore the need for enhanced AI education and practical training to improve students' preparedness for the construction industry.

Research Question Two

What is the level of engagement with AI technologies among different group of building/woodwork technology undergraduate students?

Table 2: Mean response and standard deviation scores among different group of building and woodwork technology undergraduate students on engagement with AI technologies (N = 165)

S/N	Engagement Indices	M_1	SD_1	M_2	SD_2	M_3	SD_3	M_t	SD_t
1	I have participated in AI-related courses or workshops.	2.34	0.73	2.46	0.92	2.07	0.93	2.29	0.86
2	I use AI tools or software frequently in my coursework.	1.89	0.67	2.32	0.76	2.35	0.75	2.19	0.73
3	I interact with AI tools regularly.	2.45	0.58	2.48	0.73	2.00	0.71	2.31	0.67
4	I am motivated to learn more about AI technologies.	2.52	0.89	2.08	0.87	2.18	0.78	2.26	0.85
5	I am interested in AI technologies.	2.51	0.99	2.06	0.64	2.47	0.88	2.35	0.84
		2.34	0.77	2.28	0.78	2.21	0.81	2.28	0.79

Key: M_1 = Mean of University students, SD_1 = Standard deviation of university students, M_2 = Mean of Polytechnic students, SD_2 = Standard deviation of Polytechnic students, M_3 = Mean of College of education students, SD_3 = Standard deviation of college of education students

The total average mean score of 2.28 as shown in Table 2 indicates moderate engagement with AI technologies among building and woodwork technology students, with university students showing the highest engagement (M_1 = 2.34, SD_1 = 0.77) and college of education students the lowest (M_3 = 2.21, SD_3 = 0.81). The lowest mean score (2.19) for frequent use of AI tools in coursework suggests limited practical interaction with AI, particularly among university students (M = 1.89). The average standard deviation of 0.79 reflects moderate variability in engagement levels, with the highest variability (SD = 0.86) in participation in AI-related courses or workshops, indicating diverse experiences across groups. These findings highlight the need for increased opportunities for hands-on AI engagement to enhance students' preparedness for the construction industry.

Research Question Three

What is the readiness level of building and woodwork technology undergraduate students to engage with AI technologies for industry practice?

Table 3: Mean response and standard deviation scores among different group of building and woodwork technology undergraduate students readiness to engage with AI technologies (N = 165)

S/N	Readiness Indicators	M_1	SD_1	M_2	SD_2	M_3	SD_3	M_t	SD_t
1	I feel prepared to use AI technologies in my future career.	2.03	0.91	2.45	0.76	2.00	0.88	2.16	0.85
2	I am confident in applying AI technologies in real-world construction scenarios.	2.32	0.77	2.45	0.90	2.25	0.76	2.34	0.81

3	I have completed internships or practical experiences where AI was used.	2.45	0.65	2.08	0.77	2.04	0.72	2.19	0.71
4	My practical experiences have prepared me well for using AI in the industry.	2.01	0.78	2.03	0.67	2.09	0.76	2.04	0.74
5	The education I am receiving adequately prepares me for using AI technologies in construction.	2.00	0.99	2.04	0.82	2.46	0.84	2.17	0.88
6	I need more practical training on AI applications to be ready for the industry.	2.56	0.83	2.23	0.85	2.87	0.93	2.55	0.87
7	I feel I need some improvement in my education to better prepare me for using AI in the construction industry	2.42	0.85	2.03	0.93	2.98	0.87	2.48	0.88
		2.26	0.83	2.04	0.81	2.38	0.82	2.16	0.85

Key: M_1 = Mean of University students, SD_1 = Standard deviation of university students, M_2 = Mean of Polytechnic students, SD_2 = Standard deviation of Polytechnic students, M_3 = Mean of College of education students, SD_3 = Standard deviation of College of education students

