

AI-IMPACTED CONSTRUCTION PEOPLE READINESS VIA SKILL VALUATION AND TALENT TRAJECTORIES

Yaxian Dong¹, Sangaa Chatterjee², Zijun Zhan³, Yuqing Hu⁴, Daniel Mawunyo Doe⁵, & Zhu Han⁶

ABSTRACT

Artificial intelligence (AI) is reshaping architecture, engineering, and construction (AEC) workflows by redistributing cognitive and coordination tasks across human and digital resources, thereby changing cost structures and value generation mechanisms in lean construction. However, domain-specific and data-driven evidence on how AI restructures the construction workforce remains limited. Framing the construction industry as a production system that allocates work to capable resources, this study examines how AI exposure varies across construction roles and how it influences career transitions and capability development. Using job postings from Indeed, we quantify AI exposure across diverse AEC positions. Results show the emergence of AI-specific roles (e.g., AI trainers), high exposure in administrative positions, and comparatively low exposure in executive, human resources, and certain roles related to building information modeling. To understand workforce dynamics, we construct a directed graph of construction professionals' career trajectories from LinkedIn data and model transition patterns. By mapping transition-level task and skill gaps to an AI capability taxonomy, we quantify alignment between required capability upgrades and AI-performable functions. The results offer a structural perspective on how AI exposure gradients may reshape capability flows within the construction production system and inform workforce adaptation strategies.

KEYWORDS

Construction workforce, Artificial Intelligence, collaboration, reliable promising.

INTRODUCTION

Lean construction conceptualizes projects as production systems where tasks are assigned to capable resources to generate value and maintain reliable flow (Ouma et al., 2025; Zelenko & Maxwell, 2024). As artificial intelligence (AI) increasingly enters architecture, engineering, and construction (AEC) practices (Lagos et al., 2024), it introduces a new class of cognitive and coordination resources into this production system. Tasks such as meeting documentation

¹ Ph.D. student, Department of Architectural Engineering, The Pennsylvania State University, University Park, USA, yzd5221@psu.edu

² Undergraduate student, Department of Computer Science and Engineering, The Pennsylvania State University, University Park, USA, sjc6940@psu.edu

³ Ph.D. student, Department of Electrical and Computer Engineering, University of Houston, Houston, USA, zzhan@uh.edu

⁴ Assistant Professor, Department of Architectural Engineering, The Pennsylvania State University, University Park, USA, yfh5204@psu.edu

⁵ Assistant Professor, Department of Electrical and Computer Engineering, Prairie View A&M University, Prairie View, USA, dmdoe@pvamu.edu

⁶ Moores Professor, Department of Electrical and Computer Engineering, University of Houston, Houston, USA, zhan2@uh.edu

and information processing can now be partially automated and verified by humans (Chen et al., 2025), changing how tasks are distributed across roles. Beyond efficiency improvement, this redistribution restructures capability requirements, shifts responsibility boundaries, and potentially compresses traditional experiential learning pathways. In a context of current workforce shortages (Dong, Hu, et al., 2025), reallocating human effort toward value-generating and coordination-intensive activities becomes increasingly critical. However, while AI may reduce information-processing waste, it may also reshape career progression and skill development structures that underpin long-term production system stability. In lean construction, reliable promising depends on the ability of teams to make feasible commitments based on complete and accurate information. AI exposure facilitates this process by improving information availability, enhancing situational awareness, and supporting planning decisions. AI can thus strengthen reliable promising by reducing uncertainty and improving commitment feasibility. Recent studies suggest that value in construction is increasingly generated through improved information flow, decision-making, and coordination enabled by AI and digital technologies (Mora et al., 2025; Zhao et al., 2025). AI enhances value by improving information quality and timeliness for more reliable planning (Lagos et al., 2024; Rad & Ilbeigi, 2025), reducing non-value-adding efforts through automation, and increasing workflow reliability via reasoning and robotic systems (Jing et al., 2025; Powell, 2024; Wang et al., 2026). These transformations position AI as a value-enabling mechanism within lean construction systems. To balance productivity improvement with respect for construction people (Skinnarland et al., 2025), it is necessary to understand how AI is embedded in construction tasks and how it influences career mobility across roles.

In the construction field, as emerging technologies are integrated into traditional practices (Dong et al., 2024; Dong, Zhan, et al., 2025; Zhao et al., 2025), job positions and required skillsets for these positions are varying. Some studies have considered this and discussed the skill demand. For example, Musonda and Okoro (2021) used questionnaires (Musonda & Okoro, 2021) for construction professionals to assess the critical skills required in the near-future job market, including safety competence, problem-solving, decision-making, and leadership skills. Based on their quantitative study results, the skills about new technologies, like data mining and internet of things, are not regarded to be critical. This might be because managerial skills in construction are derived from domain-specific knowledge and industrial experience, making them more difficult to replace. In contrast, technological skills may be more easily supported by AI, like ChatGPT, which can offer guidance, generate code, and explain complex concepts to assist with technical tasks. Conversely, Adepoju and Aigbavboa (2021) reported the significant skills gap regarding human-machine communication and data analysis and recommended conducting associated workforce training for re-skilling (Adepoju & Aigbavboa, 2021). Overall, while there have been studies on construction workforce re-skilling from an industrial perspective, there is a lack of research that investigates how AI-driven changes influence individual skillset development and reshape career trajectories. Therefore, there is a need to examine current construction job positions with associated tasks and required skills first. It is also worthwhile exploring which skills in these roles may be potentially replaced or augmented by AI skillset.

