Exploring Engineering Employment Trends: A Decade-long Deep Dive into Skills and Competences Included in Job Advertisements

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ABSTRACT (Academic)

My dissertation explores how Natural Language Processing (NLP) can support job advertisement discipline classification to help workforce researchers in analyzing labor market trends and relate it back to higher education. In particular, this study investigates how NLP can be used to identify discipline-specific and education-level skill demands from pre-classified large-scale online job advertisements form Burning Glass Technologies. Although engineering education has made long steps in preparing students with foundational knowledge, employers continue to report a misalignment between the skills students acquire in school and the skills needed in practice. A key challenge in addressing this issue is the effective interpretation of semi-structured labor market data such as online job postings, which contain rich but inconsistently labeled skill information. To address this, I developed an NLP classification system that applies pattern-based text classification and flexible regular expression (regex) matching to identify relevant engineering job postings across Civil (CE), Electrical (EE), and Mechanical (ME) Engineering.

The classification framework leverages a dictionary of O*NET job title terms and engineering-specific vocabulary to refine the labeling of jobs originally mapped using Standard Occupational Classification (SOC) codes. To validate the classification accuracy, I evaluated results using confusion matrix metrics (accuracy, precision, recall, F1-score) and performed manual spot-checking of 100 job ads from each discipline. The final classification system achieved high F1-scores across CE (94.2%), EE (91.7%), and ME (93.0%), showing strong alignment with human-judged classifications. This step was essential to ensure accurate discipline-specific labeling for subsequent skill demand analysis.

Guided by the SABER-Workforce Development (SABER-WfD) framework, the study then addresses two additional research questions. The second research question examines how skill demands differ by engineering discipline and by degree level (bachelor's, master's, doctoral). Using skill mention proportions and statistical analyses such as ANOVA and Cohen's d, the study reveals that foundational technical skills like Drafting and Engineering Design, CAD, and Microsoft Office tools are dominant across all three disciplines at the bachelor's level. At the graduate level, postings increasingly emphasize management-oriented competencies such as Project Management, Budgeting, and Scheduling, particularly in civil and mechanical engineering. EE showed a higher graduate-level demand for specialized tools like MATLAB, Python, and Simulation.

The third research question explores how skill requirements have changed over time from 2010 to 2022. Longitudinal analysis shows a growing emphasis on digital and programming tools (e.g., Python, MATLAB) across all disciplines, especially at the graduate level. Simultaneously, demand for traditional skills such as Drafting, Project Management, and Engineering Design has remained steady or increased, signaling that core engineering competencies remain essential. These time-based trends highlight the dual importance of technical depth and managerial fluency in modern engineering roles.

This study demonstrates the potential of NLP-based classification and analysis techniques to extract meaningful trends from complex labor market datasets. In doing so, my dissertation contributes to ongoing discussions about curriculum reform by providing a replicable framework for aligning engineering education with workforce needs. The methodology introduced in this study also offers guidance for researchers and institutional stakeholders aiming to apply NLP in large-scale skill demand analysis, thereby expanding access to labor market insights that support engineering workforce development.

Exploring Engineering Employment Trends: A Decade-long Deep Dive into Skills and Competences Included in Job Advertisements

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GENERAL AUDIENCE ABSTRACT

My dissertation investigates how engineering education can better align with workforce demands by analyzing skill trends in online job postings using Natural Language Processing (NLP). Despite the increasing need for specialized engineering talent, a persistent skills mismatch exists between what graduates learn and what employers expect. This gap reflects the slow adaptation of engineering curricula to fast-evolving technological and industrial landscapes.

To explore this issue, I analyzed over 3.4 million civil, electrical, and mechanical engineering job postings from 2010 to 2022. One key challenge in using job advertisement data is the inaccuracy of pre-labeled occupational classifications. To address this, my study developed an NLP classification system using pattern-based text analysis and regular expression (regex) matching to refine the mapping of engineering jobs by discipline. This method improved classification accuracy significantly, achieving F1-scores above 90% across Civil, Electrical, and Mechanical Engineering job postings, and ensured more reliable insights into employer skill demands.

The results reveal distinct skill patterns across engineering disciplines and educational levels. In civil engineering, job ads emphasized Drafting and Engineering Design, Project Management, Budgeting, and Scheduling skills are essential for infrastructure planning and execution. Foundational tools like CAD and Microsoft Office remained dominant across all levels, with managerial competencies increasing in graduate-level roles. In electrical engineering, core technical skills such as Circuitry, Signal Processing, Drafting and Engineering Design, and Engineering Software appeared frequently, along with growing mentions of administrative skills like Project Management and Scheduling. CAD, MATLAB, and Python were in increasing demand, especially in graduate-level positions that also required Simulation and Electronic Hardware proficiency. For mechanical engineering, traditional skills such as Drafting and Engineering Design, Equipment Maintenance, and Product Development were consistently emphasized. Job postings also highlighted the need for Project Management, Budget Management, and Business Process Analysis skills. Tools like SolidWorks, Excel, and CAD were commonly required across all education levels, while MATLAB and Python were increasingly expected at the graduate level.

Finally, I integrated big data analytics and NLP with the SABER-Workforce Development framework, this study offers a scalable approach to understanding how employer expectations have

changed over time. The findings provide actionable insights for educators, curriculum designers, and policymakers, encouraging reforms that equip engineering graduates with both the technical foundations and professional skills needed for success in a rapidly evolving job market

Dedication

To my family, for always supporting me through the years and believing in me.

Acknowledgments

First and foremost, I want to thank Dr.Knight for being an amazing and kind advisor and mentor. I truly appreciate your support, patience, and encouragement throughout my PhD journey. Thank you for introducing me to the world of big data analytics without your guidance, I wouldn't have discovered this path or grown the way I did. Your mentorship has shaped how I think, solve problems, and approach research. I'm deeply grateful for the impact you've had on both my academic and personal growth.

To my co-advisor, Dr. Katz, thank you for your support and for introducing me to machine learning and the world of Natural Language Processing. I've learned a lot from you, and I'm deeply grateful for that. Your guidance and mentorship have been truly valuable and have played a big role in my growth.

I sincerely thank you both of my advisors for standing by me, even during my lowest moments, when I doubted whether I could finish my degree in 2022. Your kindness and encouragement through the highs and lows meant the world to me. I feel truly fortunate to have been guided by you over these years. Honestly, words can't fully express my gratitude. Thank you for being by my side through it all

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To my family: thank you for always being there for me. To my oldest brother, Abdullah, thank you for listening to all my endless talk about NLP and always being patient and supportive. To my sister, Alya, thank you for your kind words, your care, and always lifting my spirits.

To my cousins and close friends: thank you for listening to me, encouraging me when I was tired, and always reminding me to keep going. Thank you for checking in on me, making me laugh when I needed it, and just being there.

I truly couldn't have done this without all of you. Thank you from the bottom of my heart.

AI Statement

I used Generative Artificial Intelligence (GAI) tools such as: ChatGPT, Grammarly, and Elicit. To support the development of this dissertation. Below, I describe how and why I used each tool.

- Writing Support
  - To improve grammar and clarity in my writing, I used ChatGPT and Grammarly. I asked ChatGPT to review my text for grammar issues using prompts like:
  - "You are an expert editor for academic writing. Please fix any grammatical errors without changing the structure, content, or tone."
  - I also used Grammarly to check for sentence clarity, grammar, and punctuation throughout the document. In both cases, I reviewed and revised all suggested changes before finalizing the content.

- Code Editing and Plot Generation
  - I mostly used ChatGPT to troubleshoot and refine my Python codes used in developing the NLP classification code and figure generation. This included prompts like:
  - "You are a Python expert. Please help me fix errors in my code"
  - "I have given my code please edit my code to efficiently generate a line plot using the variables I specify, and I want the plot to be separated by these skills each one is a group of skill which must be in a separate plot."
  - ChatGPT helped identify bugs, suggested efficient coding practices, and provided edited codes for the plots. It helped streamline the technical programming aspect of dealing with big data. I reviewed and revised all suggested changes before finalizing the codes.

- Literature Review Support
  - To find relevant literature on my topic, I used Elicit, an AI-powered research assistant. Because literature on certain aspects of engineering labor market analysis using NLP was limited, Elicit helped me identify papers.

I carefully reviewed all AI-generated outputs and made edits before including them in the final manuscript. I take full responsibility for the content and interpretations presented in this dissertation.

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Chapter One: Introduction

Engineering skills are in high demand in the labor market today, with technological innovation requiring specialized expertise across various engineering disciplines (The STEM Labor Force of Today: Scientists, Engineers, and Skilled Technical Workers, 2021). However, supply shortages in the workforce and skills mismatches between what graduates possess and what employers want to persist in many engineering occupations (Brun-Schammé & Rey, 2021; Handel, 2003). This imbalance between supply and demand for specific engineering skills highlights the need for a more significant understanding of the specific abilities and qualifications sought by employers.

In today's competitive job market, job seekers face challenges in identifying employability skills in the highest demand. Multiple research studies show that the education system needs to adequately prepare students for the modern workplace (Fiore et al., 2017; Heider et al., 2009; Yang, 2019). According to a National Center for Education Statistics (NCES) report, acquiring textbook knowledge remains critically important, yet traditional academic learning is insufficient. Students also need adaptable, real-world skills to apply knowledge (Fiore et al., 2017). While educational institutions still prioritize traditional curricula, they must evolve to provide students with the versatile competencies required in the evolving job landscape. Moreover, the shifting global economic and societal landscape and rapid technological advancements are reshaping life, work, and the skills needed for success by employees, employers, and job seekers.

As technology and industry evolve rapidly, the specific skills required for engineering roles today differ from those needed a decade ago (Ghassoul & Messaadia, 2023; Kamaruzaman et al., 2019; Pasek, 2005). The skills expected of engineers in the past are insufficient. However, engineering curricula in higher education have yet to adapt quickly enough to align with these shifting demands (Fiore et al., 2017; Mitchell et al., 2021). With the pace of development in technology and business accelerating, engineers must now gain new expertise to stay relevant. Engineering programs must update curricula to ensure graduates have the skills matched to current industry needs.

1.1 Online Job Advertisements: An Opportunity to Understand Skills Demands

My research will focus on online job advertisements, which I refer to as job postings or job ads in different places in this dissertation. These online job advertisements can serve as dynamic indicators of industry demands, reflecting the evolving needs of employers and broader economic trends (Hershbein & Kahn, 2018a). Engineering job postings are potentially rich data sources that reveal the competencies and skills prioritized by the industry and can be studied over time. Rather than viewing these postings solely as vacancy advertisements, they could also be viewed as offering valuable insights into the dynamic nature of employer expectations and needs for different

skill sets (Deming & Noray, 2020). By systematically collecting and analyzing data from engineering job listings, higher education institutions also can better assess how well their curricula align with the current needs of the engineering workforce (Fleming et al., 2024). Such analyses can uncover patterns in required skills, thereby providing a quantitative mechanism that can enhance the dialogue between academia and industry to help educational programs remain relevant and responsive to market demands.

1.2 Purpose of study

My study aims to identify the skills in demand for engineering roles as stated in online job postings, given evidence of a growing mismatch between engineering education and preparation needed for the modern workplace (Brun-Schammé & Rey, 2021; Donovan et al., 2022; Handel, 2003; Harry J., 2013; Nikolov et al., 2018). As technology and industry evolve rapidly, engineering curricula should align with the practical competencies required by employers and the job market. My proposed study aims to determine the various important skills of the engineering workforce by analyzing a large-scale historical data set of engineering online job postings. While large-scale datasets offer valuable insights, they present inherent challenges (e.g., data inaccuracies and inconsistencies). To overcome these limitations, particularly the inaccuracies and inconsistencies in pre-labeled Standard Occupational Classification (SOC) codes, this study first developed a Natural Language Processing (NLP) classification system as one of its contributions. Using pattern-based text classification and flexible regex matching, the system refines the Occupational Information Network (O*NET) SOC code mapping for the Burning Glass Technologies (BGT) dataset, helping overcome challenges with noisy data and complex job taxonomies.

Additionally, this study determined how the technical skills employers want to vary across engineering disciplines and education levels. It also seeks to guide discussions about curriculum changes to help students gain essential engineering knowledge and practical skills for the real world. These skills and competencies are important for career success and help smooth transitions into the workforce. This study has important implications for engineering program leaders in higher education and those designing curricula. The results can be useful data point for conversations about curricular alignment with the key skills employers' demand, enabling engineering programs to better prepare graduates with the competencies needed in today's workforce.

The following research questions guided the study:

- RQ1: How well can pattern text classification and flexible regex matching categorize pre-classified (SOC code) job postings into engineering disciplines (e.g., Civil, Electrical, and Mechanical engineering)?

- RQ2: How do the proportions of different skills required for engineering jobs, as indicated in job postings, vary across:
    - Levels of requisite education (i.e., bachelor's, master's, doctoral)?
    - Engineering disciplines (i.e., Civil, Electrical, and Mechanical engineering)

- RQ3: How have the proportions of different skills required for engineering jobs, as indicated in job postings, changed across the period of 2010-2022, considering both levels of requisite education and the specific disciplines of Civil, Electrical, and Mechanical Engineering?

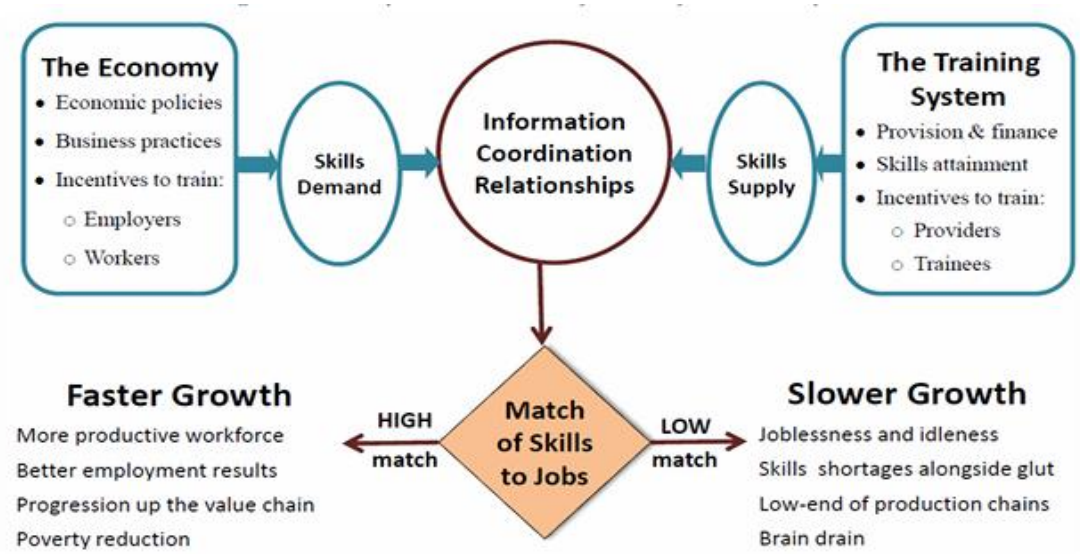
1.3 Conceptual Framework

The evolution of engineering education has long wrestled with balancing theoretical knowledge and practical skills, as documented through historical shifts in curriculum development (Seely, 2005). Although multiple research studies calls for better alignment between education and workforce needs, achieving this alignment remains a significant challenge (Fleming et al., 2024; National Academy of Engineering, 2004, 2012). My study addresses this persistent challenge through an innovative approach: analyzing large-scale historical job posting data to understand employer skill demands. To frame this analysis, I employ the Systems Approach for Better Education Results in Workforce Development (SABER-WfD) framework (Tan et al., 2013), as adapted by Fleming et al. (2024). This framework examines the relationship between two critical components: the supply side (skills provided by engineering programs) and the demand side (skills required by employers). Although previous research has extensively examined the supply side through curriculum analysis and educational outcomes, the demand side has received comparatively less attention across various sectors (Bills et al., 2017).

