The Impact of Generative AI and BI on Generation Z Career Motivation and Construction Industry Transitions

F. Henry Abanda. *Ecole Nationale Supérieure des Travaux Publics, Cameroon*

Abstract

The construction industry is facing a critical transformation driven by the dual pressures of a widening skills gap and a generational disinterest among young professionals. This study investigates how Generative Artificial Intelligence (Gen AI) and Generative Business Intelligence (Gen BI) can serve as catalysts to modernize the sector and align it with the values and technological fluency of Generation Z (Gen Z). Through qualitative interviews with eleven participants, three key findings emerged from the study. First, both Gen AI and Gen BI were found to significantly enhance task efficiency and clarity in construction workflows—Gen AI automated cost and project planning tasks, while Gen BI transformed complex data into intuitive visualizations, improving communication across technical and non-technical stakeholders. Second, exposure to Gen AI and Gen BI elicited short-term enthusiasm and positive career-oriented perceptions. Most participants indicated that these technologies could strengthen their willingness to remain in the construction sector, particularly if employers and training providers offer sustained, structured digital upskilling. Nearly all respondents also expressed a desire to pursue further training in Gen AI/Gen BI to support their continued career development in the industry. More specifically, participants reported enhanced career self-efficacy, clearer perceptions of career pathways, and stronger intentions to remain in or re-enter the construction sector, suggesting that Gen AI and Gen BI influence not only task performance but also career decision-making and professional identity formation. Third, the study emphasized the necessity of educational reform and industry collaboration, advocating for updated curricula, hands-on learning experiences, and targeted rebranding efforts to reshape the public image of construction as a digital and purpose-driven field. The findings suggest that successful digital adoption requires a balanced approach that enhances, rather than replaces, traditional expertise. With thoughtful implementation and sustained commitment to digital transformation, Gen AI and Gen BI can help reposition construction as an attractive, future-ready career path for the next generation.

Keywords: BIM, Construction Projects, Gen AI, Gen BI, Gen Z, Skills gap

Over the past decades, both the United Kingdom and Canada have struggled to keep pace with the growing demand for infrastructure and housing. In the United Kingdom, housebuilding continues to fall behind that of European neighbours (Wind, 2024). A recent report highlights a severe shortfall, with Britain missing approximately 4.3 million homes from its national housing stock (Centre for Cities, 2024). Canada faces a similar crisis. Relative to its Organisation for Economic Co-operation and Development (OECD) peers, it underperforms in delivering affordable housing. Estimates show a need for an additional 575,000 social housing units to align with the OECD average (Laberge, 2025) and a staggering 3.5 million affordable housing units by 2030 to restore housing affordability (CMHC, 2022).

In addition to housing, infrastructure in both countries is in a state of decline. In Canada, nearly 40% of roads and bridges are rated in fair, poor, or very poor condition, with around 80% exceeding 20 years in age (FCM, 2019). Similarly, 30–35% of recreational and cultural facilities fall into these lower condition categories (FCM, 2019). Meanwhile, the U.S. construction sector also indicative of broader North American trends is predicted to need an additional 439,000 workers in 2025 alone to meet growing demands (National Institute of Building Sciences, 2025b).

The infrastructure and housing crises are compounded by a pressing labour shortage. The construction industry in both the United Kingdom and Canada faces a dual challenge: a shrinking workforce due to retirements and difficulty attracting new entrants (Ahmed, 2024). In Canada, BuildForce projects a need to recruit 309,000 new construction workers between 2021 and 2030, with 259,100, about 22% of the current workforce expected to retire during this period (Boscariol & Killam, 2024).

This labour shortfall is further aggravated by global geopolitical instability and a rise in protectionist policies that restrict immigration. Such policies limit the flow of migrant workers both documented and undocumented who could otherwise help fill these labour gaps (Turner & Townsend, 2024). Beyond economic consequences, this shortage threatens national security. Vulnerabilities include dependency on foreign labour and technology, reduced disaster preparedness, compromised climate resilience, and risks to military and critical infrastructure (National Institute of Building Sciences, 2025b). Recognizing the urgency, the Elevate 2025 conference, scheduled for September 2025, aims to convene policymakers, industry leaders, and stakeholders to assess the full scale of the built environment workforce crisis and explore strategic interventions (National Institute of Building Sciences, 2025a).

Bridging the labour gap requires the construction sector to become more inclusive and appealing to younger generations, particularly Gen Z (born between 1997 and 2012). This generation is increasingly turning to trade careers, often seen as more secure than traditional academic paths. However, some trade professions such as building inspectors, electricians, and plumbers face some of the highest unemployment rates (Royle, 2025). Nevertheless, 78% of Americans have reported observing more young people taking up skilled trades like welding, electrical work, and carpentry (Royle, 2025). This trend aligns with global forecasts identifying frontline construction roles as among the fastest-growing job categories over the next five years (World Economic Forum, 2025).

Despite this positive trend, the construction industry lags in adopting emerging technologies, particularly Artificial Intelligence (AI) and Business Intelligence (BI). Yet, automation holds promise: approximately 50% of construction jobs could potentially be automated (Hoover et al., 2018). In the long term, this could enhance productivity and elevate wages for those with advanced skills (Chui & Mischke, 2019). During the transition, likely spanning over a decade demand for highly skilled workers will surge, while those performing repetitive tasks may face wage stagnation or displacement.

Interestingly, while Gen Z may be increasingly attracted to trade roles, the long-term viability of these positions may be undermined by automation and low wage trajectories unless paired with digital skillsets. The World Economic Forum (2016) forecasted that 65% of children entering primary school in 2016 would eventually work in jobs that do not yet exist. This dynamic labour landscape underscores the critical need to prepare Gen Z for future careers in construction through emerging technologies.

Motivating Gen Z to pursue careers in construction increasingly depends on leveraging advanced technologies. Recent grey literature points to this opportunity. Cure (2023) emphasized the potential of digital tools to entice younger generations into the industry. Burns (2025) argued for the modernization of training and upskilling programs to align with Gen Z preferences.

A key research question thus arises: To what extent can emerging technologies, particularly Gen AI and Gen BI, be used to attract and retain Gen Z talent in the construction industry? This question is echoed by BuildingTalk (2025), which provocatively asks, “Will AI bring younger people into construction?” This study seeks to investigate whether emerging technologies, specifically Gen AI and Gen BI, can motivate Gen Z to engage with careers in the construction sector. The following objectives guide the investigation:

1. Evaluate the Usability and Impact of Gen AI and Gen BI in Construction Workflows
    - Assess user perceptions of Gen AI’s effectiveness in automating tasks such as cost estimation and project planning.
    - Identify limitations of Gen AI in terms of accuracy and practical implementation.
    - Analyze the necessity and role of human oversight in refining AI-generated outputs.
    - Evaluate how Gen BI dashboards improve decision-making and stakeholder collaboration.

2. Investigate the Influence of Digital Tools on Career Motivation and Skills Development
    - Explore how exposure to Gen AI/BI tools influences Gen Z’s career interests in construction.
    - Assess current and projected demand for AI/BI training among students and young professionals.

- Determine the extent to which digital tools enhance retention and engagement in construction careers.

3. Propose Strategies for Industry and Education to Foster Digital Adoption
    - Identify best practices for construction firms to attract Gen Z through a technology-driven culture (e.g., purpose-driven roles, remote flexibility).
    - Recommend strategies for integrating AI/BI into construction education (e.g., hands-on labs, interdisciplinary projects).
    - Suggest methods to rebrand the construction industry using digital platforms (e.g., social media campaigns, tech showcases).

Construction Labour Gap and Gen Z's Characteristics and Work Expectations

The construction industry is among the most critical sectors worldwide. While statistics may vary, the general consensus underscores its substantial contribution to national and global economies. Domljan and Domljan (2024) report that construction accounts for 10–12% of the global economy, while McKinsey & Company (2020) estimates that construction-related expenditures comprise approximately 13% of global GDP. Looking ahead, the sector is expected to experience fundamental transformations driven by evolving market dynamics. These include the scarcity of skilled labour, sustained cost pressures linked to infrastructure and affordable housing, increasingly stringent sustainability and safety regulations, and the rising expectations of sophisticated clients and asset owners (McKinsey & Company, 2020). Chief among these challenges is the acute shortage of skilled labour, which continues to hinder contractors' ability to deliver timely and cost-effective infrastructure and housing solutions.

To address this, there is growing advocacy for greater inclusivity within the construction workforce specifically, the integration of Gen Z. Although definitions of Gen Z vary slightly, it generally includes individuals born between 1997 and 2012. This generation differs markedly from its predecessors. Gen Z are digital natives, characterized by their fluency in technology, desire for purpose-driven work, and demand for opportunities that foster continuous growth and development (Burns, 2025). Despite their enthusiasm for technology-driven industries such as communications, data suggest that Gen Z exhibits limited interest in the construction sector. A recent study by BDO Canada (2023) found that only 18% of Canadian youth expressed strong interest in construction careers, compared to 28% globally. Furthermore, 40% of Canadian respondents reported no interest at all, compared to 29% globally.

To understand this reluctance, it is important to consider the core values and preferences of Gen Z. They are the first generation to grow up entirely in the digital age, with constant access to smartphones and social media. Gen Z is highly tech-savvy, socially aware, entrepreneurial, and prefers flexible work settings. They are more engaged with short-form, visual content (e.g., TikTok, Instagram Reels) and value authenticity in brand messaging and leadership. These preferences explain why the construction sector is often perceived by Gen Z as outdated, viewed as "not tech-enough, not Instagram-able, not white-collar enough, not flexible enough, and not progressive enough" (Orbiz, 2023).

As Copsey (2024) emphasizes, Gen Z is seeking more than just a paycheque. They prioritize continuous skills development and clear, tangible pathways for career advancement. However, conventional training approaches passive PowerPoint presentations and static classroom sessions are unlikely to resonate. Instead, training and upskilling programs must be reimagined to reflect Gen Z's digital realities. AI-driven platforms offer significant potential in this regard, enabling personalized, on-demand learning experiences that cater to individual needs and learning paces.

Unfortunately, the current training landscape in the construction sector lags behind. A review of major industry training boards such as the UK's Construction Industry Training Board (CITB) and Workforce Skills Support reveals a lack of courses in emerging technology areas aligned with Gen Z's digital lifestyles. In Canada, a similar review of BuildForce and the Construction Industry Training Network found only one BIM-related course listed on the latter's website.

The gap between Gen Z's aspirations and the construction industry's offerings has not gone unnoticed. There is a growing body of literature urging the industry to design and implement training programs that reflect the expectations of this new generation (Maqbool et al., 2024). Cure (2023) contends that doing so is essential to attracting and retaining Gen Z talent. Similarly, Burns (2025) advocates for the modernization of training programs to cultivate the next generation of construction leaders.

To evaluate whether emerging technologies such as BIM, Gen AI, and Gen BI can help close this generational gap, it is critical to examine current peer-reviewed research. The subsequent sections will therefore explore the applications of these digital tools and their potential role in workforce transformation.

Career Development Theories Relevant to Gen Z and Construction Transitions

While prior sections highlight Gen Z's work expectations and the construction labour gap, career motivation and retention are best understood through established career development theories. To address this gap, this study draws primarily on Social Cognitive Career Theory (SCCT) and Career Construction Theory (CCT), supplemented by insights from protean and boundaryless career models.

Social Cognitive Career Theory (SCCT) (Lent et al., 1994) posits that career interests and persistence are shaped by the interaction of *career self-efficacy, outcome expectations*, and *perceived supports and barriers*. From an SCCT perspective, exposure to Gen AI and Gen BI tools may enhance individuals' confidence in their ability to perform construction-related tasks (self-efficacy), while also reshaping expectations about career outcomes, such as job satisfaction, flexibility, and professional growth.

Career Construction Theory (Savickas, 2005) emphasizes how individuals actively construct career meaning through adaptability, identity formation, and narrative sensemaking in response to changing labour markets. In technology-disrupted sectors such as construction, digital tools may serve as resources that support *career adaptability* by enabling exploration, experimentation, and re-imagining of professional roles.

In addition, protean and boundaryless career models (Hall, 2004; Arthur & Rousseau, 1996) are particularly relevant to Gen Z, whose career orientations are increasingly self-directed, values-driven, and less tied to traditional organizational hierarchies. These models help explain why Gen Z may respond positively to digital construction tools that signal transferable skills, cross-sector mobility, and continuous learning opportunities.