Recent studies have examined the impact of AI on labor markets at aggregate levels. For example, Demirci et al. (2024) documented reductions in automation-prone job postings following the introduction of generative AI technologies (Demirci et al., 2024), while Felten et al. (2021) developed the AI Occupational Exposure (AIOE) index linking AI applications to general human abilities derived from O*NET (Felten et al., 2021). Similarly, the Iceberg Index (Chopra et al., 2025) and the AI Index Report (HAI, 2025) provide skills-centered and macro-level analyses of AI diffusion across industries. Although these studies offer valuable insights into occupational exposure patterns, they operate primarily at generalized occupational or

cross-industry levels and rely on predefined ability taxonomies. They do not capture domain-specific task structures, real career transition networks, or transition-level skill gap reconfigurations within construction. Consequently, there remains limited empirical understanding of how AI reshapes capability flows within the construction production system by simultaneously influencing employer demand signals and observed workforce mobility patterns.

To address this gap, this study develops a data-driven analytical framework to examine AI exposure across construction roles and to model how AI-related capability shifts influence career transitions. By integrating job posting data to represent employer demand with large-scale career trajectory data to represent observed workforce mobility, the study evaluates transition-level task and skill gaps through an AI capability taxonomy. This approach enables a systematic assessment of how AI may accelerate, reshape, weaken, or stabilize dominant mobility pathways in the construction workforce.

RESEARCH PROCESS AND DATA

This study considers a data-driven framework to examine how AI exposure to construction tasks influences diverse construction roles and their transitions, as shown in Figure 1. First, we analyze job market demand by collecting AEC job postings from Indeed and referring to AI-related words for measurement of AI exposure into each position. Second, we analyze the industry workforce by collecting large-scale construction professionals' career trajectories from LinkedIn profiles. A graph-based career mobility network is built to capture position transitions, allowing us to identify dominant career paths, frequent transitions, and structural hubs in workforce development. Third, we conduct AI exposure analysis at the career transition level. By mapping tasks and skills' gaps to an AI capability taxonomy, we examine how AI accelerates, reshapes, or weakens key career pathways or does not affect some stable career progression, revealing potential emerging mobility patterns in the AI-integrated AEC workforce.

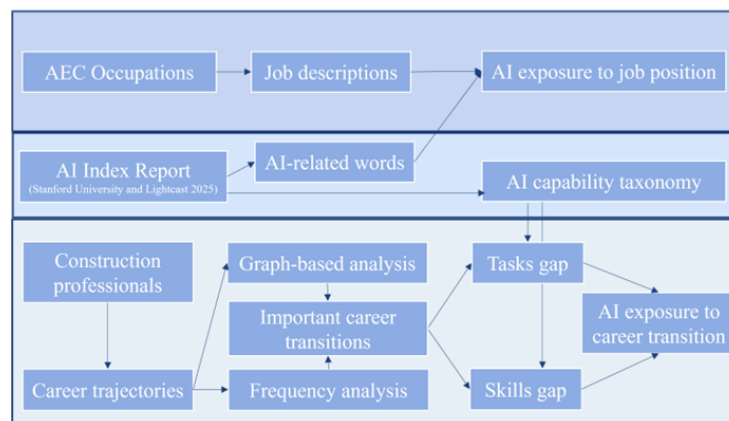


Figure 1: Research process

Regarding job position demands, to capture recent real-world demand and requirements within the construction labor market, this study conducted web scraping and collected job posting data on Indeed platform in October 2025. The Indeed platform (Indeed, 2025) was selected as the data source since it is a large job aggregator and provides a timely and comprehensive view of the labor market. For practicality, we narrowed the geographical scope from United States to one region of Pennsylvania (PA) for further focused analysis. Specifically, a total of 1,117 job postings were retrieved through a systematic keyword search, including “AI (construction)”, “BIM”, “Construction”, “Administrative (construction)”, “Executive (construction)”, and “HR (construction)”. These differentiated keywords serve as the structural foundation for further

analyzing AI-related competencies within job descriptions, considering tech-based, onsite-based, and office-based job positions. For industry-specific relevance and mitigating noise data from other domains, we added the suffix “(construction)” into search keywords for those general roles that also appear in multiple industries, such as administrative positions. After that, for collected job postings, we conducted detailed analysis of job descriptions. To explore the extent of AI-related content in job descriptions, this study referred to the “Artificial Intelligence Index Report 2025” published by Stanford University’s Human-Centered Artificial Intelligence Institute and Lightcast (HAI, 2025) to construct an AI concept dictionary, where an authoritative taxonomy of AI skills is included. For quantifying AI exposure in construction domain’s job postings, we computed the density of AI-related concepts within each job description using keyword matching. The resulting exposure score presents the proportion of AI-related content relative to the total text length, which allows comparison across different job postings. Integrating job metadata with AI exposure scores thus supports scalable analysis of AI-driven workforce transformation in the construction industry.