This study leverages BGT skill clusters, data extraction, and natural language processing techniques to analyze millions of online job postings, representing a methodological advancement in understanding employer skill demands. The data-driven approach of this research enables a thorough examination of variables and their education levels (e.g., bachelor's, master's, and doctoral) for civil, electrical, mechanical engineering (CE/EE/ME) disciplines. This method addresses a crucial gap identified by Hadgraft and Kolmos (2020), who noted that engineering educators often focus on individual course skills rather than how these skills collectively prepare graduates for workforce demands. Guided by the SABER-WfD conceptual framework (as used in

Fleming et al., 2024), this study analyzes large-scale job posting data from 2010 to 2022 to examine the demand side of engineering workforce development.

Figure 1.1: Conceptual framework adapted from (SABER-WfD) (Tan et al., 2013)



1.4 Research Design

This study analyzes trends in the engineering job market from 2010 to 2022, with a focus on the skills demanded by employers across various engineering disciplines and education levels. Utilizing pre-processed skills clusters from BGT and technical skills from O*NET, the research contains a substantial dataset of 3,490,091 data points for CE/EE/ME. Large-scale job posting datasets from companies like BGT have been widely used in research (e.g., Buckner-Petty et al., 2019; Cerioli et al., 2023; Dawson et al., 2019, 2020; Forsythe et al., 2020; Squicciarini & Nachtigall, 2021) for their extensive semi-structured historical data. However, my initial data cleaning efforts revealed that working with such large-scale datasets presents inherent challenges, particularly when dealing with pre-labeled O*NET SOC codes, which often contain inaccuracies and information discrepancies. These challenges include inconsistent categorization of the fields using occupational classification codes (i.e., SOC code). To address these methodological challenges and enhance data quality, the study developed an NLP classification system specifically tailored to improve discipline categorization. The methodology incorporates multiple data preprocessing protocols and systematic manual spot checks for error handling, ensuring reliable analysis results.

The analysis utilizes an exploration quantitative approach to the BGT dataset, refined through the NLP classification system. The analytical framework consists of three key components: First, I systematically categorized family skills and skills across CE/EE/ME and their

educational levels (bachelor's, master's, and doctoral degrees). This categorization enabled me to calculate the proportion of job postings requiring specific skills, including family and individual skills, within each segment, providing an understanding of skill demands across the engineering workforce hierarchy. Second, I conducted a longitudinal analysis spanning 2010 to 2022, examining how skill requirements have evolved and changed over time. I identified significant patterns through trend analysis techniques, including skill correlations across educational levels and the emergence of new skill demands in the engineering job market. Finally, this analysis aimed to provide actionable insights for multiple stakeholders. The results can help strategically align the key skills employers demand, enabling engineering programs to better prepare graduates with the competencies needed in today's workforce.

1.5 Anticipated Implications and Stakeholders

The implications of this research extend across multiple stakeholder groups within the engineering workforce ecosystem. Educational institutions, including universities and technical schools, can leverage these insights to enhance their curricula and align educational outcomes with market demands, while policy and regulatory bodies such as the U.S. Department of Labor and Federal Communications Commission can develop more informed workforce development strategies. Industry stakeholders, including employers, human resources (HR) departments, and professional organizations (e.g., Institute of Electrical and Electronics Engineers (IEEE), American Society of Mechanical Engineers (ASME), American Society for Engineering Education (ASEE)), can align their development programs with emerging skill demands. At the individual level, engineering students can make informed decisions about their educational pathways, while career services can provide evidence-based guidance for career planning. Furthermore, the research community can build upon this foundation to further investigate the relationship between technological advancement, skill evolution, and career success in engineering. Economic development agencies can also utilize these findings to support better regional growth initiatives based on identified skill needs. This multi-stakeholder perspective ensures that the research findings contribute to both theoretical understanding and practical applications in engineering workforce development. Finally, this research introduces a new classification method for improving the BGT dataset, which researchers use regularly.

1.6 Glossary of terms:

1.6.1 Burning Glass Technology (BGT)

A company specializing in labor market analytics collects and analyzes millions of online job postings. It provides labor market data by scraping and coding online job posts from various online job boards and company websites

1.6.2 Occupational Information Network (O*NET)

A comprehensive database developed by the U.S. Department of Labor that contains standardized, occupation-specific descriptors, including required skills, knowledge, and abilities for various occupations in the U.S. labor market.

1.6.3 Skill Family

A broad category or group of related skills that share common characteristics or serve similar purposes in professional contexts (e.g., Engineering skills and Information technology skills) developed by BGT.

1.6.4 Individual Skills

Specific skills or abilities listed within job postings representing discrete capabilities required for a position (e.g., Python, writing, data analysis, writing, writing, writing, etc.) developed by BGT.

1.6.5 CE/EE/ME Engineering discipline abbreviations representing:

Civil Engineering (CE), a discipline that focuses on designing, building, and maintaining our environment, including roads, bridges, buildings, and water systems (American Society of Civil Engineers, 2024). Electrical Engineering (EE) is a discipline that studies, designs, and uses tools and systems that work with electricity, electronics, and electromagnetism. (Barney Smith, 2019). Mechanical Engineering (ME) is a field dedicated to the design, manufacturing, and maintenance of mechanical systems, including engines, machines, and thermal devices. Mechanical engineers apply their expertise to create solutions that improve quality of life, from medical devices and autonomous vehicles to renewable energy and industrial automation (Frecker et al., 2024).

1.6.6 Natural Language Processing (NLP)

Is a branch of artificial intelligence that enables computers to understand, interpret, and analyze human language in text form. This study uses NLP techniques to systematically categorize and analyze job posting.

Chapter Two: Literature Review

2.1 The Flow of Literature Review

This chapter explores the critical aspects of engineering education, industry expectations, and the evolving labor market. It begins by examining the foundational role of educational institutions, such as universities and technical schools, along with the influence of faculty members and accreditors like the Accreditation Board for Engineering and Technology (ABET) in shaping engineering curricula. This initial discussion highlights the traditional emphasis on theoretical knowledge, often overshadowing the practical skills highly valued by industry employers, such as troubleshooting and data analysis. Building on this, the chapter explores the need for more alignment between academic programs and industry needs, noting the underrepresentation of practical competencies like teamwork, communication, and problem-solving in curricula.

Further contextualizing the discussion, the chapter situates these issues within the broader STEM fields, highlighting the increasing demand for STEM skills and the significant contributions of STEM professionals to economic growth. This analysis includes an examination of current and projected shortages in the engineering workforce, driven by rapid technological advancements and a skills mismatch, which have profound implications for economic and innovation capacities.

In continuation, the chapter reviews efforts to reform engineering education, advocating for a shift towards integrating interdisciplinary and professional skills, project-based learning, and advanced technologies. It summarizes key competencies necessary for engineering graduates, emphasizing the importance of both technical proficiency and broader professional skills. Additionally, online job advertisements are explored as valuable data sources for understanding industry skill demands, focusing on the role of human resources in shaping workforce skills through strategic job ad design. Furthermore, the Occupational Information Network is discussed as a crucial tool for providing comprehensive occupational data, aiding career planning and workforce development.

2.2 Engineering Education and Industry Demands

Engineering education aims to prepare graduates for successful careers in various engineering disciplines. Traditionally, engineering curricula are designed by faculty members, who base their decisions on their perceptions of the essential knowledge, skills, and abilities that engineering graduates will need (Fleming et al., 2024). Faculty members and accreditors play a pivotal role in shaping engineering curricula. Their decisions are influenced by their academic and research backgrounds (Brown & Knight, 2014) as well as general learning outcomes set by accreditation bodies such as ABET (Felder & Brent, 2003; Passow, 2012). ABET's criteria emphasize the importance of foundational engineering principles, theoretical knowledge, and technical competencies. Consequently, faculty members design courses that reflect these standards

and their industry experiences, ensuring that students receive a comprehensive education grounded in essential engineering concepts (Brown & Knight, 2014; Felder & Brent, 2003). This approach provides students with a robust theoretical framework and technical proficiency.

However, these perceptions may not always align with the actual demands of industry employers. This disconnect can lead to a gap between the skills engineering graduates possess and those required by employers, affecting the graduates' job readiness and performance in the professional environment (Fleming et al., 2024). Industry employers tend to prioritize practical skills and applied knowledge that directly impact job performance (National Academies of Sciences, Engineering, and Medicine, 2017). According to a survey conducted by the NACE (2017), employers value skills such as teamwork, communication, problem-solving in unfamiliar situations, and specific engineering discipline knowledge as critical for engineering graduates. These skills are essential for addressing real-world challenges and ensuring smooth operation within engineering roles.

The disconnect between academic preparation and industry requirements becomes evident when examining the most frequent work roles for engineering graduates. For instance, the NACE report on Engineering Technology Education in the United States revealed that employers frequently require graduates to perform tasks such as troubleshooting, repairing equipment, conducting quality control checks, and managing technical staff (National Academies of Sciences, Engineering, and Medicine, 2017). However, these practical skills may not be adequately emphasized in academic programs that focus heavily on theoretical knowledge and high-level mathematics. Further illustrating this gap, the report highlighted that a significant portion of employers were either unaware of or not fully informed about the specifics of engineering technology (e.g., manufacturing tools and machinery), suggesting a communication gap between academia and industry (National Academies of Sciences, Engineering, and Medicine, 2017). This lack of awareness can lead to misaligned expectations, where graduates may possess strong theoretical foundations but lack the practical skills necessary for immediate job readiness.

Research evidence further supports the existence of this disconnect. Employers indicated that engineers work on tasks such as testing and maintaining equipment, troubleshooting and repairing, and conducting quality control checks (National Academy of Engineering, 2017). Many of these tasks require hands-on experience and practical problem-solving skills, which are often underemphasized in traditional engineering curricula. Research findings also suggest that industry employers prioritize skills such as communication, decision-making, problem-solving, leadership, emotional intelligence, social ethics, and working with individuals from diverse backgrounds (Ramadi et al., 2013; Katz, 1993; Nair et al., 2009; National Academy of Engineering, 2017). Despite the critical importance of these skills, recent engineering graduates often fall short of industry expectations. This disconnect highlights the need for educational programs to better align

with the practical and interpersonal demands of modern engineering roles (Kamaruzaman et al., 2019).

To address this, disconnect, fostering stronger collaborations between academic institutions and industry partners is essential. Establishing industry advisory boards, enhancing internship and co-op programs, and integrating real-world projects into the curriculum can provide students with hands-on experience and exposure to industry practices (Havenga & Swart, 2022; Rusu et al., 2009; Schneider & Iglesias, 2023). Regular feedback from employers can help academic institutions adjust their curricula to better align with the evolving needs of the engineering workforce (Jeyamala et al., 2022; Kamaruzaman et al., 2019; Pan et al., 2023). For example, industry advisory boards can offer valuable insights into current industry trends and emerging technologies, enabling faculty to update course content accordingly. Internship and co-op programs allow students to gain practical experience and apply their theoretical knowledge in real-world settings, enhancing their job readiness upon graduation (Jeyamala et al., 2022; Kamaruzaman et al., 2019; Pan et al., 2023). Additionally, incorporating real-world projects into coursework can simulate professional challenges and encourage students to develop practical problem-solving skills.

Finally, while engineering curricula are built around the perceptions of faculty and accreditors, there is a critical need to ensure these perceptions are informed by the practical requirements of industry employers (Fleming et al., 2024). Bridging the gap between academic preparation and industry expectations, engineering education can produce graduates who are knowledgeable and well-equipped to meet the demands of their professional careers. Strengthening collaboration between academia and industry, integrating practical experiences into the curriculum, and continuously updating course content based on industry feedback are essential to achieving this alignment. My dissertation further contributes to this effort by investigating the evolving skill requirements in engineering disciplines, providing insights that can help refine educational programs to better align with current and future industry needs.

2.3 Aligning STEM Education with Industry Demands

Considering the evolving landscape of engineering education and the importance of aligning curricula with industry needs, it is essential to recognize the broader context of STEM fields. The contributions of individuals working in STEM disciplines significantly enhance a country's quality of life, economic growth, and global competitiveness. Individuals working in STEM help improve a country's quality of life, economy, and ability to compete globally. A recent 2021 report by the National Science Foundation titled "The STEM Labor Force of Today: Scientists, Engineers, and Skilled Technical Workers" asserted that the demand for STEM skills is growing faster than the labor market. The growth is significant, especially for computer and engineering occupations (The STEM Labor Force of Today: Scientists, Engineers, and Skilled

Technical Workers, 2021). These findings align with those of Kelly et al. (2018) who measured the technical innovations and advancements across industries over the last 100 years. In their findings, the computer and electronics industry are increasing in innovation along with other industries such as construction, food agriculture, and manufacturing, but not at the same rate as the computer and electronics industry in the last two decades.

For instance, employment in computer and mathematical occupations is expected to increase by 15.8% from 2020 to 2030, resulting in the addition of over half a million new jobs (Bureau of Labor Statistics, 2021). Architecture and engineering employment is projected to grow by 5.6%, construction and extraction is projected to grow by 5.7%, and life, physical, and social science is growing to 7.9% in the same timeframe (Bureau of Labor Statistics, 2021). Innovations in emerging technologies like artificial intelligence, robotics, the Internet of Things, autonomous vehicles, 3D printing, materials science, and quantum computing fuel this rapid growth. As these technologies are further integrated and adopted across sectors, demand for STEM skills will accelerate even faster. Industries from healthcare to agriculture to renewable energy all benefit from advanced STEM capabilities.

However, the supply of qualified STEM workers in the United States has not kept pace with the demand. A shortage of workers with the needed STEM skills leads to recruitment difficulties (The STEM Labor Force of Today: Scientists, Engineers, and Skilled Technical Workers, 2021). Providing training for employers to upskill their employees would be costly and timely but still beneficial for both parties. Another option is to teach students these technological advancements and skills in their respective disciplines to prepare them when they enter the workforce. According to many economists, technological advancements increase the wages of educated workers when new skills are obtained (Autor et al., 1998; Berman et al., 1994; D. Deming & Noray, 2019). Therefore, teaching or learning these skills is beneficial not only for students but also for the future workforce.

Given the evolving labor market demands, it is crucial to understand how more specific industry-wanted professional and technical skills vary among engineering disciplines and levels of education. The aim of my dissertation is to identify specific engineering skills trends over time to address and understand the evolving skills required across engineering disciplines. This understanding will enable educational institutions to better align their curricula with industry needs, ensuring that graduates are well-prepared to meet the demands of their professional careers.

