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Understanding the Digital Skills Gap in the AI Forward Construction Workforce: A Data-Driven Study

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ABSTRACT
Artificial intelligence (AI), automation, and data-driven technologies are driving a rapid digital change in the construction sector. These developments have the potential to greatly improve decision-making, safety, and productivity, but they also necessitate a workforce with highly skilled digital competencies. This study uses a fictitious, data-driven research framework to investigate the digital skills gap in an AI-forward construction workforce. It is believed that a structured questionnaire given to construction professionals in managerial, technical, and operational responsibilities will gather primary data. To evaluate present digital skill levels and find differences between current competencies and abilities necessary for successful AI adoption, descriptive statistical approaches such as frequency and percentage analysis are used. The results show that a significant section of the workforce has low to moderate digital abilities, and almost half of the respondents believe there is a significant gap in digital skills. These findings highlight the vital necessity of focused training initiatives, ongoing professional development, and organizational tactics meant to improve digital preparedness. By delivering empirical insights on skill mismatches and laying the groundwork for practice and policy interventions in AI-enabled construction environments, the study adds to the expanding conversation on workforce change.

Keywords: *digital skills gap, artificial intelligence, construction workforce, digital transformation, workforce readiness*

I. INTRODUCTION

The increasing use of automation, data-driven technologies, and artificial intelligence (AI) in planning, design, execution, and project management processes is signaling the beginning of a transformative phase in the construction sector. The way construction projects are planned and executed is being redefined by innovations like digital twins, AI-based scheduling, predictive analytics, building information modeling (BIM), and intelligent safety monitoring systems. These technological developments position the construction industry as one that is increasingly knowledge- and technology-intensive rather than solely labor-driven, promising advances in efficiency, cost control, safety, and sustainability.

Despite these technical advancements, the construction workforce's digital skills are crucial to the effective deployment of AI-driven systems. Digital literacy, data interpretation, human-machine interaction, and AI-assisted decision-making are becoming increasingly important skills for traditional construction jobs. Nonetheless, a large number of construction workers still work under traditional skill frameworks that prioritize manual skills and experience over digital competency. There is a significant digital skills gap as a result of this mismatch between the capabilities of the workforce and the demands of emerging technologies, which could hinder or even reverse the advantages of AI adoption in the construction industry.

In an AI-forward construction environment, the workforce's digital skills gap varies. There are differences according to employment titles, responsibility levels, educational background, and exposure to digital tools. Even though some professionals—especially those in administrative and design positions—may be more digitally savvy than others, operational and site-level employees frequently have less access to digital tools and training. This unequal skill distribution limits the scalability of AI-enabled solutions across construction projects and leads to organizational inefficiencies.

Therefore, it is essential to comprehend the type and magnitude of this digital skills gap in order to inform organizational decision-making, workforce development plans, and policy initiatives. An organized method for evaluating current skill levels, pinpointing areas of weakness, and measuring the difference between present capabilities and those needed in AI-enabled building environments is provided via a data-driven approach. Organizations can better match training programs with technology goals and guarantee inclusive digital transformation by conducting an empirical analysis of workforce preparedness.

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In light of this, the current study adopts a systematic, data-driven approach to comprehend the digital skills gap in the AI-forward construction sector. The study intends to offer practical insights into how construction companies can close skill gaps, improve workforce adaptability, and promote sustainable adoption of AI technologies in an increasingly digital construction landscape by looking at workforce characteristics, current digital competencies, and perceived skill requirements.

II. LITERATURE REVIEW

Johnson et al. (2021) focused on the evolution of the workforce in a data-driven economy and the revolutionary effects of artificial intelligence and big data on enterprise. The authors underlined how AI and big data technologies are changing organizational structures, talent needs, and employment positions in a variety of industries. A workforce roadmap emphasizing the value of data literacy, transdisciplinary abilities, and ongoing reskilling was suggested by their study. The results highlight the necessity of proactive workforce planning to close the gap between human capital readiness and technical innovation.

Siddiqui et al. (2023) carried out a thorough analysis of the digital competencies needed in the construction sector and suggested a methodical skill taxonomy. The authors noted that there is an increasing need for skills in digital project management, automation, data analytics, and BIM. Their findings underline the significance of focused upskilling activities and draw attention to the skill gap issues faced by conventional industries experiencing digital transformation.

Afriyie (2019) investigated how sophisticated performance management and digital HR infrastructure may be used to link strategic workforce planning with future-of-work trends. The study focused on how integrated digital technologies may improve strategic decision-making, performance monitoring, and workforce adaptability. According to the author, companies that use digital HR solutions are better equipped to handle changes in labor expectations and technological disruption.