Regarding industry workforce, based on above job positions, we selected more than 10,000 construction professionals from the LinkedIn platform as samples in July 2025. Then, their experience data is collected via web scraping for analysis. LinkedIn was chosen in this research as data source since it is a large and popular professional networking platform. Numerous professionals across various domains provide detailed profiles on LinkedIn and keep their career information up to date. To ensure data quality, we conduct data cleaning, including removing missing values and invalid data of no job transitions (e.g., only one career stage, keeping the same job position). We also recognize that, despite the same job positions, those reported by different LinkedIn users may exhibit variation in naming methods. To address this, we identify similar pairs and normalize job positions. A combination of cosine similarity with the threshold of 0.95 and human verification ensures accuracy without sacrificing key role attributes like career level indicators (e.g., intern, assistant, senior) and professional disciplinary descriptors (e.g., MEP, structural, estimator). This normalization process can reduce noise due to heterogeneous job naming practices and meanwhile maintain meaningful distinctions related to career trajectory analysis. Additionally, considering multiple stages along career trajectories, we decompose professionals’ trajectories into consecutive position transitions. For instance, a trajectory $A \rightarrow B \rightarrow C$ is represented as $A \rightarrow B$ and $B \rightarrow C$. We introduce transition count to calculate frequency of the same position transitions, where duplicated position transitions are removed. Therefore, 1826 unique job positions and 2225 unique position transitions from real-world construction professionals’ career trajectories are used for further analysis.

Beyond frequency counts, this research also considers constructing a structured representation to support career paths’ systematic analysis. Specifically, we used a directed graph to represent these career trajectories $G = (V, E)$, where each node corresponds to specific job position and each directed edge represents the transition between source-target positions. Therefore, the sequential and directional professional career development can be naturally captured. Nodes are initialized using semantic embedding generated based on the job text. The graph thus jointly encodes career transition structure and semantic relations between job positions. To learn representations of career positions, this study utilized a graph attention network (GAT) on the directed transition graph. GAT can aggregate information from predecessor positions and thus generate context-aware embeddings for target positions. When forming node representations, attention mechanisms enable the model for weighting different incoming transitions. It is useful in career trajectories data, where a job position might be reached via diverse professional career paths. Such representation learning aims to obtain structurally informed embeddings which recognize how job positions are connected within the broader career system rather than predicting individual careers. Based on learned node representations, career transition analysis is formulated as a directed link prediction task. This

research used a non-symmetric decoding function for estimating transition scores between directional position pairs, enabling the model to differ $position1 \rightarrow position2$ from $position2 \rightarrow position1$. Such directional modeling is necessary for career trajectory analysis, since reverse transitions are relatively rare regarding construction professionals' mobility. The decoder is trained with a binary classification objective for distinguishing real-world transitions from negative samples. For rigorous evaluation, we randomly divided real-world transitions as directed edges into training, validation, and testing datasets with 8:1:1, while preserving edge direction. We adopted the area under the ROC curve (AUC) to assess model performance, since it can measure the model ability to differ real-world transitions from non-observed ones. For interpretation, attention weights are learned during representation learning and analyzed to highlight significant incoming career paths for target job positions. Instead of being interpreted as transition probabilities, attention analysis aims to identify influential and representative career pathways within the holistic transition network, thus providing insights. Overall, this graph-based framework is suitable for career trajectory analysis considering the following aspects. Firstly, the directed graph formulation reflects sequential career progression. Secondly, the integration of semantic embeddings and transition structure allows analysis across diverse and evolving job positions. Thirdly, the approach can support large-scale empirical career trajectories data and systematically identify prominent career paths in complex construction professional ecosystems.

To examine how AI may reshape dominant career transition trajectories, we extend the attention-based career transition graph with an AI exposure-aware capability analysis. High-importance transition edges are first identified via edge-level attention weights to represent empirically dominant mobility pathways. For those selected transitions (e.g., $A \rightarrow B$), we extract and normalize task and skill representations of positions A and B from job postings collected from the Indeed platform using natural language processing. The transition gap is defined as the set of tasks and skills required in position B but not present in position A, which represents the core capability upgrade underlying the career progression. Each task and skill gap is then mapped to an AI capability taxonomy to determine whether it can be AI-performable, or whether it relies primarily on human judgment, social interaction, and on-site experience that are difficult for AI to replace. In this study, AI capabilities are based on the Stanford AI Index (HAI, 2025), while lean construction tasks are derived from established practices in the Last Planner System (LPS). For mapping, we introduce AI functions to bridge AI capabilities and lean construction tasks. Based on this mapping, an AI alignment ratio is computed to quantify the extent to which the transition requirements can be substituted by AI. A higher alignment ratio indicates that the transition may be weakened or reshaped in the future as AI reduces the dependency on prior job experience, whereas a lower ratio suggests that the preceding position remains a critical prerequisite for the subsequent role, forming a stable and essential career progression path. In addition, we compare these two positions' AI exposure scores to measure whether the transition leads to a higher or lower level of AI exposure. Together, these metrics enable an integrated assessment of whether dominant career trajectories are likely to be accelerated, reshaped, or constrained under increasing AI adoption.