2.4 Engineering Labor and Supply

Understanding these evolving demands (i.e., labor market demands) is particularly urgent in light of the ongoing workforce shortage of engineers and scientists, a persistent issue in the United States and other countries for decades (Arrow & Capron, 1959; Atkinson, 1990). This

shortage has influenced science education policies and led to increased funding for STEM education programs, with its roots tracing back to the end of World War II (Smith, 2017). One major consequence of the National Science Foundation's projections of an impending shortfall of 675,000 highly skilled scientists and engineers in the mid-to-late 1980s was an industry-led campaign that resulted in the establishment of the H1-B temporary visa for specialist workers as part of the 1990 Immigration Act (Smith, 2017; Weinstein, 1998). This visa program aimed to recruit highly skilled scientists and engineers from overseas, with the only eligibility requirement being a bachelor's degree or equivalent experience from a U.S. institution (Smith, 2017).

While widespread shortages across the sector are often unsubstantiated, localized, short-term shortages in specific disciplines or geographic areas may occur due to economic, political, or technological changes. Nowadays, the shortage persists with added complexity regarding candidates' skill levels because of rapid technological advancements (The STEM Labor Force of Today: Scientists, Engineers, and Skilled Technical Workers, 2021). Technological advancements and innovations can shift the job market and workforce demands by requiring specialized skills and expertise that may not be readily available in the existing workforce. This can lead to localized, short-term shortages of skilled workers in specific disciplines or geographic areas at the forefront of these technological changes (Smith, 2017). Rapid technological progress can outpace the ability of educational institutions and training programs to adapt their curricula and produce graduates with the necessary skills (The STEM Labor Force of Today: Scientists, Engineers, and Skilled Technical Workers, 2021).

These fast changes create a lag between the demand for skilled workers in emerging technologies and the supply of qualified individuals. Employers may struggle to find candidates with the specific expertise required for new technologies, leading to skill shortages in those areas, which is considered one of the reasons for STEM and engineering shortages (Smith, 2017). My work aims to address this issue by providing data that may be leveraged by educational institutions and training programs to consider whether current curricula effectively emphasize the development of these necessary skills. The lack of a strong engineering and scientific workforce can significantly affect economic growth, global competitiveness, and national security. A robust STEM workforce drives innovation and technological advancements and maintains a competitive edge in the global market (Arrow & Capron, 1959; Atkinson, 1990).

2.5 Present Engineering Workforce

In 2018, according to the U.S. Bureau of Labor Statistics (BLS), the workforce included about 2 million engineers, 700,000 engineering technicians and technologists, and 4.1 million people working in computational fields (Wilson, 2019). Engineers worked in various jobs, often requiring similar education and skills. About 75% of engineers were employed in manufacturing,

professional services, or government roles at the federal, state, and local levels (Wilson, 2019). Engineers were also found in many industries, including retail, entertainment, food services, and real estate. Almost half of the engineers in 2018 were civil, mechanical, or industrial engineers, while fewer worked as agricultural, mining, geological, or marine engineers due to the specialized nature of these fields (Wilson, 2019).

Expanding on this, a report titled "The U.S. Science and Engineering Workforce: Recent, Current, and Projected Employment, Wages, and Unemployment" from 2017 indicates that the science and engineering (S&E) workforce consisted of approximately 6.9 million individuals, representing 4.9% of the total U.S. employment; engineering roles accounted for 23.9% of those positions (Sargent Jr, 2017). Employment growth in these fields from 2012 to 2016 was significant, with a compound annual growth rate (CAGR) of 2.9%, compared to the overall U.S. employment growth rate of 1.9% CAGR (Sargent Jr, 2017).

Between 2012 and 2016, unemployment rates in science and engineering (S&E) occupations were notably lower compared to other job categories such as service, sales, and construction (Sargent Jr, 2017). Historically, professional roles, including those in S&E, have consistently maintained lower unemployment rates than the broader workforce. In 2016, most S&E occupations had unemployment rates ranging from 2.0% to 2.9%, which, although slightly higher, were still more favorable compared to other professional fields like law (0.7%) and medicine (0.5%). Life scientists, in particular, had an even lower unemployment rate of 0.6% (Sargent Jr, 2017).

Looking ahead, the BLS forecasts that from 2016 to 2026, employment in S&E fields will grow by 853,600 positions, reflecting an annual growth rate of 1.1%, which slightly outpaces the overall workforce growth rate of 0.7%. By 2026, the BLS anticipates a need for 5.179 million scientists and engineers to fill positions due to workforce exits and job transitions. This will result in a total of 6.033 million job openings in S&E occupations, including 1.265 million in engineering alone (Sargent Jr, 2017).

Despite these projections, there is ongoing debate regarding the adequacy of the current S&E workforce in the United States. While there is a broad consensus on the critical role of S&E professionals, opinions diverge on whether the current workforce is sufficient to meet the growing demand. Some argue that the shortage of scientists and engineers stems from an insufficient number of graduates with S&E degrees, while others suggest that the issue lies in a mismatch between the skills workers possess and the needs of employers (Sargent Jr, 2017).

The mismatch in skills can be attributed to various factors, including rapid technological advancements that create new skill requirements as new tools and technologies are introduced. Additionally, education curricula often fail to keep pace with the evolving demands of the job

market. My study seeks to identify the skills that employers have prioritized over the past decade, aiming to assist educational institutions in having comprehensive data to ground curricular conversations regarding alignment with dynamic industry needs.

2.6 Efforts to Improve Engineering Curricula

Many researchers have recommended different educational reforms in response to the fact that engineering curricula are not keeping pace with market demands. Some scholars have suggested that engineering education should shift from solely focusing on scientific and mathematical principles to a broader emphasis on engineering practice's societal and human aspects (Grimson, 2002; Lang et al., 1999; Walkington, 2002). These reforms should consider the needs of the engineering profession, as well as social, economic, and institutional factors, alongside student considerations (Walkington, 2002). Other researchers have argued that engineering programs should undergo substantial revisions to realign with their foundational service mission, emphasizing professional skills development (Moore & Voltmer, 2003). While minor adjustments are continually made, significant changes in the curriculum are often driven by external agencies or shifts in market demands (Heywood, 2005).

With calls to improve engineering curricula, many scholars have undertaken significant work on curricula and co-curricular development (D. B. Knight et al., 2013; D. B. Knight & Novoselich, 2017), pedagogical strategies (Borrego et al., 2013), and experiential learning (Paretti, 2008; Paretti et al., 2007; Tembrevilla et al., 2024). Moreover, these changes in engineering education have also led scholars to investigate foundational engineering competencies (e.g., mathematics, applied sciences, engineering design, problem-solving skills, and technical proficiency), which are now being complimented by a growing emphasis on interdisciplinary and professional skills like data analytics, project management, and communication (Furman & Weissman, 2020; Mitchell et al., 2021 Paretti, 2008; Paretti et al., 2007). The evolving economy reflects that engineers must excel technically and navigate the complexities of a rapidly changing professional landscape. This dynamic shift in required abilities is critical for educational institutions to understand, ensuring engineering programs adequately prepare students for the multifaceted challenges of today's workforce (Hadgraft & Kolmos, 2020). Beyond domain expertise, engineers now need versatile competencies to thrive in an interdisciplinary, rapidly advancing field. Identifying these expanding skill sets that employers seek allows academia to adapt curricula, equipping graduates for success.

However, keeping up with the evolving skills required for engineering roles has posed persistent challenges. As societies, industries, and technologies evolve, the skills in demand also change over time. This dynamic often creates a mismatch between the skills students learn via higher education and the skills employers need in the workforce. However, some studies have aimed to identify the in-demand skills and competencies for engineers across domains (Fleming et al., 2024; Kaushal & Vaghela, 2023). Technical core competencies like programming, data

analysis, and systems design remain foundational (Fleming et al., 2024; Kaushal & Vaghela, 2023; Pažur Aničić et al., 2022; Sarajlic-Basic, 2010).

My research will build upon existing knowledge by investigating how engineering skills have evolved across different engineering disciplines over the past 12 years. This overview identifies the critical skills and competencies necessary for engineers, as outlined in academic studies. However, there seems to be a gap in fully understanding and aligning these skills with the specific needs and expectations of employers. This gap points to the need for further research to ensure that engineering education not only provides students with these essential skills but also meets the evolving demands of the industry.

2.6.1 Essential Skills and Competencies in Engineering Education

The previous section highlighted the curricular advancements advocated by scholars to prepare engineering students for a competitive workforce. To ensure engineering programs remain relevant and effective, there has been a significant shift towards incorporating team-based, project-driven activities and integrated learning of professional competencies. Adopting these skills from research to practice involves creating educational environments that reflect real-world challenges and demands, fostering a holistic development of engineering graduates who are well-equipped to meet the evolving needs of the industry. Scholars emphasize that further enhancements are necessary to fully prepare engineering graduates for the challenges of the twenty-first century (Davidson et al., 2010; Gutiérrez Ortiz et al., 2021; Violante & Vezzetti, 2017). However, "this is a 21st century response to the employability challenge and is still an emergent response from some engineering institutions, but it is on the long-term horizon, and it will involve new competencies from engineering students" (Hadgraft & Kolmos, 2020, p. 7).

For instance, scholars expressed that undergraduate engineering should prioritize the enhancement of conceptual understanding, the improvement of analytical skills, and the engagement with context-rich, multifaceted problems to adequately prepare students for the complexities of professional practice (S. Brown et al., 2019; Litzinger et al., 2011). With that in mind, researchers expressed that engineering students develop a deep conceptual understanding of fundamental principles, enabling them to apply this knowledge flexibly across diverse scenarios (Litzinger et al., 2011). This foundational comprehension is crucial for the effective analysis and synthesis of engineering problems. Improving analytical skills involves not only mastering mathematical and computational techniques but also developing the ability to critically evaluate data, identify patterns, and draw informed conclusions (S. Brown et al., 2019; Litzinger et al., 2011).

As engineering education increasingly focuses on preparing students for the dynamic demands of modern industries, fostering interdisciplinary collaboration has become equally vital. The previous section underscored the importance of evolving educational strategies to equip

students with both technical and conceptual skills necessary for modern engineering challenges. However, the multifaceted nature of today's engineering problems extends beyond disciplinary boundaries, necessitating a shift towards more collaborative learning environments (Borrego & Newswander, 2010).

In response to this need, educational institutions are emphasizing interdisciplinary projects and team-based learning. This approach not only enhances problem-solving skills but also fosters essential communication and teamwork abilities. Borrego and Newswander (2010) argue that interdisciplinary learning environments enable students to tackle complex issues from various perspectives, leading to innovative solutions that address critical technological and socio-technological challenges such as sustainability and public health. Furthermore, (Alsharif et al., 2024) Alsharif et al. (2024) demonstrate that structured interdisciplinary research experiences, like those following the Vertically Integrated Projects (VIP) model, are important in developing practical, transferable skills essential for future professional roles. Thus, integrating interdisciplinary collaboration into engineering education complements the advancements discussed in the previous section, ensuring that students are well-prepared to navigate and solve complex, real-world problems.

Furthermore, research recommended exposing students to context-rich, multifaceted problems that mirror real-world challenges to enhance their ability to integrate knowledge from various domains, consider multiple perspectives, and devise innovative solutions. These educational strategies collectively foster the development of expertise, preparing students to navigate and address the novel, complex issues they will encounter in their engineering careers (S. Brown et al., 2019; Litzinger et al., 2011; Havenga & Swart, 2022). To effectively prepare students for the dynamic engineering landscape, educational strategies must evolve alongside technological advancements. Violante and Vezzetti (2017) build on this premise by highlighting the necessity for engineering education to incorporate cutting-edge technologies, such as additive manufacturing, to enhance students' problem-solving abilities and align their skills with industry demands. Their research demonstrates how integrating these technologies into curricula can transform theoretical concepts into practical, hands-on experiences, thereby fostering critical skills necessary for the modern workforce (Violante & Vezzetti, 2017).

As engineering education adapts to incorporate advanced technologies and innovative teaching methods, there is also a growing recognition of the need to integrate sustainability into the curriculum. Davidson et al. (2010) highlight this need, advocating for the inclusion of sustainability principles to better prepare engineers for the complex challenges of the 21st century. Their research highlights the importance of supporting faculty in embedding sustainable engineering concepts through various resources and community-building efforts. Despite some progress, their findings reveal significant variability in how these concepts are applied across institutions, suggesting that ongoing curriculum updates are essential to equip graduates with the

skills needed to tackle sustainability challenges effectively. This example demonstrates that over time, we would expect to see new societal problems and technological advancements reflected in what engineers need to understand, and my dissertation aims to detect such changes in the skills represented in job advertisements.

Building on the integration of advanced technologies and sustainability, Gutiérrez Ortiz et al. (2021) further emphasize the need for engineering education to cultivate a broad range of graduate attributes through engaging, open-ended activities. Their study highlights that to thrive in today's complex world, engineering graduates must not only possess technical skills but also develop transferable skills, professional values, and sustainability attributes (Gutiérrez Ortiz et al., 2021). Incorporating real-world, unsolved problems into the curriculum, such as capstone design projects and sustainability assignments, students are better equipped to enhance their collaborative, critical thinking, and multi-perspective problem-solving abilities (Gutiérrez Ortiz et al., 2021; A. Katz, Shealy, et al., 2020; Milovanovic et al., 2021).

These activities also show the importance of ethical, social, and environmental considerations in engineering practice (A. Katz, Reid, et al., 2020) Additionally, the authors emphasize the importance of engineering education needing to adjust and integrate new teaching methods constantly. They argue that these approaches can more effectively equip graduates to meet the changing needs of employers and society. The research findings highlight the essential role of incorporating open-ended problems and activities into engineering curricula for the development of versatile engineers capable of addressing the diverse challenges of the 21st century. (Gutiérrez Ortiz et al., 2021)

Moreover, researchers in the field have noted a profound transformation in the past decade, driven by rapid technological advancements and evolving industry demands (Khanna & Kumar, 2020; Melnikova et al., 2020). The incorporation of new methodologies, tools, and interdisciplinary approaches into engineering education has been crucial in shaping the skill sets of modern engineers (Melnikova et al., 2020). The emphasis on technical proficiency and digital literacy has increased due to the widespread use of advanced software tools and programming languages. As a result, engineering curricula now include comprehensive training in these areas. For example, the integration of MATLAB and other programming languages has become standard in many engineering programs, allowing students to develop strong computational and analytical skills. (Colgan, 2000; Larsen et al., 2016, 2016; Ozgur et al., 2021).

Additionally, the rise of big data and artificial intelligence has led to a greater focus on data analytics and machine learning, equipping engineers with the ability to handle complex data-driven tasks (Nti et al., 2022; Rahmani et al., 2021). However, none of these studies have examined how these skills evolve over time or utilized a dataset as extensive as the one I will be using in this study, which contains over 6 million data points. Through this analysis, I seek to contribute to the

ongoing discourse on engineering education by offering insights into effective strategies for fostering these essential skills and competencies. The findings will inform curriculum development and instructional practices, ensuring that engineering programs continue to produce graduates who are not only technically proficient but also adaptable, ethical, and capable of addressing the multifaceted challenges of the modern engineering landscape.