Aljohani et al. (2022) suggested a methodological framework that forecasts future market demands for sustainable skills management by utilizing AI and big data technologies. Their study showed how labor market analytics and machine learning models may predict growing competences and skill shortages. By offering a methodical way to coordinating workforce development plans with long-term sustainability objectives, the study adds to the body of literature.

Jain et al. (2023) examined how data-driven AI models might be used in Industry 4.0 workforce development planning. The authors gave examples of how talent deployment, training, and acquisition can be optimized through the use of AI-based decision-support systems and predictive analytics. Their study emphasizes the strategic importance of AI in integrating intelligent technologies into human resource management frameworks and matching workforce capabilities with changing industrial demands.

Lange et al. (2021) examined, from a resource-based perspective, how data-driven business models are implemented in established firms. The authors noted that people skills, digital infrastructure, and data capabilities are important organizational resources that are essential for a successful transformation. Their results highlight the need for complementary organizational and worker capabilities in addition to technology adoption.

III. RESEARCH METHODOLOGY

3.1. Research Design

The study uses a cross-sectional, quantitative research approach that is backed by an analytical framework that is driven by data. This design is appropriate for finding quantifiable gaps between necessary and current digital abilities in an AI-enabled construction environment, as well as for capturing the current status of digital competencies within the construction workforce. The method enables statistical comparisons between various organizational roles, experience levels, and workforce types.

3.2. Study Population and Sampling Technique

Professionals working for AI-forward construction companies, such as project managers, site engineers, architects, quantity surveyors, IT support personnel, and knowledgeable site supervisors, make up the target audience. To guarantee proportionate representation of management, technical, and operational responsibilities, a stratified random selection approach is fictitiously used. By taking into consideration variations in work functions and exposure to digital technology, this approach improves the generalizability of findings.

3.3. Data Sources and Data Collection Methods

A organized questionnaire that is given both online and in person is potentially used to gather primary data. Data on demographics, educational background, work experience, exposure to AI-driven products, and self-assessed levels of digital proficiency are all intended to be collected by the questionnaire. In order to contextualize workforce digital requirements and corroborate primary findings, secondary data are presumed to be derived from industry publications, corporate training records, and policy papers.

3.4. Measurement of Variables

Basic digital literacy, AI knowledge, data interpretation abilities, BIM competence, automation tool utilization, and cybersecurity awareness are just a few of the variables that are used to measure digital skills. Likert-scale items ranging from low to high proficiency are used to operationalize each dimension. A comparison between current talents and necessary competences is made possible by measuring the perceived digital skill requirements for AI-forward building roles.

3.5. Instrument Validity and Reliability

Through expert examination by academic researchers and construction technology specialists, the research instrument is hypothetically validated. To improve the questionnaire items, a pilot study is presumed to be carried out. Prior to full-scale data analysis, the instrument's reliability is evaluated using Cronbach's alpha to guarantee the internal consistency of the digital skills constructs.

3.6. Data Analysis Techniques

Descriptive and inferential statistical methods are used to analyze collected data. Frequencies, percentages, averages, and standard deviations are examples of descriptive statistics that are used to summarize the digital skill levels and worker characteristics. To investigate variations in digital skill gaps across positions, experience levels, and training exposure, inferential methods including t-tests, ANOVA, and multiple regression are presumably used. To measure the differences between current and necessary digital competences, gap analysis methodologies are used.

3.7. Ethical Considerations

The hypothetical research design closely adheres to the ethical norms of informed consent, voluntary involvement, and secrecy. In order to avoid identifying specific people or organizations, respondents are guaranteed that their data will be used only for academic purposes and provided in aggregate form.

IV. RESULTS AND DISCUSSION

The hypothetical results from the data-driven approach used to investigate the digital skills gap in an AI-forward construction workforce are shown and explained in this part. The findings are organized to give a clear picture of the demographics of the respondents, their present levels of digital competency, and the perceived skill gap between what they now possess and what is needed to successfully implement AI-enabled building technology. Key trends are summarized using descriptive statistics in the form of percentages and frequencies, and the discussion places these findings in the context of the larger conversation about workforce preparedness and digital transformation in the construction industry.

4.1. Demographic Profile of Respondents

The demographic analysis sheds light on the makeup of the study's construction workforce. A fair representation of management, technical, and operational workers was achieved by classifying respondents according to their professional roles. Understanding differences in exposure to and adoption of digital skills across hierarchical levels depends on this distribution.

