

Perceived Artificial Intelligence Skill Demand Across the Construction Project Lifecycle: Evidence from the Rwandan Construction Industry

Oluwaseun Sunday Dosumu¹, Christine Musanase², Ryan Tumusiime Kaganga³, Dieudonne Ahishakiye⁴, and Eric Iradukunda⁵

¹ Department Head, University of Rwanda College of Science and Technology, E-mail: o.dosumu@ur.ac.rw (corresponding author).

² Researcher, Information Systems Department, University of Rwanda College of Science and Technology, E-mail: musanasechristine@gmail.com

³ Construction Professional, Department of Construction Economics and Management, University of Rwanda College of Science and Technology, E-mail: tumusiimeryan11@gmail.com

⁴ Quantity Surveyor, Department of Construction Economics and Management, University of Rwanda College of Science and Technology, E-mail: ahishadonne2002@gmail.com

⁵ Student, Department of Construction Economics and Management, University of Rwanda College of Science and Technology, E-mail: ericaca2021@gmail.com

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Abstract: Artificial Intelligence (AI) is increasingly transforming construction processes, yet limited empirical evidence exists on the skills required by professionals across different stages of the construction project lifecycle, particularly in developing economies. This study evaluates the perceived demand for AI skills across the eight stages of the Royal Institute of British Architects (RIBA) Plan of Work in the Rwandan construction industry. A quantitative cross-sectional survey was conducted among 174 construction professionals representing architecture, engineering, quantity surveying and construction management. Data were collected using a structured questionnaire measuring the perceived demand for AI-related skills across the eight lifecycle stages. Descriptive statistics were used to assess and rank skill demand, while the Kruskal-Wallis H test examined differences among professional groups, and the Friedman test assessed differences across lifecycle stages. The findings show moderate-to-high demand for AI skills across all lifecycle stages. The use stage recorded the highest overall demand, followed by strategic definition, and manufacturing and construction, while handover recorded the lowest. Significant differences across lifecycle stages were identified using the Friedman test ($\chi^2 = 19.162$, $p = 0.008$), although the practical effect was very weak (Kendall's $W = 0.016$), indicating modest variation in relative intensity. Most individual skills did not differ significantly across professional groups, suggesting a substantial common set of AI competencies alongside selected discipline-specific requirements. The study's findings provide evidence for the development of targeted, stage-specific construction education, professional development and workforce strategies in Rwanda and comparable developing economies.

Keywords: Artificial intelligence; AI skills; construction industry; construction project; project lifecycle; Rwanda.

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1. Introduction

The construction industry is undergoing rapid digital transformation and shifting from fragmented, paper-based workflows to integrated, data-driven project delivery enabled by Building Information Modeling (BIM), cloud computing and Artificial Intelligence (AI) (Li et al., 2024). AI is no longer an emerging technology confined to experimentation; it has become embedded throughout the construction project lifecycle, supporting feasibility assessment, generative design, cost estimation, schedule optimization, safety monitoring, quality management, predictive maintenance and facility operations (Dosumu et al., 2026). Consequently, professional roles are evolving from performing routine technical tasks to interpreting, validating and applying AI-generated outputs. This transformation demands new competencies in data literacy, algorithmic reasoning, critical evaluation of machine-generated recommendations and effective human-AI collaboration (Obi et al., 2025). The ability of construction organizations to realize the benefits of AI, therefore, depends

not only on technology adoption but also on the availability of professionals equipped with appropriate AI-related skills (Sefa and Adisa, 2026).

AI in construction has evolved from relatively narrow rule-based applications to increasingly data-intensive, predictive and generative systems (El-Abbasy, 2025). Early applications relied on expert systems and knowledge-based scheduling, while subsequent developments in machine learning shifted the emphasis towards algorithms capable of identifying patterns in historical project data, enabling applications such as cost estimation, duration prediction, risk assessment and resource optimization (Datta et al., 2024). More recent advances in deep learning, computer vision, natural language processing and generative AI have further expanded AI from analytical and predictive functions to perceptual, interpretive and generative tasks (Iribagiza and Kirabo, 2024). The contemporary construction AI ecosystem consequently comprises interconnected technological families. Machine learning supports forecasting and classification; computer vision enables automated interpretation of photographs, video and drone imagery; natural language processing facilitates analysis of contracts, specifications and regulations; while generative AI supports the production and evaluation of design and project information (Gill et al., 2024). Increasingly, these technologies are integrated with BIM, cloud platforms and Internet of Things (IoT) systems, creating interconnected digital environments through which AI can access and process project information across organizational and lifecycle boundaries. This technological evolution has direct implications for construction professional practice. Architects may need to evaluate AI-generated design alternatives, engineers validate machine-generated technical analyses, quantity surveyors interrogate automated quantities and cost forecasts, and construction managers interpret AI-generated safety, productivity and progress indicators. AI, therefore, does not simply introduce additional software into established workflows; it alters professional tasks and creates a requirement for competencies that combine conventional construction expertise with AI-related capabilities. The workforce implications are particularly important because AI systems generate outputs rather than professional decisions. Effective use consequently requires professionals who can understand data, configure and operate AI-enabled platforms, interpret algorithmic outputs, assess their reliability and integrate machine-generated information with professional judgment.

The importance of these capabilities becomes clearer when AI applications are considered across the project lifecycle. At a strategic level, AI can support feasibility assessment, investment appraisal, cost forecasting, risk analysis and scenario modeling by processing large volumes of historical and contextual data (Shang et al., 2023). Professionals, therefore, require capabilities not only to operate AI tools but also to interpret forecasts, assess assumptions and integrate AI-generated evidence into strategic decisions. At preparation and briefing, AI can assist with analyzing client requirements, stakeholder information, project precedents, costs, regulations and other structured and unstructured information. At concept design, generative AI, optimization and simulation technologies enable professionals to generate and evaluate alternatives against cost, energy, constructability and environmental criteria (Taiwo et al., 2024). Spatial coordination increasingly relies on AI-enabled BIM for clash detection, model interrogation and constructability assessment, requiring professionals to distinguish meaningful conflicts from false-positive alerts. At technical design, AI supports automated quantity extraction, compliance checking, technical analysis, cost estimation and engineering calculations. Manufacturing and construction introduce computer vision, IoT-enabled systems and predictive analytics for safety monitoring, quality assurance, progress measurement, productivity analysis and prediction of cost or schedule deviations (Schleiss and Johri, 2024). At handover, AI can support information verification, documentation management and asset information compilation, while the Use stage increasingly relies on predictive maintenance, energy performance analysis, facility optimization and whole-life asset management (Adebawale and Agumba, 2023). The distribution of these applications suggests that AI skill requirements are unlikely to be homogeneous across a construction project. Strategic and briefing stages emphasize analytical and decision-support capabilities; design stages require generative, technical and evaluative competencies; construction stages emphasize real-time monitoring and intervention; and operational stages require predictive analytics and asset-performance interpretation. However, identifying where AI can be applied does not establish the extent to which particular skills are demanded by construction professionals. This distinction exposes an important limitation in the existing evidence base.

