Tracing the Rise of AI in Civil Engineering Work: Employer Expectations and Educational Implications from Job Posting Data (WIP)

Ruimin Feng, University of Idaho

Dr. Ruimin Feng is an Assistant Professor in the Department of Civil and Environmental Engineering at the University of Idaho. His research combines geotechnical and geological engineering with AI and advanced imaging to extract and interpret complex material and system behaviors. Before joining the University of Idaho, Dr. Feng served as a Research Associate and Postdoctoral Fellow at the University of Arkansas and the University of Calgary. In these roles, he served as a lead researcher on multiple federally funded projects supported by the U.S. Department of Transportation and the U.S. Army Corps of Engineers, focusing on AI-enhanced imaging, rock mechanics, and additive construction materials.

Yuanlu Niu, University of Arkansas

Yuanlu Niu, PhD, is an Associate Professor of Human Resource Development at the University of Arkansas. She holds a Ph.D. in Education, with a concentration in Workforce Education and Development, as well as an MBA from Southern Illinois University Carbondale. Her research interests include career development, employability, and technology adoption.

Huan Ning, Emory University

Dr. Huan Ning is a Postdoctoral Researcher of Environmental Sciences at Emory University. His research areas include geospatial artificial intelligence (GeoAI), agentic AI, and geospatial computing.

Xiao Huang, Emory University

Dr. Xiao Huang is an Assistant Professor of Environmental Sciences at Emory University. His research expertise covers in geospatial artificial intelligence (GeoAI), urban informatics, human–environment interactions, disaster mapping, and remote sensing.

Prof. Claretha Hughes Ph.D.

Dr. Claretha Hughes is Professor of Human Resource and Workforce Development at the University of Arkansas (UA. Her research interests include valuing people and technology in the workplace, technology development, diversity intelligence, learning technol

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Introduction

Artificial intelligence (AI) and data-driven technologies are increasingly influencing civil engineering practice, particularly in infrastructure planning, design, and management [1]. AI tools, including predictive modeling, digital twins, and automated design optimization, are becoming integral components of modern engineering workflows [2]. As these technologies diffuse across industry sectors, they are also changing employers' expectations for the skills and competencies required of civil engineers [3]. However, limited empirical research has examined how employers' expectations for AI-related skills have evolved over time and across geographic regions. Understanding these trends is essential for aligning civil engineering education with the rapidly changing demands of the profession. The purpose of this study is to investigate longitudinal and regional trends in employers' expectations for AI-related competencies in civil engineering job postings from 2015 to 2025. The main research question is: How have employers' expectations for AI-related skills in civil engineering job postings evolved over time and across geographic regions in the United States from 2015 to 2025?

Theoretical framework

Both skill-biased technological change (SBTC) [4] and human capital theory (HCT) [5] are used as the theoretical framework to explain how AI and data-driven technologies are reshaping civil engineering work. These theories help explain why employers' skill expectations are changing and how those expectations appear in job postings. SBTC explains shifts in employer demand for skills. HCT helps interpret job requirements as signals of valued knowledge and competencies. Skill-biased technological change argues that technological progress is not neutral [4], [6]. It increases demand for workers with advanced analytical, computational, and problem-solving skills. At the same time, it reduces the relative demand for routine or narrowly defined technical tasks. Research on earlier technological shifts, such as the information technology revolution, shows that SBTC contributed to growing gaps between higher- and lower-skilled workers [7]. In civil engineering, AI-enabled tools are now embedded in planning, design, and operations. From an SBTC perspective, these tools complement engineers with AI and data-analytic skills. They enhance productivity and support decision-making. In contrast, tasks limited to routine calculations may become less central. As a result, traditional civil engineering skills may no longer be sufficient on their own. While SBTC focuses on changes in labor demand, human capital theory addresses how skills are developed and valued. Becker [5] framed education and training as investments that increase productivity and long-term returns. Within this view, job requirements reflect the human capital employers seek.

Literature review

The integration of AI has progressed to influence the entire lifecycle of civil structures, encompassing intelligent design, construction management, and structural health monitoring [8], [9]. This shift is characterized by a transition toward a "Cyber-Physical System" where design and maintenance are linked through continuous data loops [10]. A primary area of application is structural health monitoring and predictive maintenance. Research by Al Ammairih [11] highlights the use of hybrid AI frameworks utilizing edge-cloud architectures to perform real-time anomaly detection on infrastructure such as bridges and tunnels. These systems employ convolutional neural networks and long short-term memory networks to identify temporal patterns in sensor data, facilitating early detection of structural damage and enhancing predictive modeling for seismic resilience [12], [13]. Zhang [14] demonstrates that AI-driven safety management systems can monitor personnel in real-time with an accuracy rate of 97.4%, significantly reducing the risks associated with manual supervision. In the domains of geotechnical and materials engineering, soft computing techniques, such as neural-fuzzy systems and metaheuristic algorithms, are used to predict complex soil behavior, including the ultimate bearing capacity of driven piles [15]. Furthermore, the recent emergence of generative AI represents a change in design philosophy. Large language models (LLMs) are increasingly used for conceptual ideation, assisting engineers in formulating and refining structural designs to optimize resource utilization [16].

