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# What Skills Are Construction Industry Employers Looking for in the Age of Artificial Intelligence (AI)?

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Artificial Intelligence (AI) is transforming construction management (CM), driving a demand for new forms of digital leadership and professional expertise. This study explores the skills and attributes construction employers expect from future CM professionals as AI adoption increases. Drawing on semi-structured interviews with 30 professionals from 22 U.S. construction firms, the research identifies three core competency domains: (1) AI-enabled workflow implementation, (2) reflexive learning and ethical reasoning, and (3) domain competence, interpersonal skills, and human-centered integration. Findings reveal that employers view AI literacy and adaptability as critical market differentiators. This signals an urgent need for educational reform and adaptation. The study contributes empirically grounded evidence for aligning CM education and professional development with the demands of an AI-driven industry.

Keywords: Artificial Intelligence, Construction Management, Workforce, Digital Leadership

## Introduction

The construction industry is undergoing a profound digital transformation driven by the accelerated adoption of artificial intelligence (AI) and related digital technologies. From automated progress tracking and predictive scheduling to AI-assisted estimating, AI is redefining how projects are planned, delivered, and managed (Abioye et al., 2021; Adebayo et al., 2025). These developments could have far-reaching implications for the professional competencies expected of construction managers (Elhouar & Nguyen, 2025). Traditionally valued for their technical expertise, coordination ability, and on-site problem-solving, CM professionals must now demonstrate digital leadership, including context-specific AI literacy, an emerging core competency in the Architecture, Construction, Engineering, and Operations (AECO) industry (Onatayo et al., 2024).

This includes the capacity to leverage AI and data analytics for strategic decision-making, collaboration, and innovation. AI-focused digital transformation in the AECO industry has received considerable attention in research and policy (Blanco et al., 2018; Ghimire et al., 2024; Taiwo et al., 2024). However, the human dimension, i.e., the readiness of future CM professionals, remains underexplored (Antwi et al., 2025; Cheng et al., 2024; Hosseini et al., 2025). Emerging studies highlight the need for exploring the competencies that are incidental to AI adoption in the AECO industry (Sawhney & Pitman, 2025; Torres et al., 2025) and their incorporation in construction curricula (Elhouar & Nguyen, 2025). Early work on incorporating AI in construction education has focused on identifying tools that should be taught (Elhouar & Nguyen, 2025) and understanding

educators' (Cheng et al., 2025) and students' perceptions (Kim et al., 2025). However, there is a lack of research on what construction industry employers are looking for in future hires in the AI era. This disconnect creates a widening gap between the digital ambitions of the industry and the preparedness of new graduates entering professional practice.

To address this gap, this study explores the skills and attributes construction industry employers value in the age of AI. It pays particular attention to expectations for early-career and emerging CM professionals. Drawing on qualitative interviews with thirty (30) professionals from twenty-two (22) construction firms of different sizes and market coverage, the paper seeks to find answers to the research question: What skills are construction industry employers looking for in the age of AI? By empirically defining employers' perspectives, this study advances current scholarship on AI in construction by identifying the competencies firms prioritize for early-career professionals in the AI era. The study further translates these into actionable implications for CM educators.

## Literature Review

### *AI and the Transformation of Construction Management*

AI is growing into a defining force in the transformation of CM. From predictive analytics for risk and cost control to AI-assisted scheduling, safety monitoring, and document reviews, AI is reshaping many managerial and decision-making workflows (Abioye et al., 2021; Adebayo et al., 2025). For construction managers, these developments extend beyond technological proficiency. They demand new cognitive and practical capacities (Hosseini et al., 2025). Managers must integrate AI tools into complex human systems in a people-centric industry. As such, digital transformation in CM is as much about leadership as it is about the adoption of technology (Sawhney & Pitman, 2025).

### *Emerging Competency Frameworks for AI-Empowered Managers*

Research has begun to conceptualize the competencies needed to lead in AI-enabled construction environments. Hosseini et al. (2025) identifies fundamental AI literacy, AI-informed decision-making, and ethical awareness as key domains within emerging competencies for digital construction talent in the AI era. Similarly, Buyones-Gonzalez & Quezada-Espinoza (2024) identified a set of competencies through a qualitative survey that distinguishes between generic competencies (e.g., critical thinking, professional ethics, and effective communication) and specific or technical competencies (e.g., mastery of programming languages, data analysis, and emerging software). Mäkelä & Stephany (2025) further argue that AI tends to complement rather than replace human expertise, elevating the importance of skills such as analytical reasoning, resilience, agility, and complex problem-solving. These findings resonate with broader management literature emphasizing hybrid intelligence: the collaborative interaction between human and artificial agents. For construction managers, hybrid intelligence translates into the ability to lead teams and projects that combine human judgment with AI-assisted outputs.