RESULTS

Regarding AI exposure to diverse AEC roles, we calculated the average AI exposure scores across diverse position types in the construction job market. As presented in Table 1, AI-related construction positions have the highest average AI exposure score of 0.02944, followed by administrative roles (0.02300). In contrast, executive and HR positions demonstrate substantially lower AI exposure levels, at 0.01175 and 0.01379 respectively. AI-focused construction roles exhibit direct and operational engagement with AI technologies as part of daily work activities. For example, AI trainer positions explicitly require hands-on use of

generative AI tools (e.g., ChatGPT, Microsoft Copilot, and Google Gemini), AI literacy instruction, and continuous monitoring of emerging AI applications. These roles function as intermediaries that translate generic AI capabilities into construction-specific workflows such as project management, estimating, and safety coordination. Consequently, AI concepts are deeply embedded in their job descriptions, leading to consistently high exposure scores. Administrative roles also show relatively high AI exposure. These positions frequently involve documentation, coordination, reporting, and compliance management, tasks that are information-intensive and structured. Such activities are well aligned with AI-enabled automation and augmentation, particularly in data processing and document generation. From a production-system perspective, this pattern suggests that AI integration is concentrated in roles where information-processing and coordination tasks can be partially standardized and delegated to digital resources. In contrast, executive and HR roles demonstrate lower AI exposure. Although executives are responsible for strategic decision-making and technology adoption, their job descriptions emphasize leadership, organizational oversight, negotiation, and accountability. Similarly, HR roles remain largely human-centered, focusing on recruitment, employee relations, compliance interpretation, and training coordination. These responsibilities rely heavily on judgment, social interaction, and contextual understanding, which are less directly substitutable by current AI capabilities. Taken together, the results indicate that AI diffusion within the construction industry is currently concentrated in workflow-level execution and information-processing functions rather than in high-level governance or relational roles. This distribution reflects a reallocation of cognitive tasks within the construction production system: structured and repetitive activities are increasingly supported or automated by AI, while roles centered on responsibility, coordination authority, and organizational leadership remain primarily human-dependent. Such differentiation suggests a bottom-up, task-driven pathway of AI integration, where digital tools first reshape operational layers before altering higher-level managerial functions.

Table 1: Average AI exposure score for diverse types of positions in construction job market

Category	Keyword (PA)	AI exposure score
Tech-based	AI (construction)	0.02944
	BIM	0.01601
Onsite-based	Construction	0.02105
	Administrative (construction)	0.02300
Office-based	Executive (construction)	0.01175
	HR (construction)	0.01379

Regarding industry career trajectories, based on 6,608 real-world career transitions extracted from LinkedIn construction professionals’ trajectories, we analyzed transitions with counts greater than 20 to identify frequent and stable career paths. Figure 2 visualizes these transition networks with standardized positions and directed edges weighted by frequency. Several dominant career pathways emerge. Entry-level roles (e.g., Project Engineering Intern, Field Engineer Intern, Engineer) most frequently transition into Project Development Engineer and Field Engineer, indicating these roles function as key entry gateways. From a system perspective, these gateway roles represent foundational capability accumulation stages in which technical and coordination competencies are developed before branching into more specialized or managerial tracks. From Project Development Engineer, transitions branch into both technical and managerial pathways, including Project Engineer II, Assistant Superintendent,

and Assistant Preconstruction Manager. This position functions as a structural hub that connects multiple career directions. Such hub roles concentrate cross-disciplinary exposure and operational knowledge, suggesting that they play a central role in redistributing expertise within the broader construction production system. Within the management track, intermediate roles such as Project Assistant and Assistant Superintendent form strong flows toward Project Manager and Superintendent positions. Senior-level roles (e.g., Senior Project Manager, Superintendent) show fewer outward transitions, reflecting increasing role stability and responsibility concentration at later career stages. These senior positions appear to function as system anchors, where accumulated experience and coordination authority stabilize long-term project delivery structures.

