Mapping AI-Related Skill Trends in Mechanical Engineering: Implications for Workforce Development (WIP)

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Abstract

The rapid integration of artificial intelligence (AI) and advanced automation is reshaping mechanical engineering practice, altering both the nature of engineering work and the skills employers demand. While prior research has documented the growing influence of AI in engineering broadly, limited empirical evidence exists on how employer expectations for AI-related competencies in mechanical engineering have evolved over time and across geographic regions. Drawing on skill-biased technological change and human capital theory, this study examines longitudinal and regional trends in AI-related skill demand using large-scale online job posting data. The study analyzes 508,477 U.S. mechanical engineer job postings collected from 2015 to September 2025 from LinkUp, a job market data provider that sources postings directly from employer websites. A hybrid two-stage skill identification approach was employed. First, an inductive discovery process using natural language processing and a locally deployed large language model identified engineering-specific AI and data-driven competencies from a representative sample of postings. Second, these inductively derived terms were integrated with the Lightcast-Burning Glass Skills Taxonomy to create a domain-specific AI skill dictionary, which was applied to the full dataset. Job postings were classified as AI-related if they contained at least one validated AI-related term. Temporal and geographic analyses were conducted at the state and city levels.

Preliminary results show a substantial increase in AI-related skill demand over the study period, with AI-related postings rising from approximately 10% of mechanical engineer job postings in 2015 to over 20% by 2025. Growth accelerated notably after 2020, despite short-term fluctuations linked to broader labor market volatility. The findings also reveal pronounced geographic concentration, with California, Michigan, and Texas emerging as leading hubs for AI-enabled mechanical engineering roles. The results also report the 10 most frequently requested skills. These findings highlight the growing importance of AI-related competencies in mechanical engineering and underscore the need for responsive curriculum development and ongoing professional upskilling to align engineering education and workforce development with evolving labor market demands. We prefer this work-in-progress paper to be presented as a poster.

Keywords: artificial intelligence, skill trends, job postings, mechanical engineering

Introduction

The growing integration of artificial intelligence (AI) and advanced automation is transforming the work of mechanical engineers, influencing how products are designed, manufactured, and maintained [1]. AI technologies such as generative design, robotics, digital twins, and predictive analytics are changing expectations for what engineers must know and be able to do [2], [3], [4]. As these tools reshape engineering practice, workplaces are seeking professionals who can blend traditional mechanical competencies with data-driven and computational abilities [5]. Despite this shift, little research has systematically examined how employer expectations for AI-related skills have changed over time and by location within mechanical engineering. Understanding these evolving patterns is important for aligning educational programs with contemporary workforce needs. This study aims to explore longitudinal and regional trends in employer demand for AI-related competencies in mechanical engineer job postings between 2015 and 2025. The main research question is: How have employers' expectations for AI-related skills in mechanical engineer job postings evolved over time and across geographic regions in the United States from 2015 to 2025?

We draw on skill-biased technological change (SBTC) [6] and human capital theory (HCT) [7] to explain ongoing transformations in mechanical engineering. SBTC posits that technological progress increases demand for highly skilled labor while reducing demand for routine work, a pattern historically observed during the information technology revolution [8]. In the current AI-driven context, mechanical engineering represents a new iteration of SBTC, as AI automates routine computational tasks and shifts the skill premium toward engineers with advanced analytical and integrative capabilities. Complementing this demand-side perspective, HCT conceptualizes education and skill acquisition as investments that enhance productivity and earnings [7]. From this view, the growing emphasis on AI-related competencies reflects employers' assessments of valuable human capital.

Literature Review

The skills and competencies required by the engineering workforce in the United States continually shift with changes in technology, policy, and national priorities [9], [10]. Each industrial revolution, for example, has brought about new ways that engineers learn, work, and contribute to society [11], [12], [13]. The fourth industrial revolution, commonly referred to as Industry 4.0, began in the early 21st century and is defined by rapid technological and digital innovation that includes the development of cyber-physical systems, the Internet of Things, and generative artificial intelligence [14], [15], [16], [17]. This digital transformation has led to substantial changes in workforce skill requirements [18], [19], [20]. Changes in workforce skill requirements in the current era of Industry 4.0 and the digital transformation have been studied in several engineering and engineering-adjacent sectors, with most work focusing on manufacturing [18], [19]. However, to better understand and address disciplinary workforce needs to adapt curricula and student workforce preparation, this research must be extended to a more granular scale.