### *Digital Leadership and Human-Centered Management*

Digital leadership has emerged as a pivotal construct in navigating technological change. It encompasses the ability to guide digital transformation, foster innovation, align technology with organizational goals and values, and have digital literacy (Kane et al., 2019). In construction, digital leaders act as intermediaries between technology developers, project teams, and clients (Sawhney & Pitman, 2025). They ensure that digital tools enhance performance without compromising human factors such as collaboration, safety, and ethical responsibility. However, the transition toward AI-

enabled management introduces new challenges. Construction managers must interpret AI outputs, manage potential AI biases, and cultivate team buy-in (Ghimire et al., 2024; Taiwo et al., 2024). This shift requires not only technical literacy but also cognitive flexibility and ethical reasoning. These skills underpin responsible AI use.

### *Education and the Future of Construction Management Talent*

Preparing the next generation of construction managers for AI-integrated practice probably demands a rethink of educational models. Current curricula in CM emphasize the fundamentals of key practices in project controls, estimating, etc., with limited AI integration. Professional training programs are emerging, but cost and access issues exist for students in higher education institutions. Therefore, many graduates risk entering the field lacking exposure to AI-enabled workflows for key CM tasks. Some researchers have advocated for embedding digital leadership and AI literacy into CM education (Hosseini et al., 2025; Obi et al., 2025). This involves developing hard skills in data, automation, and soft skills in collaboration, communication, and strategic adaptation (CITB, 2024). These hybrid capabilities are increasingly seen as essential for navigating uncertainty and leading digital transformation initiatives at the project and organizational levels.

### *Research Gap*

While theoretical models of digital leadership and AI-enabled competency frameworks are emerging, empirical studies that capture employers' perspectives remain limited. Most existing centers offer an academic, educational, or technology-centric view rather than from those recruiting and managing talents in practice. This study addresses this gap by examining how construction industry employers articulate the skills and attributes they expect from new and emerging CM professionals in an AI-driven landscape. Understanding these expectations provides valuable insights for aligning education, professional development, and industry transformation strategies.

## Methodology

### *Research Design*

This study adopts a qualitative, exploratory design to examine how construction industry employers conceptualize the skills and attributes required of future CM professionals in the age of AI. The research follows an interpretivist paradigm, recognizing that skill expectations and notions of digital competency are socially constructed and context-dependent (Fellows & Liu, 2015). A qualitative approach allows for a rich exploration of employers' narratives, capturing how they perceive, define, and prioritize emerging competencies in CM practice. Semi-structured interviews were chosen as the primary data collection method.

The interview guide was developed from first principles to align with the study's exploratory aim of understanding how construction employers conceptualize AI adoption and emerging skill requirements. Questions were organized to move from organizational context and current AI use to future expectations and educational implications. This enabled participants to articulate their experiences and viewpoints while allowing the interviewer to probe emerging ideas. The approach aligns with prior research in digital transformation studies that seeks to understand human and organizational adaptation to new technologies (Buyones-Gonzalez & Quezada-Espinoza, 2024).

### *Participant Selection and Sampling*

Participants were primarily selected purposively from the Professional Advisory Board (PAB) of a CM program based on their formal responsibility for recruiting, hiring, or developing early-career construction professionals. The PAB firms are among the primary employers in the regional construction labor market. To broaden perspectives beyond the advisory group, additional participants who fit the eligibility criteria of being in a recruiting or hiring position were identified through snowball referrals from the initial interviewees. This approach facilitated access to a wider cross-section of professionals actively engaged in AI and data analytics within their organizations.

In total, 30 professionals representing 22 regional, national, and international construction companies operating in the U.S. participated in the study. The sample included senior executives, project managers, technology specialists, and field supervisors. This provided representation across organizational levels and functional areas. In some cases, two or three individuals represented the same company. This allowed for richer intra-organizational perspectives. This heterogeneity ensured a comprehensive understanding of how employers across different contexts conceptualize digital leaders and skill requirements for emerging CM professionals.

### *Data Collection*

Interviews were conducted between January 2025 and May 2025. To accommodate participants' schedules and geographical distribution, interviews were conducted in three formats:(1) virtual interviews via Zoom or Microsoft Teams; (2) in-person interviews at company offices or neutral meeting spaces; and (3) telephone interviews in cases where video conferencing was not feasible. Interviews ranged from 25 to 65 minutes, were audio recorded with participant consent (IRB#17612), and subsequently transcribed verbatim. Transcripts were manually cleaned to remove filler words, verify accuracy, correct grammar, and preserve the integrity and nuance of participants' accounts.