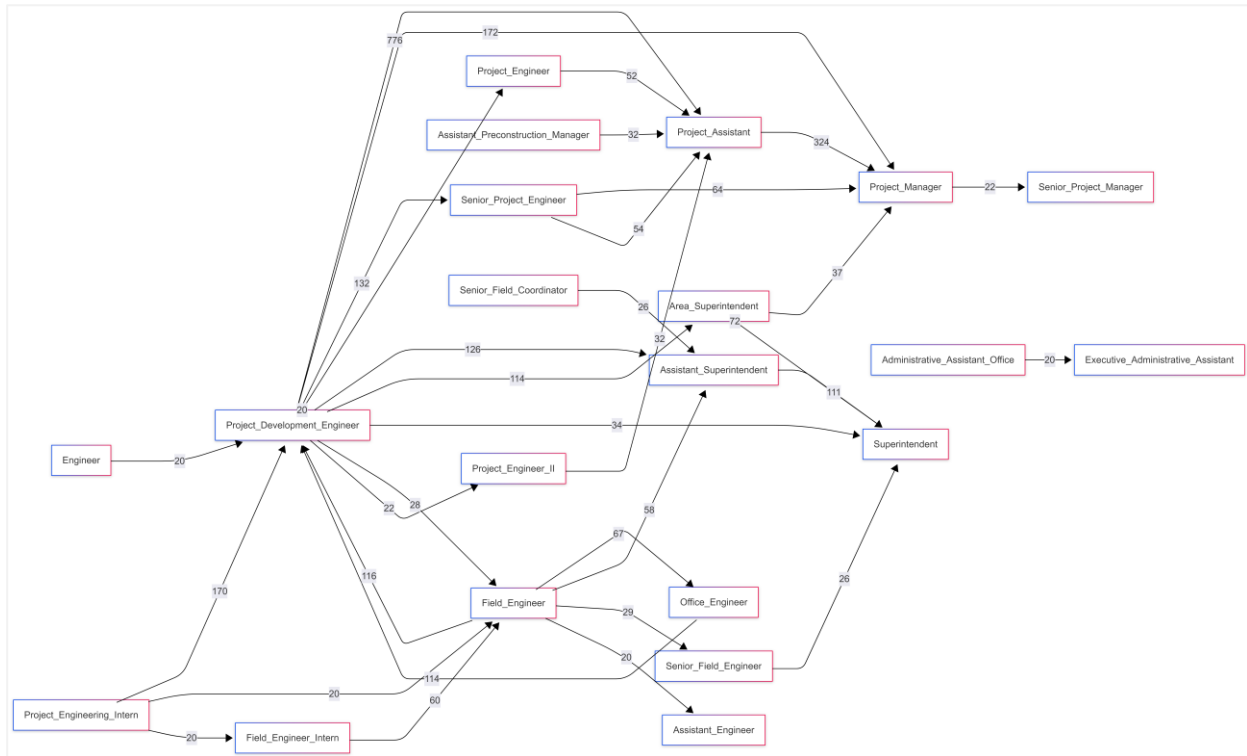


Figure 2: Frequent career transition networks

In addition to frequency analysis, we conduct result analysis regarding directed GAT-based career trajectory modeling. The directed GAT model demonstrates strong and stable performance in modeling career transitions. Across training iterations, the model achieves the best validation AUC of 0.87, with the corresponding test AUC of 0.88. It indicates a high ability to distinguish observed career transitions from unobserved ones. Given the complexity and noise inherent in real-world LinkedIn career trajectory data (e.g., heterogeneous job titles, diverse career paths, sparse transition patterns), this performance presents that the model effectively captures meaningful structural and semantic patterns in career mobility. Additionally, attention weights learned by the GAT provide interpretability into career transition structures. By analyzing attention scores on directed edges, we identify significant incoming career paths that contribute most strongly to the representation of target positions. As illustrated in Figure 3, high-attention transitions align with intuitive and domain-consistent career progressions, such as transitions from technical or assistant-level roles to supervisory, coordination, or managerial positions. For example, transitions from estimator-related roles to managerial positions present prominent pathways. Estimators typically develop strong cost control, project feasibility assessment, and cross-disciplinary coordination skills, which are directly transferable to project or preconstruction management roles. It indicates that cost-

oriented expertise serves as a common foundation for subsequent leader roles. Similarly, transitions from technical engineering or drafting roles to coordination and management-oriented positions, such as *CAD Operator* → *BIM Coordinator*, show a gradual shift from task-level execution to system-level oversight. These pathways highlight how technical familiarity with drawings, models, and site conditions facilitate progression into roles that require broader coordination and decision-making. The model also identifies transitions from assistant or intern-level positions to specialized or supervisory roles, indicating early-stage career pathways where individuals consolidate foundational skills before advancing into more responsibility-intensive positions. These transitions demonstrate the multi-stage nature of career development and emphasize the importance of intermediate roles as stepping stones rather than endpoints. These results reflect the relative structural importance of predecessor roles in shaping the representation of a given position within the career network. However, there are negative samples generated by randomly sampling non-observed directed edges from the training graph. For example, a pair such as *Cook/Dishwasher* → *Senior Architect*, which does not appear in the empirical career trajectory data and represents a non-existing transition in the directed graph.