Despite rapid advances in AI applications, research has focused predominantly on technological capabilities and organizational adoption rather than workforce competence. Previous studies have examined AI applications, adoption determinants, enabling technologies and implementation barriers such as fragmented project environments, poor data quality, high implementation costs and limited regulatory support (Tinyimana and Dosumu, 2026; Haefner et al., 2023). While this literature explains what AI can achieve and why organizations adopt it, it provides considerably less empirical evidence on the competencies required to operationalize these technologies. Consequently, the demand for AI skills remains comparatively underexplored (Osuizugbo et al., 2026). AI competence itself is multidimensional and cannot adequately be represented by generic digital literacy. AI literacy encompasses the ability to understand AI, recognize its applications, use AI systems appropriately, critically evaluate their outputs and understand their broader implications (Almatrafi et al., 2024). In construction, relevant capabilities include data literacy, AI technical literacy, digital and platform skills, analytical skills, AI-supported decision-making, and human-AI collaboration. Data literacy involves acquiring, organizing, interpreting and critically assessing project data, while AI technical literacy concerns the ability to configure, operate and interrogate AI-enabled tools without necessarily developing AI models.

Evidence from developing countries suggests that conventional data-handling and BIM capabilities may be stronger than advanced AI-specific competencies, making data literacy an important foundation for developing progressive AI capabilities (Oyelami et al., 2026). Digital and platform skills are equally important because AI increasingly operates through BIM platforms, common data environments, cloud collaboration systems and project management applications (Mutoni, 2025). Analytical and decision-making skills enable professionals to interpret AI-generated forecasts, risk scores, classifications and optimization outputs and integrate them with professional knowledge, project constraints and contextual judgment. Human-AI collaboration further requires professionals to verify outputs, identify circumstances that

require human intervention, and communicate AI-informed decisions appropriately. Egwim al. (2024) similarly identified data literacy, AI and machine-learning fundamentals, digital collaboration, AI-driven decision-making, cybersecurity awareness, adaptability, and communication and collaboration as important AI-related competency domains. These multidimensional requirements become more significant when professional differences are taken into account. Construction projects are delivered through multidisciplinary teams, and AI-enabled tasks are not necessarily distributed equally among architects, civil and structural engineers, Mechanical, Electrical and Plumbing (MEP) engineers, geotechnical engineers, quantity surveyors and construction managers. AI-supported generative design may be particularly relevant to architects, automated technical analysis to engineers, automated measurement and cost forecasting to quantity surveyors and safety, progress and productivity analytics to construction managers. Consequently, an aggregate measure of AI skill demand may conceal important occupational variation. Yet empirical evidence establishing whether AI skill demand differs significantly among professional groups, and how such differences interact with project lifecycle stages, remains scarce. This evidence gap is particularly important in developing economies. Research from such contexts remains limited despite differences in digital infrastructure, training opportunities and institutional capacity compared with the developed countries that dominate the literature (Awodele et al., 2024).

Across Africa, the rapid diffusion of AI and digital technologies is creating both opportunities for improving construction productivity and significant challenges for workforce capability development. African countries are increasingly incorporating AI, digital transformation and emerging technologies into national development agendas, while construction organizations are progressively adopting digital platforms, BIM, automation, data analytics and AI-enabled applications (Younis et al., 2026; Samawi et al., 2026). However, the benefits of this transition are constrained by uneven digital infrastructure, limited access to advanced technologies, shortages of specialized digital and AI competencies, and gaps between industry requirements and available workforce capabilities (Dosumu et al., 2026). These challenges are particularly important for the construction sector, where fragmented project environments, diverse professional roles and varying levels of digital maturity create significant differences in professionals' capacity to adopt and use AI effectively. Consequently, the African digital transformation agenda requires attention not only to technology adoption but also to the development of construction professionals who possess the data, analytical, AI-related and human-AI collaboration competencies needed to translate technological capabilities into project value. Yet empirical evidence on the specific AI skills demanded by construction professionals, and on how these requirements vary across project lifecycle stages and professional groups, remains limited in Africa. This creates a need for contextual evidence to guide the development of education, professional training and workforce strategies that can support Africa's transition towards AI-enabled construction.

Rwanda provides an appropriate setting in which to address this limitation. The country has positioned digital transformation as a national development priority through initiatives such as the Smart Rwanda Master Plan and the ICT Sector Strategic Plan, while digital technologies, including BIM and project management platforms, are increasingly being adopted in the construction sector (MINICT, 2024; Mutoni, 2025). At the same time, Rwanda faces challenges common to many developing economies, including limited formal AI training, evolving digital infrastructure and an emerging professional workforce (Umuhoza and An, 2024). Understanding which AI competencies are demanded, when they are required and whether their importance varies among professional groups is critical to ensuring that technological transformation is accompanied by appropriate human-capital development. The study, therefore, draws on both established theoretical and technology-adoption literature and recent empirical research on AI in construction to provide a balanced foundation for examining emerging AI competency requirements.

The practical implications of this gap are substantial. Without evidence on stage-specific and profession-sensitive AI skill demand, higher education institutions risk developing curricula that are disconnected from emerging industry requirements; employers may invest in generic training programs without clear evidence of priority competencies; professional bodies may lack an empirical basis for continuing professional development; and policymakers may struggle to formulate effective digital workforce strategies. The challenge is therefore not simply whether construction professionals should acquire AI skills, but which skills to develop, at what stage of the project lifecycle, and for which professional functions.