2.6.2 Engineering Education in Industry 4.0 Era

The previous sections examined the research efforts, and the essential skills required for engineering students based on a comprehensive literature review. However, this discussion did not fully address the implications of the Fourth Industrial Revolution, a transformative economic era characterized by rapid technological advancements and digital innovation. The Fourth Industrial Revolution, or Industry 4.0, introduces new paradigms such as automation, artificial intelligence, the Internet of Things (IoT), and advanced data analytics, which are reshaping industries and the workforce.

As we transition into this new era, the rise of Industry 4.0 has created a pressing need for significant changes in engineering education. To effectively prepare students for the demands of an increasingly digital and automated industrial landscape, educational institutions must adapt their curricula to incorporate the latest technological advancements and methodologies (Kamaruzaman et al., 2019; Khanna & Kumar, 2020; Ustundag et al., 2018). Recent research highlights several critical areas where engineering education must evolve to support innovative product development and prepare graduates for future challenges. It is essential to integrate data and computing technologies into engineering curricula, teaching skills in data modeling, big data analytics, and machine learning (Kamaruzaman et al., 2019; Khanna & Kumar, 2020; Ustundag et al., 2018). This is crucial for handling the large amounts of data generated in modern industrial processes and for developing predictive and prescriptive analytics capabilities. Engineering programs should provide comprehensive training in these areas to equip students with the necessary skills for data-driven decision-making and innovation (Ustundag et al., 2018). Incorporating value-added automated operations into education is crucial. This includes teaching robotics, automation, smart and embedded systems, and additive manufacturing.

Engineering programs should provide practical, hands-on experience with these technologies to enhance students' technical competencies and understanding of complex automated systems (Ustundag et al., 2018). Another important aspect is to emphasize innovation and entrepreneurship in engineering education, which includes teaching students about innovative materials, new business models, and the skills needed for entrepreneurship in a rapidly changing technological landscape. Engineers must innovate and adapt to new technologies and market demands in the industry 4.0 era. Educational institutions should focus on developing entrepreneurial skills alongside technical knowledge to prepare graduates for leadership roles in innovation.

To ensure that engineering education remains relevant and effective, it is very important to integrate the competencies and skills required for success in this new era. This includes not only mastering emerging technologies but also developing a deep understanding of how these technologies intersect with traditional engineering practices. For instance, competencies in data analytics and machine learning have become increasingly important as industries leverage big data to drive decision-making and innovation. My study aims to identify the skills needed for the Fourth Industrial Revolution by analyzing a large dataset of job advertisements. It seeks to uncover the specific skills in demand for engineering disciplines and contribute to aligning engineering education with evolving industry needs.

2.7 Traditional and Modern Approaches: Online Job Posting Analysis

In the context of evolving industry demands and technological advancements, it is important to evaluate how well engineering education aligns with the skills sought by employers. To bridge this gap, one effective approach is to utilize online job advertisements, commonly known as job postings or job ads. These advertisements can serve as important indicators of shifting industry demands and broader economic trends. They offer a dynamic reflection of employers' evolving needs and preferences (Hershbein & Kahn, 2018). Specifically, engineering job postings provide a wealth of information on the competencies and skills that the industry prioritizes. Rather than merely representing vacant positions, these advertisements should be viewed as valuable sources of insight into what employers expect and require from prospective candidates (D. J. Deming & Noray, 2020).

There are a variety of different ways to study the alignment between industry skill requirements and educational outcomes, and researchers within engineering education have followed a variety of different approaches, each with a set of tradeoffs. For example, some studies have gathered extensive national data through surveys directed at employers and recent graduates. These surveys are designed to reveal any gaps between the skills needed in the workplace and those emphasized in undergraduate programs (e.g., Lattuca et al., 2014; Volkwein et al., 2004). Other research has adopted a longitudinal perspective, following students from their capstone projects through their early career stages. This approach employs brief surveys and reflective evaluations to identify transitional issues and preparation gaps (e.g., Ford et al., 2019). Additionally, some studies have involved interviewing recent graduates to assess their views on their job readiness (Martin et al., 2005).

However, in the last decade, many researchers have started using job advertisements as a method to investigate the skills sought by employers. For instance, Hartmann and Jahren (2015) explored job postings in construction and engineering, examining 66 ads to assess the focus on leadership skills. Similarly, Watson and Lyons (2011) analyzed 77 job ads to evaluate the demand

for technical and professional skills among chemical and ME PhDs. Graham and Porterfield (2018) expanded this research by studying 82 engineering job ads from the Chicago area, emphasizing the prevalence of professional skills. Early studies in this field examined a relatively small sample of job advertisements relative to the volume of ads available at the time, which limited the overall scope analysis.

Passow & Passow, (2017) conducted a thorough meta-analysis of 36,100 job ads, extracting qualitative data on engineering competencies and integrating findings from 25 studies. A more recent study highlighted empirical evidence from a dataset of 26,103 job advertisements to inform debates about the alignment of engineering curricula with workforce needs (Fleming et al., 2024). For example, the prevalence of skills like problem-solving and teamwork raises questions about whether curricula enable students to develop these skills sufficiently. Additionally, the salary premiums associated with certain technical skills provide insights into the tradeoffs programs and students face regarding skill development (Fleming et al., 2024).

With the advancement of technology in the past decade, job advertisements have become more detailed and accessible, providing new opportunities for analyzing the labor market. Previous studies by Watson and Lyons, (2011), Hartmann and Jahren, (2015), and Graham and Porterfield, (2018) have provided valuable insights but were limited by small sample sizes. Even more extensive analyses, like Passow and Passow's (2017) meta-analysis of 36,000 job ads and Fleming et al.'s (2024) study of 26,103 ads, do not fully utilize the capabilities of big data analytics. To address these limitations, my study analyzed a larger and more comprehensive dataset of job advertisements (N=3,490,091) from 2010 to 2022.

Expanding on existing research, my study analyzed job advertisements from the past 12 years to understand how the demand for engineering skills has changed across different engineering disciplines and educational levels. This research contributes to the discussion on how engineering education can better meet emerging industry needs and technological advancements. By using larger datasets, the study provides a more comprehensive view of job market trends and skill demands, reducing the risk of anomalies and offering a clearer picture of prevailing patterns. With six million job ads, my research identified subtle trends and correlations that may not be apparent in smaller samples. The objective is to deliver a more robust analysis that can help shape the development of engineering curricula, ensuring they are aligned with current industry needs and technological advancements.

2.8 Occupational Information Network (O*NET)

The Occupational Information Network (O*NET) is comprehensive data on job roles, including detailed descriptions of tasks, required skills, and necessary qualifications (Cifuentes et al., 2010). O*NET is a database of occupational information that has become a vital resource for

career planning, job matching, and workforce development. Developed and maintained by the U.S. Department of Labor's Employment and Training Administration, O*NET provides detailed information on the knowledge, skills, abilities, and other characteristics required for a wide range of occupations (Cifuentes et al., 2010; Peterson et al., 2001). One of the features of O*NET is its detailed occupational descriptions, which include information on the tasks, tools and technologies, work activities, and work context associated with each occupation (Cifuentes et al., 2010). The comprehensive database by O*NET helps individuals explore career options, identify occupations that match their interests and skills, and plan educational and training pathways (Cifuentes et al., 2010). Another important aspect is how organizations like the O*NET contribute to this process. O*NET provides comprehensive data on job roles, including detailed descriptions of tasks, required skills, and necessary qualifications (Cifuentes et al., 2010).

The database, which supports over 900 occupations, provides detailed information about job requirements, skills, education, and other relevant attributes, facilitating aligning workers' skills and knowledge with appropriate job roles. Key features of O*NET, such as the Occupation Taxonomy, My Next Move, Bright Outlook and Green Occupations, and the O*NET Interest Profiler, offer great tools for job seekers and employers (Mujtaba & Mahapatra, 2019). These tools enable users to search for careers based on industry, skills, and interests, predict future job trends, and explore new occupations aligned with their personal attributes (Mujtaba & Mahapatra, 2019). Furthermore, O*NET's utility in career planning is reinforced by its ability to create coherent occupational clusters, aiding in the formation of job families and facilitating effective career transitions (Peterson et al., 2001).

Finally, the Occupational Information Network is a valuable resource for a range of stakeholders, including individuals, employers, educators, and policymakers. Providing detailed, up-to-date information on occupational characteristics, O*NET supports informed decision-making and enhances the functioning of the labor market. In my research, I utilized O*NET occupation codes to identify engineering disciplines within the extensive dataset employed in this study, ensuring a precise mapping of occupational engineering jobs to their respective disciplines.

2.9 Conceptual Framework

The Systems Approach for Better Education Results Workforce Development (SABER-WfD) framework was developed by the World Bank with the aim of improving workforce skills by providing a tool for systematically assessing workforce development policies across different nations (Tan et al., 2013). The framework, as outlined by Tam et al., (2013), has its roots in addressing challenges where economies, particularly in developing countries, struggle with a mismatch between the skills workers possess and those required by employers. This mismatch often manifests as unemployment among educated individuals and complaints from industries about a lack of practical skills among potential employees, especially soft skills (Tan & Nam, 2012).

Furthermore**,** The SABER-WfD framework was created by a dedicated team at the World Bank; its development was driven by the goal of equipping World Bank partner countries with better tools to evaluate their workforce development (WfD) strategies systematically (Tan et al., 2013). This initiative followed the World Bank's Education Strategy 2020, launched in 2011, which emphasized the need for rigorous diagnostic tools to assess and enhance education systems globally (Weltbank, 2011). The main purpose of the SABER-WfD framework is to bridge the gap between workforce education and employer demands by enabling data-driven policy dialogues (Tan et al., 2013). It strategically examines workforce development systems, ensuring workers learn market-relevant skills. This systematic analysis helps policymakers create conditions that boost economic growth through better-aligned training programs.

This framework has been tested and refined in various countries, including Chile, Ireland, Singapore, South Korea, and Uganda, confirming its value in identifying relevant workforce development priorities and guiding cross-country knowledge exchange (Tan et al., 2013). Building on the previous discussion, my research examines workforce skills requirements through the lens of employers by looking at online job postings. Understanding their needs through online job postings, the study bridges the critical gap between engineering education and industry demands. This approach can facilitate meaningful, data-driven policy discussions to better prepare future engineers for the workplace.

2.10 Dimensions of the SABER-WfD Framework

The framework is built around three main dimensions, which are strategic framework, system oversight, and service delivery:

1. **Strategic Framework**: This dimension evaluates the alignment between a nation's workforce development policies and its economic objectives. It considers how policies contribute to meeting labor market demands by fostering skills that match economic and social needs. The framework assesses policy actions like planning, setting priorities, and coordinating across sectors to achieve WfD goals (Tan et al., 2013).

2. **System Oversight**: This dimension focuses on the governance and regulatory mechanisms that shape workforce development. It examines how government policies influence the behavior of key stakeholders, including employers and training providers. Key aspects of oversight include monitoring and evaluating training quality, regulations to enforce standards, and incentives for stakeholder participation (Tan et al., 2013).

3. **Service Delivery**: The final dimension pertains to the mechanisms by which workforce training services are delivered. This includes evaluating the management and funding of

institutions that provide training, ensuring resources reach intended beneficiaries, and identifying how well training programs meet industry needs. In practical terms, this dimension explores the accessibility, relevance, and effectiveness of training services in each country (Tan et al., 2013).

Each of these dimensions encompasses specific variables (sub-dimensions), such as policy goals, actions, and desired outcomes. For instance, Service Delivery might include sub-variables like curriculum relevance to industry demands, practical skill training, and assessment standards that reflect real-world needs.

2.11 Components of the SABER-WfD Framework

According to Tan et al. (2013), the SABER-WfD Framework has four main components. First, the economy represents the skills businesses demand. Second, the training system delivers the skills people learn. Third, information flows, coordination activities, and relationships connect these elements. Fourth, the framework examines how well skills match available jobs. Figure 2.1 illustrates these interconnected components, and I explain each component in detail below.

2.11.1 The Economy (Skills Demand) include:

- **Economic Policies**: Government policies that impact the labor market, such as wage regulations, tax incentives, and investment in infrastructure, can influence the demand for certain skills in the economy.

- **Business Practices**: Businesses' operational practices, including hiring, training, and investment in innovation shape the types and levels of skills they require.

- **Incentives to Train (Employers and Workers)**: Economic incentives, such as financial support, career progression, and job security, influence employers' willingness to invest in training and workers' motivation to acquire new skills. The demand for these skills is shaped by what the economy requires in terms of workforce skills.

2.11.2 The Training System (Skills Supply) includes:

- **Provision & Finance**: This refers to how workforce training programs are funded and provided, including the role of public and private institutions in offering training.

- **Skills Attainment**: The focus is on ensuring that training programs equip individuals with relevant skills that meet labor market needs.

- **Incentives to Train (Providers and Trainees)**: These incentives ensure that training providers design programs aligned with industry needs and motivate trainees to complete skill development programs. These may include accreditation for providers and financial aid or job placement opportunities for trainees.

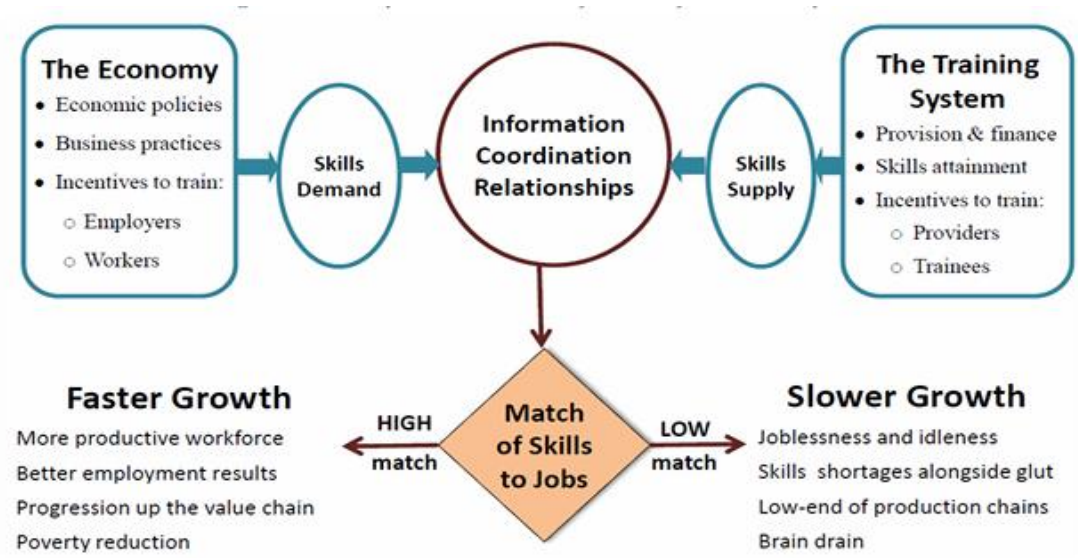
2.11.3 Information, Coordination, and Relationships

This central part of the framework highlights the interaction and information flow between the demand and supply sides of labor markets. It emphasizes the need for effective communication and coordination to ensure that training systems align with current and future job market demands. Strong relationships among policymakers, training providers, employers, and trainees are important for creating a balanced workforce development ecosystem.