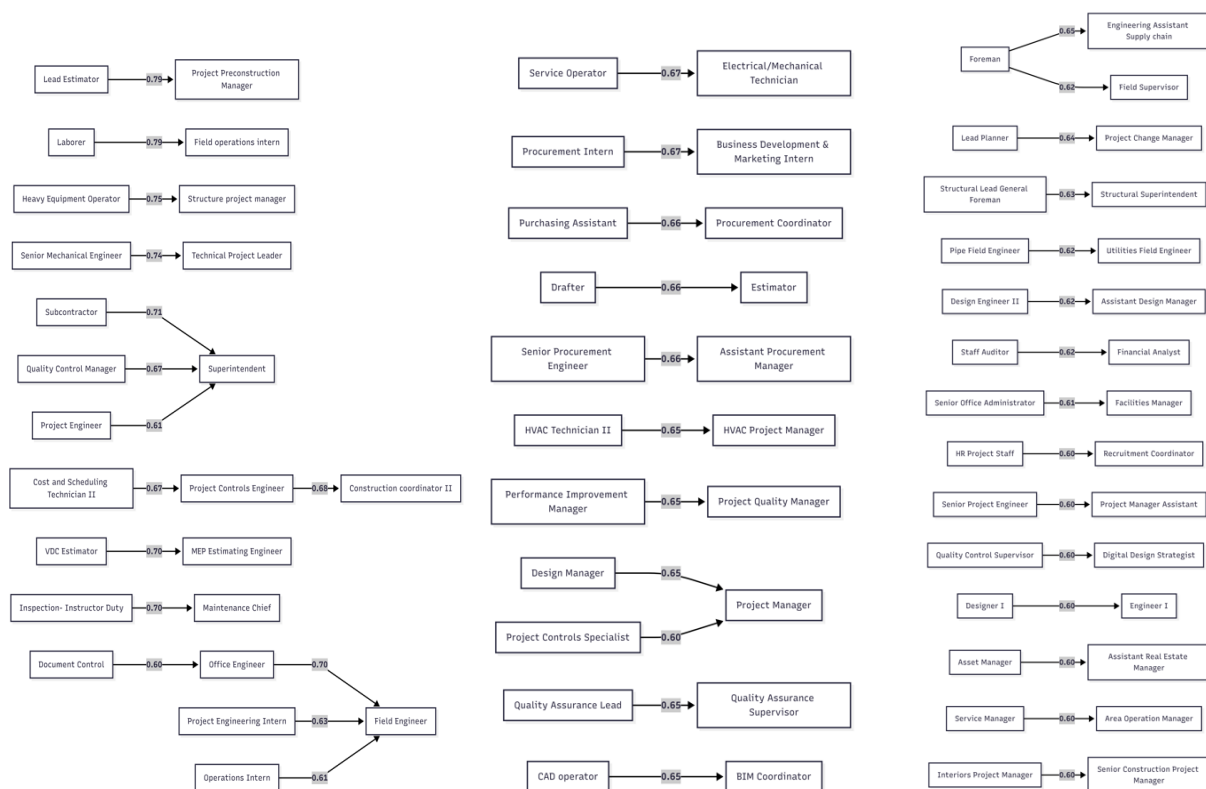


Figure 3: High-attention career transitions

As for AI exposure to role transition, to systematically interpret how AI may reshape career mobility within the construction domain, each AI capability is operationalized into executable functions and linked to corresponding lean construction tasks, as summarized in Table 2. This mapping provides a clear and detailed connection between AI capabilities and lean construction tasks. Traditional reliable promising in lean construction is primarily based on human judgment, negotiation, and interpersonal trust among project participants. With the introduction of AI, this process becomes increasingly supported by data-driven insights. AI functions (e.g., real-time progress tracking, information retrieval, and predictive analysis) enhance information completeness and reduce uncertainty, thereby improving the feasibility of commitments. However, AI does not replace human coordination. Instead, it transforms reliable promising into a human-AI collaborative process, where AI augments decision-making while humans

retain responsibility for commitment and accountability. This shift represents a transition from experience-based coordination to data-augmented coordination in lean construction.

Table 2: AI functions mapping to lean construction tasks

AI capabilities (HAI, 2025)	AI functions	Lean construction tasks
Language	Understanding	Meeting summarization
	Generation	Report generation
	Retrieval Augment Generation	Information retrieval
Speech	Speech Recognition	Conduct meeting transcription
Image and Video	Understanding	Progress detection
		Hazard detection
	Generation	Synthetic data generation
	Coding	Code generation
	AI Agents	Workflow automation
	Mathematics	Quantitative analysis
Reasoning	Planning	Planning and decision
Autonomous Motion	Robotics	Automated operations
	Self-Driving Cars	N.A.