### *Data Analysis*

Data analysis was conducted using NVivo 15 qualitative data analysis software to support systematic coding and theme development. The study employed a reflexive thematic analysis approach, which emphasized the researcher's active and interpretive role in meaning-making rather than the pursuit of coding consensus (Braun & Clarke, 2006; Nowell et al., 2017). As a single-author study, the analytic process was intentionally reflexive (Byrne, 2022), acknowledging the influence of the researcher's positionality, professional background, and interpretive lens throughout the analysis. In line with reflexive thematic analysis, themes were developed through interpretive meaning-making rather than frequency-based coding or quantification. The process unfolded in six iterative stages (Braun & Clarke, 2006):

1. **Familiarization** – Each transcript was read two to three times to gain an in-depth understanding of the data.
2. **Generating initial codes** – Relevant features of the data were systematically coded across the entire dataset.
3. **Searching for themes** – Codes were collated into potential themes that captured recurring patterns of meaning.
4. **Reviewing themes** – The preliminary themes were reviewed and refined for internal coherence and alignment with the coded data and overall dataset.
5. **Defining and naming themes** – Thematic maps were developed to illustrate the conceptual relationships and to articulate the essence of each theme.
6. **Producing the report** – The analytic insights were integrated with illustrative quotations to substantiate findings and address the research questions.

Throughout the process, reflexivity was consistently practiced. The researcher maintained detailed analytic memos to record interpretive decisions and reflections on how professional experience in CM and digital transformation research might shape understanding of participants' accounts.

### *Trustworthiness*

To ensure methodological rigor, the study adhered to qualitative trustworthiness criteria (Stahl & King, 2020), adapted for a single-research design. The following strategies were implemented:

- **Credibility:** Data was sourced from professionals across multiple sectors of construction (commercial, specialty contracting, and residential) and firm scales (regional, national, and international). This enabled source triangulation and strengthened the depth and validity of insights. The researcher engaged in prolonged immersion through iterative transcript readings and coding cycles over two months (June-July 2025), revisiting early transcripts as themes evolved. Informal, non-evaluative consultations with academic peers and industry practitioners were used to test the clarity and resonance of emerging interpretations.
- **Dependability:** A detailed audit trail was maintained, including interview protocols, evolving codebooks, coding memos, and dated theme maps. This documentation demonstrates the procedural transparency of how initial codes were refined into final themes.
- **Confirmability:** The researcher engaged in reflexive journaling throughout data collection and analysis to identify potential biases, preconceptions, and interpretive assumptions. Findings were grounded in verbatim excerpts to preserve participants' voices and ensure that interpretations were supported by the data.
- **Ethical integrity:** Participants were provided with written consent information before interviews and were free to decline recording or withdraw at any time. All data were handled confidentially, stored securely, and anonymized in reporting.

While the study was conducted by a single researcher, the systematic documentation of analytic steps, reflexive practices, and source triangulation across diverse participant perspectives enhanced the credibility, dependability, and transparency of the findings. These measures collectively ensure that the interpretations presented are robust, contextually grounded, and reflective of the participants' authentic perspectives.

## Findings

### *Profile of Study Participants*

The study involved 30 professionals from 22 companies that ranged in size from 10 to 8500 employees and annual revenues of $6 million to $15 billion. Participants' experience ranged from 5 to 32 years, providing a broad representation of views across different time periods of the evolution of digital practice. In some cases, one company was represented by two or three people.

### *Current and Emerging Implementations of AI in Construction*

While some (n = 2) companies had not started using AI in their operations, the majority (n=20), had begun using AI in some form. Three broad application contexts for AI in construction were identified in the study. These included:

- **Preconstruction Applications:** Participants noted that early adoption use cases are frequently evident during the preconstruction phase. Reported applications include the use of AI for reviewing plans and specifications, generating preconstruction reports, AI-assisted

estimating, design and rendering, scheduling optimization, and sustainability analysis. One participant illustrated this emerging trend by explaining, *"… a lot of the current use right now is more for what I am going to call the text-based documents… Others are, you know, trying to go train it for looking at the actual construction documents and find gaps or, you know, missing elements, improperly designed, wrong details, and then we use a lot of it too on the back end just in helping search through specifications and stuff like that..."*