2.11.4 Match of Skills to Jobs

The framework categorizes the match between skills and jobs as either a “High Match” or a “Low Match”. For instance, the high match is when the alignment between skills supply and demand is strong, and the workforce is more productive, resulting in faster economic growth, better employment outcomes, value chain progression, and poverty reduction (Tan et al., 2013). On the other hand, low Match is when there is a mismatch, it can lead to slower growth, with potential consequences such as joblessness, skill shortages coexisting with a surplus of other skills, and stagnation at the lower end of production chains, often resulting in "brain drain" (skilled workers leaving the country for better opportunities) (Tan et al., 2013).

Figure 2.1: Conceptual Framework for Workforce Development (Tan et al., 2013)



The alignment of skills with job requirements, whether strong or weak, has significant implications for the economy. This framework demonstrates that synchronizing educational and training systems with economic needs can foster economic growth and reduce poverty. Conversely, a lack of alignment can hinder growth, increase unemployment rates, and lead to skill shortages. This conceptual framework serves as a guide for my research exploring workforce skill requirements from the employers' perspective by analyzing online job postings. The study aims to bridge the critical divide between engineering education and industry expectations. This approach will facilitate meaningful, data-driven policy discussions aimed at better preparing future engineers for the workforce.

2.11.5 Research Application

My study applies the SABER-WfD framework to analyze job advertisements, utilizing BGT skills and O*NET technical skills with the help of natural language processing (NLP) and data extraction techniques on a large dataset. This method aligns with the framework's aim of using data to enhance policy discussions. By categorizing job ads across engineering disciplines—such as civil, electrical, and mechanical—and educational levels, including bachelor's, master's, and doctoral degrees, the study provides a clear view of in-demand skills and trends across various engineering domains. This comprehensive approach represents a notable advancement over earlier studies that often relied on smaller samples or survey-based data (Watson & Lyons, 2011; Hartmann & Jahren, 2015; Passow & Passow, 2017; Graham & Porterfield, 2018; Fleming et al., 2024). The extensive dataset allows for in-depth analysis over multiple years and diverse skill categories.

The study's longitudinal perspective is essential for understanding long-term trends and shifts in skill demands, which is critical for developing adaptive education and training programs. Fleming et al. (2024) highlight the importance of such longitudinal skill analysis using online job ads. The SABER-WfD framework emphasizes the importance of aligning education systems with market needs to build a productive workforce that contributes to economic growth. This research examined a decade's worth of job ads, and identified stable, emerging, and declining skill demands, offering a roadmap for future curriculum development. This approach also addresses a gap noted by engineering education researchers, such as (Hadgraft & Kolmos, 2020), who observed that engineering programs often emphasize individual course skills over an integrated skill set that aligns with industry expectations.

The insights from this study hold practical value for policymakers, educators, and employers. The finding helps align training with demand trends observed over an extended period. Educational institutions can equip graduates with skills that meet current and anticipated industry needs. This alignment reduces skills mismatches, supports higher employment rates, and enhances workforce productivity—outcomes central to the SABER-WfD framework's objectives for fostering economic growth. Additionally, the study's findings can inform policy discussions on investing in engineering education, guiding resources toward skills and fields with sustained or increasing demand.

Chapter Three: Methodology

This study analyzed trends in online job postings for civil, electrical and mechanical engineering (CE/EE/ME) disciplines to understand these dynamics from January 2010 to December 2022. This period of records includes significant events such as the COVID-19 pandemic, which allows one to observe how job postings change over different external conditions. This study utilized pre-processed skills data provided by Burning Glass Technology (BGT) to identify the key skills employers frequently seek when hiring engineers.

This chapter introduces a methodological framework that enhances the analytical capabilities for processing and interpreting the data from job posts using natural language processing (NLP). The classification system utilized an NLP framework specifically designed for identifying engineering disciplines, noted as a need during data cleaning efforts, which could be replicated to identify other disciplines or fields using the appropriate data and following the steps introduced in this chapter. The methodology employed a hybrid approach combining pattern matching and job title terms from O*NET for classification purposes.

In this framework, I utilized both O*NET terminology for job titles and NLP text regular expression and pattern matching to address critical gaps in job classification using O*NET SOC codes for pre-collected data. Using data from companies like BGT is not uncommon for research purposes (e.g., Dawson et al., 2019, 2020; Forsythe et al., 2020; Squicciarini & Nachtigall, 2021) as they provide large semi-structured historical data for job postings. However, scraping or collecting large amounts of data can lead to information discrepancies, and my early data-cleaning efforts demonstrated a need for this additional step to enhance data quality.

The literature shows that BGT's datasets incorporate O*NET SOC codes to categorize occupations into their appropriate fields (e.g., Squicciarini & Nachtigall, 2021). However, the SOC codes within these datasets are not always accurate; in 2014, the SOC code mapping accuracy rate for BGT data was only 73% (Carnevale et al., 2014). Since Carnevale et al. (2014) conducted their study over 10 years ago, data collection methods and technology have significantly evolved. To improve the accuracy of O*NET SOC code classification within the dataset used in this study, developing a refined classification system was necessary to ensure reliable results. My research introduces a new approach that automates job occupation classifications pre-classified with SOC codes data (e.g., BGT data), creating a scalable framework to process massive volumes of job posting data.

The methodology implements multiple data preprocessing protocols and manual spot checks for error handling to address inherent challenges in data analytics, such as information sparsity and inconsistent entries. These preprocessing steps are critical for maintaining research integrity and ensuring reliable outcomes. Given the general use of BGT and other big data sources (e.g., online job advertisements) in labor market research, this framework provides valuable

support for categorizing large volumes of job postings. The following research questions guide the study:

- RQ1: How well can pattern-based text classification and flexible regex matching categorize pre-classified (SOC code) job postings into engineering fields (e.g., Civil, Electrical, and Mechanical engineering)?
- RQ2: How do the proportions of different skills required for engineering jobs, as indicated in job postings, vary across:
    - Levels of requisite education (i.e., bachelor's, master's, doctoral)?
    - Engineering disciplines (i.e., Civil, Electrical, and Mechanical engineering)
- RQ3: How have the proportions of different skills required for engineering jobs, as indicated in job postings, changed across the period of 2010-2022, considering both levels of requisite education and the specific disciplines of Civil, Electrical, and Mechanical Engineering?

3.1 Data Source

The data for this study were sourced from a large dataset of engineering job postings. Initially, the dataset contained 6,710,028 online postings, each of which included several pieces of information across different fields. In my study, I analyzed 3,490,091 job postings across civil, electrical, and mechanical engineering disciplines. Specifically, the dataset consists of daily engineering job postings spanning over a decade, from 2010 to 2022, which provides a comprehensive view of the evolving job market in engineering in the United States over this time.

This most recent period of record of available data was chosen because it covers significant technological advancements, shifts in industry demands, and potentially associated changes in educational requirements for engineering jobs. This longitudinal dataset has been compiled from career websites across diverse industries, encompassing job postings across all core engineering disciplines. Leveraging such a large dataset enables insights into the evolving skill demands within each engineering discipline and across the engineering profession. The dataset has been professionally acquired through a paid data provision agreement between the Departments of Economics and Engineering Education at Virginia Tech and The Burning Glass Institute. This agreement ensures compliance with job boards' terms of service and copyright policies.

3.2 NLP Classification Addressing Q1

NLP techniques have expanded to handle diverse classification tasks, including categorizing industry codes and healthcare incident reports, laying a foundation for methods that address challenges like noisy labels and complex taxonomies (T. Jiang et al., 2023; Young et al., 2019). A recent systematic review examined how NLP techniques classify incident reports and adverse events in healthcare, focusing on identifying incident types, medication error types, and harm severity from free-text data (Young et al., 2019). The review explained how researchers use

different NLP methods to categorize information, such as multi-label classification, predefined taxonomies, and network-based techniques. While these approaches may vary in their application, they demonstrate how NLP can assist in automating qualitative data analysis (e.g., Alsharif et al., 2022; Katz et al., 2021).

Recent studies have successfully employed classification systems like Standard Industrial Classification (SIC) and International Standard Industrial Classification (ISIC) codes to categorize organizations. Researchers have effectively leveraged NLP to classify entities within food system ontologies and assign SIC codes (Béchara et al., 2022; T. Jiang et al., 2023). In their research, Smith et al. (2023) trained NLP models using online text data and SIC code to classify organizations (e.g., American Rivers and Heal the Ocean) according to their environmental conservation and sustainability efforts. Their classification included water conservation, waste management, and biodiversity protection categories.

Environmental classification used the structured hierarchy of the PPOD ontology, while the SIC classification relied on a four-level hierarchical framework. This approach proved practical for automatically populating knowledge graphs, though it faced data quality challenges due to text source variations. Similarly, Bechara et al. (2022) demonstrated NLP's effectiveness in classifying businesses with ISIC codes. Their study showed that transformer-based models, such as DistilBERT, accurately predicted division-level ISIC codes in multi-class classification tasks, emphasizing the role of classification systems to improve model performance.

Building on these foundations, this study adopts a dictionary-based approach for classifying job descriptions, utilizing pre-classified data and O*NET terminology in a structured two-layer filtering process. The first layer filters the BGT job posting data based on the pre-classified data using the O*NET SOC codes, while the second layer refines the classifications further with O*NET terminology to ensure that the SOC codes align accurately with specific occupations. This classification aims to fine-tune the O*NET SOC code mapping for the BGT dataset, addressing common issues with noisy data and complex taxonomies. This approach integrates O*NET job title terminology and structured text matching, resulting in more accurate and relevant job classification outcomes.

In the following section, I outlined the detailed procedures for obtaining, processing, and refining the data for the analysis in this research. Then, I explained the steps and protocols for utilizing the O*NET SOC code classification system with NLP when dealing with semi-structured datasets that contain such variables. Theoretically, this system could also be used with other classification codes, such as the North American Industry Classification System (NAICS) or the European Skills, Competences, Qualifications and Occupations (ESCO) Classification.

3.3 Variables in the dataset

The dataset contains 57 variables (see Appendix B for all of the variables in the dataset), but not all will be used to address the research questions. Table 3.1 lists the variables, their descriptions, and the subset of variables the study utilized to address the research questions. These variables are used to analyze how the proportions of different skills vary across levels of requisite education, engineering disciplines, and over time from 2010 to 2022. I describe each variable used to answer the research questions in the following subsections.

Table 3.1: Variables Used in the Research

Variable	**Description**
JobID	Unique identifier for each job posting
CleanJobTitle	Job title
JobDate	Date when the job was posted
JobText	Online job posting description
ConsolidatedO*NET	Consolidated O*NET SOCs occupation code
CanonSkillClusters	Skill clusters associated with the job posting
CanonMaximumDegree	Maximum educational degree required
CanonMinimumDegree	Minimum educational degree required
Major	Specific major fields required

3.3.1 Variable: Job ID

It is a unique identifier for each job posting provided in the dataset by BGT. It was used to ensure each job posting was represented only once in the dataset, preventing duplicate entries that could skew analysis results. It was also used to track job postings when needed to be investigated for data quality purposes.

3.3.2 Variable: CleanJob Title.

A clean version of raw job titles is provided by BGT for each job posting in the dataset. Serves as an input variable for the NLP classification system to facilitate matching with O*NET SOC occupational codes.

3.3.3 Variable: Job Date

The date when each job posting was first published online, as captured by BGT. This variable Enables tracking of job market trends over time and allows for seasonal pattern identification to help support longitudinal analysis.

3.3.4 Variable: Job Text

The complete job description content for the job posts contains detailed information about the position, including role requirements, responsibilities, and qualifications as written by employers. This variable enables job content patterns and skill requirements analysis and was used as an input variable for the NLP classification system.

3.3.5 Variable: ConsolidatedO*NET

To systematically categorize engineering occupations within this extensive dataset (approximately 4TB), I utilize the hierarchical structure of O*NET SOC codes. Specifically, I filter occupations using the general engineering classification code (17-2000), then further refine the categorization using specialized sub-codes within this engineering hierarchy. For instance, civil engineers are identified through codes 17-2050.00, 17-2051.00, and 17-2051.01; electrical engineers through 17-2070.00, 17-2072.00, and 17-2072.01; and mechanical engineers through 17-2140.00, 17-2141.00, and 17-2081.01. This study exclusively focuses on the occupations flagged as these three disciplines.

Using O*NET SOC codes for occupational classification represents a well-established methodological approach in literature. Numerous scholars have employed O*NET SOC to categorize and analyze occupational data systematically (Buckner-Petty et al., 2019; Cerioli et al., 2023; Dawson et al., 2019, 2020; Forsythe et al., 2020; Squicciarini & Nachtigall, 2021).

3.3.5 Variable: CanonSkillClusters

I used skill clusters created by BGT. The dataset contains “skill clusters” to organize and categorize individual skills. Skill clusters represent groups of related skills that share similar functionality, can be trained concurrently, and frequently co-occur in job postings. A skill cluster encompasses a broader scope than an individual skill but maintains a more granular focus than a higher-level “skill cluster family.” Skill cluster families are the most general layer of the skill taxonomy. Each skill cluster, and by extension each skill, belongs to exactly one family.

To understand the detailed information of how CanonSkillClusters variable was developed, Burning Glass published a report in 2021 called “Speaking the Same Language: A Machine Learning Approach to Classify Skills in Burning Glass Technologies Data” which presents a methodology to classify over 17,000 unique skill keywords from the Burning Glass dataset into

61 broader skill cluster categories using a pre-existing expert-driven taxonomy (et al., 2021). The approach used in this paper employs a semi-supervised machine learning algorithm, which combines both labeled and unlabeled data to classify skills that appear in the job posting. Specifically, it leverages BERT (Bidirectional Encoder Representations from Transformers), a language model trained on a large corpus of text to 'understand' the English language. The BERT model was further fine-tuned for the specific task of classifying skill keywords into the taxonomy's categories.

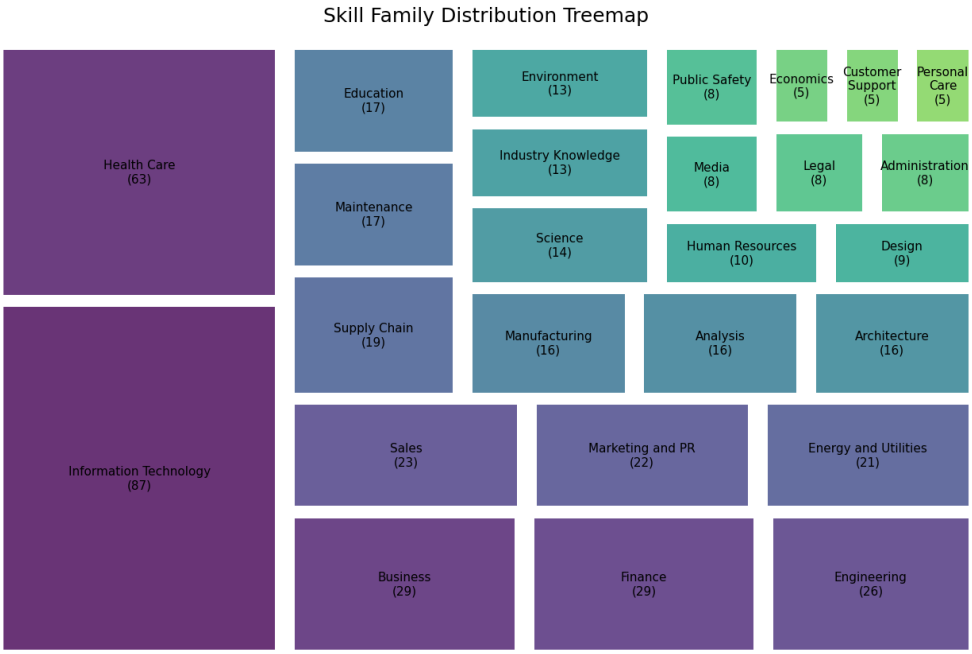
BGT developed its taxonomy of broader skill cluster categories. This taxonomy largely builds upon the existing skill categorization framework from the O*NET database, which organizes skills, knowledge, and abilities required for various occupations into a clear hierarchical structure. For instance, the skill "Python" would belong to the "Scripting Languages" skill cluster, which is part of the "Information Technology" skill cluster family. Each skill is assigned to precisely one skill cluster within the taxonomic framework employed in this study. Table 3.2 shows examples of a family of skills with associated skills, and Figure 3.1 below shows all families of skills and the number of skills within each family. Please refer to Appendix A for the full family and individual skills list.