While mechanical engineering is one of the broadest engineering disciplines, there are certain skills and competencies that are shared among mechanical engineers. ABET, the global accreditation organization for post-secondary, degree-granting engineering programs, documents mechanical engineering curriculum requirements for accreditation. These include “principles of engineering, basic science, and mathematics” and “applications of these topics to modeling, analysis, design, and realization of physical systems, components, or processes” [21]. While these core skills remain important for current mechanical engineers and students, the latter competencies are being transformed with the emergence of AI and other modern digital technologies. Several shifts that are occurring in mechanical engineering as a result of this digital transformation include the emergence of generative design, data-driven optimization, and predictive maintenance, among others[22], [23], [24]. The integration of artificial intelligence, machine learning, and other digital advancements in mechanical engineering has shifted necessary competencies from traditional analytical and design skills toward hybrid skills that combine domain expertise with proficiency in using, creating, and interpreting results from AI-augmented workflows [25], [23]. Advances in computing, artificial intelligence, and digital technologies has led to the development of generative design, which draws on advanced algorithms and machine learning to rapidly develop and optimize designs based on user-defined constraints, allowing for must faster and more complete exploration of the design space [1], [26], [27], [28]. Generative design is transforming the design process, requiring mechanical engineers to translate previously manual, iterative approaches to design to clear objectives, parameters, and constraints enabling the software to more rapidly create and optimize components [1], [29], [30]. Engineers must then rely on their engineering judgment and expertise to refine the design and the constraints to finalize the design while also developing a deep understanding of the new capabilities of generative design [26], [30]. This is changing a core engineering design skill from being able to model the part in specific software programs to defining parameters and constraints and critically evaluating resultant designs [31].

Closely related to and integrated with advances in generative design, optimization and analysis are undergoing major shifts enabled by accelerated data-driven modeling [1], [29], replacing the traditional, time-consuming, trial-and-error approaches [32]. In many ways, this is also closely associated predictive maintenance, or the ability to use real and simulated system data to predict remaining useful life, optimize maintenance, and predict failures in systems and equipment [33], [34], [35]. Predictive maintenance and process optimization has been made possible with advanced algorithms, machine learning, the development of digital twins, real-time monitoring and computer vision, and the rapid generation of large amounts of simulated data [22], [32], [35]. Advancements in these areas of mechanical engineering will likely lead to mechanical engineers needing more expertise in the technologies and tools that have enabled and will continue to drive these transformations. With these and other rapid changes in the discipline, it is likely that the skills demanded by mechanical engineering employers are changing in response. The literature, for example, highlights the importance of engineers accepting these new tools and approaches [36], developing the know-how to fully capitalize on these tools and approaches[26], [36], [37], and being able to make, understand, and explain AI-driven or AI-augmented decisions [32]. Other work supports growing emphases on engineering judgment and critical thinking skills more broadly [38], [39] and overarching changes in the ways engineers must think in the AI-era [40]. This study aims to explicitly document these evolving expectations and skill requirements over the last decade so that mechanical engineering educators can adapt curricula and students can more easily develop skills aligned with the needs of the labor market.

Regional variation in the labor market across the United States is generally acknowledged, with industry clusters like Detroit's automotive companies and Silicon Valley's tech organizations representing two of the most well-known regional clusters [41], [42], [43], [44]. Economists and sociologists have long studied these regional variations and their causes [43], [45], [46]. A recent report, for example, discusses variation in skill demands by region or metropolitan statistical area (MSA) that reflects talent needs of a specific area, including case studies examining regional trends in manufacturing, digital marketing, and cybersecurity [47]. However, there is limited work on discipline-specific regional trends, with one paper details regional robotics-related skill demand across the United States in 2015, finding higher concentrations of jobs requiring robotics skills in the Midwest and Southeast United States [48]. This study builds on and contributes to this body of work by documenting longitudinal regional trends in the AI and data science skill demand required of mechanical engineers in the United States.

Method

This study employs a quantitative analysis of online job postings (OJPs) to examine AI-related skill demand in mechanical engineering. The primary data source is a longitudinal dataset of U.S. job postings provided by LinkUp. OJPs offer a real-time, forward-looking view of labor market demand and are well-suited for analyzing technological transitions because they signal firms' intended adoption of new technologies before such changes appear in patents or products [49]. By detailing employer skill requirements, job postings serve as a proxy for emerging human capital needs. To ensure data quality, we rely on LinkUp, which indexes postings directly from employer websites, reducing duplication, expired listings, and job board spam [50]. LinkUp has been widely used in prior labor market research [51], [52], supporting the reliability of longitudinal analyses. Job postings include structured metadata (e.g., job title, employer, location, posting date, and ONET occupation codes) and unstructured job description text. Using the ONET SOC code for Mechanical Engineers (SOC 17-2141.00), we identified 535,602 postings from 2015 to September 2025. After excluding postings with missing descriptions, the final analytic sample consisted of 508,477 OJPs.