Unlike previous studies that have largely examined AI applications, adoption factors, or general competency requirements in construction, this study advances existing knowledge by linking AI skill requirements explicitly to the eight stages of the Royal Institute of British Architects (RIBA) Plan of Work. The RIBA Plan of Work 2020 provides a structured lifecycle framework comprising eight stages: (1) strategic definition, (2) preparation and briefing, (3) concept design, (4) spatial coordination, (5) technical design, (6) manufacturing and construction, (7) handover, (8) use. These stages represent the progressive development, delivery and operation of construction projects, from strategic decision-making and briefing through design, construction, handover and asset use (RIBA, 2020). The framework is therefore useful for examining AI skill demand because the nature of professional activities, information requirements and decision-making changes across these stages. Mapping AI competencies onto the RIBA stages consequently provides a consistent basis for identifying when particular skills are required and how their importance varies throughout the project lifecycle. It empirically identifies the AI skills demanded at each lifecycle stage and examines whether these demands vary across professional groups. This lifecycle and profession-sensitive perspective provides a more granular understanding of AI competency requirements and offers an evidence base for targeted curriculum development, professional upskilling, organizational workforce planning, and digital policy in Rwanda and comparable developing economies. By examining AI skill demand across the project lifecycle, the study responds directly to the limitations of application-centered AI research. It moves beyond documenting what AI technologies can do towards examining the human capabilities required to operationalize them across the project lifecycle.

Although developed in the UK, the RIBA Plan of Work is applied in this study as a generic project-lifecycle framework rather than as a regulatory or contractual standard for Rwanda. Its sequential representation of strategic definition, briefing, design, construction, handover and use provides a transferable structure for analyzing professional activities and AI skill requirements across construction projects, irrespective of national context. Nevertheless, differences in procurement practices, regulatory arrangements and industry maturity may limit direct equivalence between the RIBA stages and Rwandan practice; therefore, the framework is used primarily as an analytical structure rather than as a claim of exact contextual correspondence. Therefore, this study evaluates the demand for AI skills across the construction project lifecycle in the Rwandan construction industry. It assesses the demand for AI skills across lifecycle stages, compares that demand and identifies the most critical AI skills required by construction professionals. Accordingly, the study addresses the following research questions: (1) What is the level of AI skill demand across the eight stages of the construction project lifecycle? (2) Do AI skill demands differ significantly across the lifecycle stages? (3) Do AI skill demands differ significantly among construction professional groups?

2. Theoretical and Conceptual Framework

This study is primarily grounded in the Resource-Based View (RBV), which conceptualizes valuable, rare, difficult-to-imitate and non-substitutable resources and capabilities as sources of organizational competitive advantage (Barney, 1991). In construction, AI skills are human capabilities that enable organizations to leverage AI technologies to improve project performance, productivity, quality and decision-making. The AI skill demand identified in this study, therefore, represents more than a training requirement; it indicates the workforce capabilities that construction organizations need to develop to derive value from AI investment.

The RBV is complemented by Dynamic Capabilities Theory (DCT), which explains how organizations continuously develop and reconfigure capabilities in response to technological and environmental change (Teece, 2007). This perspective is particularly relevant to AI because its applications are continually evolving across project stages. Consequently, construction organizations require ongoing reskilling and capability development rather than a one-off investment in AI training. Human Capital Theory (HCT) further provides an individual-level perspective by viewing education and training as investments that enhance knowledge, skills and productivity (Schultz, 1961; Becker, 1964). These perspectives establish that AI skills are simultaneously an organizational strategic capability, a dynamic resource requiring continual adaptation, and an investment in individual professional competence.

Based on these theories, the study conceptualizes AI skill demand as lifecycle-dependent. Different stages of the construction project lifecycle entail distinct AI-enabled tasks and information requirements, which in turn generate corresponding competency requirements. As illustrated in Fig. 1, the framework links RIBA lifecycle stages to AI-enabled tasks, required AI skills level, AI skill demand, and workforce development priorities. This sequence guided the identification and assessment of AI skills across the eight lifecycle stages and provided the basis for examining differences in demand between stages and among professional groups. The resulting evidence supports the identification of common AI competencies and stage or profession-specific skills that can inform curriculum development, professional training, organizational reskilling and workforce planning.

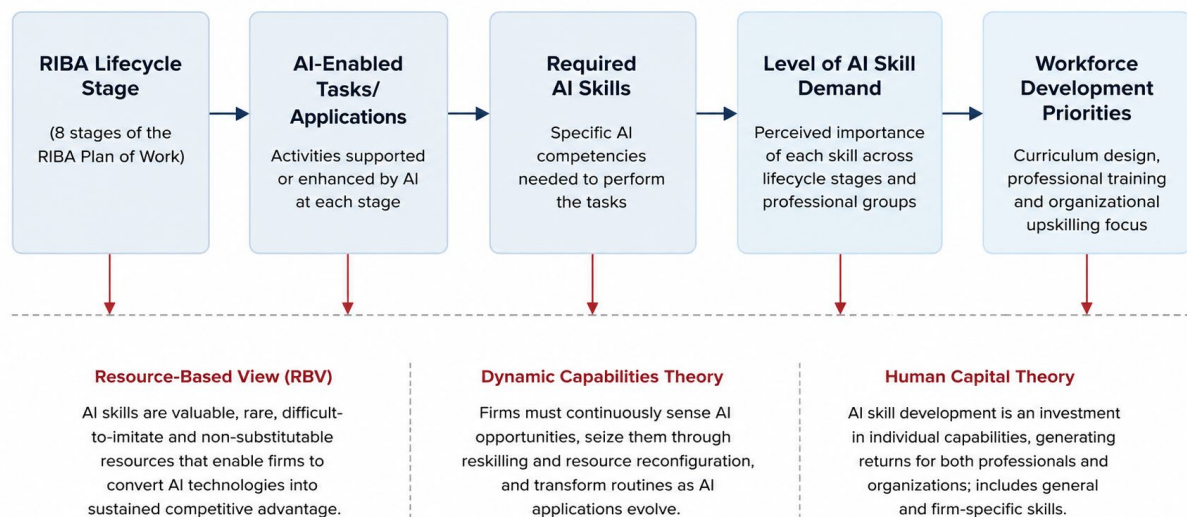


Figure 1. Framework linking construction project lifecycle stages, AI-enabled tasks, AI skill demand and workforce development priorities (Source: original).

3. Method

This study adopted a quantitative, cross-sectional survey design to measure, compare and prioritize AI skill demand across the eight stages of the RIBA Plan of Work 2020 (RIBA, 2020) and among construction professional groups in Rwanda. The quantitative approach was appropriate because the objectives required numerical measurement and statistical comparison of perceived skill demand. The study targeted architects (145), structural engineers (21), mechanical engineers

(16), electrical engineers (52), plumbing engineers (10), geotechnical engineers (8), quantity surveyors (175) and construction managers (91), giving a total population of 518 professionals. These groups represent the principal professional disciplines involved throughout the construction project lifecycle.