The diffusion of AI tools is fundamentally altering the professional identity and daily practice of the civil engineer, moving the discipline toward a paradigm of intelligent design, construction, and maintenance [10]. Practitioners are transitioning from reactive maintenance to predictive paradigms, where the focus is on managing the remaining useful life of infrastructure assets through data-driven insights [17]. This transformation requires engineers to combine machine learning with physical laws, such as elasticity [9]. This integration ensures that AI-generated solutions remain physically realistic and consistent with established engineering principles. This evolution also introduces new requirements for decision-making transparency and professional accountability. Hasan and Lu [18] identify a critical need for explainable AI in safety-sensitive applications to ensure that the logical reasoning behind automated conclusions is clear to the engineer. Therefore, the skill sets expected within the profession are expanding to include interdisciplinary fluencies. Research indicates that civil engineering curricula must now integrate knowledge-based expert systems and AI methodologies to equip students with the data literacy needed to navigate modern construction requirements [19, [20]. The role of the engineer is thus evolving from purely manual oversight to the management of complex, intelligent monitoring ecosystems and the validation of algorithmic outputs.

Online job postings (OJPs) are increasingly used to examine changes in labor market skill demand. Unlike patents or academic publications, which reflect past innovation, job postings are forward-looking. They signal firms' intentions to adopt new technologies before those technologies become embedded in products or formal outputs [21]. For this reason, OJPs are well suited for studying technological transitions and workforce adaptation [22]. Job postings also provide detailed information about the competencies employers seek. The required skills listed in job advertisements serve as indicators of emerging human capital needs. This makes OJPs particularly useful for examining how new technologies reshape occupational skill profiles over time. Compared to traditional labor statistics, job postings allow for more fine-grained analysis of technical skill requirements and their diffusion across industries and regions. Recent studies [22, [24] have increasingly used OJPs to analyze skill demand in engineering and other STEM fields. Employer-sourced datasets further strengthen this approach by reducing duplicate listings and job board noise [25]. This body of work supports the use of OJPs as a valid and timely data source for examining how AI and data-driven competencies are reshaping professional work.

Methodology

This study uses a quantitative analysis of online job postings from LinkUp. LinkUp collects postings directly from employer career websites. The dataset includes both structured metadata and full-text job descriptions. Metadata fields include job title, employer, location, posting date, and O*NET occupation codes. Job descriptions provide information on responsibilities, qualifications, and required skills. The analysis focuses on U.S.-based civil engineering–related occupations identified using O*NET Standard Occupational Classification (SOC) codes. These include Civil Engineers (17-2051.00), Transportation Engineers (17-2051.01), Water/Wastewater Engineers (17-2051.02), Environmental Engineers (17-2081.00), Mining and Geological Engineers (17-2151.00), and Hydrologists (19-2043.00). The study period spans from 2015 through September 2025. The final analytic sample consists of 684,323 job postings.

This study employs a two-stage strategy to identify AI-related and data-driven competencies in civil engineering job postings. The approach balances domain specificity with computational efficiency. In the first stage, an inductive discovery process was conducted using a random sample of 10,000 job postings from 2024. This year was selected due to increased adoption of AI and data-driven technologies in engineering practice. Natural language processing (NLP) was performed using a local deployment of the OpenAI GPT-OSS-20B model. The model was run on a dedicated workstation equipped with an NVIDIA GeForce RTX 4090 GPU, a 13th Gen Intel® Core™ i9-13950HX CPU, and 64 GB of system memory. The model was prompted to identify explicit terms and latent competencies related to AI and data-driven methods within civil engineering contexts. This process produced a domain-specific vocabulary tailored to civil and environmental engineering applications. In the second stage, the inductively derived vocabulary was integrated with the Lightcast-Burning Glass Skills Taxonomy (LBG-ST). This step ensured consistency with established labor market classifications. The finalized dictionary was applied to the full dataset using keyword-based searches. The finalized dictionary consisted of 337 validated terms and phrases. To ensure domain specificity, the vocabulary includes explicit technical competencies such as structural health monitoring, geotechnical data fusion, and smart city AI application. A job posting was classified as AI-related if it contained at least one validated term from the dictionary. Postings referencing data-driven competencies were also classified as AI-related, given their foundational role in AI applications. AI-related job postings were aggregated by year and geographic location. Each posting was assigned to a U.S. state based on employer-reported information. This structure enabled analysis at a state level. The approach supported examination of longitudinal trends and regional variation in AI-related skill demand across civil engineering fields.