Table 3.2: Examples of Family Skills and Individual Skills

Family Skills	**Skills**				
Manufacturing and Production	Lean Manufacturing	Manufacturing Processes	Brazing and Soldering	Computer-aided manufacturing	Product Development
Supply Chain and Logistics	Transportation Operation and Management	Procurement	Material Handling	TSA Regulation	Supplier Relationship Management
Engineering	Hardware Description Languages	Optical Engineering	Process Engineering	Simulation	Automation Engineering

** To see Family Skills and Individual Skills refer to Appendix A

Figure 3.1: Skill Family Distribution Tree map



3.3.5 Variables: Educational Degrees:

CanonMaximumDegree, CanonMinimumDegree. These variables show the educational degrees that employers require or prefer for job postings. They help us understand the maximum and minimum levels of education that employers are looking for. Understanding these variables helps grasp the educational qualifications valued across different engineering disciplines and how these requirements correlate with the skills and competencies employers' demand. Table 3.3 shows the missing records for these variables. In the analysis, I used only the complete records for CanonMaximumDegree and CanonMinimumDegreeof to understand the education requirements for job postings. I explained the mapping to traditional education levels such as bachelor's, master's, and doctoral in a subsequent section.

3.3.6 Variable: Major

This variable specifies the major field required for job posting. It was created by mapping the SOC (i.e., the occupation codes from O*NET using the ConsolidatedO*NET code). This means that each code will be mapped to an engineering discipline (e.g., CE/EE/ME), ensuring a representation of the educational background needed for different engineering roles.

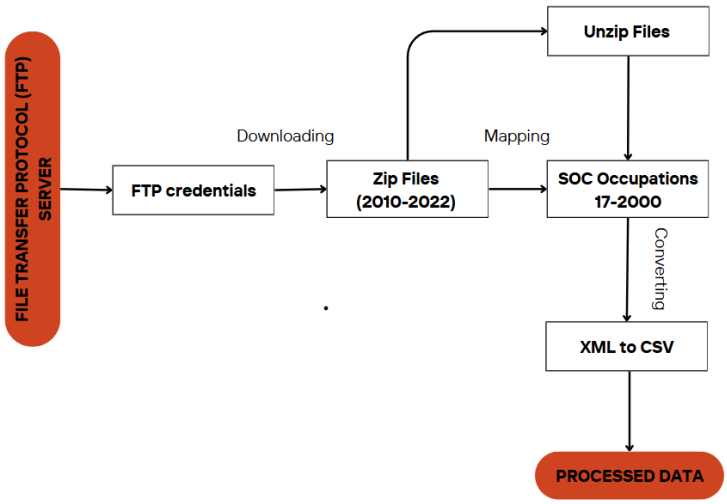
3.4 Data Processing and Cleaning

3.4.1 Downloading and Preparing Data

The data cleaning process begins with retrieving raw data from a File Transfer Protocol (FTP) server, a software application used to transfer files across a network securely. The server contains approximately 4TB of zip files that house occupational data from 2010 to 2022. After successfully authenticating with the FTP credentials, I download these zip files to a local processing environment to access the data. Given the large size of the dataset, unpacking and processing it is time-consuming and requires a high-performance computer with sufficient memory storage. To streamline the process and focus on the relevant information for this study, I specifically target Standard Occupational Classification (SOC) codes beginning with 17-20, which correspond to engineering-related occupations. Using these SOC codes, I selectively unzip only the files related to engineering fields, thereby reducing the data volume and focusing on the subset pertinent to the study.

After filtering the data by SOC codes (e.g., the SOC code for civil engineers is 17-2051.00), I perform a systematic extraction process where the contents of the compressed XML files are transformed into a more analysis-friendly CSV format. This step is crucial as it standardizes the raw data, making it accessible and ready for further manipulation and analysis. By converting the data into CSV format, I lay the groundwork for the subsequent stages of the research, ensuring the information is in a structured format that supports efficient processing because this data is large, as I am dealing with millions of rows. Figure 3.2 below illustrates the steps in this initial data cleaning and preparation process, highlighting the transition from raw, compressed data to a standardized, analysis-ready dataset.

Figure 3.2: Initial Data Acquisition and Preprocessing



In the data preparation phase, I started with 6,710,028 job postings covering all engineering fields classified under O*NET 17-20 SOC codes. To ensure data quality, I removed records with missing or insufficient job descriptions, eliminating 182,472 from CanonSkillClusters and 90 from JobText.

A missing values analysis by SOC code, major, and date found no discernible date patterns. A review of 100 records missing CanonSkillClusters revealed no anomalies, suggesting the omissions resulted from data collection issues or human error. These records spanned 2010 to 2022, with no systematic missing data patterns. After filtering, the dataset contained 6,527,466 records with complete CanonSkillClusters and JobText fields. I then narrowed the focus CE/EE/ME, totaling 3,421,241 job postings—52% of all engineering jobs in the dataset. Table 3.3 details missing values across all engineering disciplines, with 6,710,028 before separation and 3,490,091 for standalone CE/EE/ME.

Table 3.3: Counts and Percentage of Missing Values for All Engineering Disciplines and CE/EE/ME

	All Engineering Disciplines (Mapped)		**CE/EE/ME**	
Variable	**NaN Count**	**Percentage**	**NaN Count**	**Percentage**
JobID	0	0%	0	0.00%
CleanJobTitle	1476	0.02%	437	0.01%
JobDate	0	0%	0	0.00%
JobText	90	0.00%	30	0.00%
ConsolidatedONET	0	0%	0	0.00%
CanonSkillClusters	182472	3%	68820	1.97%
CanonMaximumDegree	5073898	76%	2625962	75.24%
CanonMinimumDegree	1771449	26%	867239	24.85%
Total Values in Datasets	6710028		3490091	
Total Values in Datasets**	6527466		3421247	

Note. Total Values in datasets** (Subtraction of NaN on SkillClusters and Jobtext)

The analysis of missing data across all engineering disciplines and CE/EE/ME disciplines shows distinct variations in the extent of missing values among different variables. CanonMaximumDegree consistently showed the highest proportion of missing data, with 76% missing values in all engineering disciplines, compared to 75.24% in the CE/EE/ME dataset. On the other hand, CanonMinimumDegree has 2% in All Engineering compared to 24.85 in the CE/EE/ME dataset. It should be noted that in the degree analysis, I used only CanonMinimumDegree and the corresponding CanonMaximumDegree. In the BGT data structures, the degree requirements are defined as follows: if an online job posting specifies that

only a PhD is required, then a PhD is considered the minimum degree for that position. For jobs that require either a bachelor's or a master's degree, the requirement is set as a minimum for a bachelor. Notably, CanonSkillClusters presented a notable discrepancy, with 3% missing in the overall dataset versus 1.97% in CE/EE/ME. Core fields like JobID, JobDate, and ConsolidatedONET were fully populated across both datasets, indicating robust data availability for these variables. CleanJobTitle and JobText had minimal missing data, demonstrating better data integrity for job descriptors to perform skill analysis further.

3.5 Data Processing Refinement and Classification (RQ1)

3.5.1 Overview

This section is associated with developing the NLP classification system, which I evaluated to answer the first research question. The data processing starts with 53 separate CSV files for each year. I combine these files into 12 main files. This merging simplifies the dataset, reduces the number of files we need to handle, and makes it easier to analyze the data later. Then the data cleaning pipeline is crucial for refining the dataset and preparing it for analysis. This stage uses dictionary-based filtering and classification techniques to enhance data accuracy and relevance, focusing on the three main engineering disciplines present in the dataset: Civil, Electrical, and Mechanical Engineering. The primary goal is to clean the BGT data since the SOC codes identifying Civil, Electrical and Mechanical engineering occupations appeared to have some errors in the dataset. This step represents a contribution of my work, as it appears prior research has relied on BGT data with the SOC variable to sort the data. Carnevale and others (2014) found that using the SOC code to organize the BGT is only 73% accurate. However, their data is from 2014, and data collection methods have changed since then. This work is important because past research has used BGT data without specifying how to clean it and has depended only on the SOC variable to sort the data. The BGT data is only 73% accurate in how it categorizes jobs, and this result is outdated, dating back to 2014 (Carnevale et al., 2014)

3.5.2 Dictionary and Terminology Development

The filtration process incorporates job title terms from O*NET and synonyms terminology to those job titles (see Appendix A). For example, I utilized the O*NET list of job titles and their synonyms to develop filtering terms for CE/EE/ME jobs. These O*NET titles were then used as matching criteria to identify relevant positions by scanning job descriptions and titles in the dataset. Moreover, I developed a dictionary to implement this approach containing key engineering terms (e.g., circuits, hydraulic) for job titles drawn from O*NET and its synonyms. For example, I filtered the dataset using the O*NET SOC code to classify electrical EE jobs and separated it into its own datasets (e.g., EE_DF dataset). Then, I implemented a dictionary-based approach with specific exclusion terms. When processing job titles like "Test Engineer," the system checks against exclusion terms such as "civil engineering/engineer," "aerospace engineering/engineer," and "mechanical engineering/engineer" (full list available in the appendix). If a job posting

contains any exclusion terms, such as 'mechanical engineering,' the system classifies it as 'non-electrical major' even if it initially appears in the EE_DF dataset.

3.5.3 Handling Overlapping Titles

It should be noted that some engineering job titles from O*NET can overlap with each other. For example, "Engineer" and its synonym "Professional Engineer" may refer to different CE/EE/ME roles. However, since the data was already pre-labeled with SOC codes, I treated each dataset separately for each CE/EE/ME field. For example, I applied the classification system to only the initially classified SOC in the CE data frame; I then used exclusion terms to filter out unrelated roles (i.e., terms like ME if they show up in the job description of the CE data frame it will be classified as non-civil-major). I did the same for the remaining datasets (e.g., EE and ME data frames). The full list of the exclusion terms is available in the appendix.

3.5.4 Patterns Matching

The classification process used NLP techniques. For example, I employed regular expressions to match engineering terms in job postings, allowing for flexible and case-insensitive identification. I also handled variations in job title terms by testing patterns (Table 3.4) such as "electrical engineer," "electricalengineer," and "electrical engineers" to accommodate morphological and compound formations (e.g., 'circuit design engineer,' 'power systems engineer') in electrical engineering.

Table 3.4: Testing Patterns for Electrical Engineer Term

Testing patterns	Match
electrical engineer	matches ✓
electricalengineer	matches ✓
electrical-engineer	matches ✓
electrical engineers	matches ✓
electrical engineering	matches ✓

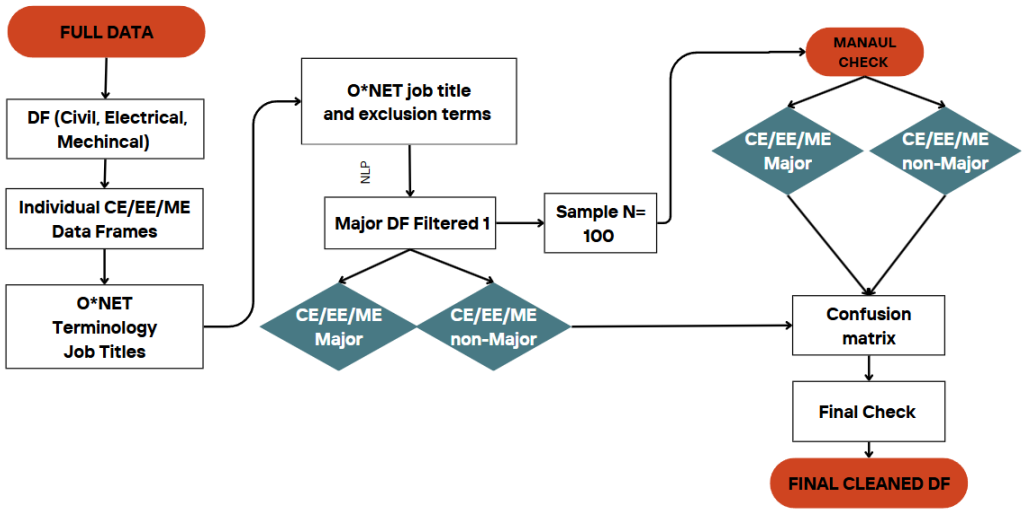
3.5.5 Human-in-the-loop Process

The human-in-the-loop (HITL) method is a process where a machine-automated system makes an initial decision, then a human review evaluates that decision. This process was a key part of the process to ensure the reliability of the classification results. While the NLP classification system automatically assigned job ads to engineering disciplines, human judgment was used to verify and refine these classifications. This approach helped catch errors the model might have made, especially in cases where job titles or descriptions were unclear or misleading and resulted in a false classification. Including this manual review step made the results of this review suitable for the evaluation method “Confusion Matrix,” which is explained later in this section

3.5.6 Summary

To optimize memory usage and processing efficiency, I processed the dataset in chunks of 50,000 rows. The pipeline implemented a multi-stage transformation protocol within each segment, establishing unique job identifiers and standardizing text by using string type. Consolidating job descriptions into a text field facilitated regex-based pattern matching, where terms were categorized as 'electrical-major' or 'non-electrical-major' based on the match of the dictionary terms (i.e., the NLP system searches for words to match with a predefined dictionary. If a match is found, it categorizes the output as ‘major’; if no match is found, it categorizes it as ‘non-major’). After the automated classification of all the jobs for a given discipline, I conducted a manual review of a sample (N=100) for each major (Civil, Electrical, and Mechanical Engineering), known as ground truth labeling. This involved assigning accurate labels to the dataset by reviewing job descriptions and titles. During this process, I identified specific terms for exclusion, such as differentiating between roles with similar titles but unrelated disciplines. For example, a "structural analyst" might be coded under CE based on title or skills but was classified as aerospace if specified in the job description. For these terms, see Appendix A. Finally, I calculated a confusion matrix to evaluate the accuracy of the automated process (further details are discussed in the following chapter). This validation confirmed that the dataset classification, with relevant skill information, was accurately assigned to the appropriate engineering disciplines. Figure 3.3 illustrates the key steps in this final stage, highlighting dictionary-based filtering and validation procedures, ensuring that the dataset is ready for detailed analysis and research purposes.