The population was developed from registered construction organizations identified through the relevant professional bodies in Rwanda, including the Rwanda Institution of Quantity Surveyors, the Institute of Engineers in Rwanda, and the Rwanda Institute of Architects. Organizations were eligible where they were actively involved in construction-related consultancy, contracting, development or public-sector project activities. A stratified random sampling technique was used for architects, quantity surveyors and construction managers, while a total census sampling was used for structural, geotechnical, and MEP engineers because of their relatively small populations. Sample sizes for the stratified groups were determined using Yamane's formula at a 10% margin of error. Thus, 59 architects, 64 quantity surveyors, 48 construction managers, 21 structural engineers, 78 MEP engineers, and 8 geotechnical engineers give a sample size of 278. Of the 278 questionnaires distributed, 174 were valid, representing a response rate of 62.6%.

The AI skill items were developed using a literature review and a Delphi technique involving AI experts with experience in construction project execution. The experts reviewed the eight RIBA Plan of Work 2020 stages and their associated construction tasks and identified the AI skills required at each stage. The items were iteratively reviewed, refined, consolidated, and mapped to the relevant RIBA stage and task. The resulting items were subsequently validated through an expert workshop involving both the AI experts who generated them and construction professionals, the intended users. The workshop assessed the relevance, clarity, applicability, and alignment of each item with the corresponding construction task and RIBA stage. Ambiguous, repetitive, or poorly aligned items were revised or removed. The final instrument comprised the validated AI skill items mapped across the eight RIBA stages.

Data were subsequently collected using a structured questionnaire developed using AI skills and the RIBA Plan of Work, which contains standardized, universally accepted construction lifecycle stages and core tasks. The final questionnaire measured respondents' perceived demand for AI skills at each of the eight lifecycle stages using a five-point Likert scale ranging from 1 (Not Demanded) to 5 (Highly Demanded). Demographic and organizational characteristics were also collected. Data analysis combined descriptive and non-parametric inferential statistics. Means and standard deviations were used to assess and rank the level of demand for individual AI skills at each lifecycle stage. Internal consistency of the instrument was assessed using Cronbach's alpha, which produced an overall coefficient of 0.984, indicating excellent reliability. The Kruskal-Wallis H test was used to examine differences in AI skill demand among the eight professional groups. Where significant differences were identified, Dunn's post hoc test with Bonferroni adjustment was used to determine the specific groups responsible for the differences. Differences in AI skill demand across the eight lifecycle stages were examined using the Friedman test, as the same respondents evaluated all stages. Kendall's coefficient of concordance (W) was reported as the corresponding effect-size measure to assess the magnitude and degree of agreement in the observed stage differences. The use of non-parametric procedures was appropriate given the ordinal nature of the Likert-scale responses and the study's repeated-measures structure. Participation was voluntary and based on informed consent obtained through a screening question before the questionnaire commenced. Respondent and organizational information were treated confidentially and reported in an anonymized, aggregated form.

4. Results

The sample was broadly balanced between contractors and consultants (38.5% each), with smaller representation from government agencies (13.2%) and development/client organization (9.8%), and drew on professionals with a Bachelor's degree (70.1%) and one to six years of experience (80.4% combined), reflecting a relatively young professional workforce consistent with the broader profile of Rwanda construction sector. Notably, only 31.6% of respondents reported having received any formal AI or related training, while 68.4% had not, and a further 26.4% reported never or rarely engaging with AI-related technologies.

Tables 1 to 8 present the mean levels of demand, item rankings, and Kruskal-Wallis test results for AI skills across the eight RIBA lifecycle stages, reported on the five-point Likert scale described in the research methodology (1 = no demand, 5 = High Demand). It is worth noting that mean scores are based on a five-point Likert scale (1 = Not Demanded; 5 = Highly Demanded). Decision categories are defined as Not Demanded (1.00-1.49), Slightly Demanded (1.50-2.49), Averagely Demanded (2.50-3.49), Demanded (3.50-4.49), and Highly Demanded (4.50-5.00). Group comparisons were conducted using the Kruskal-Wallis test; $p < 0.05$ indicates a significant difference, and $p > 0.05$ indicates no significant difference.

Table 1 shows that sustainability analytics and simulation recorded the highest AI skill demand, followed by energy and performance data interpretation, forecasting and scenario analysis. AI for initial cost forecasting, regression-based modeling, and feasibility assessment had the least demand at the strategic definition stage. The Kruskal-Wallis results indicate no statistically significant differences among respondent groups for any skill ($p > 0.05$), suggesting broadly consistent perceptions of AI skill demand at this stage.

Table 2 indicates that comparison and evaluation of AI-supported options had the highest perceived demand at the preparation and briefing stage, followed by translating client requirements using AI-assisted briefing tools. The comparison of AI-generated project options and scenarios had the lowest demand, suggesting low maturity within Rwanda's construction industry. The Kruskal-Wallis tests revealed no significant differences across respondent groups for any skill ($p > 0.05$), indicating general agreement regarding AI skill requirements during preparation and briefing.

Table 1. AI skill demand at the 'strategic definition' stage (DEMAND_S0)

AI Skills (Cronbach's Alpha = 0.92)	Item Mean	Rank	Overall rank	Decision	X ² (H)	P-value	Significant
Sustainability analytics and simulation	3.68	1	1	Demanded	5.89	0.55	NO
Energy and performance data interpretation	3.61	2	4	Demanded	7.40	0.39	NO
Forecasting and scenario analysis	3.53	3	15	Demanded	6.45	0.49	NO
AI-supported feasibility assessment and decision making	3.50	4	22	Demanded	9.93	0.19	NO
AI-based risk management, viability prediction, and strategic decision support	3.45	5	33	Demanded	9.29	0.23	NO
AI for initial cost forecasting, regression-based modeling, and feasibility assessments	3.33	6	46	Averagely Demand	13.28	0.07	NO

Table 2. AI skill demand at the 'preparation and briefing' stage (DEMAND_S1)

AI Skills (Cronbach's Alpha = 0.895)	Item Mean	Rank	Overall rank	Decision	X ² (H)	P-value	Significant
Comparison and evaluation of AI-supported option	3.52	1	17	Demanded	6.26	0.51	NO
Translate client requirements using AI-assisted briefing tools	3.51	2	19	Demanded	5.65	0.58	NO
Interpretation of codes and standards with AI and text analysis	3.48	3	26	Averagely Demand	7.53	0.38	NO
Analyze stakeholder needs using AI-based stakeholder tools	3.39	4	40	Averagely Demand	9.88	0.20	NO
AI-assisted budget estimation, scenario forecasting, and cost benchmarking	3.37	5	43	Averagely Demand	12.64	0.08	NO
AI-powered requirement prioritization, brief analysis, and stakeholder data integration	3.33	6	46	Averagely Demand	11.06	0.14	NO
Compare AI-generated project options and scenarios	3.28	7	52	Averagely Demand	4.19	0.76	NO

Table 3 shows that scenario comparison and simulation using AI was the most demanded skill, followed by generating and evaluating design alternatives using AI tools. AI-assisted early-stage structural analysis had the lowest demand at the concept design stage. A statistically significant difference was observed only for AI-optimized cost alternative modeling and quantity extraction from design concepts ($H = 20.75$, $p < 0.001$), indicating that perceptions of demand for this skill differed significantly among respondent groups. All other skills showed no significant group differences ($p > 0.05$).