- **Project Delivery Applications:** Many AI applications were described by participants in this cluster. The reported uses included AI-enabled submittal reviews, automated report generation, procurement management, progress tracking, contract analysis, and the drafting of meeting minutes. Interviewees also noted broader applications such as automated schedule analysis, equipment obstacle detection and avoidance, quality control monitoring, site logistics coordination, and the use of task-oriented robots, such as layout or laser/LiDAR scanning robots, for repetitive or precision-based tasks. An advanced example of an application that combined AI-enabled progress tracking and data analytics was shared by one company: *"We are tracking production rates… It's becoming more of how efficient we can be as builders. It is how you estimate, Mr. Subcontractor, when you actually put these numbers together. Is that really what's actually happening out in the field?... We are finding a lot of tremendous benefits on that side, even to the point now we are looking at trying to figure out how to do daily pay with the trades..."*

- **Back office or Corporate Applications:** To enhance efficiency and streamline administrative operations, several companies reported adopting AI tools for corporate and back office functions. Applications described included AI-enabled phone answering systems, website chatbots, and virtual assistants for managing emails and calendars. The use of large language model (LLM)- based content generation was also highlighted as an emerging practice, particularly for marketing, sales, inventory tracking, and warranty management. The latter was particularly evident in the residential construction sector, where one participant noted: *"So, we are using AI right now to help us rewrite and write home descriptions. We sell about 400 homes a year, and creating descriptions for 400 homes a year gets pretty monotonous. I am trying not to use the same words over and over again. So, we use ChatGPT a lot to help us come up with some different ways to describe that."*

### *Required and Emerging Competencies*

Participants noted that they expect AI adoption in construction to accelerate significantly over the next five (5) to ten (10) years and suggested competencies they envision will become critical for new hires. The competencies were not predefined but emerged inductively through the reflexive thematic analysis. Recurrent references to skills and expectations of early-career CM professionals in the AI era were coded and iteratively grouped into higher-order patterns of meaning, from which the three competency categories were identified. These were selected because they were conceptually and analytically coherent and recurrent across different sectors, firm sizes, and roles. The three broad groups of skills and attributes (Figure 1) are discussed in the subsequent subsections.

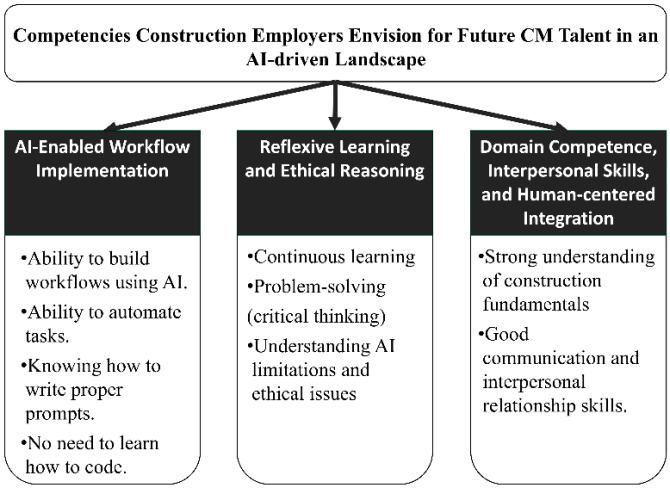


**Figure 1.** Required and emerging competencies instigated by AI adoption in CM. (Author's own work)

*AI-Enabled Workflow Implementation*

Professionals interviewed emphasized that future professionals must be capable of designing and operationalizing AI-enabled workflows that enhance project efficiency, accuracy, and decision-making. Rather than requiring deep programming expertise, employers highlighted the importance of AI integration skills. This covers the ability to embed intelligent tools within existing processes through effective prompting, automation pipelines, and digital platform manipulations. As one participant reflected: *"You do not need to know how to code. That is [something] somebody else can help with, or you can hire a third-party online." Another added, "It is going to have to be that they can, you know, write those prompts, figure that stuff out with ChatGPT or whatever it ends up, you know, taking over at the time."*

*Reflexive Learning and Ethical Reasoning*

Reflexive learning involves exploring one's experiences to become more conscious, open-minded, and self-critical, leading to independent thinking and production of tangible ideas (Afolayan, 2016). Participants identified continuous learning and ethical reflexivity as essential traits for navigating AI's evolving role in construction. As tools advance rapidly, professionals must be able to adapt to new technologies, critically assess AI-generated insights, and anticipate the potential consequences of automating with AI. One participant noted, *"You need to constantly be able to learn, and you need motivated students who can change and learn systems and implement them and communicate with, you know, maybe the age group that is phasing out into retirement."* Reflexive and ethical reasoning allows professionals to balance technological innovation with human judgment, fairness, and accountability. This ensures that AI supports, rather than undermines, professional integrity and safety.