The total average mean score of 2.23 indicates low to moderate readiness among building and woodwork technology students to engage with AI technologies, with college of education students reporting the highest readiness (M_3 = 2.38, SD_3 = 0.82) and polytechnic students the lowest (M_1 = 2.04, SD_1 = 0.81). High mean scores for needing more practical training (M = 2.55) and educational improvement (M = 2.48) suggest a perceived deficiency in current training, particularly among college of education students (M_3 = 2.87, 2.98). The average standard deviation of 0.82 reflects moderate variability, with the greatest variability in educational adequacy (SD = 0.88) and improvement needs (SD = 0.88), indicating diverse perceptions across groups. These findings highlight the urgent need for enhanced practical AI training and curricular reforms to improve industry preparedness.

Hypotheses One

There is no statistically significant impact of the level of awareness of AI technologies on readiness of building/woodwork technology undergraduate students.

Table 4: Simple Linear Regression Analysis Results for AI Awareness Impact on Readiness

Parameter	Value	SE	t-value	p-value	R^2	Adjusted R^2
Intercept (β_0)	3.4113	-	-	-		
Slope (β_1, Awareness)	-0.6004	0.4780	-1.256	> .05	.6134	.2268

A simple linear regression analysis as shown in Table 4 revealed no statistically significant impact of AI technologies awareness on readiness among building and woodwork technology undergraduate students (N = 165, aggregated into 3 groups), with (b = -0.6004, t(1) = -1.256, p > .05). Awareness accounted for 61.34% of the variance in readiness (R^2 = .6134), though the negative slope was unexpected. The null hypothesis was not rejected, indicating that awareness does not significantly predict readiness.

Hypothesis Two

There is no statistically significant impact of the level of engagement of AI technologies on readiness of building/woodwork technology undergraduate students

Table 5: Simple Linear Regression Analysis Results for AI Engagement Impact on Readiness

Parameter	Value	SE	t-value	p-value	R^2	Adjusted R^2
Intercept (β_0)	4.5837	-	-	-		
Slope (β_1, Engagement)	-1.0357	2.4519	-0.4224	> .05	.1522	-.6956

A simple linear regression analysis in Table 5 showed no statistically significant impact of AI technologies engagement on readiness among building and woodwork technology undergraduate students (N = 165, aggregated into 3 groups), with (b = -1.0357, t(1) = -0.4224, p > .05) (Nule et al., 2025). Engagement accounted for only 15.22% of the variance in readiness (R^2 = .1522), and the negative slope was unexpected. The null hypothesis, stating no significant impact of engagement on readiness, was not rejected.

Hypothesis Three

There is no statistically significant relationship between levels of awareness and engagement with AI technologies and building/woodwork technology undergraduate students' readiness for practice in industry.

Table 6: Pearson correlation between AI technologies awareness and engagement among building/woodwork technology undergraduate students (N = 165)

		Awareness	Engagement
Awareness	Pearson Correlation	1	.325**
	Sig. (2-tailed)		.000
	N	165	165
Engagement	Pearson Correlation	.325**	1
	Sig. (2-tailed)	.000	
	N	165	165

Table 6 illustrates the Pearson correlation coefficient analysis conducted to assess the connection between levels of awareness and engagement with AI technologies, and the readiness of undergraduate students in building/woodwork technology for industry practice ($r = .325$, $n = 164$, $p = .000$). The results indicate a positive correlation between awareness and engagement, suggesting that students with a deeper understanding of AI technologies are more inclined towards feeling equipped to utilize them in their prospective professional endeavours.

DISCUSSION OF FINDINGS

The findings of this study present's a significant understanding into the current state of AI awareness, engagement, and professional readiness among building and woodwork technology students in Nigerian tertiary institutions. The results demonstrate moderate levels of AI awareness across all institution types, with polytechnic students exhibiting marginally higher awareness than their university and college of education counterparts as shown in Table 1. This finding aligns with previous research by Ogunbayo et al. (2019), who similarly noted variations in technological awareness between different types of Nigerian institutions. The relatively low mean scores for awareness items, particularly regarding specific AI applications in construction, suggest substantial gaps in curricular coverage of emerging technologies, supporting Li et al.'s (2020) assertions about the need for enhanced AI content in technical education programmes.