Table 3. AI skill demand at the 'concept design' stage (DEMAND_S2)

AI Skills (Cronbach's Alpha = 0.923)	Item Mean	Rank	Overall rank	Decision	X ² (H)	P-value	Significant
Scenario comparison and simulation AI skill	3.55	1	11	Demanded	8.44	0.30	NO
Generate and evaluate design alternatives using AI tools	3.52	2	17	Demanded	9.37	0.23	NO
Assess AI-predicted ground and soil conditions	3.48	3	26	Averagely Demand	9.05	0.25	NO
Analyze AI-generated environmental and energy simulations	3.48	3	26	Averagely Demand	9.08	0.25	NO
AI-optimized cost alternative modeling and quantity extraction from design concepts	3.43	5	35	Averagely Demand	20.75	0.00	YES
Use of Generative AI for design optimization and value engineering alternatives	3.34	6	45	Averagely Demand	10.43	0.17	NO
Apply AI-assisted early-stage structural analysis	3.33	7	46	Averagely Demand	9.97	0.19	NO

Table 4 indicates moderate demand for all three AI skills at the spatial coordination stage. AI-integrated BIM tools for clash detection and coordination had the highest demand, followed by AI-based constructability optimization, and AI-enhanced BIM analytics for cost implications and clash impact assessment. The Kruskal–Wallis results showed no significant differences among respondent groups for any skill ($p > 0.05$), suggesting consistent perceptions across groups.

Table 5 demonstrates that AI for multimodal analysis of text, images and data in technical specifications was the most demanded skill, followed by AI-driven tender document analysis and discrepancy detection. AI-generated geotechnical simulations for foundation design recorded the lowest demand. Significant group differences were found for generating and verifying quantities and costs using AI tools ($H = 14.98$, $p = 0.04$) and AI-generated geotechnical simulations for

foundation design ($H = 14.78$, $p = 0.04$). The other skills showed no statistically significant differences among respondent groups.

Table 4. AI skill demand at the 'spatial coordination' stage (DEMAND_S3)

AI Skills (Cronbach's Alpha = 0.893)	Item Mean	Rank	Overall rank	Decision	X ² (H)	P-value	Significant
Use of AI-integrated BIM tools for clash detection and coordination	3.48	1	26	Averagely Demand	5.86	0.56	NO
Optimize designs for constructability using AI-based insights	3.43	2	35	Averagely Demand	11.65	0.11	NO
AI-enhanced BIM analytics for cost implication detection, and clash impact assessment	3.40	3	39	Averagely Demand	5.32	0.62	NO

Table 5. AI skill demand at the 'technical design' stage (DEMAND_S4)

AI Skills (Cronbach's Alpha = 0.938)	Item Mean	Rank	Overall rank	Decision	X ² (H)	P-value	Significant
AI for multimodal analysis (text + image + data) in technical specifications	3.51	1	19	Demanded	9.04	0.25	NO
AI-driven tender document analysis, and discrepancy detection	3.49	2	23	Averagely Demand	8.88	0.26	NO
Automated documentation review and drafting	3.45	3	33	Averagely Demand	5.82	0.56	NO
AI-powered compliance checking, and regulatory verification	3.43	4	35	Averagely Demand	10.65	0.16	NO
Perform and validate AI-assisted detailed structural analysis	3.43	4	35	Averagely Demand	12.71	0.08	NO
Generate and verify quantities and costs using AI tools	3.39	6	40	Averagely Demand	14.98	0.04	YES
AI-automated quantity takeoff, and bill of quantities (BoQ) generation	3.33	7	46	Averagely Demand	8.54	0.29	NO
Apply AI-generated geotechnical simulations to foundation design	3.32	8	50	Averagely Demand	14.78	0.04	YES

Table 6 shows that AI skill demand was relatively high during manufacturing and construction. Responding to AI-generated safety alerts and hazard predictions had the highest demand, followed by schedule and productivity analytics. AI-based variation prediction, claim analysis and cost-overrun forecasting ranked lowest. A significant difference among respondent groups was identified only for AI-based variation prediction, claim analysis and cost-overrun forecasting ($H = 17.78$, $p = 0.01$). All other skills showed no significant group differences.

Table 6. AI skill demand at the 'manufacturing and construction' stage (DEMAND_S5)

AI Skills (Cronbach's Alpha = 0.946)	Item Mean	Rank	Overall rank	Decision	X ² (H)	P-value	Significant
Respond to AI-generated safety alerts and hazard predictions	3.59	1	8	Demanded	13.08	0.70	NO
Schedule and productivity analytics	3.56	2	10	Demanded	7.14	0.42	NO
Interpret AI-generated construction progress data	3.55	3	11	Demanded	9.46	0.22	NO
Monitor and control project costs using AI variance analysis	3.55	3	11	Demanded	9.86	0.20	NO
AI/IoT for dynamic resource allocation and predictive delay/risk management	3.53	5	15	Demanded	9.06	0.25	NO
AI for real-time quality control and defect detection	3.51	6	19	Demanded	5.34	0.62	NO
AI-based variation prediction, claim analysis, and cost overrun forecasting	3.49	7	23	Averagely Demand	17.78	0.01	YES
Interpreting real-time AI progress tracking data	3.48	8	26	Averagely Demand	12.42	0.09	NO
Identify and manage quality issues using AI detection systems	3.39	9	40	Averagely Demand	7.18	0.41	NO

Table 7 indicates that AI-supported documentation management and reporting was the most demanded skill at the handover stage, followed by AI-assisted planning for operational readiness. A statistically significant difference among respondent groups was found for organizing and validating handover information using AI systems ($H = 14.67$, $p = 0.04$).