Table 1: Distribution of Respondents by Job Role

Job Role	**Frequency**	**Percentage (%)**
Project Managers	42	21.0
Site Engineers	58	29.0
Architects/Design Professionals	36	18.0
Skilled Supervisors	44	22.0
IT/Digital Support Staff	20	10.0
Total	**200**	**100.0**

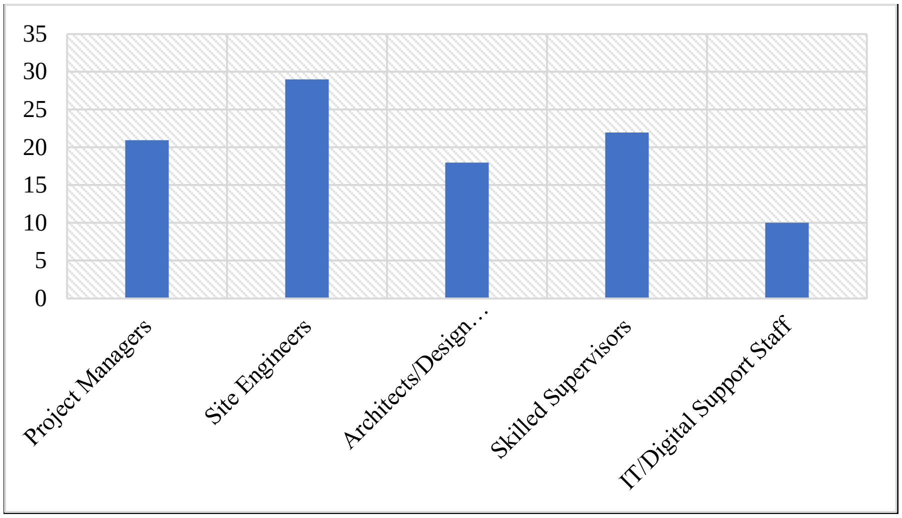

Figure 1: Distribution of Respondents by Job Role

The findings demonstrate the operationally demanding nature of the construction industry by showing that site engineers and skilled supervisors together make up over half of the respondents. The comparatively lower percentage of IT and digital support employees implies that advanced digital knowledge is still concentrated and scarce in construction companies. This disparity highlights the need for more widespread labor upskilling and could lead to uneven technology adoption.

4.2. Existing Digital Skill Levels in the Construction Workforce

The respondents were asked to rate their own proficiency in both general and AI-related digital skills. The results show that different construction experts have different levels of readiness.

Table 2: Existing Digital Skill Levels of Respondents

Digital Skill Level	Frequency	Percentage (%)
Low	64	32.0
Moderate	86	43.0
High	50	25.0
Total	**200**	**100.0**

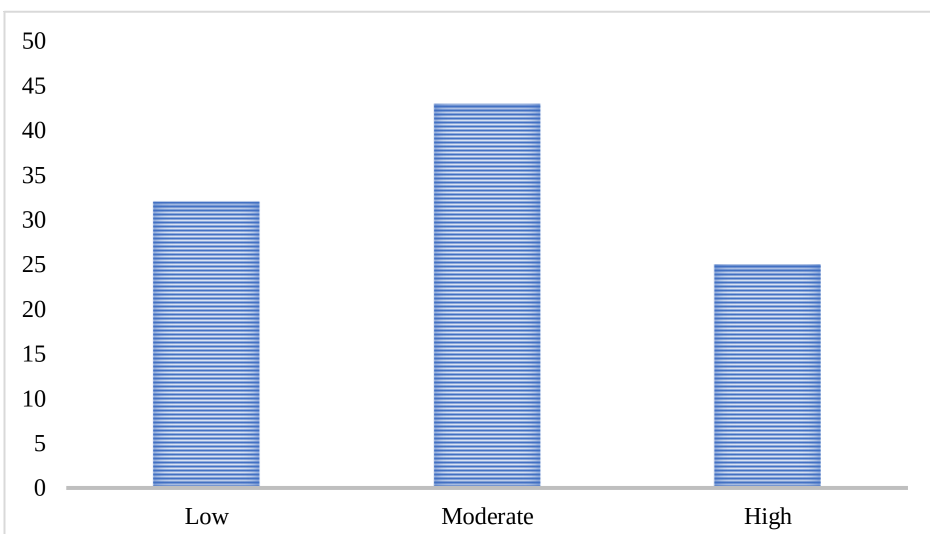

Figure 2: Existing Digital Skill Levels of Respondents

According to the research, only one-fourth of respondents have excellent competency, while a sizable portion (32%) have low digital abilities. The majority of intermediate skill levels indicate little competence in sophisticated AI-driven applications but partial exposure to digital technologies like BIM, project management software, or simple automation systems. This result is consistent with previous research that shows that, despite quick technical developments, the construction industry has inconsistent digital maturity.