Together, these frameworks provide a theoretical lens for interpreting how Gen AI and Gen BI influence not only task performance, but also broader career development processes, including motivation, adaptability, and intentions to remain in or re-enter the construction sector.

BIM Applications in Construction

BIM is among the most recent and widely adopted technologies in the construction industry, yet significant efforts are still required to enhance its uptake across various regions and disciplines. As highlighted in the literature, BIM offers a robust digital framework that addresses numerous challenges in construction practice, including inefficiencies in design, cost control, scheduling, sustainability, and workforce productivity. A foundational application of BIM lies in 3D modelling—commonly referred to as 3D BIM—using authoring tools such as Autodesk Revit. Creating a 3D model is typically the first step in a BIM-enabled project, serving as the basis for more advanced applications. One such application is 4D BIM, which integrates time-related data into the 3D model to facilitate project scheduling and planning. Tools like Synchro and Vico enable the development of BIM-based construction programmes that incorporate risk variables, allowing for dynamic risk visualization and proactive mitigation (Musa et al., 2015; Musa et al., 2016).

Cost estimation represents another key dimension of BIM, known as 5D BIM. It involves the generation of cost plans linked to design elements through automated quantity takeoffs, typically aligned with standards such as the UK's New Rules of Measurement (NRM). This integration enables real-time cost tracking as designs evolve, leading to improved budgetary control and decision-making. Furthermore, the application of semantic web technologies and ontologies within BIM enhances consistency reduces human error and enables simultaneous evaluation of design alternatives in terms of cost and schedule (Abanda et al., 2015; Abanda et al., 2017a). BIM is also extensively used to address sustainability challenges, typically referred to as 6D BIM. It supports lifecycle analysis, energy simulation, and carbon footprint assessment by integrating BIM models with sustainability databases like the Inventory of Carbon and Energy (ICE). Tools such as Green Building Studio allow professionals to test the environmental impacts of different design scenarios, from material selection to building orientation (Abanda & Byers, 2016; Abanda et al., 2017b). Moreover, 6D BIM enables post-construction applications like asset management and predictive maintenance planning, ensuring long-term performance optimization (Abanda et al., 2025).

Beyond these technical domains, BIM plays a significant role in enhancing labour productivity and workforce performance. While fewer in number, existing studies collectively underscore BIM's potential in reshaping organizational structures and workforce strategies. Wu and Issa (2013) reveal that BIM implementation necessitates a strategic overhaul of talent acquisition practices, emphasizing job profiling, skills gap analysis, and industry-academia collaboration. Despite the growing demand for roles such as BIM Coordinators and Managers, the industry still lacks standardized job descriptions and competency frameworks. Case studies from Patna and Malaysia further demonstrate that BIM adoption leads to improved labour productivity by minimizing rework, improving site supervision, and fostering better coordination (Mishra & Sakale, 2025; Hashim et al., 2024). These findings align with post-pandemic strategies that advocate for digital transformation, emphasizing BIM and related technologies such as AI and wearable devices to address labour shortages and safety concerns (Nwaogbe et al., 2025).

Additionally, social media has emerged as a complementary tool to support BIM workflows. Platforms like X (formerly Twitter) and YouTube facilitate informal knowledge exchange, professional networking, and real-time collaboration through hashtags, video tutorials, and interactive comment sections. Social media aids in closing BIM-related knowledge gaps and encourages stakeholder participation, especially among fragmented project teams or non-technical actors (Durmus et al., 2023; Hodorog et al., 2019). Its integration into BIM processes can enhance communication, foster innovation, and build a more inclusive and collaborative construction environment.

Gen AI Applications in Construction

Gen AI is increasingly being applied across multiple aspects of the construction industry, offering significant improvements in efficiency, creativity, sustainability, and decision-making. In civil and structural engineering, Gen AI tools like ChatGPT and Bard have been integrated into workflows to optimize design processes. These applications include design generation, structural simulation interpretation, material research, and the development of seismic-resistant infrastructure. Engineers are using Gen AI to explore diverse design options, automate documentation, and support collaborative project management, ultimately producing safer, more efficient, and cost-effective structures (Rane, 2024).

In transportation engineering, Gen AI has enabled smarter planning and operation of systems. It supports traffic management through real-time data analysis, optimizes public transport schedules using user feedback, and aids in the design of infrastructure with reduced environmental impact. The technology also contributes to the development of autonomous vehicles by simulating human-vehicle interactions, enhancing user safety and acceptance. Furthermore, it supports predictive maintenance and supply chain logistics, leading to more responsive and sustainable transportation systems (Rane, 2024).

Environmental and water resources engineering has also benefited from Gen AI applications. In climate science, AI models analyze vast environmental datasets to support climate modelling, scenario planning, and emissions forecasting. In water resource management, Gen AI tools are used to simulate hydrological systems, optimize water infrastructure, and predict water quality. Additionally, they support sustainable waste management, enabling material recycling and circular economy practices, while also aiding in the development and evaluation of environmental policies (Rane, 2024).

In architectural design, Gen AI contributes significantly to early-phase design visualization. By generating photorealistic renderings of building façades based on textual prompts or location-specific identity models, Gen AI enhances communication between architects, clients, and communities. This is particularly useful in remodelling projects and urban planning, where visual representations help capture the aesthetic and cultural context of a location. These tools reduce the time and resources required to produce high-quality design alternatives, allowing for quicker iterations and broader stakeholder engagement (Rane et al., 2023).

Gen AI also plays a critical role in advancing sustainability in construction. Through integration with tools such as Digital Twins and simulation platforms, Gen AI can optimize energy use, reduce material waste, and support climate-resilient design. It helps identify low-carbon construction methods and encourages the use of renewable energy sources. Moreover, AI-driven monitoring systems improve site safety and efficiency by tracking performance in real time and alerting stakeholders to potential risks.

From a business and innovation standpoint, Gen AI enhances the innovation performance of construction enterprises by supporting knowledge-based dynamic capabilities (KDC) and enterprise AI capabilities (EAIC). It allows firms to rapidly prototype new ideas, access and integrate large volumes of technical knowledge, and develop more agile strategies. This leads to improved adaptability, creativity, and competitiveness in a rapidly digitalizing market. In project management, Gen AI tools like ChatGPT streamline the scheduling and planning of construction projects. They can generate logical sequences of tasks, assign resources, and suggest adjustments based on real-time feedback. These capabilities reduce the time spent on administrative work and improve communication across project teams. In simple to moderately complex projects, Gen AI provides rapid, reliable support that enhances overall project delivery.

Lastly, generative design (GD) tools powered by AI are transforming how architects and engineers approach design. By embedding performance, cost, and sustainability parameters into the design process, GD enables the creation of optimized design alternatives within BIM platforms. This integration allows stakeholders to visualize and evaluate options comprehensively, leading to smarter, data-informed decisions and a more sustainable built environment (Chew et al., 2024).

Implementation Pathways for Integrating GenAI in Construction: Systems, Processes, and Replicable Themes. Although the preceding section summarizes best-practice applications (e.g., design support, documentation, planning, sustainability analysis, and generative design), construction value is mostly realized when GenAI is embedded into organizational systems and delivery processes rather than used as isolated experiments. Recent AEC-focused reviews emphasize that implementation barriers cluster around data readiness, workflow integration, validation/assurance, governance, and skills and argue for structured implementation pathways that move from pilots to scalable adoption (Taiwo et al., 2025).

Evidence from AEC literature indicates that repeatable integration typically uses four mutually reinforcing mechanisms:

1. BIM–AI information backbone (data and interoperability): Construction organizations with stronger BIM and information management maturity can integrate AI/Gen AI more effectively because models, documents, schedules, and cost data become accessible for retrieval, traceability, and reuse. BIM-AI integration research increasingly frames implementation as a layered system (data layer → analytics layer → application layer), where information structures and interoperability determine whether AI outputs can be trusted and reused across projects (Alves et al., 2025).

2. Workflow integration via stage-gates (human verification and sign-off): Studies of LLM use in construction planning and management show that LLM outputs become practically usable when embedded into formal review and approval gates, for example, AI-drafted schedules, work breakdown structure (WBS), method statements, or risk registers are treated as “draft artefacts” that require discipline checks and benchmarking before entering contractual deliverables (Erfani and Mansouris., 2026). In schedule-oriented contexts, research also shows that LLM-generated or enhanced schedule data benefits from structured evaluation rubrics and domain checks, supporting a repeatable “generate → evaluate → correct” loop rather than one-shot automation (Singh and Hsieh, 2026).

3. Organizational implementation frameworks (capabilities & governance): Construction digital transformation research indicates that adoption is accelerated when organizations treat AI implementation as a capability-building programme, linking tools to roles, resourcing, and

routines rather than as ad hoc experimentation. For example, enterprise-level analyses of Gen AI in construction report that value is mediated through knowledge integration and knowledge absorption capabilities, implying that organizational learning processes are central to diffusion beyond early adopters (Shi et al., 2025). In parallel, Construction 4.0 and AI implementation frameworks grounded in institutional/resource-based perspectives emphasize leadership commitment, resource readiness, and institutional pressures as key levers shaping organization-wide adoption (Zhang and Wang, 2026).

4. Pilot-to-scale diffusion using adoption theory lenses: Construction adoption literature (often built around BIM) shows that diffusion is influenced by technology factors (e.g., relative advantage and complexity), organizational factors (e.g., readiness, training, and top management support), and environmental factors (e.g., clients, regulation, and competition). Scoping and conceptual studies on BIM diffusion and implementation in firms show that pilot projects including demonstrable performance gains and capability development are repeatable mechanisms for scaling digital innovations. More recent empirical work applying Unified Theory of Acceptance and Use of Technology 2/Technology-Organization-Environment (UTAUT2/TOE) to AI adoption by design engineers similarly finds that organizational readiness and perceived usefulness strongly condition uptake, reinforcing the need for structured implementation programmes rather than purely technical rollouts (Katebi & Tehrani, 2025).

The aforementioned mechanisms represent process patterns rather than one-off technological solutions and are therefore replicable across construction contexts. The AEC literature increasingly converges on four core implementation themes: (a) BIM-anchored information management to ensure traceable and reliable inputs, (b) workflow embedding with verification and approval gates to manage risk and liability, (c) capability development and knowledge management to extend adoption beyond individual champions, and (d) pilot-to-scale diffusion strategies aligned with organizational and environmental drivers (Taiwo et al., 2025).

This implementation-oriented framing directly advances the objectives of the present study by translating the preceding section catalogue of Gen AI best practices into an adoption pathway that can be systematically evaluated. Specifically, it enables analysis of (a) how Gen AI and Gen BI reshape workflows and decision-making, (b) how skills development and structured learning mechanisms influence Gen Z attraction and retention, and (c) which organizational levers facilitate scaling beyond pilot projects. In doing so, it provides a clear bridge from “what Gen AI can do” to “how firms institutionalize Gen AI and build workforce capability,” consistent with research identifying capability development and knowledge integration as key mediators of Gen AI value in construction enterprises (Shi et al., 2025).

Gen BI in Construction Practice

Traditionally, model authoring and analysis tools have been the primary means of searching and querying information within BIM models. However, these tools often present significant challenges for professionals with limited BIM expertise. Their interfaces are typically not user-friendly, and they require a steep learning curve to operate effectively. As a result, there has been a growing interest in using data analytics tools within the construction industry, particularly in integrating these tools with BIM platforms (Abanda, 2022).

This shift has sparked a surge in research on the application of Business Intelligence (BI) in construction practice. For instance, Abanda (2022) proposed a reverse engineering approach for integrating digital construction technologies specifically BIM and Microsoft tools to simplify the management of increasingly complex and heterogeneous data associated with smart cities. Similarly, Harode, Ensafi and Thabet (2022) introduced the use of Power BI dashboards to enhance access to and visualization of lifecycle data embedded within BIM models. Valinejadshoubi, Moselhi, Iordanova, Valdivieso, and Bagchi (2024) developed an integrated framework that enables the automatic extraction and visualization of construction quantities directly from BIM models. Meanwhile, Rodrigues, Alves, and Matos (2022) proposed a methodology for managing construction data through the combined use of BIM and BI analysis tools. Additionally, Al-

Sulaiti, Mansour, Al-Yafei, Aseel, Kucukvar, and Onat (2021) designed a data analytics and visualization system that supports effective project progress reporting and performance monitoring, utilizing an Entity Relationship Diagram implemented in Microsoft Power BI for analytical and visualization purposes.