Additionally, we conceptualize transition-level exposure gradients into four structural types: high-to-high, high-to-low, low-to-high, and low-to-low transitions. High-to-high transitions occur when both predecessor and successor roles exhibit relatively strong AI alignment. Examples include documentation- and data-intensive pathways such as *Drafter* (0.020) → *Estimator* (0.019). In such transitions, task and skill gaps are concentrated in structured analytical activities including quantity takeoff, cost modeling, and documentation management. Because both stages rely heavily on information processing and standardized analytical procedures, AI has strong augmentation or substitution potential across the entire pathway. From a production system perspective, these transitions are most susceptible to capability compression, as experiential differentiation between stages may narrow under automation. High-to-low transitions represent pathways in which early-stage roles exhibit higher AI exposure while subsequent roles rely more heavily on human-centered coordination and accountability. The pathway from *Office Engineer* (0.055) to *Field Engineer* (0.007) illustrates this pattern. Early roles emphasize documentation tracking, reporting, and structured coordination tasks that align strongly with AI support. In contrast, *Field Engineer* positions require engineering judgment, onsite compliance authority, crew leadership, and real-time problem-solving under uncertainty. These competencies remain human-critical. Such transitions represent while AI may improve efficiency at foundational stages, these early roles traditionally function as experiential learning platforms. Significant compression of documentation-intensive roles may weaken the depth of experiential accumulation required for stable execution-level leadership in later stages. Low-to-high transitions describe pathways

where initial roles are relatively human-dominant but subsequent roles require greater digital or AI-integrated competencies, which rarely happen in practice as shown in Figure 3. Low-to-low transitions occur when both stages remain predominantly human-centered, such as *Subcontractor* (0.005) → *Superintendent* (0.003). These pathways emphasize negotiation, contractual accountability, stakeholder alignment, and workforce coordination. These transitions function as structural anchors within the production system, demonstrating relative stability. Overall, AI influences task distribution and career pipelines' structural integrity within construction production system.

CONCLUSION

This study frames the construction workforce as a production system where value and reliable delivery depend on allocating work to capable resources. As AI becomes a practical cognitive and coordination resource, it not only augments task execution but also reshapes capability requirements and career mobility structures that support long-term system stability. To provide domain-specific and data-driven evidence, this paper developed an analytical framework that integrates employer demands from job postings with observed workforce mobility patterns from large-scale career trajectories. The job posting analysis shows that AI-specific roles (e.g., AI trainers) have emerged, administrative positions exhibit relatively high AI exposure, and executive and HR roles remain comparatively low in exposure due to their reliance on judgment, accountability, and relational governance. BIM-related roles also show lower observed AI exposure in current postings, suggesting that AI adoption in these roles may be less explicitly articulated in hiring despite broader discussions of AI potential in modeling workflows. Beyond role-level exposure, the career trajectory analysis reveals dominant mobility pathways and enables transition-level interpretation through exposure gradients. By mapping transition task and skill gaps to an AI capability taxonomy, we conceptualize four structural transition types based on AI exposure scores: high-to-high, high-to-low, low-to-high, and low-to-low, each implying a different mechanism through which AI may reconfigure capability ladders. High-to-high transitions are most susceptible to capability compression because AI alignment remains strong across both stages. High-to-low transitions indicate foundational roles with high AI alignment often function as experiential learning platforms for later authority-bearing roles with low AI substitutability, so excessive automation may weaken the capability pipeline. Low-to-high transitions reflect upskilling pressure, which rarely happens in practice. Low-to-low transitions remain anchored in human-centered leadership and accountability and are comparatively stable under AI integration. Collectively, these findings suggest that AI does not uniformly “replace” construction roles. It redistributes structured cognitive work while leaving responsibility-bearing coordination and leadership functions primarily human-dependent. Regarding limitations, first, more granular task decomposition and longitudinal validation will be used to evaluate how AI integration influences the stability of capability pipelines over time, supporting sustainable human-AI coordination in construction production systems. Second, as Indeed and LinkedIn datasets primarily reflect digitally documented and formal job market segments. To better capture broader variations in lean practices, future research work could incorporate data from less digitized regions and alternative sources for analysis. Using Pennsylvania data provides a representative sample and future work can expand the dataset to multiple states or countries to examine whether AI exposure varies across regions in the construction job market. Third, while AI keyword list from the Stanford AI Index provides a standardized approach for large-scale analysis, AI exposure score captures the textual presence of AI-related terms in job descriptions, which might not fully reflect implicit AI-related tasks.