The remaining three skills showed no significant group differences ($p > 0.05$), indicating relatively consistent perceptions of AI skill demand at the handover stage.

Table 7. AI skill demand at the 'handover' stage (DEMAND_S6)

AI Skills (Cronbach's Alpha = 0.924)	Item Mean	Rank	Overall rank	Decision	X ² (H)	P-value	Significant
AI-supported documentation management and reporting	3.49	1	23	Averagely Demand	9.51	0.20	NO
Support operational readiness using AI-assisted planning tools	3.46	2	32	Averagely Demand	12.40	0.09	NO
Organize and validate handover information using AI systems	3.29	3	51	Averagely Demand	14.67	0.04	YES
AI-automated final account reconciliation, variation settlement, and handover documentation review	3.24	4	53	Averagely Demand	8.11	0.32	NO

Table 8 shows that AI skill demand at the use stage was generally high, with seven of the nine skills classified as demanded. Analyzing AI-generated building performance and energy data had the highest demand, followed by asset data interpretation and tracking, and AI predictive maintenance and smart building management dashboards. The lowest demand was recorded for AI-driven lifecycle cost prediction and whole-life costing. The Kruskal–Wallis results show that only AI in facility management optimization and energy and use-pattern analytics differed significantly across respondent groups ($H = 19.68$, $p = 0.01$). All other skills showed no statistically significant group differences ($p > 0.05$), indicating broadly consistent perceptions of AI skill demand at the use stage.

Table 8. AI skill demand at the 'use' stage (DEMAND_S7)

AI Skills (Cronbach's Alpha = 0.947)	Item Mean	Rank	Overall rank	Decision	X ² (H)	P-value	Significant
Analyze AI-generated building performance and energy data	3.66	1	2	Demanded	14.00	0.05	NO
Asset data interpretation and tracking	3.63	2	3	Demanded	6.00	0.54	NO
AI predictive maintenance and smart building management dashboards	3.61	3	4	Demanded	7.89	0.34	NO
AI in facility management optimization, and energy and use pattern analytics	3.61	3	4	Demanded	19.68	0.01	YES
Interpret AI-generated predictive maintenance outputs	3.60	5	7	Demanded	9.72	0.21	NO
AI-supported decommissioning planning and Analysis	3.58	6	9	Demanded	7.07	0.42	NO
Recovery and reuse analytics	3.55	7	11	Demanded	8.73	0.27	NO
Apply AI-based lifecycle cost and whole-life performance analysis	3.48	8	26	Averagely Demand	11.38	0.12	NO
AI-driven lifecycle cost prediction and whole-life costing	3.36	9	44	Averagely Demand	13.38	0.06	NO

Table 9 shows that AI skill demand varied significantly across the eight RIBA construction project lifecycle stages (Friedman $\chi^2 = 19.162$, $df = 7$, $p = 0.008$). The use stage (DEMAND_S7) recorded the highest mean score, indicating the greatest overall perceived demand for AI skills. This was followed by strategic definition (DEMAND_S0) and manufacturing and construction (DEMAND_S5). In contrast, the handover stage (DEMAND_S6) had the lowest overall AI skill demand, followed by preparation and briefing (DEMAND_S1). The significant Friedman test indicates that AI skill demand was not uniform across the lifecycle stages; rather, respondents perceived some stages as requiring greater AI competencies than others. However, the practical effect of the difference was very small, as indicated by Kendall's $W = 0.016$. Thus, although the differences are statistically significant, lifecycle stage explains only a very small proportion of the variation in AI skill demand.

5. Discussion

The findings indicate that demand for AI skills is moderate to high across the entire construction project lifecycle, although the pattern is not entirely uniform. This supports the literature showing that AI applications have expanded from isolated analytical functions to design, coordination, construction monitoring and asset management (Li et al., 2024). The generally moderate-to-high mean scores across all eight RIBA stages further suggest that construction professionals perceive AI capability as increasingly relevant to project delivery. This is consistent with Obi et al. (2025), who identify data literacy, AI fundamentals, digital collaboration and AI-driven decision-making among emerging competency domains in construction. The findings, therefore, extend the technology-focused literature by demonstrating that the diffusion of AI is accompanied by a corresponding demand for workforce capabilities. At the strategic definition stage, sustainability analytics and simulation, energy and performance data interpretation, and forecasting and scenario analysis were the most

in-demand skills. This is consistent with the strategic applications of AI identified in the literature, particularly its use in feasibility assessment, forecasting, risk analysis and data-driven decision-making (Abioye et al., 2021). The relatively strong demand for sustainability- and energy-related skills is noteworthy, as it suggests that AI competence at this stage extends beyond conventional cost and schedule forecasting to encompass project performance and sustainability considerations. The Preparation and Briefing stage produced comparatively lower demand than strategic definition, although AI-supported option evaluation and translation of client requirements remained the leading skills. This aligns with the literature identifying AI-assisted information interpretation and decision support as emerging applications in early project definition (Egwim et al., 2024).

Table 9. Comparison of AI skill demand across construction project lifecycle stages

Stage	Mean Score	Rank	Mean rank	Friedman χ^2	Kendall's W	p-value	Significant
(DEMAND_S7)	3.57	1	5.03	19.162	0.016	0.008	YES
(DEMAND_S0)	3.52	2	4.42				
(DEMAND_S5)	3.52	3	4.85				
(DEMAND_S2)	3.45	4	4.51				
(DEMAND_S3)	3.44	5	4.36				
(DEMAND_S4)	3.42	6	4.35				
(DEMAND_S1)	3.41	7	4.24				
(DEMAND_S6)	3.37	8	4.24				

Note: $N = 174$, $df = 7$. The Friedman χ^2 and Kendall's W statistics test the overall difference across all eight stages jointly and are reported once for the omnibus test. Kendall's $W = \chi^2 / [N(k-1)] = 19.162 / (174 \times 7) = 0.016$, recalculated here from the reported χ^2 , N and df (the original draft listed $W = 0.008$, identical to the p-value almost certainly a transcription duplication rather than an independently computed effect size; please verify against the original SPSS/software output before submission).