Integrating the theoretical framework with the methodology, HCT justifies the use of job postings as observable signals of industry value, while SBTC informs the two-stage NLP approach by highlighting the need to inductively identify biased technological competencies that complement traditional engineering depth. There are several limitations in this study. OJPs primarily capture recruitment-phase expectations rather than real-world engineering practice and may underrepresent small-firm hiring. In addition, identifying AI-specific skills is subject to the evolving nature of technical vocabulary, where the boundary between traditional computational modeling and modern AI is often fluid. Lastly, 2025 data reflect only a partial year (through September), and automated text extraction carries inherent risks of classification error.

Primary results

The longitudinal and geographic analysis of the LinkUp dataset (N=684,323 OJPs from 6,895 unique companies) reveals a distinct shift in the civil engineering labor market. Table 1 summarizes the annual growth of AI-related requirements relative to the total number of OJPs. The data indicates that while total job postings varied across years, the percentage of AI-related JOPs nearly doubled from 2015 to 2025. This suggests that AI is becoming a baseline expectation rather than a niche specialty. Table 2 shows the AI-related OJPs distribution by O*NET occupational classification. To address regional variations, Table 3 compares the absolute volume of postings against the proportional demand for AI skills in top-ranking states. Table 4 compares the general civil engineering labor market against the AI-related subset to identify shifts in educational and experience baselines. The Total OJPs (%) column provides a standard industry benchmark for all civil engineering roles, while the AI-related OJPs (%) column represents the proportion of postings that are AI-related within each category subgroup.

Table 1. Annual distribution of AI-related civil engineering OJPs (2015-2025)

Year	Total OJPs	AI-related OJPs	Percent	Year	Total OJPs	AI-related OJPs	Percent
2015	17,050	677	4.0%	2021	68,416	3,314	4.8%

2016	26,607	1,245	4.7%	2022	94,609	5,800	6.1%
2017	36,969	1,420	3.8%	2023	112,316	6,638	5.9%
2018	43,521	1,717	3.9%	2024	116,893	7,899	6.8%
2019	49,682	1,925	3.9%	2025	80,001	5,886	7.4%
2020	38,259	1,436	3.8%				

Table 2. AI-related OJPs distribution by O*NET occupational classification (2015-2025)

SOC Code	Occupational Title	Total OJPs	AI-related OJPs	Percent
17-2051.00	Civil Engineers	486,982	18,143	3.7%
17-2051.01	Transportation Engineers	16,838	1,542	9.2%
17-2051.02	Water/Wastewater Engineers	15,082	1,199	7.9%
17-2081.00	Environmental Engineers	153,361	15,055	9.8%
17-2151.00	Mining and Geological Engineers	7,441	995	13.4%
19-2043.00	Hydrologists	4,619	1,023	22.1%

Table 3. Regional AI demand (Top 10 States)

State	Total OJPs	AI-related OJPs	Percent	State	Total OJPs	AI-related OJPs	Percent
CA	75,063	4,315	5.7%	VA	30,376	1,619	5.6%
TX	64,291	3,345	5.2%	WA	23,967	1,484	6.2%
FL	45,818	2,590	5.7%	MA	15,633	1,362	8.7%
NY	30,345	1,839	6.1%	NC	29,219	1,228	4.2%
CO	25,155	1,730	6.9%	AZ	21,908	1,157	5.3%

Table 4. AI-related OJPs across Different Educational Levels and Years of Work Experience

Education	Total OJPs (%)	AI-related OJPs (%)	Experience	Total OJPs (%)	AI-related OJPs (%)
High School	0.02%	7.6%	0 year	6.49%	5.9%
Associate	14.23%	2.9%	1-3 years	16.45%	4.6%
Bachelor	35.64%	4.5%	4-6 years	13.17%	5.2%
Master	0.11%	16.9%	7-10 years	16.18%	5.7%
PhD	3.25%	9.0%	10+ years	0.03%	12.6%
Missing	46.75%	6.9%	Missing	47.68%	5.9%

Conclusion

This study empirically tracks the digital transformation of civil engineering, showing that AI-related competencies have evolved from niche requirements into central pillars of the profession. The significance of this research lies in its ability to quantify how skill-biased technological shifts are redefining the modern engineer's professional identity. The findings demonstrate that employers increasingly value a hybrid of deep domain expertise and data literacy. As AI becomes embedded in infrastructure lifecycles, this work provides a necessary baseline for aligning civil engineering curricula with industrial reality. Therefore, the study underscores that AI is not a replacement for engineering judgment but a critical augmentation, necessitating a paradigm shift in how to prepare future engineers for a data-driven workforce.

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