Literature Findings

Gaps in Integration of BIM, Gen AI and Gen BI in Education Curriculum

Although BIM has been utilized for some time, research has predominantly emphasized its practical applications in the construction industry. Key areas of focus include sustainability (Abanda et al., 2014; Abanda et al., 2017a), cost estimation (Abanda et al., 2017b), and other technical use cases. From a pedagogical standpoint, some research has explored the integration of BIM into academic programs. Naddeh, Maya, Mahfouz, and Youssef (2025), for instance, investigated barriers to BIM adoption in architectural curricula at Tartus University, identifying institutional resistance due to weak industry-academia collaboration, outdated teaching approaches, limited resources, and insufficient faculty expertise. Papuraj, Izadyar, and Vrcelj (2025) similarly reported systemic challenges, including inconsistent curricula and a lack of interdisciplinary collaboration opportunities, which hinder students' development of consistent BIM competencies. In contrast, studies such as Abouelkhier, Shafiq, Rauf, and Alsheikh (2024) demonstrated how immersive 4D-BIM-based virtual reality (VR) tools could enhance student learning in construction project management. During the COVID-19 pandemic, Abanda, Almukhtar, and Austin (2025) examined the virtual delivery of BIM education and found that well-designed remote instruction could sustain engagement and even boost motivation among learners. However, while such studies address aspects of teaching and learning, they do not directly explore BIM's role in motivating Gen Z students toward construction careers.

Similarly, research on Gen AI and Gen BI has largely focused on their practical implementation, emphasizing *how* to apply these technologies in practice rather than *how* to integrate them into educational curricula. For example, Chew, Wong, Tang, Yip, and Maul (2024) demonstrated Gen AI's role in visualizing and evaluating design options for sustainable construction. Rane (2024) highlighted its potential to promote circular economy practices and shape environmental policymaking. In the context of Gen BI, Harode, Ensafi, and Thabet (2022) emphasized the benefits of Power BI dashboards in improving access to lifecycle data embedded in BIM models, while Abanda (2022) illustrated how Gen BI can simplify the management of complex smart city data.

Despite these advances, literature exploring the pedagogical integration of Gen AI and Gen BI, particularly within construction-related disciplines remains sparse. Some cross-disciplinary studies, however, shed light on their broader educational implications. Alasadi and Baiz (2023) examined Gen AI's transformative role in learning environments. Meli, Taouki, and Pantazatos (2024) advocated increased Gen AI literacy among educators and raised awareness of ethical implications in classroom contexts. Întorsureanu, Oprea, Bâra, and Vespan (2025) conducted a bibliometric analysis of over 3,500 academic publications to map the educational uses of Gen AI, while Khlaif, Alkouk, Salama, and Abu Eideh (2025) developed a framework for rethinking assessments in the Gen AI era. On the Gen BI side, Sorour and Atkins (2024) explored the integration of AI transformers with BI tools to support the monitoring of learning outcomes in higher education.

While these contributions highlight educational opportunities, most are either conceptual or not specific to construction disciplines. Moreover, very few studies have investigated how Gen AI and Gen BI might serve as motivational tools to attract Gen Z students to the construction industry. Exceptions include Abanda, Almukhtar, and Austin (2025), who observed improved student engagement following virtual BIM instruction, and Khlaif, Alkouk, Salama, and Abu Eideh (2025), who identified pedagogical adaptations spurred by Gen AI innovations. However, these findings were part of broader inquiries and not focused specifically on student motivation.

Research Focus

In summary, the existing body of literature primarily concentrates on the technical and professional applications of BIM, Gen AI, and Gen BI, with limited emphasis on their educational integration, particularly in construction-related disciplines. An even more critical gap exists in understanding how these technologies might actively motivate Gen Z students to enrol in construction-related courses, join the construction profession, or pursue related career pathways.

Given this dual gap, the present study will focus specifically on the latter issue: how Gen AI and Gen BI can be leveraged to actively engage and motivate Gen Z students toward the construction sector. This focus is intentional and strategic, before exploring how Gen AI and Gen BI can be embedded into higher education curricula, it is essential to first determine whether their inclusion can genuinely stimulate interest and motivation among Gen Z learners. Establishing this foundation will ensure that any subsequent curriculum integration efforts are both relevant and impactful.

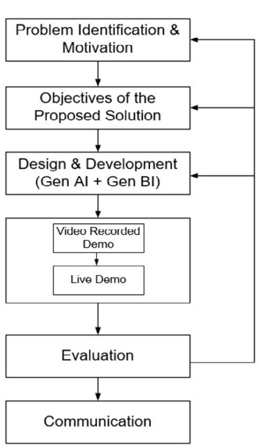
Accordingly, this study does not aim to explain technology adoption per se, nor does it claim to measure long-term career development outcomes. Rather, it examines how exposure to Gen AI and Gen BI functions as a career-relevant stimulus that shapes early career cognitions, including self-efficacy, outcome expectations, and perceived career fit. The paper therefore contributes to career development literature by illuminating how digital experiences intersect with career meaning-making during school-to-work and early-career transitions, rather than by advancing models of organizational technology adoption.

Method

According to Peffers, Tuunanen, Rothenberger, and Chatterjee (2008), the design science research methodology consists of six key stages: (1) problem identification, (2) definition of solution objectives, (3) design and development, (4) demonstration, (5) evaluation, and (6) communication (See Figure 1). The problem identification stage involves recognizing existing challenges and understanding their implications, thereby establishing a foundation for the research. This leads to the formulation of objectives aimed at addressing the identified problems. Next, the design and development phase involve creating a solution, in this case, an artefact comprising both graphical and non-graphical data that is intended to meet the specified objectives. The demonstration and evaluation phases ensure that the artefact functions as intended. The artefact is validated and rigorously tested to confirm that it aligns with the original objectives and provides measurable improvements over existing solutions. Throughout the process, data is collected and analyzed, not only to verify success but also to identify limitations, which can inform further refinements. Finally, the communication phase involves sharing the outcomes with relevant academic and professional audiences, ensuring that the knowledge generated can be tested, replicated, and applied more broadly.

Figure 1

Research Method Framework



Problem Identification and Motivation

Designing and estimating the cost of a building remains a time-intensive and fragmented process. Traditionally, the design must be completed manually or using CAD tools before it is transferred to a cost estimator, who calculates costs either manually or using tools such as Microsoft Excel. This linear, siloed approach is slow, labour-intensive, and prone to errors.

While BIM has streamlined some aspects of this workflow through 4D (time) and 5D (cost) integration, it still presents notable limitations. A typical BIM-based process begins with creating the 3D model using authoring tools such as Autodesk Revit. The model is then exported to a 5D BIM tool (e.g., iTWO CostX) for cost computation. This workflow presents several challenges:

- Client-designer communication: The process heavily relies on clients providing accurate requirements to architects. Due to clients' non-technical backgrounds, these requirements are often vague or incomplete, resulting in multiple iterations before a satisfactory design is achieved.
- Expertise shortage: BIM authoring tools and 5D BIM platforms require specialized knowledge, which is scarce in many organizations.
- Scalability issues: For multiple projects, each design must be completed and exported individually making batch processing for cost estimation time-consuming and inefficient.
- Comparative analysis limitations: Once models are developed, comparing them with similar past projects is difficult due to the lack of accessible data and standardization in assumptions and conditions.

Similarly, project scheduling (4D BIM) has traditionally relied on tools like MS Project or Primavera, often integrated manually with BIM models. To produce a 4D BIM model, the 3D design and project schedule must be developed separately and manually linked. This requires detailed technical expertise and results in a rigid model that is difficult to isolate for individual component analysis or modification. The end product is visually impressive but lacks flexibility for dynamic, scenario-based planning.

Objectives of the Solution

This study has two primary objectives:

- Automated design and estimation: To demonstrate how GenAI can be used to automate the design and cost estimation of construction projects, streamlining the process while reducing manual effort. This will serve as a foundation for investigating how such tools might increase Gen Z's engagement with construction technologies.
- Isolated and interactive 4D/5D models: To address the limitations of current 4D BIM models, this study also aims to develop a framework that allows for the isolation and independent analysis of specific building components, time-based activities, and cost data within an integrated model.

Results

Case 1: Design and Development Using Gen AI

The proposed solution addresses the identified challenges by leveraging Gen AI, implemented through ChatGPT, to automate the design and estimation process. The workflow includes the following steps:

- A well-structured prompt is submitted to ChatGPT to generate a conceptual design for a typical 3-bedroom house in the UK.
- A subsequent prompt refines the output to produce detailed 2D architectural plans.
- A final prompt is used to generate a comprehensive bill of quantities, suitable for use in competitive tender submissions.

It should be noted that outputs generated by ChatGPT are probabilistic rather than deterministic.

Consequently, the same prompt submitted by two different users, or by the same user on different days, may result in outputs that are similar in structure and intent but not identical in wording, assumptions, or numerical values. Variations may arise due to differences in prior conversational context, user-level personalization settings, and periodic system or model updates. For this reason, the outputs presented in this study are not intended to demonstrate exact reproducibility, but rather to illustrate the functional capability of Gen AI in supporting early-stage construction design, planning, and costing workflows.

Where user-specific personalization settings are enabled, ChatGPT may generate responses that are more consistent in tone, structure, or prioritization for a given user across sessions. However, such personalization does not guarantee identical outputs and may further differentiate results between users submitting the same prompt. As such, personalization enhances contextual relevance rather than output uniformity.

This AI-driven process eliminates the need for extensive client–designer back-and-forth. Clients can express their needs directly using natural language, which ChatGPT interprets and transforms into technical outputs. Moreover, unlike traditional BIM processes that require repeated modelling for multiple scenarios, prompts can be adapted once and reused, dramatically reducing development time. This approach partially assumes that clients are able to communicate their requirements using natural language; however, it does not presume perfect clarity or completeness of input. Where client requirements are vague, incomplete, or inconsistent, iterative clarification remains necessary and professional judgment is required to validate and refine AI-generated outputs. The proposed workflow therefore reduces, but does not eliminate, traditional requirement elicitation processes.

Finally, prompts can also be designed to retrieve data from similar past projects, enabling real-time benchmarking and comparative analysis, something that traditional BIM tools struggle to support.

In this study, four text prompts were utilized with DALL-E, an advanced AI system developed by OpenAI that generates images from textual descriptions within the ChatGPT environment. DALL-E merges natural language understanding with image generation capabilities, enabling users to create original, highly detailed visuals based solely on written input. The four prompts, used sequentially, are as follows:

1. Create one 3D model of a standard UK-style residential house as an image.
2. Generate the 2D floor plan with a blue floor colour.
3. Generate the cost estimate table with columns for WBS (main and sub-sections), Units, Quantity, Unit Rate, and Total Cost.
4. Create a Gantt chart to outline the work plan.

The selected prompts were intentionally designed to reflect a typical early-stage construction workflow, encompassing conceptual visualization, plan representation, cost estimation, and construction scheduling. The wording of each prompt was structured to constrain output type, format, and level of detail (e.g., specification of table columns or visual characteristics), thereby aligning the generated outputs with established construction practice. Prompt phrasing is recognized as a significant factor influencing Gen AI outputs; even minor changes in wording may affect assumptions, formatting, and scope. Accordingly, the prompts are treated as controlled inputs for methodological demonstration rather than as an exhaustive exploration of prompt engineering possibilities. The outputs from the implementation or editing of these prompts in DALL-E is presented in Figure 2.

Case 2: 4D/5D BIM with Revit and Power BI

In the second case, a BIM model is developed in Autodesk Revit and then exported to Power BI for enhanced 4D and 5D visualization. In this setup:

- The geometric model (3D) is linked to scheduling and cost data in Power BI.
- Dashboards are developed to interact with the BIM model, enabling dynamic exploration of construction sequences and cost breakdowns.
- Users can isolate and analyze specific components, making the model more versatile than traditional static BIM outputs.