Figure 3.3: Data Refinement and Classification



3.7 Classification Output

Table 3.5 Distribution of Classified CE/EE/ME Job Ads

Major	Count	Total
civil-major	766,288	973,451
non-civil-major	207,163	
electrical-major	1,223,953	1,317,338
non-electrical-major	93,385	
mechanical-major	876,133	1,199,302
non-mechanical-major	323,169	
Total CE/EE/ME None-Major	623,717	
Total CE/EE/ME Major	2,866,374	
Total CE/EE/ME Major and None-Major	3,490,091	

Table 3.5 presents a breakdown of NLP classification output of engineering job advertisements across three major disciplines: civil, electrical, and mechanical engineering. The total number of civil engineering job ads is 973,451, with 766,288 specifically classified as civil-major roles and 207,163 categorized as non-civil-major. Similarly, electrical engineering job ads comprised 1,317,338 ads, of which 1,223,953 were classified as electrical-major, leaving 93,385 as non-major electrical. Mechanical engineering had a total of 1,199,302 where 876,133 were classified as mechanical-major and 323,169 non-major. Collectively, the data show that

classification for CE/EE/ME job ads are 2,866,374 postings, while non-major designations account for 623,717. The overall total is 3,490,091. The method of evolution is discussed later in this chapter.

Table 3.6 Examples of Non-Major Job Ads

JobID	JobText	CleanJobTitle	Major
270607973	952020 Animal Health - Reliability Engineer 05/20/2011 United States-West Virginia-Willow Island	Animal Health - Reliability Engineer	non-mechanical-major
355642171	California Gourmet Pizza Logo Design - Logo Design	Gourmet Pizza Logo Design - Logo Design	non-electrical-major
39377385626	Lead Prevention Navigator HIV Health Navigation Project - East McDowell Rd-Sign on Bonus Qualifications: Bachelor's Degree in behavioral health, public health, or related field and at least two years of relevant experience.	Lead Prevention Navigator Hiv Health Navigation Project	non-civil-major

Note: The job descriptions “JobText” were cut short for demonstration purposes

Table 3.6 shows examples of non-major job ads that fall outside the scope of core engineering disciplines. One ad for an "Animal Health – Reliability Engineer" reflects engineering work in a veterinary setting, thus classified as non-mechanical-major. Another, titled "Gourmet Pizza Logo Design," involves creative branding work, labeled non-electrical-major. A third ad for a "Lead Prevention Navigator" in public health is categorized as non-civil-major.

3.8 Classified data for analysis

Table 3.7 Distribution of Classified CE/EE/ME Job Ads (NaN Degree Requirements Removed)

Major	Count	total
civil-major	621,131	734,076
non-civil-major	112,945	
electrical-major	949,648	987,730
non-electrical-major	38,082	
mechanical-major	697,810	901,033
non-mechanical-major	203,223	
Total CE/EE/ME None-Major	354,250	
Total CE/EE/ME Major	**2,268,589**	
Total CE/EE/ME Major and None-Major	2,622,839	

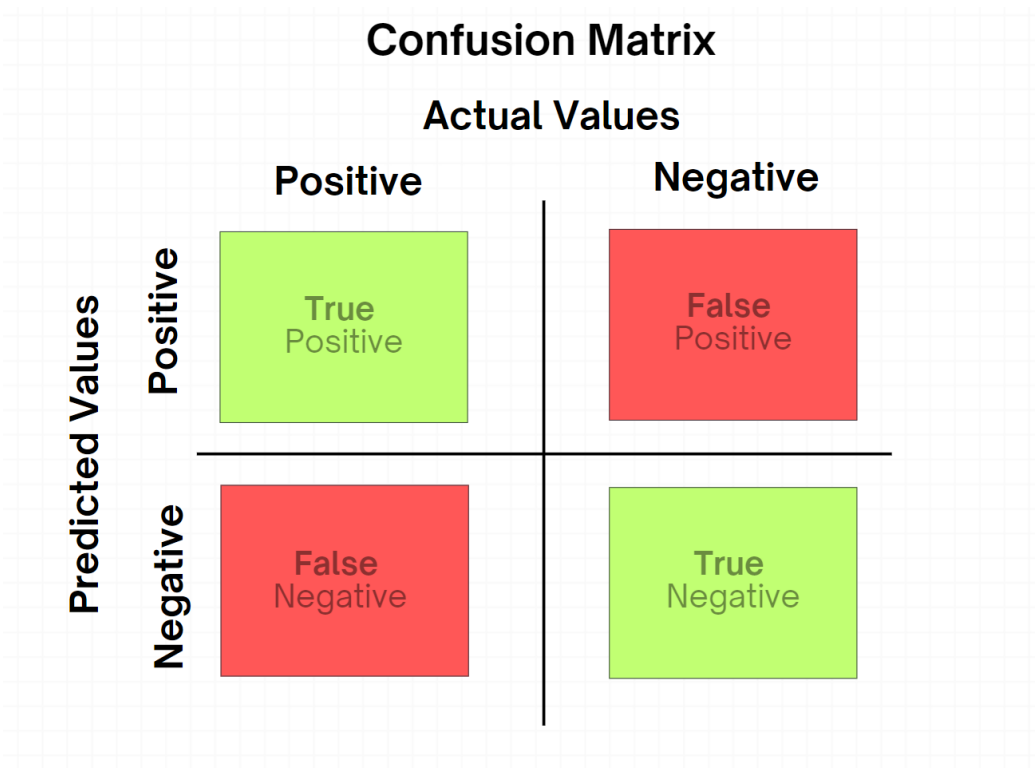
Table 3.7 presents a breakdown of the NLP classification output of engineering job advertisements across three major disciplines civil, electrical, and mechanical engineering based on a dataset that excludes any entries with missing (NaN) values in the degree requirement field. This data cleaning step ensured the use of a complete and analyzable dataset for addressing Research Questions 1 and 2, which examine patterns in educational qualifications and discipline-specific demand. The total number of civil engineering job ads is 734,076, with 621,131 specifically classified as civil-major and 112,945 as non-civil-major. Electrical engineering accounts for 987,730 job ads, of which 949,648 are electrical-major and 38,082 are non-major. Mechanical engineering shows a total of 901,033 postings 697,810 classified as mechanical-major and 203,223 as non-mechanical-major. the classified CE/EE/ME-major postings amount to 2,268,589 with an additional 354,250 classified as non-major within the CE/EE/ME fields. Altogether, the dataset comprises 2,622,839. The classified CE/EE/ME-major postings amount to 2,268,589 classified job advertisements were used to answer Research Questions 1 and 2.

3.6 Evaluate Classification System

Using a confusion matrix to evaluate the accuracy of a classifier algorithm is a common approach in machine learning (Düntsch & Gediga, 2019, 2020; Heydarian et al., 2022). It provides a conclusion of a model's predictions by displaying the counts of true positives, true negatives, false positives, and false negatives in a matrix format. (Fawcett, 2006). Each cell in the matrix represents the outcomes of the model's classification decisions, enabling a detailed assessment of the algorithm's performance across different classes (Düntsch & Gediga, 2019). Figure 3.4 shows the representation of a confusion matrix, with actual results populated in Chapter 4.

The matrix is a statistical tool that helps us understand classifier performance through four key metrics: accuracy, precision, recall, and F1-score. Fawcett (2006) demonstrates how accuracy quantifies a model's prediction success rate, while precision reflects how often positive predictions prove correct. Recall demonstrates how well a classifier detects all relevant instances in a dataset, showing its detection power (Fawcett, 2006). The F1 score combines precision and recall into one powerful metric, particularly excelling at evaluating models with imbalanced datasets. This framework allows researchers to understand classification models across diverse applications (Powers, 2020).

Figure 3.4: Confusion Matrix



The four key metrics in applying a confusion matrix to a classifier are accuracy, precision, recall, and F1-score. These metrics, derived from the confusion matrix, provide insights into the classifier's predictive capabilities by measuring different aspects of its performance (Fawcett, 2006).

- Accuracy: Accuracy measures the proportion of correctly classified instances out of the total number of instances. It is calculated as the sum of true positives and true negatives divided by the total number of predictions (Chicco & Jurman, 2020; Fawcett, 2006). The formula is as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

- Precision: Precision assesses the proportion of true positive predictions out of all positive predictions made by the model. It measures how many of the predicted positive instances are positive (Chicco & Jurman, 2020; Fawcett, 2006). The formula is as follows:

$$Precision = \frac{TP}{TP + FP}$$

- Recall: measures the model's ability to identify all relevant instances by calculating the proportion of true positives out of all actual positives. (Chicco & Jurman, 2020; Fawcett, 2006). The formula is as follows:

$$Recall = \frac{TP}{TP + FN}$$

- F1-Score: The F1-score is the harmonic means of precision and recall, providing a balanced metric that accounts for both false positives and false negatives. It is useful for imbalanced datasets and ranges from 0 to 1, with 1 indicating perfect precision and recall. (Chicco & Jurman, 2020; Fawcett, 2006). The formula is as follows:

$$F1Score = 2 \times \frac{Precision\ x\ Recall}{Precision + Recall}$$

Using these four key metrics (e.g., accuracy, precision, recall, and F1-score). We have a statistically well-established approach to evaluating our NLP O*NET classification system. In Figure 3.3, as previously mentioned, this system utilizes a binary output when analyzing job descriptions using the terms in the prelabeled dictionary. This output is categorized as either "CE/EE/ME" equal to 1 or "Non-CE/EE/ME" equal to 0. Thus, in this study, the definitions of true positive, false positive, true negative, and false negative are as follows:

- True Positives (TP): The classification result is correctly predicted as positive.
    - For example, in a binary classification task for detecting from job posting data that this job is CE/EE/MEengineering discipline, true positives are the classification system correctly classified as CE/EE/MEengineering discipline.

- False Positives (FP): The classification result inaccurately predicted as positive.
    - For example, in a binary classification task for detecting from job posting data that a job belongs to the CE/EE/ME discipline, false positives are instances where the

classification system incorrectly labels jobs that do not belong to the CE/EE/ME engineering discipline as CE/EE/ME engineering discipline.

- True Negatives (TN): The classification result is correctly predicted as negative.
    - For example, in a binary classification task for detecting from job posting data that a job belongs to the CE/EE/ME discipline, true negatives are instances where the classification system correctly identifies jobs that do not belong to the CE/EE/ME engineering discipline and labels them as Non-CE/EE/ME.
    -
- False Negatives (FN): The classification result is inaccurately predicted to be negative.
    - For example, in a binary classification task for detecting from job posting data that a job belongs to the CE/EE/ME engineering discipline, false negatives are instances where the classification system fails to identify actual CE/EE/ME discipline jobs and incorrectly classifies them as Non-CE/EE/ME.

After applying these formulas to evaluate the classification system, we can determine whether the classified CE/EE/ME data is ready for further analysis. This process ensures that data quality meets the required standards. Typically, a score of 0.93 or higher is regarded as excellent, while a score above 0.8 is considered good (Vujović, 2021). All these calculations will be presented in Chapter 4.

3.7 Skill Categorization Procedures

After completing the data preparation process, I prepared the dataset for skill categorization. The goal was to understand the distribution of skill clusters provided by BGT. To achieve this, I needed to break down the clusters into individual skill entries, effectively transforming the data frame into a long-form format. I began by examining the structure of the skill entries within the dataset to identify patterns that would help me organize the data effectively. Most entries adhered to a consistent format: "Skill Family: Skill; Skill Type." For instance, an entry such as "Information Technology: Microsoft Office and Productivity Tools; Specialized Skills" could be decomposed into three distinct components: the skill family ("Information Technology"), the specific skill ("Microsoft Office and Productivity Tools"), and the skill type (“Specialized Skills”). This structured format enabled me to differentiate broader categories (skill families) from individual competencies, laying the groundwork for a more in-depth dataset analysis. An example of the BGT skills cluster includes a mix of entries:

“Specialized Skills|Specialized Skills|Information Technology: Programming Principles;Specialized Skills|Maintenance, Repair, and Installation: Equipment Operation;Specialized Skills|Marketing and Public Relations: Social Media;Specialized Skills|Information Technology: JavaScript and Query;Specialized Skills|Business: Product Management;Specialized Skills|Specialized Skills|Specialized Skills|Information Technology:

Scripting Languages;Specialized Skills|Media and Writing: Media Production;Specialized Skills|Administration: Scheduling;Specialized Skills|Customer and Client Support: Advanced Customer Service;Specialized Skills|Information Technology: Software Development Principles;Specialized Skills|Information Technology: Technical Support;Specialized Skills|Supply Chain and Logistics: Transportation Operations Management;Specialized Skills|Specialized Skills|Specialized Skills"

However, not all entries followed this pattern. Some were labeled only as "Specialaized Skills" with no Skill family listed. These generalized entries represented skills that did not fit neatly into a specific category or were broadly applicable across various domains. Additionally, some skill families and skills appeared multiple times within a cluster, suggesting either high relevance or redundancy. To address these issues, I used a multi-step approach. First, I split skill entries using the "|" separator to isolate individual skills. Then, I checked each entry for the "Skill Family: Skill; Skill Type" format and parsed them accordingly. Entries without a skill family, like "Specialized Skills" or "Common Skills," were treated as standalone types and later excluded from the final dataset.

Key columns such as Major, FamilySkill, and Skill were retained, ensuring that the data captured essential details about each skill's presence across multiple job postings over time. This approach significantly increased the dataset's length, allowing for a more detailed analysis of skill requirements. For instance, the restructuring resulted in 8,522,340 rows for Electrical Engineers from 1,127,472, showing the expanded dataset's scope after capturing the multiple skills associated with each job entry.

Table 3.8: Example Long Format Data Frame for Skill Breakdown

Row	JobID	Major	FamilySkill	Skill
0	1754	Electrical Eng	Architecture and Construction	Electrical Construction
1	1754	Electrical Eng	Engineering	Drafting and Engineering Design
2	1754	Electrical Eng	Engineering	Electrical and Computer Engineering
3	1754	Electrical Eng	Engineering	Engineering Practices
852	3939	Electrical Eng	Information Technology	Microsoft Office and Productivity Tools
852	3939	Electrical Eng	Information Technology	Project Management Software
852	3939	Electrical Eng	Information Technology	System Design and Implementation
852	3939	Electrical Eng	Manufacturing and Production	Manufacturing Standards

3.8 Analysis of Research Questions

The study aims to develop a framework for pre-labeled SOC code job posting data as these types of large data are used in economic and workforce research (e.g., Buckner-Petty et al., 2019; Cerioli et al., 2023; Dawson et al., 2019, 2020; Forsythe et al., 2020; Squicciarini & Nachtigall, 2021). The study also aims to investigate trends and variations in CE/EE/ME O*NET SOC occupations from 2010 to 2022. In this study, I explored skill demands for engineering jobs, as indicated in job postings from 2010 to 2022, using classified data from the developed NLP framework.

3.9 Technical Skills

In the study conducted by Fleming et al. (2024), technical skills are described as the specific competencies and tools required for engineering roles. This includes proficiency in software, programming languages, and the analytical and operational tools relevant to each engineering discipline. The study examined the technical skills of CE/EE/ME from 2010 to 2022, focusing on the skills identified by O*NET and Fleming et al. (2024).