Engagement levels followed a similar pattern of modest attainment as presented in Table 2, with university students reporting slightly higher engagement than those in other institutions. This finding corresponds with Fredricks et al.'s (2004) conceptualisation of engagement as a multidimensional construct, where behavioural participation often depends on institutional resources and opportunities. The data indicate that while students show interest in AI technologies, their actual usage of AI tools in coursework remains limited reinforcing the need for more practical, hands-on learning experiences as advocated by Zhong et al. (2019).

The study's most concerning finding relates to professional readiness as shown in Table 3, where students across all institutions expressed limited confidence in their ability to apply AI technologies in workplace settings. This result substantiates Fugate et al.'s (2004) employability model, which positions practical competency as fundamental to workforce preparedness. The high scores for items regarding the need for additional training and curricular improvements strongly suggest that current educational approaches are failing to adequately prepare students for industry demands, further echoing similar concerns raised by Akinwale (2020) in the Nigerian context.

The regression analysis yielded unexpected results as shown in Table 4 and 5, with awareness and engagement showing negative, though non-significant, relationships with readiness. This counterintuitive finding may reflect the complex interplay between theoretical knowledge and practical application in technical education. As Olawale and Adedeji (2019) observed, Nigerian polytechnic students often develop strong theoretical understanding but lack opportunities to translate this knowledge into practical skills a phenomenon that may extend to AI technologies across institution types. This study's findings must be interpreted within the context of Nigeria's unique educational challenges, including limited technological infrastructure and variable faculty expertise (Ogunbayo et al., 2019). While the results demonstrate clear gaps in AI education, the findings also provide opportunities for targeted interventions. The positive correlation between engagement and readiness as shown in Table 6 suggests that increased hands-on experience with AI tools could enhance professional preparedness, supporting Zhang et al.'s (2019) recommendations for industry-academic partnerships. These findings contribute to ongoing discussions about technology integration in vocational education, particularly in resource-constrained environments. They reinforce the need for curriculum reforms that balance theoretical instruction with practical application, while acknowledging the infrastructural and training challenges facing Nigerian institutions. Future research should explore longitudinal developments in AI competency and examine the effectiveness of intervention strategies in bridging the gap between education and industry requirements.

CONCLUSION

In conclusion, this study shows that while awareness and engagement with AI technologies are moderate among building and woodwork technology undergraduates, students generally feel unprepared to use AI technologies for professional practice in the construction industry after graduation. This finding reinforces the need for academic institutions to enhance AI-related content in their curricula and provide more opportunities for hands-on engagement with AI technologies. Furthermore, the positive relationship between awareness, engagement, and readiness suggests that improving students' exposure to AI technologies could enhance their industry preparedness.

RECOMMENDATIONS

Based on the findings of the study, the following recommendations were made:

1. Academic institutions offering building and woodwork technology programmes should integrate AI-related content more comprehensively into their curricula. This integration can include courses on AI applications in construction, such as machine learning, predictive analytics, and automation systems. By doing so, students will develop a deeper understanding of the role of AI in the construction industry, making them more prepared for industry demands after graduation.
2. Tertiary institutions should provide more practical training opportunities, such as workshops, internships, and projects involving AI tools. This will not only improve students' engagement with AI technologies but also give them the opportunity to apply theoretical knowledge in real-world construction scenarios. Collaborating with industry players to offer AI-related internships and fieldwork can enhance students' readiness for professional practice after the completion of their training.
3. Tertiary institutions should invest in the professional development of faculty members through training and workshops focused on AI applications in construction. By equipping educators with up-to-date knowledge and skills in AI technologies and its applications, they can effectively teach and guide students, thereby increasing both awareness and engagement levels. This approach can bridge the gap between academic preparation and industry requirements.

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