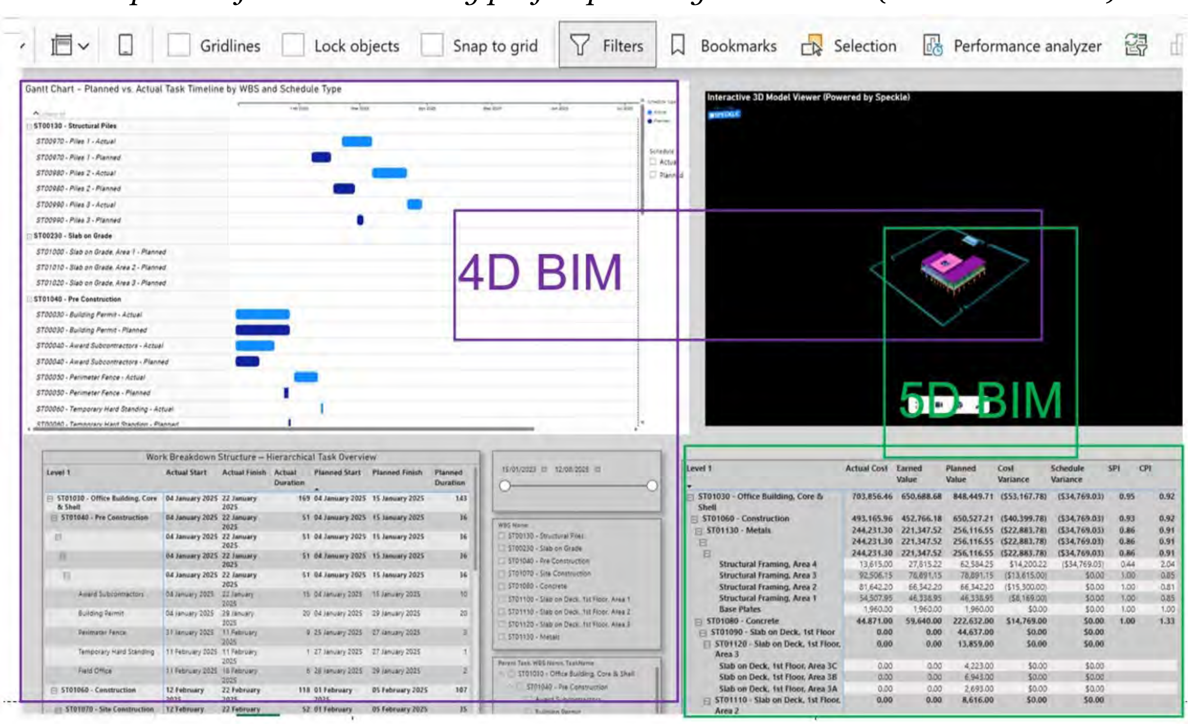
As illustrated in Figure 3, the 4D and 5D BIM dimensions are integrated with the 3D model within Power BI. This integration enables dynamic interaction between various parameters such as time, cost, and geometry, allowing users to visualize and analyze how changes in one dimension affect the others in real time. This integration of Revit with Power BI bridges the gap between design and data analytics, creating an interactive planning and estimation environment.

Figure 2

Design and Development of Cost and Building Project Planning in ChatGBT

Figure 3

Design and development of cost and building project planning in Power BI (Source: Author's)



Demonstration of Both Cases

The demonstration of the ChatGPT-based workflow was implemented and documented through a step-by-step video and live demo. Due to the novelty of the process, video materials were shared with prospective interviewees to enable thorough review prior to interviews. The demonstration followed a two-phase approach:

- Pre-interview demonstration: Participants were provided with a recorded demonstration showing the use of ChatGPT for 3D design generation, 2D plan development, and cost estimation. Similarly, they were provided with a recorded demonstration of 4D and 5D BIM in Power BI to watch before the second, online live demonstration.
- Live demonstration: Immediately before the interview, a live walkthrough of the process was conducted to reinforce understanding and clarify any uncertainties.

A total of eleven participants were purposively selected for the qualitative interviews. The question of "how many interviews are enough" remains a persistent and debated issue among qualitative researchers in the social sciences (Bekele & Ago, 2022). Similarly, the adequacy of the eleven participants chosen for this study may be questioned. As noted by Bekele and Ago (2022), there is no universally agreed-upon minimum sample size for qualitative interviews. They argue that the appropriate number depends on various factors, including the point of data saturation and the homogeneity or heterogeneity of the sample. Nonetheless, some scholars have provided empirical guidance. Guest et al. (2006) suggest that between 6 and 12 interviews may be sufficient for a single qualitative study, especially when the sample is relatively homogenous. Hennink and Kaiser (2022) also found that saturation can often be reached within a narrow range, typically between nine and 17 individual interviews, or four to eight focus group discussions, particularly in studies involving homogenous populations and narrowly defined research objectives.

While the purposive sampling strategy enabled in-depth exploration of perceptions among a digitally literate cohort, the findings are not intended to be statistically generalizable to the entire construction industry. Instead, they provide analytical insights into attitudes and perceived impacts of GenAI within a specific context. Further studies involving a broader range of construction professionals, organizational types, and geographic settings are recommended to assess the transferability of these findings.

In this study, the sample of eleven participants can be considered relatively homogenous. Five participants were millennials and six were Gen Zs. Ten of the eleven had just completed an MSc in BIM and Management from the same university (hereafter referred to as X University). All ten had studied BIM and Power BI applications and completed at least two coursework assignments related to these technologies. While none had formally completed assignments in GenAI, all had practical experience using LLMs, such as ChatGPT. Notably, three had developed ChatGPT-based tools as part of their MSc dissertations. Of these ten, five were employed full-time in UK-based construction firms, while the other five were actively seeking employment. The eleventh participant, slightly more senior, was a second-year PhD candidate with an MSc in Construction Project Management and five years of industry experience as a BIM manager. While the purposive sampling strategy enabled in-depth exploration of perceptions among a digitally fluent cohort, the findings are not intended to be statistically generalizable to the construction industry as a whole. Instead, the study offers analytical insights into how Gen AI/Gen BI exposure may shape perceptions and early career-related cognitions within a specific subgroup of emerging professionals. Accordingly, claims are bounded to this context, and transferability to other segments of the workforce (e.g., apprenticeship pathways, non-digitalized firms, or regions with lower BIM maturity) should be treated as an empirical question requiring further study.

Interpretive Scope and Participant Pre-Exposure

Because most participants had substantial prior exposure to BIM, Power BI and AI-enabled workflows (including prior coursework and, for several, building ChatGPT-based tools), their perceptions are likely shaped by this pre-exposure. Prior experience can influence perceived usefulness and ease of use and can also shape which risks users foreground, meaning themes reported here may reflect an "early-adopter" perspective rather than the views of Gen Z broadly (Davis, 1989; Venkatesh et al., 2003). Accordingly, references in this paper to "Gen Z" should be read as referring to digitally fluent emerging professionals in construction-related graduate education.

Transferability to Entry-Level and Apprenticeship Populations

The findings are therefore most transferable to emerging professionals (i.e., graduate trainees and early-career roles) and not necessarily to entry-level, apprenticeship, or earlier-stage learners whose training environments, task contexts, and access to digital tools can differ markedly (Lincoln & Guba, 1985). In less digitally privileged contexts, limited access to devices, licensed software and structured instruction may alter both the perceived benefits and barriers of Gen AI/Gen BI, consistent with evidence on digital inequality and the "second-level digital divide" (Hargittai, 2010; van Dijk, 2020).

Implications and Future Work

Readers should therefore interpret reported motivational effects as indicative of how Gen AI/Gen BI may be perceived by digitally literate, construction-focused graduates. Future research should extend sampling to: (a) apprenticeship and college-level trades programmes, (b) earlier-stage learners, and (c) organizations with lower BIM maturity, to assess whether similar motivation and retention mechanisms hold under different conditions (Patton, 2015; Succar, 2009).

Given the similarities in academic background, technological exposure, and professional orientation, the sample can reasonably be considered homogenous. Thus, the choice of eleven interviewees is justified and aligns well with recommendations from Guest, Bunce, and Johnson (2006) and Hennink and Kaiser (2022).

Evaluation of Both Cases. An evaluation was conducted immediately following the live demonstration. Participants were invited to share their perceptions of the workflow's usability, accuracy, and potential to improve design and project planning estimation processes in Gen AI and Gen BI. The approach building on recorded videos and just after a life demonstration ensured that feedback was grounded in a clear and recent understanding of the workflow, thereby enhancing the reliability and validity of the responses.

Communication of Findings. This manuscript serves as the primary vehicle for disseminating the findings of this study. It aims to inform both academic researchers and industry professionals about the potential of GenAI and BI tools to transform construction project planning and cost estimation while also exploring their role in inspiring the next generation of construction professionals.

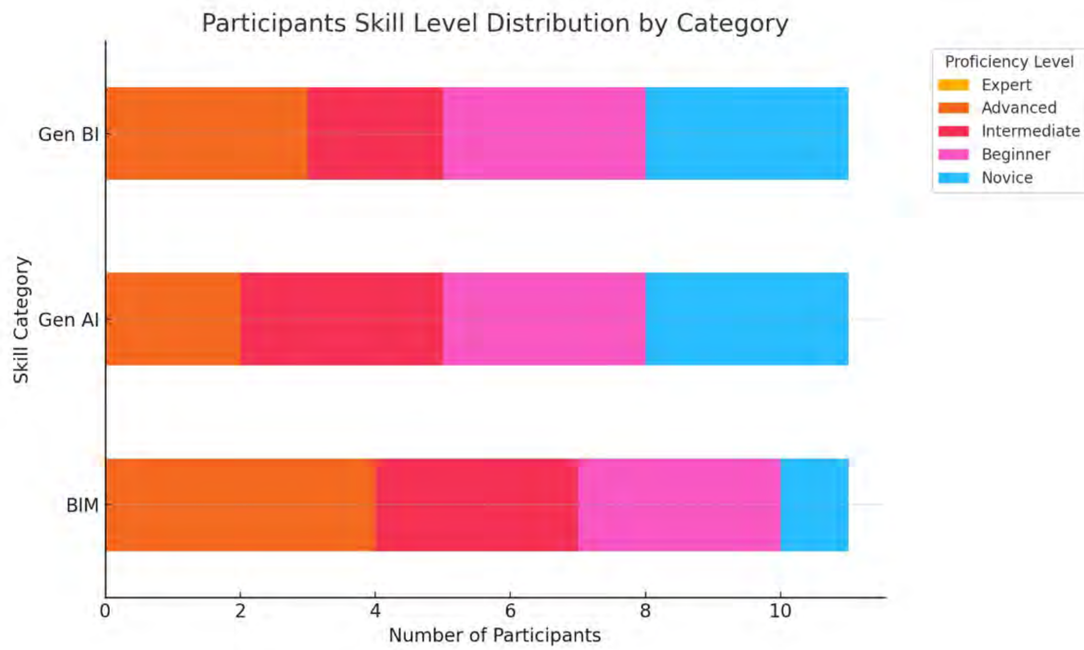
Methodological Considerations and Limitations. This study is subject to several limitations First, GenAI outputs may vary due to non-deterministic model behaviour and system updates. Second, participant responses may reflect novelty effects associated with emerging technologies. Third, the relatively homogenous participant profile limits direct transferability to the wider construction industry. Despite these limitations, the study provides valuable exploratory insights into the perceived role of Gen AI and Gen BI in contemporary construction practice. Finally, the small and relatively homogenous sample limits generalizability; therefore, findings should be interpreted as exploratory and mechanism-oriented, serving as a foundation for subsequent studies with broader and more heterogeneous industry populations.

Discussion

As discussed in the Demonstration section, the eleven interviewees constituted a relatively homogenous group. Ten of them had recently completed an MSc in BIM and Management at the same university, while the eleventh participant was pursuing a PhD in Digital Twins at the same institution. Although his MSc was in Construction Project Management from a different university, he brought five years of industry experience as a BIM manager, which further contributed to the group's overall relevance and coherence. The level of experience of the participants in BIM, Gen AI and Gen BI are presented in Figure 4.

Figure 4

Skill Levels of Interviewees



Despite their shared academic background and having completed coursework in both BIM and Gen BI, the participants tended to be conservative in their self-assessment of skill levels. As illustrated in Figure 4, none of them identified as experts. When probed further, two interviewees explained that, in their view, an "expert" is someone with extensive, hands-on industry experience in a specific domain over several years. According to the data shown in Figure 4, only one participant considered themselves a novice in BIM, while three identified as novices in Gen AI and Gen BI. This cautious self-evaluation reflects a level of humility and realism, which enhances the credibility and trustworthiness of their responses. A comprehensive breakdown of the analysis of their responses is presented in the ensuing section.