At concept design, scenario comparison and simulation, and AI-supported generation and evaluation of design alternatives emerged as the most demanded skills. This finding is consistent with recent research identifying generative AI and simulation as important emerging applications for design exploration and evaluation (Gao et al., 2025). However, AI-assisted early-stage structural analysis recorded the lowest demand within this stage. The significant professional-group difference in AI-optimized cost-alternative modeling and quantity extraction further demonstrates that some AI competencies are more occupationally specific than others. The results for spatial coordination show a relatively consistent and moderate level of demand, with AI-integrated BIM for clash detection ranking highest. This closely aligns with recent research linking AI to BIM-enabled coordination and automated clash detection (Koo et al., 2025). In technical design, multimodal analysis of technical specifications and AI-driven tender document analysis were the most in-demand skills. This indicates a growing requirement for professionals to interrogate large volumes of structured and unstructured project information. The significant differences observed in AI-generated quantities and costs, as well as in geotechnical simulations, indicate greater variation among professional groups for specialized technical applications. This contrasts with the more uniform pattern observed during spatial coordination and suggests that the professional role becomes more influential where AI applications are closely linked to discipline-specific technical expertise. The manufacturing and construction stage recorded some of the strongest overall skill demands. Responding to AI-generated safety alerts and hazard predictions ranked first, followed by schedule and productivity analytics. This is consistent with recent construction research identifying AI applications in safety monitoring, productivity analysis and site-based risk management (Adebowale and Agumba, 2023). The relatively high demand at this stage reflects the importance of real-time AI-supported decision-making, in which professionals must interpret machine-generated information and respond appropriately. However, variation prediction, claim analysis and cost-overrun forecasting showed significant differences among professional groups. This suggests that while AI-enabled safety and productivity capabilities are broadly relevant, commercially specialized applications remain more occupationally differentiated. The handover stage recorded the lowest overall demand, with all four skills classified as being demanded on average. This contrasts with the relatively stronger demand observed at strategic definition, manufacturing and construction, and use. Nevertheless, the significant differences in how handover information is organized and validated indicate that professional roles influence the perceived importance of AI in information-intensive handover activities. The use stage recorded the highest overall AI skill demand, particularly for analyzing building performance and energy data, interpreting asset data and predictive maintenance and smart building management. This finding is consistent with literature identifying predictive maintenance, energy analytics and asset optimization as important applications of AI during the operational phase (Tinyimana and Dosumu, 2026). Rather, the growing availability of operational data and smart-building technologies creates substantial demand for AI-related analytical capabilities after project completion.

The Friedman test confirms that AI skill demand differs significantly across the eight lifecycle stages ($\chi^2 = 19.162$, $p = 0.008$). This provides empirical support for the study's central proposition that AI skill demand varies statistically significantly across project lifecycle stages, although the observed difference is very small in practical terms. However, the Kendall's W of 0.016 indicates a very small effect, meaning that the differences between stages are statistically significant but practically weak. The Friedman result should therefore not be interpreted as evidence that AI skill requirements differ dramatically across stages. Rather, it indicates a statistically detectable yet relatively subtle variation in demand intensity. A further important finding is that most AI skills did not differ significantly among professional groups. The limited number of significant differences suggests that AI is not becoming the preserve of particular

construction professions; rather, many AI-enabled activities require a common set of transferable competencies across professional boundaries. This may reflect the increasing integration of AI with shared project information environments such as BIM, cloud platforms and project-management systems, where different professionals interact with the same data and AI-generated outputs. The significant differences observed for specialized skills, therefore, appear to reflect differences in professional task responsibilities rather than fundamentally different AI competency foundations. Significant differences occurred only in selected specialized skills, including cost and quantity modeling, geotechnical simulation, variation and claims analysis, handover information validation, and facility management analytics. This pattern suggests that a substantial core of AI competencies is cross-disciplinary, particularly those involving data interpretation, AI-supported decision-making, BIM, monitoring and information management. At the same time, discipline-specific applications generate more differentiated competency requirements. This finding is consistent with the multidimensional competency perspective advanced by Obi et al. (2025) and extends it by demonstrating empirically that some competencies are shared across professional boundaries, whereas others are occupationally specific. Previous research has established where AI can be applied. The present study demonstrates that the corresponding skills are demanded across all lifecycle stages, although their intensity and degree of professional specialization vary. The results therefore support lifecycle-oriented curriculum development and professional upskilling, combining a common foundation in AI, data and analytical capabilities with targeted discipline- and stage-specific competencies. For Rwanda and comparable developing economies, this approach is particularly relevant because it allows constrained training resources to be directed towards demonstrable industry needs rather than generic AI training.

The findings also provide empirical support for the study's conceptual framework by demonstrating statistically significant variation in AI skill demand across lifecycle stages, with a small practical effect, and indicating profession-specific differences in selected specialized competencies. This provides a basis for developing a common construction AI competency framework with profession-specific extensions. Based on the DCT, this pattern highlights the need for organizations to continually adapt their workforce capabilities as AI applications expand across the project lifecycle. Similarly, the perspectives of the RBV and HCT suggest that developing these capabilities represents both a strategic organizational resource and an investment in workforce competence. From an RBV perspective, AI-skilled professionals constitute a strategic human resource; DCT explains the need to continuously acquire, integrate and reconfigure AI competencies as technologies evolve, and HCT positions AI skills as investments that enhance individual and organizational productivity. Hence, the findings suggest a lifecycle-based AI competency perspective in which AI applications generate task-specific competency requirements that vary according to professional roles and lifecycle activities. Thus, AI competency demand can be conceptualized as the interaction between AI application, lifecycle stage and professional function. Although the findings are derived from the Rwandan construction industry, the identified lifecycle-based pattern of AI skill demand provides a useful framework for the construction industry of other countries. Hence, the results can serve as a benchmark for assessing AI competency requirements across the eight RIBA Plan of Work stages, while specific priorities should be adapted to local conditions, including levels of digital maturity, professional roles, regulatory environments, technological infrastructure, and patterns of AI adoption. Countries with similar construction and digital-development characteristics may use the identified common AI competencies to inform curriculum development, professional training, and workforce upskilling, while conducting contextual assessments to identify additional or differently prioritized skills.

6. Implications of the Study

The findings of this study provide managers with a basis for making more targeted workforce development decisions. Managers can prioritize AI training investments based on the level of skill demand identified at each lifecycle stage, allocate training resources to high-demand competencies, and develop role-specific programs for professional groups requiring specialized AI capabilities. The findings can also inform organizational AI adoption strategies by identifying the competencies to develop before or alongside the implementation of AI-enabled technologies. Thus, rather than adopting generic AI training, managers can align workforce development with specific project activities, professional responsibilities and emerging AI requirements. Further, the findings have educational, theoretical, social and policy implications. Educationally, the findings provide evidence that construction curricula and professional development align with emerging AI competencies. Theoretically, the study extends understanding of AI skill demand by demonstrating its lifecycle and profession-specific nature. Socially, targeted AI skills development can support workforce adaptability and inclusive participation in digital construction. For policymakers and professional bodies, the findings provide an evidence base for AI competency frameworks, digital workforce strategies and continuing professional development.