A central methodological challenge was identifying AI-related competencies embedded within highly specialized engineering language. Existing approaches often rely on general-purpose skill taxonomies, such as the Lightcast-Burning Glass Skills Taxonomy (LBG-ST), which tend to overrepresent IT-oriented skills and undercapture engineering-specific AI applications. To address this limitation, we adopted a hybrid two-stage approach that balances domain specificity with computational scalability. In the first stage, we conducted an inductive discovery process on a random sample of 10,000 postings from 2024, a year characterized by heightened AI adoption. Using natural language processing with a locally deployed large language model, we identified explicit and latent AI-related competencies within the mechanical engineering context. Data-driven competencies, as a foundational component of AI, were also considered AI-related. This process generated a domain-specific vocabulary capturing engineering-relevant AI applications often overlooked by standardized taxonomies. In the second stage, the inductively derived vocabulary was integrated with LBG-ST terms to ensure alignment with prior labor market research. This finalized dictionary was then applied to the full dataset using keyword-based searches. A posting was classified as AI-related if it contained at least one validated term. This hybrid strategy combines the contextual accuracy of LLM-assisted extraction with the efficiency required for large-scale analysis. To examine temporal and spatial patterns, AI-related postings were aggregated by year and geographic location (state and city), enabling analysis of longitudinal trends and the identification of emerging regional hubs for AI-enabled mechanical engineering work.

Preliminary Results

In 2015, the dataset identified 1,917 job postings requiring AI-related skills, representing approximately 10.3% of the total mechanical engineer OJPs. Between 2015 and 2019, both the absolute volume and the relative share increased incrementally, reflecting an early adoption phase where data-driven methods began to permeate traditional engineering roles. This gradual growth is consistent with the broader adoption of "Industry 4.0" frameworks, which emphasize the integration of cyber-physical systems and preliminary data analytics in manufacturing and design [53]. A marked acceleration in demand is observed after 2020. Between 2020 and 2022, the volume of AI-related postings more than doubled, rising from 4,744 (14.7%) to 12,669 (19.3%). While a temporary contraction in absolute volume occurred in 2023 (10,901 postings, 15.2%), this likely reflected broader tech sector restructuring following pandemic-era overhiring, economic uncertainty, and rising interest rates, rather than declining AI demand. By 2025, AI-related competencies rebounded strongly and reached their highest observed prevalence, accounting for over 20.6% of all mechanical engineer OJPs (9,960 postings), demonstrating sustained long-term demand despite short-term market volatility.

The results indicate a highly uneven geographic distribution of AI-related mechanical engineering vacancies. California emerges as the dominant market, with 14,755 postings, which substantially exceeds all other states. This concentration reflects California's robust ecosystem in advanced manufacturing, automation, robotics, and technology-driven engineering, supported by its proximity to major technology firms, research institutions, and industrial innovation clusters. Michigan ranks second with 10,847 postings, underscoring the continued transformation of the automotive and mobility sectors toward AI-enabled design, manufacturing, and intelligent systems. Texas follows with 5,996 postings, reflecting its large-scale industrial base and growing investments in smart manufacturing, energy systems, and engineering automation. Beyond these primary hubs, a second tier of states exhibits notable AI-related demand, including Washington with 3,349 postings; New York with 3,191 postings; Massachusetts with 2,883 postings; Virginia with 2,812 postings; Illinois with 2,740 postings; Ohio with 2,580 postings; and Florida with 2,411 postings. The analysis shows a clear hierarchy of AI and data-driven skills in mechanical engineer OJPs. The results report the 10 most frequently requested skills, which capture the majority of AI-related demand, including AI-assisted data analysis, Python, machine learning, artificial intelligence, computer vision, Torch, deep learning, TensorFlow, image processing, and AI-integrated systems. This paper is a work in progress; we will continue to analyze how the AI-related JOPs and skills vary across different levels of education and professional experience.

Implications and Next Steps

This study highlights how AI-related skill demands are reshaping mechanical engineering from purely technical tasks toward managing and integrating complex systems. By using job postings as market signals, these findings inform a curricular roadmap where AI is integrated into core sequences: transitioning foundational programming to Python-based analytics, embedding generative design in CAD courses, and incorporating data-driven modeling into mechanics labs. Such updates are essential to align education with industry needs, reducing skill gaps by emphasizing AI-in-the-loop workflows in capstone projects. Furthermore, the results show the necessity of continuous upskilling as AI automates routine tasks, shifting the engineer's value toward higher-order competencies and professional judgment. Methodologically, this study demonstrates the utility of combining large-scale job posting data with domain-specific identification to track technological transitions in specialized engineering occupations.

Future work on this topic will include a more in-depth analysis of our findings. This may suggest additional directions, including developing a better understanding of the role of AI in engineering workplaces through future human subject studies conducting exploratory analyses to see if these emerging AI skillsets correlate with demand for other skillsets in mechanical engineering. This, in combination with other research in this emerging area, could provide a clearer roadmap for curricular and instructional changes that must occur to better prepare mechanical engineering students for the changing labor market.

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