The Usability and Impact of Gen AI and Gen BI in Construction Workflows

This study examined the practical applications and perceived value of Gen AI and Gen BI tools in construction workflows, specifically focusing on their implementation in cost planning (5D BIM) and project planning (4D BIM) through ChatGPT and Power BI demonstrations. The findings reveal three key dimensions of user experience and technological impact.

Initial Reactions to Gen AI in Construction Planning

Participants reported overwhelmingly positive first impressions of Gen AI's capabilities in handling complex construction tasks. Nine of the eleven interviewees described the demonstrations as "impressive" or "amazing," particularly noting the speed and simplicity of generating cost estimates and project plans through simple prompts. Interviewee 5 marvelled at the ability to produce comprehensive outputs, including 3D models, 2D plans, and cost estimations from a single input, while Interviewee 6 emphasized the dramatic time savings compared to traditional methods.

The technology was widely perceived as a valuable support tool, with eight participants characterizing it as a "smart assistant" or "starting point." Participant 9 noted its particular usefulness for early-stage planning and less experienced professionals, where perfect accuracy is less critical. However, this enthusiasm was tempered by significant concerns about practical implementation. Seven participants questioned the absolute accuracy of outputs, with Interviewee 5 arguing that its accuracy was around 30%, emphasizing the need for training with real-world data. This aligns with a study by Aladağ (2023) that ChatGPT was less accurate in identifying construction risk.

All the 11 interviewees revealed four critical limitations affecting Gen AI's reliability:

- Need for human verification of automated outputs: With respect to the comparison between AI-generated (projected) outputs and real-world (actual) construction results, participants noted that the demonstrations provided indicative rather than validated outcomes. While Gen AI outputs were perceived as directionally plausible and useful for early-stage planning, cost approximation, and scenario exploration, interviewees emphasized that these results had not been benchmarked against completed projects or post-construction data. As such, the AI-generated outputs were understood as conceptual and exploratory rather than predictive or contractually reliable. This limitation highlights the need for future research that systematically compares Gen AI-assisted estimates and schedules with actual project performance data across multiple case studies.
- Inability to account for real-world complexities like lead times and site conditions.
- Potential to generate misleading information without proper oversight: Several participants further cautioned against over-reliance on Gen AI outputs, particularly given the technology's susceptibility to hallucinations, oversimplifications, and contextually inappropriate assumptions. Interviewees emphasized that while Gen AI can rapidly generate plausible construction-related outputs, these outputs cannot be treated as authoritative without professional validation. This reinforces the continued necessity of human oversight and domain expertise to interpret, verify, and contextualize AI-generated results, especially in safety-critical and cost-sensitive construction decision-making. Participants therefore viewed Gen AI not as a replacement for professional judgement, but as an augmentative tool whose value depends on informed human control.
- Data dependency—outputs heavily reliant on input quality ("garbage in, garbage out"): This limitation highlights a critical dependency between Gen AI performance and the quality, structure, and contextual richness of user prompts. While participants acknowledged the efficiency gains offered by Gen AI, they consistently emphasized that poorly defined or incomplete inputs could lead to inaccurate, misleading, or oversimplified outputs. This finding underscores a key reliability constraint of Gen AI in construction workflows and indicates a need for further empirical investigation into prompt engineering standards, domain-specific training datasets, and validation mechanisms. Future research should examine how structured prompting frameworks and hybrid human–AI verification models can mitigate these risks in real-world construction contexts.

In addition to interviewees' factors that affect reliability, updates to GenAI systems may influence response patterns over time. In this study, reliability is therefore interpreted at the level of task performance, namely, the model's continued ability to generate concept designs, planning artefacts, cost structures, and schedules, rather than at the level of exact textual or numerical equivalence across sessions.

Despite these limitations, participants reported a transformed perception of traditional construction tasks. Specifically, tasks such as cost estimation, scheduling, and sequencing, previously perceived as manual, time-intensive, and cognitively demanding were reframed as higher-level analytical and decision-support activities when assisted by Gen AI. Participants noted that automation reduced repetitive effort, allowing greater focus on interpretation, scenario evaluation, and strategic judgement. This shift altered how participants valued these tasks, positioning them as intellectually engaging rather than operationally burdensome. Eight interviewees described cost estimation and sequencing as significantly easier and less tedious when assisted by AI, allowing professionals to focus on higher-value decision-making rather than manual calculations.

The Transformative Potential of Gen BI in BIM Implementation

The integration of BIM data with Gen BI tools emerged as particularly impactful, with nine of eleven participants reporting enhanced clarity in project planning and cost management. The visualization capabilities of Power BI were universally praised for transforming complex data into accessible, interactive formats. These findings are consistent with the recent study by Mingsamorn and Singhuang (2024), which demonstrated that Power BI's interactive dashboards are not only user-friendly but also significantly enhance users' ability to comprehend and interpret complex project information. One of the interviewees characterized these tools as "empowering exploratory instruments," which captured the general sentiment. Key features that drove user engagement included:

- Dynamic linking between 3D models and dashboard data.
- Advanced scenario simulation and predictive analytics.
- Intuitive filtering and data slicing capabilities.
- Real-time KPI tracking and visualization.
- Efficient resource management interfaces.

The unanimous agreement on improved decision-making accessibility was particularly noteworthy. Professionals at all technical levels reported benefits, with non-technical stakeholders especially appreciating the ability to understand project status visually rather than through traditional reports. Interviewee 9 and Interviewee 2 highlighted the tools' value in improving meeting efficiency and team coordination.

The Professional Impact: Empowerment vs. Displacement Concerns

The study revealed a strong consensus (eight of eleven participants) that these technologies are fundamentally empowering for construction professionals. Interviewee 3's observation that "it's not taking jobs away; it's changing what those jobs look like" encapsulated this perspective. Participants emphasized how automation liberates professionals from repetitive tasks, enabling greater focus on innovation and strategic thinking. This perspective is supported by Zirar, Ali, and Islam (2023), who observed that automation enables individuals to engage more fully in the creative and strategic dimensions of their roles.

However, three interviewees raised concerns about potential job displacement, especially for professionals who are reluctant or slow to upskill. This concern is echoed by Willcocks (2020), who argued that a lack of continuous reskilling may lead to job losses as technological advancements reshape the workforce. Interviewee 2 warned of threats to those who fail to update their skills, while Interviewee 11speculated about possible role reductions in certain specialties. These concerns highlight the importance of continuous learning and adaptation in the evolving technological landscape.

While participants frequently described increased confidence after interacting with Gen AI and Gen BI tools, this confidence reflects task-level assurance and perceived competence with digital workflows, rather than established measures of career self-efficacy, which typically require longitudinal assessment and validated instruments. Accordingly, the findings are interpreted as indicative of perceived empowerment and reduced task anxiety, not as evidence of durable career self-efficacy.

The Influence of Gen AI and Gen BI on Career Motivation and Skills Development

In this study, career motivation refers to participants' self-reported interest and enthusiasm toward construction careers following exposure to Gen AI and Gen BI demonstrations. Engagement denotes immediate cognitive and emotional involvement during and after the demonstrations, reflected through expressed curiosity, excitement and perceived relevance. Retention intention is used cautiously to describe participants' stated willingness to remain in or return to the construction sector, rather than verified long-term career commitment. The study pursued three key objectives to understand how exposure to Gen AI and Gen BI tools influence the career aspirations of Generation Z in the construction industry.

First, the research sought to examine how exposure to these advanced digital tools shapes career aspirations among Gen Z professionals. The findings revealed overwhelmingly positive attitudes, with all eleven interviewees expressing optimism about the industry's future. Participants consistently described construction as undergoing a "digital transformation," evolving into a more data-driven field that appeals to tech-savvy individuals. Interviewee 7 characterized the sector as being in a "stage of digital transformation," while Interviewee 8 emphasized that these tools "open a lot of possibilities" in professional practice. Interviewee 11 further noted that the rapid adoption of such innovations creates a sense of urgency, as "nobody wants to be left out." This reflects how digital tools are transforming perceptions of careers in construction, making the sector more appealing to a generation that prioritizes technological integration. This view aligns with Bolpagni, Gavina, Ribeiro, and Arnal (2022), who highlight the evolving image of the construction industry through digitalization, and is further supported by Ma & Fang (2024), who emphasize that technology-driven environments resonate strongly with younger professionals.

Second, the study investigated whether digital tool adoption strengthens retention intentions among Gen Z professionals. Interpreted through a SCCT lens, participants' reactions suggest that Gen AI and Gen BI primarily influence career self-efficacy and outcome expectations rather than long-term career commitment. Participants frequently described feeling more capable of engaging with complex construction tasks after exposure to these tools, indicating increased task-specific self-efficacy. At the same time, Gen AI and Gen BI reshaped outcome expectations by portraying construction careers as technologically advanced, intellectually engaging, and aligned with Gen Z's preferences for innovation and flexibility.

From a Career Construction Theory perspective, the findings also reflect early-stage processes of career adaptability, particularly concern (future orientation), curiosity (exploration of new roles), and confidence (belief in managing career challenges). Exposure to AI-enabled workflows enabled participants to reframe construction work from manual and rigid to adaptive and future-oriented, supporting identity reconstruction rather than mere task appreciation. Importantly, while participants expressed strong enthusiasm and intentions to remain in or return to the construction sector, these responses should be interpreted as proximal motivational indicators rather than evidence of stable career trajectories. Consistent with career development theory, durable career commitment typically emerges through repeated mastery experiences and institutional support over time.

Importantly, participants' narratives suggest that Gen AI and Gen BI exposure influences not only perceived competence but also career identity and perceived career viability. Several interviewees described feeling more "future-ready" and better aligned with emerging professional roles that combine construction expertise with data analytics and AI-supported decision-making. These perceptions reflect early identity alignment, whereby individuals begin to see their skills, interests, and values as compatible with a given occupational domain. However, consistent with career development theory, these effects should be interpreted as proximal motivational indicators rather than evidence of stable or long-term career trajectories, which typically require repeated mastery experiences and institutional reinforcement over time.

The responses indicated a clear trend: exposure to Gen AI and BI tools reinforced participants' commitment to the industry. All interviewees expressed a strong inclination toward roles involving AI or BI, with Interviewee 7 describing such specializations as a "natural extension" of their professional interests. Notably, nine out of eleven participants reported that the demonstrations strengthened their interest in remaining in or returning to the construction sector. Interviewee 3, for instance, viewed this shift as a "golden period" for the industry, while Interviewee 11highlighted how these tools lower barriers to entry by simplifying complex tasks for newcomers. These insights underscore the potential of digital tools to mitigate attrition rates by aligning career pathways with Gen Z's expectations for innovation and efficiency (Ling & Lew, 2024).

Finally, the study explored participants' willingness to pursue advanced training in AI and BI tools to enhance their professional capabilities. The results were unequivocal: all eleven interviewees expressed a strong desire for further training in digital construction technologies. Interviewee 6 deemed such upskilling "mandatory," framing it as an inevitable requirement for future relevance in the industry. Interviewee 7 similarly emphasized its importance for maintaining competitiveness and making meaningful contributions.

This unanimous interest in continuous learning reflects Gen Z's recognition of technological proficiency as a critical career enabler, as well as their proactive approach to adapting to industry advancements. This perspective is consistent with Ali (2023), who highlights Gen Z's strong inclination toward lifelong learning as a strategy for thriving in a rapidly transforming professional landscape.

The findings suggest that Gen AI and Gen BI serve as a powerful catalyst for career motivation primarily through experiential exposure rather than pre-existing perceptions. For most participants, the catalyst was not an abstract awareness of AI, but direct interaction with live demonstrations that revealed tangible, construction-specific applications. The results further indicate that optimal outcomes emerge from a socio-technical combination of three elements: (a) the technology's capabilities, (b) the user's domain knowledge and critical judgement, and (c) the quality of prompts used to translate intent into actionable outputs. This interaction underscores that Gen AI effectiveness is not technologically deterministic but co-produced through human—AI collaboration. By aligning the industry with digital innovation, these technologies not only reshape career aspirations but also foster a culture of continuous learning and professional growth. For industry stakeholders, these insights highlight the importance of integrating advanced digital tools into both workplace practices and educational frameworks to meet the expectations of the next-generation workforce.