*Domain Competence, Interpersonal Skills, and Human-centered Integration*

The interviewees underscored that AI implementation in construction will only succeed when grounded in human-centered integration. Digital leadership requires more than technical capacity. It demands deep domain knowledge, communication skills, and collaborative acumen. This was

captured by one participant who emphasized, "*They need to have the firm structure of being able to read plans and specs, all those hard skills. Because I think if they come out and they cannot do those basic things or do not have a good foundation of that, then I mean for the tech, they are not quite ready to translate one [the tech knowledge].*" Participants stressed that future professionals must be able to align multidisciplinary teams, bridge generational divides, and contextualize AI applications within real project constraints. As one interviewee put it, "…*they are smart, they are savvy, they are tech savvy, but people skills are still needed*."

## Discussion and Conclusion

The findings reveal that AI adoption in CM is expanding across preconstruction, project delivery, and administrative operations. While most companies are in exploratory stages, most participants described tangible applications that indicate a clear shift from traditional workflows. These include using AI for document and contract reviews, AI-enabled estimating, progress tracking, automated reporting, website chatbots, and marketing content generation. These early implementations align with the current literature identifying AI's growing presence in data-intensive and repetitive workflows (Abioye et al., 2021; Adebayo et al., 2025). Participants agreed that adoption will accelerate over the next 5 to 10 years, with AI emerging as a market differentiator, a finding consistent with broader industry projections (Growth Shuttle, 2025).

### *Evolving Competencies*

Employers envision future CM professionals as digital leaders capable of integrating AI into workflows, interpreting data insights, and relating or leading cross-disciplinary teams. This reflects emerging AI literacy and data-driven decision-making frameworks (Buyones-Gonzalez & Quezada-Espinoza, 2024; Hosseini et al., 2025). Three interrelated skill domains emerged. First, AI-enabled workflow implementation emphasizes automating tasks, navigating tools, and effective prompting rather than deep programming. Second, reflexive learning and ethical reasoning involve questioning AI outputs, anticipating unintended consequences, and maintaining human oversight. Third, domain competence and human-centered integration remain foundational for grounding AI use in construction knowledge, teamwork, and communication (Kane et al. (2019);López-Figueroa et al. 2025),

### *Implications for CM Education*

These findings carry significant implications for CM education and workforce development. As firms adopt AI-enabled workflows, curricula must move beyond teaching discrete tools toward cultivating integrative digital competencies (Elhouar & Nguyen, 2025; Hosseini et al., 2025). Core modules in estimating, scheduling, and project management should strive to align fundamental skills such as communication, visual-spatial, and logical-mathematical skills with technical AI fluency to reflect contemporary practice. This may be implemented by modifying assignments that assess these skills to include AI-enabled workflows. Educators should further cultivate a reflexive and lifelong learning orientation, as AI evolves faster than curricula (Cheng et al., 2025). Experiential approaches, including AI-focused electives and sustained industry-partnered projects, can support adaptive and job-ready competence (Antwi et al., 2025).

### *Limitations and Future Research*

The study's qualitative design and sampling approach limit generalizability, as most participants are early AI adopters, potentially narrowing the worldview of decision makers. The sample also included a mix of general contractors (GC), specialty contractors, logistics, and residential contractors, with

GCs dominating. Future studies should examine perspectives from lagging adopters and compare subsectors to understand contextual differences. Further research should also evaluate how AI-integrated curricula influence graduate readiness and career outcomes. Quantitative validation of the proposed competency clusters would strengthen their general applicability.

### *Conclusion*

This study contributes empirical insight into how construction employers define the competencies required of early-career professionals in the AI era. It identifies three competency domains: (1) AI-enabled workflow implementation, (2) reflexive learning and ethical reasoning, and (3) domain competence with human-centered capabilities alongside technical fluency. In this sense, AI is no longer peripheral to CM education; it is reshaping what it means to be a construction manager. Employers are beginning to seek professionals who can integrate AI into traditional workflows, critically evaluate its implications, and lead human-machine collaboration. The next generation of CM professionals must therefore be adaptive, ethically grounded, and human-centered digital leaders with deep domain knowledge. For educators and industry alike, the imperative is clear: curricula must be refined and entry-level domain expectations clarified to prepare graduates for the AI-enabled construction landscape.

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