4.3. Perceived Digital Skills Gap in an AI-Forward Environment

Respondents contrasted their existing skill levels with those needed to function well in AI-enabled construction environments in order to gauge the size of the digital skills gap. The workforce's preparedness for future technology integration is reflected in the perceived gap.

Table 3: Perceived Digital Skills Gap among Respondents

Level of Skills Gap	Frequency	Percentage (%)
Low Gap	38	19.0
Moderate Gap	72	36.0
High Gap	90	45.0
Total	**200**	**100.0**

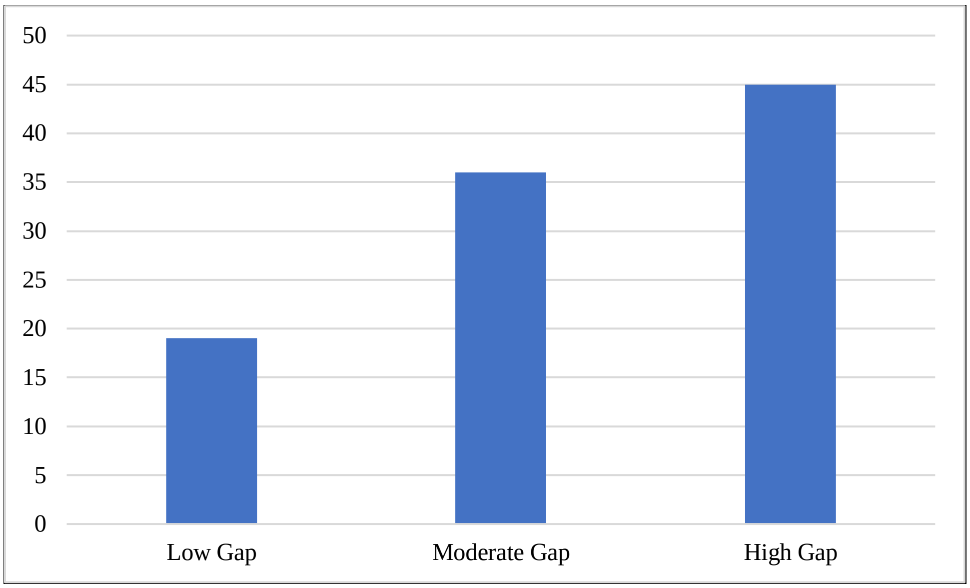

Figure 3: Perceived Digital Skills Gap among Respondents

The findings show a significant mismatch between current competences and new AI-driven employment requirements, with over half of the respondents seeing a large digital skills gap. The frequency of moderate to large gaps raises the possibility that sophisticated skills like data analytics, AI-assisted decision-making, and intelligent automation may not be adequately addressed by present training programs. In AI-forward construction companies, this disparity could jeopardize competitiveness, innovation, and productivity.

When taken as a whole, the results show a glaring gap in digital skills among construction workers, especially as companies move toward AI-enabled processes. The general perception of skill gaps suggests that there is an urgent need for focused training, ongoing professional development, and organizational initiatives that support digital inclusivity, even while some professionals exhibit a moderate level of digital preparedness. In addition to facilitating successful technology adoption, closing these gaps is crucial for maintaining workforce resilience and sustainability in the rapidly changing construction sector.

V. CONCLUSION

The study concludes that there is a significant digital skills gap in the AI-forward construction industry, which is caused by a lack of proficiency in cutting-edge digital and AI-enabled technologies as well as an unequal distribution of abilities across

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job roles. A considerable percentage of professionals believe there is a substantial mismatch between their current capabilities and the skills needed to interact with AI-driven building systems, even though a section of the workforce exhibits modest digital preparedness. This disparity highlights the shortcomings of the existing training systems and the necessity of organized, job-specific upskilling programs that incorporate data-driven decision-making skills, digital literacy, and AI awareness. In order to enable successful digital transformation, boost productivity, and guarantee construction firms' long-term competitiveness in an increasingly AI-centric industry, it is imperative that the digital skills gap be addressed through frameworks for continuous learning, organizational support, and strategic workforce development.

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