Strategies for Industry and Higher Education to Foster Digital Adoption

This section's findings reveal critical insights into how higher education institutions and the construction industry can better prepare students, particularly Gen Z to embrace the sector by cultivating interest in Gen AI and Gen BI. The discussion is structured around three key areas of intervention.

First, the research examined how higher education institutions should adapt to prepare students for a digitally transformed construction industry. Participants emphasized the need for curricula that bridge theory and practice through hands-on experience with cutting-edge tools. Seven interviewees strongly advocated embedding real-world technologies like BIM, AI, and BI into coursework, complemented by project-based learning. As Interviewee 3 and Interviewee 5 noted, this requires annual curriculum updates to keep pace with technological advancements. Two participants emphasized the importance of interdisciplinary collaboration and industry partnerships, particularly through guest lectures and internship opportunities. This perspective is supported by Adekunle, Oyeyipo, Aigbavboa, Ebekozien, Aliu, and Ejohwomu (2026), who advocate for the involvement of industry professionals in delivering BIM-focused guest lectures. Similarly, Mohamed, Arabaine, Botchway, and Daoud (2025) highlight the value of internship experiences, noting that they play a vital role in helping students bridge the gap between theoretical knowledge acquired in the classroom and practical application in the industry. Notably, Interviewee 10 and Interviewee 6 called for greater emphasis on programming and Gen AI fundamentals, with Interviewee 2 suggesting such training should begin as early as primary school. However, as Interviewee 2 and Interviewee 11cautioned, these efforts depend on faculty development. Universities must prioritize training educators to ensure they can effectively teach these evolving technologies.

Second, the study identified best practices for construction firms to attract Gen Z talent through technology-driven workplace cultures. Nine participants stressed that companies must visibly champion digital adoption, whether through BIM implementation, drone use, or AI-powered chatbots. Flexible work arrangements and clear career progression paths emerged as crucial differentiators, mentioned by two interviewees. This aligns with Ling and Lew (2024) and Ayoobzadeh, et al (2024), who found that job flexibility is the most important motivator for Gen Z. Gen Zs (often called Zoomers) increasingly prefer hybrid work arrangements that combine fieldwork with desk-based tasks, offering a balance between autonomy and engagement. Four others emphasized that Gen Z prioritizes purpose-driven work, urging firms to highlight their commitments to sustainability, diversity, and social impact. Three participants specifically called for increased investment in emerging technologies and more transparent communication about innovation initiatives. As Interviewee 9 and Interviewee 2 observed, overcoming the industry's outdated "dirty and manual" reputation requires rebranding construction as a tech-forward field a shift that demands both internal changes and external messaging. Leadership plays a pivotal role in this transformation: six interviewees urged executives to model openness to change, while four emphasized co-creation with young professionals to align workplace practices with Gen Z expectations.

Lastly, the findings explored methods to reshape public perceptions of construction through strategic showcasing of digital tools. Eight participants believed that highlighting technologies like Gen AI and BI could redefine the industry's image from "dirty and dangerous"to "digital and dynamic," as Interviewee 7 phrased it. Interviewee 10 noted that emphasizing the sector's overlap with data science and AI could attract talent from unrelated disciplines. For outreach, Interviewee 8 and Interviewee 2 recommended leveraging platforms like Instagram and TikTok to demonstrate innovation, while others advocated for open-door events to demystify the industry. These efforts, Interviewee 9 noted, must be sustained over time to counteract deep-seated stereotypes.

These findings reflect immediate post-demonstration perceptions and stated intentions. They should not be interpreted as evidence of long-term retention or career commitment. Future work could test whether early enthusiasm translates into sustained career outcomes using longitudinal designs and validated instruments.

Given that this study examined Gen Z experiences primarily within degree-based programmes, it is also important to consider what the findings imply for apprenticeship and other non-degree pathways. From a career development perspective, apprenticeship and non-degree pathways represent critical mechanisms for school-to-work transitions, particularly in applied sectors such as construction (OECD, 2010; Schoon & Heckhausen, 2019). Career Construction Theory emphasizes that learning-through-doing contexts support career adaptability and identity formation, especially when individuals develop career meaning through practical experiences and evolving work roles (Savickas, 2005; Savickas, 2013). Participants' enthusiasm for hands-on interaction with Gen AI and Gen BI tools suggests that digitally enriched apprenticeships may enhance both skill acquisition and career meaning by expanding opportunities for exploration and competence development in authentic work tasks (Fuller & Unwin, 2004; Savickas, 2013). Embedding AI-enabled planning, visualization, and data interpretation tasks into apprenticeships can support mastery experiences and strengthen career self-efficacy, a core mechanism in Social Cognitive Career Theory (SCCT) particularly for early entrants who may otherwise perceive construction as limiting or outdated (Lent et al., 1994; Bandura, 1997). Moreover, digitally augmented non-degree pathways align with protean and boundaryless career orientations by enabling individuals to accumulate portable, technology-enabled competencies that are transferable across employers and roles (Arthur & Rousseau, 1996; Hall, 2004). This reframing, positions apprenticeships not as secondary alternatives to university education, but as viable, future-oriented career pathways capable of attracting and retaining Gen Z talent in a digitalizing construction sector (OECD, 2010; Hall, 2004).

These strategic implications are further interpreted in the ensuing section through established career development theories, with particular attention to career mechanisms and equity considerations.

Career Development, Career Mechanisms, and Equity Implications of Gen AI and Gen BI

The findings indicate that Gen AI and Gen BI function as both career attractors and career scaffolding mechanisms, serving distinct but complementary roles in early career development. As career attractors, these technologies enhance the symbolic and experiential appeal of construction careers by aligning the sector with Gen Z's technological fluency, values, and expectations of modern work. Participants consistently described construction as becoming more innovative, data-driven, and intellectually stimulating following exposure to AI-enabled workflows, suggesting that technology plays a critical role in reshaping occupational image and initial career interest. At the same time, Gen AI and Gen BI operate as career scaffolding mechanisms by lowering perceived barriers to entry and reducing task-related cognitive load. By automating or simplifying complex planning, costing, and data interpretation tasks, these tools enable early mastery experiences that support confidence building and exploration. From an SCCT perspective, such mastery experiences strengthen self-efficacy, while from a Career Construction perspective, they support adaptability by enabling experimentation with emerging professional roles. The dual function of attraction and scaffolding helps explain why participants expressed both heightened enthusiasm and stronger intentions to remain in or return to the construction sector following hands-on exposure.

While the findings highlight the motivational potential of Gen AI and Gen BI, they also raise important considerations related to equity and access. The participant group consisted primarily of digitally fluent graduates with prior exposure to BIM, BI, and AI-enabled tools, positioning them as early adopters. Consequently, the observed motivational and identity-related effects may not readily generalize to underrepresented or marginalized youth who lack similar access to advanced education, licensed software, or structured digital training. From a career development standpoint, unequal access to formative learning experiences may constrain self-efficacy development and limit perceived career viability, reinforcing existing inequalities in construction career pathways. These findings underscore the importance of inclusive strategies, such as digitally enriched apprenticeships, open-access learning platforms, and employer-supported upskilling to ensure that AI-enabled transformation serves as a democratizing force rather than a new form of career gatekeeping.

Conclusion

The construction industry stands at a critical juncture, facing the dual challenge of a widening skills gap and a persistent image problem. For decades, the sector has struggled to attract and retain young talent, and, with an increasing number of experienced professionals retiring, the urgency for transformation has become more pronounced. The rise of digital technologies, particularly Gen AI and Gen BI, presents a unique opportunity to reverse these trends. By strategically integrating these tools into education systems and workplace practices, the industry can reinvent itself to better align with the interests, values, and digital fluency of Gen Z.

This opportunity arises during a time of broader global disruption. As the adage goes, “Never let a good crisis go to waste.” Geopolitical tensions and a move toward isolationist policies have led to restricted labour mobility, exacerbating workforce shortages in construction. However, these constraints can also serve as a catalyst for transformation. Digital tools such as BIM, Gen AI, and Gen BI offer immense potential to increase productivity, bridge the skills gap, and improve efficiency. At the same time, the general reluctance of recent graduates to enter or stay in the construction industry raises the important question: can their strong affinity for technology be used as a “carrot” to engage and retain them?

This study set out to explore that very question through three main objectives. First, it evaluated the usability and impact of Gen AI and Gen BI within construction workflows. Second, it investigated how digital tools influence career motivation and skills development among young professionals. Third, it proposed actionable strategies for both educational institutions and industry leaders to foster digital adoption. The research revealed that Gen AI was perceived as highly effective in automating routine tasks such as cost estimation and project scheduling, while Gen BI improved data interpretation and supported more informed decision-making processes. Given the qualitative design and purposive sample of eleven digitally fluent, construction-related emerging professionals, the findings should not be interpreted as representing the construction industry at large. Rather, they provide a proof-of-concept indication of how technology exposure may shape perceptions, motivation, and career-related beliefs, warranting validation through larger and more diverse samples.

These conclusions are grounded in interviews with a small, purposively selected sample of digitally fluent, construction-related graduate participants, many of whom had prior exposure to BIM, BI, and AI-enabled tools. Accordingly, references to increased attraction or retention should be interpreted as context-specific perceptions rather than as evidence of broad Gen Z engagement or sustained career commitment across the construction workforce. The findings reflect immediate post-demonstration responses and should be understood as exploratory rather than generalizable to all Gen Z entrants, particularly those in apprenticeship or earlier-stage training pathways.

These conclusions are grounded in interviews with digitally fluent, construction-related graduate participants, many of whom had prior exposure to BIM/BI and practical experience with AI tools. As such, findings should be interpreted as reflecting perceptions of emerging professionals rather than the full diversity of Gen Z entrants to construction, particularly apprenticeship or earlier-stage learners who may face different access constraints and training needs (Lincoln & Guba, 1985; Hargittai, 2010).

More importantly, this study should be understood as a proof-of-concept examination of how Gen AI and Gen BI may function as career-relevant stimuli within construction, rather than as a definitive assessment of long-term attraction or retention outcomes. This study captures immediate post-demonstration perceptions rather than longitudinal career outcomes. While participants articulated strong enthusiasm and anticipated career alignment with digitally enabled construction roles, such perceptions should not be interpreted as evidence of sustained career commitment or retention. Future research should employ longitudinal designs and validated career development instruments to examine whether early enthusiasm translates into long-term career trajectories.

To harness this potential, universities must modernize their curricula and prioritize faculty development to keep pace with digital innovation. The implications of these findings differ across higher education, apprenticeship pathways, and industry practice. For higher education, the findings highlight the importance of experiential exposure to AI- and BI-enabled construction workflows within curricula, supported by faculty development and interdisciplinary learning environments. Such exposure appears to shape early career self-efficacy and perceived career viability rather than technical competence alone. For apprenticeships and non-degree pathways, the findings suggest that digitally enriched learning-through-doing environments may play a critical role in supporting career adaptability and identity formation, particularly for learners who might otherwise perceive construction as outdated or limiting. Embedding AI-supported planning, visualization, and data interpretation tasks into apprenticeships could strengthen mastery experiences and confidence during early school-to-work transitions. For industry, the findings underscore the need for structured digital upskilling, visible commitment to human-AI complementarity, and career pathways that integrate technological capability development with professional progression, rather than treating digital tools as isolated productivity enhancements. These findings suggest that future construction education and industry adoption strategies should prioritize experiential AI exposure and prompt literacy alongside technical tool deployment. Incorporating hands-on labs, interdisciplinary projects, and real-world applications of AI and BI technologies will not only enrich the learning experience but also demonstrate the relevance of construction careers in a tech-driven world. For employers, success lies in adopting a culture of continuous learning, investing in staff training, and embedding smart technologies into day-to-day operations. Rebranding the construction industry through social media campaigns, virtual showcases, and strategic storytelling can help reshape public perception, making the sector more appealing to digitally inclined young people.

However, while the integration of Gen AI and Gen BI offers exciting possibilities, it must be approached with caution. Domain knowledge and traditional construction workflows should not be discarded in the rush to digitize. Instead, these innovations should complement conventional practices, ensuring that foundational principles are preserved for quality assurance and accountability. As highlighted by Mai, Doan, and Ghaffarian Hoseini (2025), multitasking and hybrid workflows are essential in modern construction settings. Over-reliance on AI systems, particularly those susceptible to hallucination or error, underscores the importance of human oversight and domain expertise.