REFERENCES

- Adepoju, O. O., & Aigbavboa, C. O. (2021). Assessing knowledge and skills gap for construction 4.0 in a developing economy. *Journal of Public Affairs*, 21(3), e2264. <https://doi.org/10.1002/pa.2264>
- Chen, G., Alsharef, A., Ovid, A., Albert, A., & Jaselskis, E. (2025). Meet2Mitigate: An LLM-powered framework for real-time issue identification and mitigation from construction meeting discourse. *Adv. Eng. Inform.*, 64(C), 17. <https://doi.org/10.1016/j.aei.2024.103068>
- Chopra, A., Bhattacharya, S., Salvador, D., Paul, A., Wright, T., Garg, A., Ahmad, F., Schwarze, A. C., Raskar, R., & Balaprakash, P. (2025). The Iceberg Index: Measuring Skills-centered Exposure in the AI Economy. <https://doi.org/10.48550/arXiv.2510.25137>
- Demirci, O., Hannane, J., & Zhu, X. (2024). Who is AI Replacing? The Impact of Generative AI on Online Freelancing Platforms. *CESifo Working Paper No. 11276*. <http://dx.doi.org/10.2139/ssrn.4991774>
- Dong, Y., Hu, Y., Cai, J., Xu, X., & Li, S. (2025, 2025/10/01). Improving Construction Workforce Entry by Examining Construction Equipment Operators' Employment Practices. *Journal of Construction Engineering and Management*, 151(10), 04025138. <https://doi.org/10.1061/JCEMD4.COENG-15865>
- Dong, Y., Hu, Y., Li, S., Cai, J., & Han, Z. (2024, 2024/12/15/). BIM-blockchain integrated automatic asset tracking and delay propagation analysis for prefabricated construction projects. *Automation in Construction*, 168, 105854. <https://doi.org/10.1016/j.autcon.2024.105854>
- Dong, Y., Zhan, Z., Hu, Y., Doe, D. M., & Han, Z. (2025, 2025/12/01/). AI BIM coordinator for non-expert interaction in building design using LLM-driven multi-agent systems. *Automation in Construction*, 180, 106563. <https://doi.org/10.1016/j.autcon.2025.106563>
- Felten, E., Raj, M., & Seamans, R. (2021). Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses. *Strategic Management Journal*, 42(12), 2195-2217. <https://doi.org/10.1002/smj.3286>
- HAI, S. (2025). *The 2025 AI Index Report*. <https://hai.stanford.edu/ai-index/2025-ai-index-report>
- Indeed. (2025). <https://www.indeed.com/>
- Jing, Y., Lin, W., Sheil, B., & Acikgoz, S. (2025, 2025/10/01/). 3D multimodal feature for infrastructure anomaly detection. *Automation in Construction*, 178, 106388. <https://doi.org/10.1016/j.autcon.2025.106388>
- Lagos, C. I., Herrera, R. F., Cawley, A. M., & Alarcón, L. F. (2024, 2024/07/01). An AI Copilot for Make-Ready Planning in the Last Planner System. Proceedings of the 32nd Annual Conference of the International Group for Lean Construction (IGLC 32), Auckland, New Zealand. <https://doi.org/10.24928/2024/0155>
- Mora, M., Tang, P., & Toledo, M. (2025, 2025/06/02). Towards Enabling Sustainability-aware Operations in Housing Manufacturing with AI-driven Value Stream Mapping: a Review. Proceedings of the 33rd Annual Conference of the International Group for Lean Construction (IGLC 33), Osaka and Kyoto, Japan. <https://doi.org/10.24928/2025/0266>
- Musonda, I., & Okoro, C. (2021). Assessment of current and future critical skills in the South African construction industry. *Higher Education, Skills and Work-based Learning*, 11(5), 1055-1067. <https://doi.org/10.1108/heswbl-08-2020-0177>
- Ouma, L., Leicht, R., & Messner, J. (2025, 2025/06/02). A Target Value Maturity Model for Performance Target Management in the Design Phase of Lean Construction Projects. Proceedings of the 33rd Annual Conference of the International Group for Lean Construction (IGLC 33), Osaka and Kyoto, Japan. <https://doi.org/10.24928/2025/0278>

- Powell, D. J. (2024). Artificial intelligence in lean manufacturing: digitalization with a human touch? *International Journal of Lean Six Sigma*, 15(3), 719-729. <https://doi.org/10.1108/ijlss-05-2024-256>
- Rad, M. H. G., & Ilbeigi, M. (2025, 2025/06/02). Generative AI in Lean Construction: a Scoping Review. Proceedings of the 33rd Annual Conference of the International Group for Lean Construction (IGLC 33), Osaka and Kyoto, Japan. <https://doi.org/10.24928/2025/0195>
- Skinnarland, S., Alves, T. d. C. L., & Desmarais, D. (2025, 2025/06/02). The Meaning of Work in Construction: an Individual Well-being Perspective. Proceedings of the 33rd Annual Conference of the International Group for Lean Construction (IGLC 33), Osaka and Kyoto, Japan. <https://doi.org/10.24928/2025/0279>
- Wang, G., Ying, Q., Jing, Y., Wysocki, O., & Sheil, B. (2026). *ActionReasoning: Robot Action Reasoning in 3D Space with LLM for Robotic Brick Stacking*. <https://doi.org/10.48550/arXiv.2602.21161>
- Zelenko, D., & Maxwell, D. (2024, 2024/07/01). Lean Construction for Innovation: A Systematic Review of IGLC Proceedings. Proceedings of the 32nd Annual Conference of the International Group for Lean Construction (IGLC 32), Auckland, New Zealand. <https://doi.org/10.24928/2024/0111>
- Zhao, X., Kuang, W., & Kim, Y.-W. (2025, 2025/06/02). Leveraging Multi-agent System Powered by Large Language Model to Improve Transparency and Reliability in Automated Supply Chain Coordination. Proceedings of the 33rd Annual Conference of the International Group for Lean Construction (IGLC 33), Osaka and Kyoto, Japan. <https://doi.org/10.24928/2025/0102>