7. Limitations of the Study

This study has several limitations. First, AI skill demand was measured through professionals' perceived demand rather than through objective indicators such as job market requirements, employer competency frameworks or organizational AI adoption. The findings should therefore be interpreted as evidence of perceived industry demand. Future research should endeavor to triangulate these perceptions with employer interviews, job advertisements, competency frameworks and organizational AI-adoption data. Second, the cross-sectional design captures AI skill demand at a single point in time and therefore cannot establish how these demands may evolve as AI adoption progresses. Third, the study focuses on the Rwandan construction industry; therefore, the findings may not be directly generalizable to other countries with different technological, institutional and economic conditions. Future research should address these limitations through longitudinal and multi-country studies.

8. Conclusion

The study demonstrates that demand for AI skills is moderate to high across all eight stages of the construction project lifecycle in Rwanda and confirms that AI competence is becoming a cross-cutting workforce requirement. Although AI skill demand differs significantly across lifecycle stages, the very small Kendall's W (0.016) indicates that these differences are statistically detectable but practically weak, suggesting limited substantive variation in AI skill demand across stages. The "use, strategic definition, and manufacturing and construction" stages recorded the highest overall perceived demand, while "handover and preparation and briefing" recorded the lowest. Most individual skills did not differ significantly across professional groups, suggesting a common set of AI competencies alongside discipline-specific requirements. The study recommends that universities, construction organizations and professional bodies develop lifecycle-oriented AI training programs that combine common competencies in AI literacy, data analytics, digital platforms, critical evaluation and human-AI collaboration with stage- and discipline-specific skills. Attention should be given to the relatively higher-demand areas identified in the strategic definition, manufacturing and construction, and use. Targeted specialist training should also be developed for skills that demonstrate greater professional differentiation, including AI-based cost and quantity modeling, geotechnical simulation, claims analysis and facility management analytics. Collaboration between universities, professional institutions, industry and government is recommended to ensure that AI curricula and continuing professional development programs remain aligned with evolving industry requirements. Future research should examine AI skill supply and competency gaps by comparing the skills currently possessed by construction professionals with the demand established in this study. Longitudinal studies could investigate how AI skill requirements evolve as adoption increases. Further research should also develop professional-group-specific competency frameworks, validate the findings using larger samples across other developing economies and investigate the relationships among AI skill demand, skill supply, competency gaps, barriers, upskilling strategies and workforce readiness using data from job markets, employer competency frameworks or organizational AI adoption to triangulate perceived responses.

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Institutional Review Board (IRB) Statement

The study involved a voluntary questionnaire survey of construction professionals. Informed consent was obtained from participants through a screening question presented before the questionnaire commenced. Participation was voluntary, and respondents could decline to proceed. No personally identifiable information was collected, and the confidentiality of responses was maintained.

Declaration of Artificial Intelligence (AI) Tools

The authors used ChatGPT solely for language editing and to improve readability. The authors reviewed and verified all content and take full responsibility for the accuracy and integrity of the manuscript

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Oluwaseun Sunday Dosumu is an Associate Professor and Head of the Department of Construction Economics and Management at the University of Rwanda, with over seventeen years of academic, research, and professional experience across Nigeria, South Africa, and Rwanda. He holds a Ph.D. in Building from the University of Lagos and completed a Postdoctoral Research Fellowship at the University of Johannesburg through the Global Excellence Stature Award. He is a Chartered Construction Manager with the Chartered Institute of Building (CIOB) in the UK and a corporate member of the Nigerian Institute of Building. His research focuses on sustainable construction, digital transformation, Artificial Intelligence, Industry 4.0/5.0, circular economy, construction innovation, and future construction skills. He has authored more than 45 scholarly publications, including journal articles, conference papers, book chapters, and a research book. He has received international recognition, including a Global Excellence Stature Award and a Best Paper Award. His academic leadership extends to curriculum development, postgraduate supervision, research, staff development, and industry-academia collaboration, with a strong commitment to learner-centered education and to developing future-ready construction professionals.



Christine Musanase is an academic and researcher in Information Systems at the University of Rwanda, where she serves in the School of ICT and has contributed to the leadership of the Information Systems program. She holds a bachelor's degree in information technology and a master's degree in information systems from the University of Rwanda, and completed her Ph.D. by Research in Wireless Intelligent Sensor Networks through the African Center of Excellence in Internet of Things. Her research interests include Internet of Things, Artificial Intelligence, machine learning, data analytics, wireless intelligent sensor networks, and informatics, with research applications particularly in agriculture and smart technologies. She has published research on machine-learning-based agricultural applications and soil-quality prediction, and holds professional certifications in Oracle database development, Python, data science, R programming, and IoT.



Ryan Tumusiime Kaganga is a construction professional and emerging researcher with a background in Quantity Surveying and Construction Economics and Management. He is a recent graduate of the University of Rwanda, College of Science and Technology, with an interest in the changing relationship between technology and the construction industry. His research interests focus particularly on the evolution and application of artificial intelligence in construction, including how emerging AI technologies can be integrated into construction processes, professional practice, project management, and the wider built environment. He is interested in understanding not only the technological potential of AI, but also the skills, capabilities, and workforce transformations required for its effective adoption within the industry. His broader interests lie in construction management, quantity surveying, digital transformation, emerging technologies, and the future of the construction workforce, with a particular interest in how these developments can contribute to more efficient, innovative, and sustainable construction practices.



Dieudonné Ahishakiye is a Quantity Surveyor and construction researcher from Rwanda who completed a Bachelor's degree in Quantity Surveying under the Department of Construction Economics and Management, graduating with First-Class Honors and currently awaiting formal graduation. He has professional experience working as a Quantity Surveyor with Baoye Hubei Construction Company, FDG Africa, and Covenant Construction Company. His research interests focus on artificial intelligence and digital transformation in construction, emerging skills, workforce development, labor market integration, innovation, and sustainable construction. He has contributed to research that underpins a book on AI skill gaps and upskilling pathways in the construction industry and has been involved in a Mastercard Foundation-supported research project modeling labor market integration pathways for vulnerable youth in Rwanda's construction sector. He is passionate about using research and innovation to support evidence-based solutions and the transformation of Rwanda's construction industry.



Eric Iradukunda is an immediate alumnus of the Department of Construction Economics and Management at the University of Rwanda.