From a career development perspective, this study contributes to research and practice in three key ways. First, it extends Social Cognitive Career Theory and Career Construction Theory into a digitally disrupted construction context, demonstrating how experiential exposure to emerging technologies shapes self-efficacy, outcome expectations, and early career identity. Second, it conceptualizes Gen AI and Gen BI not merely as productivity tools, but as career attractors and scaffolding mechanisms that support exploration, confidence-building, and perceived career viability. Third, it offers practical insight for educators, training providers, and employers seeking to design digitally inclusive career pathways that support early-career development while avoiding technology-driven gatekeeping.

The findings underscore the need for a balanced, human-centric approach to digital transformation. Gen AI and Gen BI should be viewed not as replacements for human skills but as powerful tools that augment expertise and enhance communication between technical and non-technical stakeholders. Their successful implementation requires careful change management, strong organizational support, and sustained investment in both data infrastructure and workforce capabilities. Ultimately, the construction industry's ability to attract and retain the next generation will depend on how effectively it integrates technological innovation with cultural renewal, educational reform, and a compelling new narrative for the future of work. As Lingard, Turner, and Pirzadeh (2025) suggest, such alignment may inspire young people to view construction not merely as an option, but as the industry of choice. As such, the study provides an empirically grounded starting point for future longitudinal and comparative research examining how digitally mediated experiences influence career development trajectories across diverse construction education and training contexts.

References

Abanda, F. H. (2022). Reverse engineering for digital twinning of climate smart cities. In B. Barroca (Ed.), *BIM et enjeux climatiques* (EDUBIM 2022): Ingénierie et architecture/enseignement et recherche (pp. 5–15). Eyrolles.

Abanda, F. H. (2025). *Digital technologies for engineering construction information productivity*. Routledge. https://doi.org/10.1201/9781003476740

Abanda, F. H., Almukhtar, A., & Austin, M. (2025). Lessons from the virtual delivery of building information modelling modules in the COVID-19 era. *Buildings*, *15*(2), Article 215. https://doi.org/10.3390/buildings15020215

Abanda, F. H., & Byers, L. (2016). An investigation of the impact of building orientation on energy consumption in a domestic building using emerging BIM (Building Information Modelling). *Energy*, *97*, 517–527. https://doi.org/10.1016/j.energy.2015.12.135

Abanda, F. H., Kamsu-Foguem, B., & Tah, J. H. M. (2015). Towards an intelligent ontology construction cost estimation system: Using BIM and new rules of measurement techniques. *International Journal of Industrial and Manufacturing Engineering*, *9*(1), 294–299. https://doi.org/10.5281/zenodo.1099290

Abanda, F. H., Kamsu-Foguem, B., & Tah, J. H. M. (2017a). BIM – New rules of measurement ontology for construction cost estimation. *Engineering Science and Technology, an International Journal*, *20*(2), 443–459. https://doi.org/10.1016/j.jestch.2017.01.007

Abanda, F. H., Nkeng, G. E., Tah, J. H. M., Ohandja, E. N. F., & Manjia, M. B. (2014). Embodied energy and CO2 analyses of mud-brick and cement-block houses. *AIMS Energy*, *2*(1), 18–40. https://doi.org/10.3934/energy.2014.1.18

Abanda, F. H., Oti, A. H., & Tah, J. H. M. (2017b). Integrating BIM and new rules of measurement for embodied energy and CO2 assessment. *Journal of Building Engineering*, *12*, 288–305. https://doi.org/10.1016/j.jobe.2017.06.017

Abouelkhier, N., Shafiq, M. T., Rauf, A., & Alsheikh, N. (2024). Enhancing construction management education through 4D BIM and VR: Insights and recommendations. *Buildings*, *14*(10), Article 3116. https://doi.org/10.3390/buildings14103116

Adekunle, S. A., Oyeyipo, O., Aigbavboa, C. O., Ebekozien, A., Aliu, J., & Ejohwomu, O. A. (2026). A practical approach to teaching emerging technologies: A case of BIM. *Engineering, Construction and Architectural Management*, *33*(4), 2827–2839. https://doi.org/10.1108/ECAM-10-2024-1366

Ahmed, A. (2024, February 27). *Fewer workers means fewer homes: Fixing the construction labour shortage*. Policy Magazine. https://www.policymagazine.ca/fewer-workers-means-fewer-homes-fixing-the-construction-labour-shortage

Aladağ, H. (2023). Assessing the accuracy of ChatGPT use for risk management in construction projects. *Sustainability*, *15*(22), Article 16071. https://doi.org/10.3390/su152216071

Alasadi, E. A., & Baiz, C. R. (2023). Generative AI in education and research: Opportunities, concerns, and solutions. *Journal of Chemical Education*, *100*(8), 2965–2971. https://doi.org/10.1021/acs.jchemed.3c00323

Ali, S. S. (2023). The future of work in the age of automation: Exploring new roles and opportunities. *Al-Behishat Research Archive*, *1*(1), 55–62. https://al-behishat.com/index.php/20/article/view/8

Al-Sulaiti, A., Mansour, M., Al-Yafei, H., Aseel, S., Kucukvar, M., & Onat, N. C. (2021). Using data analytics and visualization dashboard for engineering, procurement, and construction project's performance assessment. In *2021 IEEE 8th International Conference on Industrial Engineering and Applications*

(ICIEA) (pp. 207–211). IEEE. https://doi.org/10.1109/ICIEA52957.2021.9436728
Alves, J. L., Palha, R. P., & Almeida Filho, A. T. de. (2025). Towards an integrative framework for BIM and artificial intelligence capabilities in smart architecture, engineering, construction, and operations projects. *Automation in Construction*, *174*, Article 106168. https://doi.org/10.1016/j.autcon.2025.106168
Arthur, M. B., & Rousseau, D. M. (Eds.). (1996). *The boundaryless career: A new employment principle for a new organizational era*. Oxford University Press.
Ayoobzadeh, M., Schweitzer, L., Lyons, S., & Ng, E. (2024). A tale of two generations: A time-lag study of career expectations. *Personnel Review*, *53*(7), 1649–1665. https://doi.org/10.1108/PR-02-2022-0101
Bandura, A. (1997). *Self-efficacy: The exercise of control*. W. H. Freeman.
BDO Canada. (2023, September 21). *Reshaping the construction industry for Gen Z talent*. https://www.bdo.ca/insights/from-crisis-to-opportunity-reshaping-the-construction-industry-for-gen-z-talent
Bekele, W., & Ago, F. (2022). Sample size for interview in qualitative research in social sciences: A guide to novice researchers. *Research in Educational Policy and Management*, *4*(1), 42–50. https://doi.org/10.46303/repam.2022.3
Bolpagni, M., Gavina, R., Ribeiro, D., & Arnal, I. P. (2022). Shaping the future of construction professionals. In M. Bolpagni, R. Gavina, & D. Ribeiro (Eds.), *Industry 4.0 for the built environment* (pp. 1–26). Springer. https://doi.org/10.1007/978-3-030-82430-3_1
Boscariol, C., & Killam, D. (2024, July 24). *Addressing the shortage of construction workers in Canada: The role of LIMA based work permits in recruiting foreign talent*. Watson Goepel LLP. https://www.watsongoepel.com/insight/shortage-of-construction-workers-in-canada/
BuildingTalk. (2025, February 27). *Will AI bring younger people into construction?* https://buildingtalk.com/guest-article-will-ai-bring-younger-people-into-construction/
Burns, J. (2025, January 30). *Attracting Gen Z to construction: What works in 2025? Cornerstone Projects*. https://www.cornerstoneprojects.co.uk/blog/attracting-gen-z-to-construction-what-works-in-2025/
Canada Mortgage and Housing Corporation (CMHC). (2022). *Canada's housing supply shortage: Restoring affordability by 2030*. https://www.cmhc-schl.gc.ca/blog/2022/canadas-housing-supply-shortage-restoring-affordability-2030
Centre for Cities. (2024). *Restart housebuilding*. https://www.centreforcities.org/housing/
Chew, Z. X., Wong, J. Y., Tang, Y. H., Yip, C. C., & Maul, T. (2024). Generative design in the built environment. *Automation in Construction*, *166*, Article 105638. https://doi.org/10.1016/j.autcon.2024.105638
Chui, M., & Mischke, J. (2019). *The impact and opportunities of automation in construction*. McKinsey & Company. https://www.mckinsey.com/capabilities/operations/our-insights/the-impact-and-opportunities-of-automation-in-construction
Copsey, S. (2024, October 1). *How AI can attract Gen Z to address the US construction labor shortage*. Construction Today. https://construction-today.com/news/ai-is-bringing-gen-z-into-the-construction-industry-making-them-more-productive-engaged-and-sustainable/
Cure, L. (2023). *Leading the Gen Z construction workforce requires refreshed tactics*. Construction Management Association of America. https://www.cmaanet.org/sites/default/files/resource/Leading_GenZ_RWorkforce_CE.pdf
Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008
Domljan, I., & Domljan, V. (2024). Major challenges in the construction industry. In I. Karabegović, A. Kovačević, & S. Mandžuka (Eds.), *New technologies, development and application VII* (pp. 396–403). Springer. https://doi.org/10.1007/978-3-031-66271-3_43
Durmus, D., Klinc, R., & Turk, Ž. (2023). The role of social media in BIM-based projects. In *Proceedings of the 2023 European Conference on Computing in Construction: 40th International CIB W78 Conference* (pp. 807–813). European Council on Computing in Construction. https://doi.org/10.35490/EC3.2023.160
Erfani, A., & Mansouri, A. (2026). Applications of multimodal large language models in construction industry. *Advanced Engineering Informatics*, *69*, Article 103909. https://doi.org/10.1016/j.aei.2025.103909
Federation of Canadian Municipalities (FCM). (2019). *Canadian infrastructure report card 2019*. http://canadianinfrastructure.ca/downloads/canadian-infrastructure-report-card-2019.pdf

Fuller, A., & Unwin, L. (2004). Expansive learning environments: Integrating organizational and personal development. In H. Rainbird, A. Fuller, & A. Munro (Eds.), *Workplace learning in context* (pp. 126–144). Routledge.

Guest, G., Bunce, A., & Johnson, L. (2006). How many interviews are enough? An experiment with data saturation and variability. *Field Methods*, *18*(1), 59–82. https://doi.org/10.1177/1525822X05279903

Hall, D. T. (2004). The protean career: A quarter-century journey. *Journal of Vocational Behavior*, *65*(1), 1–13. https://doi.org/10.1016/j.jvb.2003.10.006

Hargittai, E. (2010). Digital na(t)ives? Variation in Internet skills and uses among members of the "Net Generation." *Sociological Inquiry*, *80*(1), 92–113. https://doi.org/10.1111/j.1475-682X.2009.00317.x

Harode, A., Ensafi, M., & Thabet, W. (2022). Linking BIM to Power BI and HoloLens 2 to support facility management: A case study approach. *Buildings*, *12*(6), Article 852. https://doi.org/10.3390/buildings12060852

Hashim, M. Z., Harun, N. A., Othman, I., Hassan, S. H., & Musa, M. K. (2024). The impact of building information modelling (BIM) on labor productivity. *International Journal of Academic Research in Business and Social Sciences*, *14*(9), 55–66. https://dx.doi.org/10.6007/IJARBSS/v14-i9/22787

Hennink, M., & Kaiser, B. N. (2022). Sample sizes for saturation in qualitative research: A systematic review of empirical tests. *Social Science & Medicine*, *292*, Article 114523. https://doi.org/10.1016/j.socscimed.2021.114523

Hodorog, A., Alhamami, A., Alhamami, S., Petri, I., Rezgui, Y., Kubicki, S., & Guerriero, A. (2019). Social media mining for BIM skills and roles for energy efficiency. In *2019 IEEE International Conference on Engineering, Technology and Innovation* (ICE/ITMC) (pp. 1–10). IEEE. https://doi.org/10.1109/ICE.2019.8792571

Hoover, S., Snyder, J., & Menard, A. (2018). *Automation and robotics: Rethinking engineering and construction jobs*. FMI Corporation. https://fmicorp.com/wp-content/uploads/2018/05/BuiltWorldsMachine_FINAL_0418.pdf

Întorsureanu, I., Oprea, S.-V., Bâra, A., & Vespan, D. (2025). Generative AI in education: Perspectives through an academic lens. *Electronics*, *14*(5), Article 1053. https://doi.org/10.3390/electronics14051053

Katebi, A., & Tehrani, M. (2025). Adoption of AI in construction design: Insights from UTAUT2 and TOE frameworks. *Results in Engineering*, *26*, Article 104981. https://doi.org/10.1016/j.rineng.2025.104981

Khlaif, Z. N., Alkouk, W. A., Salama, N., & Abu Eideh, B. (2025). Redesigning assessments for AI-enhanced learning: A framework for educators in the generative AI era. *Education Sciences*, *15*(2), Article 174. https://doi.org/10.3390/educsci15020174

Laberge, M. (2025, February 28). *Solving the housing crisis is a marathon not a sprint*. Canada Mortgage and Housing Corporation. https://www.cmhc-schl.gc.ca/blog/2025/solving-housing-crisis-marathon-not-sprint

Lent, R. W., Brown, S. D., & Hackett, G. (1994). Toward a unifying social cognitive theory of career and academic interest, choice, and performance. *Journal of Vocational Behavior*, *45*(1), 79–122. https://doi.org/10.1006/jvbe.1994.1027

Lincoln, Y. S., & Guba, E. G. (1985). *Naturalistic inquiry*. Sage.

Ling, F. Y. Y., & Lew, E. J. Y. (2026). Strategies to recruit and retain Generation Z in the built environment sector. *Engineering, Construction and Architectural Management*, *33*(1), 713–731. https://doi.org/10.1108/ECAM-08-2024-1109

Lingard, H., Turner, M., & Pirzadeh, P. (2025). Is construction my industry of choice? Examining the factors affecting career choice decision-making of young workers. *Engineering, Construction and Architectural Management*, *33*(4), 3264–3283. https://doi.org/10.1108/ECAM-08-2024-1125

Ma, K., & Fang, B. (2024). Exploring Generation Z's expectations at future work: The impact of digital technology on job searching. *European Journal of Training and Development*, *48*(9), 933–953. https://doi.org/10.1108/EJTD-05-2023-0076

Mai, T. P. A., Doan, D. T., & Ghaffarian Hoseini, A. (2025). Utilizing multiskilled resources in addressing labor shortage issues in off-site construction: Benefits, challenges, and best practices. *Journal of Construction Engineering and Management*, *151*(4), Article 04025014. https://doi.org/10.1061/JCEMD4.COENG-15275

Maqbool, R., Rashid, Y., Altuwaim, A., Shafiq, M. T., & Oldfield, L. (2024). Coping with skill shortage within the UK construction industry: Scaling up training and development systems. *Ain Shams Engineering Journal*, *15*(2), Article 102396. https://doi.org/10.1016/j.asej.2023.102396

McKinsey & Company. (2020). *The next normal in construction: How disruption is reshaping the world's largest ecosystem*. https://www.mckinsey.com/capabilities/operations/our-insights/the-next-normal-in-construction-how-disruption-is-reshaping-the-worlds-largest-ecosystem

Meli, K., Taouki, J., & Pantazatos, D. (2024). Empowering educators with generative AI: The GenAI Education Frontier Initiative. In *EDULEARN24 Proceedings* (pp. 4289–4299). IATED. https://doi.org/10.21125/edulearn.2024.1077

Mingsamorn, P., & Singhuang, N. (2024). An interactive dashboard system for budget allocation using Power BI. *Journal of Technology Management and Digital Innovation*, *1*(2), 51–67. https://ph05.tci-thaijo.org/index.php/TMDI/article/view/167

Mishra, S. K., & Sakale, R. (2025). A study on the effects of BIM on the labour productivity of building construction projects in Patna City. *International Journal of Advanced Research and Multidisciplinary Trends* (IJARMT), *2*(2), 486–491. https://www.ijarmt.com/index.php/j/article/view/241

Mohamed, A. G., Arabaine, O., Botchway, B., & Daoud, A. O. (2025). Visionary constructs: Revolutionizing students' internships through BIM and extended reality synergy. *Architectural Engineering and Design Management*, *21*(5), 889–915. https://doi.org/10.1080/17452007.2024.2415391

Musa, A. M., Abanda, F. H., & Oti, A. H. (2015). Assessment of BIM for managing scheduling risks in construction project management. In *Proceedings of the 32nd International Conference of CIB W78* (pp. 559–568). https://itc.scix.net/paper/w78-2015-paper-058

Musa, A. M., Abanda, F. H., Oti, A. H., Tah, J. H. M., & Boton, C. (2016). The potential of 4D modelling software systems for risk management in construction projects. In N. Achour (Ed.), *Proceedings of the 20th CIB World Building Congress 2016: Advancing products and services* (Vol. V, pp. 988–999). Tampere University of Technology. http://irepo.futminna.edu.ng:8080/jspui/bitstream/123456789/12031/1/The%20Potential%20of%204D%20Modelling%20Software%20Systems%20for%20Risk%20Management%20in%20Construction%20Projects.pdf

Naddeh, Z., Maya, R., Mahfouz, W., & Youssef, M. A. (2025). Integrating BIM into architectural education: Pedagogical challenges and future prospects–Case study: Tartus University. *International Journal of BIM and Engineering Science*, *10*(2), 20–37. https://doi.org/10.54216/IJBES.100202

National Institute of Building Sciences. (2025a). *Elevating the built environment workforce shortage threatening our nation*. https://www.buildinginnovation.org/elevate

National Institute of Building Sciences. (2025b). *Why the built environment workforce shortage is a threat to national security*. https://nibs.org/why-the-built-environment-workforce-shortage-is-a-threat-to-national-security/

Nwaogbe, G., Ekpenyong, E., & Urhoghide, O. (2025). Managing workforce productivity in the post-pandemic construction industry. *World Journal of Advanced Research and Reviews*, *25*(1), 572–588. https://doi.org/10.30574/wjarr.2025.25.1.0051

Orbiz. (2023). *The missing link: Why Gen Z is turning its back on the construction industry*. LinkedIn. https://www.linkedin.com/pulse/missing-link-why-gen-z-turning-its-back/

Organisation for Economic Co-operation and Development. (2010). *Learning for jobs*. OECD Publishing. https://doi.org/10.1787/9789264087460-en

Papuraj, X., Izadyar, N., & Vrcelj, Z. (2025). Integrating building information modelling into construction project management education in Australia: A comprehensive review of industry needs and academic gaps. *Buildings*, *15*(1), Article 130. https://doi.org/10.3390/buildings15010130

Patton, M. Q. (2015). *Qualitative research & evaluation methods* (4th ed.). Sage.

Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2008). A design science research methodology for information systems research. *Journal of Management Information Systems*, *24*(3), 45–77. https://doi.org/10.2753/MIS0742-1222240302

Rane, N. L. (2024). Potential role and challenges of ChatGPT and similar generative artificial intelligence in architectural engineering. *International Journal of Artificial Intelligence and Machine Learning*, *4*(1), 22–47. https://doi.org/10.51483/IJAIML.4.1.2024.22-47

Rane, N. L., Choudhary, S. P., & Rane, J. (2023). Integrating ChatGPT, Bard, and leading-edge generative artificial intelligence in architectural design and engineering: Applications, framework, and challenges. *International Journal of Architecture and Planning*, *3*(2), 92–124. https://dx.doi.org/10.2139/ssrn.4645595

Rodrigues, F., Alves, A. D., & Matos, R. (2022). Construction management supported by BIM and a business intelligence tool. *Energies*, *15*(9), Article 3412. https://doi.org/10.3390/en15093412

Royle, O. R. (2025, July 2). *Gen Z is ditching college for 'more secure' trade jobs–but building inspectors, electricians and plumbers actually have the worst unemployment*. Fortune. https://fortune.com/2025/07/02/gen-z-ditching-college-secure-trade-jobs-blue-collar-electricians-and-plumbers-worst-unemployment-rate-than-office-jobs/

Savickas, M. L. (2005). The theory and practice of career construction. In S. D. Brown & R. W. Lent (Eds.), *Career development and counseling: Putting theory and research to work* (pp. 42–70). John Wiley & Sons.

Savickas, M. L. (2013). Career construction theory and practice. In R. W. Lent & S. D. Brown (Eds.), *Career development and counseling: Putting theory and research to work* (2nd ed., pp. 147–183). John Wiley & Sons.

Schoon, I., & Heckhausen, J. (2019). Conceptualizing individual agency in the transition from school to work: A social-ecological developmental perspective. *Adolescent Research Review*, *4*(2), 135–148. https://doi.org/10.1007/s40894-019-00111-3

Shi, Q., Liu, Z., Wu, J., Guo, Z., & Wu, H. (2025). Generative AI on innovation performance of construction enterprises: A knowledge-based dynamic capabilities perspective. *Journal of Engineering and Technology Management*, *76*, Article 101871. https://doi.org/10.1016/j.jengtecman.2025.101871

Singh, A. K., & Hsieh, S.-H. (2026). Multi-LLM-based augmentation and synthetic data generation of construction schedules and task descriptions with SLM-as-a-judge assessment. *Advanced Engineering Informatics, 69*, Article 103825. https://doi.org/10.1016/j.aei.2025.103825

Sorour, A., & Atkins, A. S. (2024). Integrating artificial intelligence transformers with business intelligence systems for monitoring learning outcomes in higher education institutions. In F. Adedoyin & B. Christiansen (Eds.), *Generative AI and multifactor productivity in business* (pp. 36–54). IGI Global Scientific Publishing. https://doi.org/10.4018/979-8-3693-1198-1.ch003

Succar, B. (2009). Building information modelling framework: A research and delivery foundation for industry stakeholders. *Automation in Construction*, *18*(3), 357–375. https://doi.org/10.1016/j.autcon.2008.10.003

Taiwo, R., Bello, I. T., Abdulai, S. F., Yussif, A.-M., Salami, B. A., Saka, A., Ben Seghier, M. E. A., & Zayed, T. (2025). Generative artificial intelligence in construction: A Delphi approach, framework, and case study. *Alexandria Engineering Journal*, *116*, 672–698. https://doi.org/10.1016/j.aej.2024.12.079

Turner & Townsend. (2024). *International construction market survey 2024*. https://publications.turnerandtownsend.com/international-construction-market-survey-2024/

Valinejadshoubi, M., Moselhi, O., Iordanova, I., Valdivieso, F., & Bagchi, A. (2024). Automated system for high-accuracy quantity takeoff using BIM. *Automation in Construction*, *157*, Article 105155. https://doi.org/10.1016/j.autcon.2023.105155

van Dijk, J. A. G. M. (2020). *The digital divide* (2nd ed.). Polity.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425–478. https://doi.org/10.2307/30036540

Willcocks, L. (2020). Robo-apocalypse cancelled? Reframing the automation and future of work debate. *Journal of Information Technology*, *35*(4), 286–302. https://doi.org/10.1177/0268396220925830

Wind, S. (2024, June 25). *The UK needs 4.3 million homes to fix housing shortage: CityLab Daily*. Bloomberg. https://www.bloomberg.com/news/newsletters/2024-06-25/the-uk-needs-4-3-million-homes-to-fix-housing-shortage-citylab-daily

World Economic Forum. (2016). *The future of jobs: Employment, skills, and workforce strategy for the Fourth Industrial Revolution*. https://www3.weforum.org/docs/WEF_Future_of_Jobs.pdf

World Economic Forum. (2025). *The future of jobs report 2025*. https://reports.weforum.org/docs/WEF_Future_of_Jobs_Report_2025.pdf

Wu, W., & Issa, R. R. A. (2013). Impacts of BIM on talent acquisition in the construction industry. In S. D. Smith & D. D. Ahiaga-Dagbui (Eds.), *Proceedings of the 29th Annual ARCOM Conference* (pp. 35–45). Association of Researchers in Construction Management. https://www.arcom.ac.uk/-docs/proceedings/ar2013-0035-0045_Wu_Issa.pdf

Zhang, Q., & Wang, L. (2026). AI in smart buildings and construction 4.0: Implementation areas and influencing factors in construction organizations. *Automation in Construction*, *181*, Article 106623. https://doi.org/10.1016/j.autcon.2025.106623

Zirar, A., Ali, S. I., & Islam, N. (2023). Worker and workplace artificial intelligence (AI) coexistence: Emerging themes and research agenda. *Technovation*, *124*, Article 102747. https://doi.org/10.1016/j.technovation.2023.102747