- **Software and Tools**: Microsoft Excel, AutoCAD, SolidWorks, MATLAB, SCADA (Supervisory Control and Data Acquisition), Microsoft Office Project, Civil 3D, Revit, Creo, CADD (Computer-Aided Design and Drafting)
- **Programming and Analysis**: Python, FMEA (Failure Modes and Effects Analysis), FEA (Finite Element Analysis), PLC (Programmable Logic Controller),

An NLP dictionary was created using the relevant skills terminology and applied to the CC, EE, and ME data sets to determine the frequency and proportions of these skills. The method employs a straightforward string-matching approach to align the technical skills with those specified in the job descriptions.

3.10 Research Question One

How well can pattern-based text classification and flexible regex match pre-classified (SOC code) job postings into engineering fields (e.g., Civil, Electrical, and Mechanical engineering)?

To address the research question effectively, I developed a pattern-based text classification and flexible regex classifier that was evaluated using confusion matrices. This approach utilized NLP to determine relevant skills and keywords tied to SOC codes found in job postings. The classification process involves applying our classifier to categorize each job posting according to CE/EE/ME discipline one at a time. The Python script compiles a list of regex patterns to match engineering terms from O*NET in the text; it allows for optional forms (e.g., "engineer," "engineers," or “engineering”) and performs case-insensitive matching, making the patterns flexible for identifying relevant terms in different formats. Additionally, the validation process

included a manual review of 100 random job postings from each engineering discipline (CE/EE/ME) to ensure alignment between classifier results and human judgment. The classification accuracy was evaluated using a confusion matrix framework to identify true positives, false positives, true negatives, and false negatives, strengthening the reliability of our job posting mappings and capturing both accurate and inaccurate classifications.

In the data analysis section, I utilize a confusion matrix to evaluate the classifier's performance by comparing predicted classifications against pre-labeled SOC codes and human judgment. The evaluation employs four key metrics:

- Accuracy measures the ratio of correctly classified instances to the total number of cases. It is calculated by dividing the sum of true positives and negatives by the total predictions. The formula is: $Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$
- Precision measures the ratio of true positive predictions to all positive predictions made by the model, indicating the accuracy of positive instances.: $Precision = \frac{TP}{TP+FP}$
- Recall measures the classifier's ability to identify relevant cases by calculating the proportion of true positives to all actual positives (Chicco & Jurman, 2020; Fawcett, 2006). The formula is: $Recall = \frac{TP}{TP+FN}$
- F1-score is the harmonic means of precision and recall, balancing false positives and negatives. It ranges from 0 to 1, with one indicating perfect precision and recall, making it useful for imbalanced datasets. (Chicco & Jurman, 2020; Fawcett, 2006). The formula follows: $F1Score = 2 \times \frac{Precision\ x\ Recall}{Precision + Recall}$

The study compares performance metrics (Accuracy, Precision, Recall, and F1-Score) across all three confusion matrix evaluations to assess the classification system's overall effectiveness on job posting data.

3.11 Research Question Two

RQ2: How do the proportions of different skills required for engineering jobs, as indicated in job postings, vary across:

- Levels of requisite education (i.e., bachelor’s, master’s, doctoral)?
- Engineering disciplines (i.e., Civil, Electrical, and Mechanical Engineering)?

The analysis determined the proportion of job postings that mention specific skills within each defined category. I identified the overall proportion of skills and highlighted the top skills in engineering job postings, providing a baseline for understanding the skill landscape across the CE/EE/ME discipline. The formula for calculating this proportion is:

$$Skill\ Mentions\ Proportion\ = \frac{Job\ postings\ mentioning\ the\ skill}{Total\ job\ postings}$$

$$Degree\ Skill\ Proportion = \frac{Skill\ mentions\ in\ degree-level\ postings}{Total\ postings\ for\ degree\ level}$$

Examining differences in these proportions across education levels and disciplines helps identify differences in the demand for various skills across these contexts, revealing which skills are predominantly sought after. To address the research question in my dissertation, I conducted a detailed analysis across CE/EE/ME disciplines from 2010 to 2022. This approach includes:

1. **Top 30 Skill by Overall Proportions**
    - Examined proportions for the total period 2010 to 2022 to identify top 30 skills.
2. **Top Engineering Family Skill**
    - Examined the relative proportions of these skills to determine their significance within each field
3. **Engineering Skills Statistical Analysis**
    - Examined proportions of technical skills across the three disciplines (CE/EE/ME) and their educational levels (i.e., bachelor's degree, master's degree, and doctoral Degree) for 12 years (2010-2012) to further understand how these skills align with degree requirements.
    - **Analysis of Variance (ANOVA) and Cohen's d**
        - Examined the distributions of engineering skills
        - I examined whether skills requirements significantly differed across degree levels (i.e., bachelor's, master's, and doctoral) within each of the CE, EE, and ME disciplines.
        - To assess differences in skills requirements among engineering disciplines, I conducted separate one-way ANOVA tests for each degree level. First, I filtered the dataset for bachelor's degree data and examined differences among CE, EE, and ME. I then repeated the analysis for master's and doctoral degree levels.
        - Applied Cohen's d to measure the effect size and assess the magnitude of differences in skill requirements between degree levels (i.e., bachelor's degree, master's, and doctoral degrees).
        - Provided statistical conclusion on both the ANOVA and Cohen's D
        - Cohen' D effect sizes effect sizes were interpreted as follows: values of d equal to or less than 0.2 were considered small, those greater than 0.5 but less than 0.8 were considered medium, and values equal to or exceeding 0.8 were considered large (Sullivan & Feinn, 2012)

4. **Technical Skills Proportions**
    - Assessed the Proportions of the technical skills mentioned in the job posts for CE/EE/ME and their degree levels.
    - Provided statistical summaries into how skill requirements vary with educational degrees.

3.12 Research Question Three

RQ3: How have the proportions of different skills required for engineering jobs, as indicated in job postings, changed between 2010 and 2022, considering both levels of requisite education (i.e., bachelor's, master's, doctoral) and specific disciplines (civil, electrical, and mechanical engineering)?

This research question builds on the previous one by examining annual variations in the proportions of jobs requiring specific skills from 2010 to 2022. The analysis is segmented by education level (e.g., bachelor's, master's, and doctoral) to reveal patterns and trends over time. I presented the findings year-by-year, using a proportions formula that calculates the skill percentage for each year from 2010 to 2022 to measure the increase or decrease in demand for specific skills. This approach helps identify trends; the formula is as follows:

$$Year\ \ Skill\ Mentions\ Proportion\ =\ \frac{Job\ postings\ mentioning\ the\ skill}{Total\ \ job\ postings}$$

$$Year\ Degree\ Skill\ Proportion = \frac{Skill\ mentions\ in\ degree{-}level\ postings}{Total\ postings\ for\ degree\ level}$$

To uncover trends in skill demands over time from 2010 to 2022 for my research across all CE/EE/ME, I carried out the following analyses:

1. **Top 30 Skill by Overall Proportions**
    - Examined proportions across 2010 to 2022 to identify trends and changes within the top 30 skills.
2. **Time-Based Frequency Analysis for Top Skills**
    - I analyzed the proportional counts of the top 30 skills over time to track changes in demand across disciplines.
    - I grouped the skills into their respective categories and created individual plots to improve the visibility of trend lines.
3. **Time-Based Frequency Analysis for Technical Skills**
    - I analyzed the proportional counts of the technical skills over time to track changes in demand across disciplines.
    - I divided the technical skills into two groups in the plots to provide better visibility to spot changes across the timeline from 2010 to 2022.

4. **Educational-Level Frequency Analysis for Technical Skills**
    - Assessed the proportions of the technical skills mentioned in the job posts for bachelor's, master's, and doctoral degrees across time from 2010 to 2022.
    - Provided statistical summaries into how skill requirements vary with educational degrees.

3.13 Researcher Positionality

As an international student with a background in industrial engineering, I have strong analytical skills and technical knowledge. My background is different from many of my peers, offering me a unique view of the challenges and opportunities in engineering. Studying and working abroad has helped me become adaptable and good at solving problems. These experiences have made me realize how important it is for engineering education to keep up with fast-changing technology and industry needs. Working in the industry as a data scientist changed my perspective on using data to guide decisions. I was responsible for analyzing and interpreting complex data sets to provide valuable insights into the company's decision-making process. My perspective influences how I approach engineering, aiming to connect what we learn in university with the skills needed in today's job market, leveraging insights from big data.

This industry experience and my academic training have enhanced my awareness of the importance of aligning engineering curricula with the real-world skills demanded in today's job market. I see a growing need for educational programs to emphasize data-driven decision-making, as the ability to extract valuable insights from big data is becoming a critical competency for making decisions. As a researcher, I recognize that my role as the study designer, along with my perspectives and past experiences, shapes how I approach research focus, questions, and methods. In this research study, I aim to bridge the gap between what we learn in university and the practical skills needed in the workforce. My goal is to leverage data to inform educational practices and enhance the overall quality of higher education.

Chapter Four: Analysis and Results

This study aims to analyze online job advertisements to uncover key skills, trends, and market dynamics within civil, electrical, and mechanical engineering occupations over 13 years from 2010 to 2022. My research also seeks to enhance the accuracy of mapping these postings to O*NET occupation titles (e.g., Civil Engineering Occupations) by developing an NLP binary classification system. The performance of this system will be evaluated using a confusion matrix to measure its effectiveness in refining the mapping process to address the following:

- ***RQ1: How well can pattern-based text classification and flexible regex matching be used to categorize job postings into engineering disciplines (e.g., civil, electrical, mechanical engineering)?***
- ***RQ2: How do the proportions of different skills required for engineering jobs, as indicated in job postings, vary across levels of requisite education (i.e., bachelor's, master's, doctoral) and engineering disciplines (i.e., Civil, Electrical, and Mechanical Engineering)?***
- ***RQ3: How have the proportions of different skills required for engineering jobs, as indicated in job postings, changed across the period of 2010-2022, considering both levels of requisite education and the specific disciplines of Civil, Electrical, and Mechanical Engineering?***

Understanding the evolving demands for engineering skills is crucial for addressing the workforce's needs and aligning educational outcomes with industry requirements. This study explores how the proportions of skills required for engineering jobs vary by education levels (bachelor's, master's, doctoral), engineering disciplines (Civil, Electrical, and Mechanical), and over time from 2010 to 2022. The following analysis addresses these dimensions, providing insights into how skill demands have shifted across education levels and disciplines over a decade. The analysis examines the distribution of skills across job postings, shedding light on how demand varies across educational levels and engineering disciplines (e.g., Civil, Electrical, and Mechanical). Addressing Research Question 2 (RQ2) highlights the differences in skill requirements across job postings. It explores how these demands change based on the level of education (bachelor's, master's, doctoral) and field of specialization. This method offers insights into educational paths that emphasize specific skills, enhancing understanding of how education meets industry expectations and workforce demands. To complement this exploration, differences in skill proficiency across education levels were examined using an Analysis of Variance (ANOVA). This statistical analysis assessed whether the mean differences among degree groups within each CE\EE\ME separately were significant. The findings from the ANOVA test highlight the relationship between education and skill development, setting the stage for effect size analyses (Cohen's d) to further evaluate the magnitude of these differences.

Furthermore, the analysis examines skill trends over a decade, from 2010 to 2022, providing a temporal perspective on shifts in demand for engineering skills. This longitudinal analysis will answer Research Question 3 (RQ3) by evaluating how skill proportions have evolved, considering the relationship with education levels and specific engineering disciplines. Understanding these trends will provide a comprehensive view of how the engineering industry has adapted to technological advancements, market needs, and shifting priorities.

4.1. Research Question One

How well can pattern-based text classification and flexible regex matching be used to categorize job postings into engineering disciplines (e.g., civil, electrical, mechanical engineering)?

4..1.2. NLP Text Classification Evaluation

In this section, I will evaluate the text classification NLP system and calculate four main metrics for this evaluation for each one of the datasets CE, EE, and ME datasets: I will apply Accuracy, Precision, Recall, and F1-Score to evaluate the model**.**

4.1.3. Civil Engineering Confusion Matrix

To validate the effectiveness of the pattern-based text classification and flexible regex matching approach, I conducted a manual validation of 100 randomly selected samples from the CE-specific dataset. The confusion matrix shows that out of 89 instances predicted as positive, 81 were correctly classified (true positives) and 8 were misclassified (false positives). Among the 9 instances predicted as negative, 7 were correctly identified (true negatives) and 2 were misclassified (false negatives). The high number of true positives and relatively low false positives and negatives suggest that the flexible regex matching patterns effectively captured the CE job from the jobs ads data while maintaining good precision.

The confusion matrix table format is as follows:

Table 4.1: Confusion Matrix Table Format

Type	Positive	Negative
Positive	True Positive	False Positive
Negative	False Negative	True Negative

Table 4.2: CE Performance Evaluation (n=100)

Type	Positive	Negative
Positive	81	8
Negative	2	7

Table 4.3: CE Classification Performance

Accuracy	Precision	Recall	F1 Score
0.8980	0.9101	0.9759	0.9419

The pattern-based classification model demonstrated strong performance across all evaluation metrics. Table 4.3 shows that the model achieved an accuracy of 89.80%, indicating that nearly 90% of all predictions were correct. The precision score of 91.01% reflects the model's ability to minimize false positives, while the high recall of 97.59% shows it successfully identified most of the true positive cases. The F1 score of 94.19%, which represents the harmonic mean of precision and recall, confirms the model's balanced performance between precision and recall. These results suggest that the pattern-based classification approach is reliable and for the job ads classification task.

4.2. Electrical Engineering Confusion Matrix

To evaluate the effectiveness of the pattern-based text classification and flexible regex matching approach for electrical EE classification, I conducted a manual validation of 100 randomly selected samples from the EE-specific dataset. Out of 87 instances predicted as positive, 77 were correctly classified (true positives) and 10 were misclassified (false positives). Among the 10 instances predicted as negative, 6 were correctly identified (true negatives) and 4 were misclassified (false negatives). The high number of true positives and a relatively moderate number of false positives and negatives suggest that the flexible regex matching patterns classified EE occupation while maintaining reasonable precision.

Table 4.4: EE Performance Evaluation (n=100)

Type	Positive	Negative
Positive	77	10
Negative	4	6

Table 4.5: EE Classification Performance

Accuracy	Precision	Recall	F1 Score
0.8557	0.8851	0.9506	0.9167

The pattern-based classification model demonstrated solid performance across all evaluation metrics. As shown in Table 4.5 the model achieved an accuracy of 85.57%, indicating that approximately 86% of all predictions were correct. The precision score of 88.51% reflects the model's ability to minimize false positives, while the high recall of 95.06% shows it successfully identified most of the true positive cases. The F1 score of 91.67%, which represents the harmonic mean of precision and recall, confirms the model's balanced performance between precision and recall. These results suggest that the pattern-based classification approach effectively classified EE occupations within the job posting data.

4.3. Mechanical Engineering Confusion Matrix

To evaluate the pattern-based text classification and flexible regex matching approach, I manually validated 100 randomly selected from the ME-specific dataset. In Table 4.6, the results show that out of 88 instances predicted as positive, 80 were correctly classified (true positives) and 8 were misclassified (false positives). Among the 10 instances predicted as negative, 7 were correctly identified (true negatives), and 3 were misclassified (false negatives). The high number of true positives and relatively moderate false positives and negatives suggest that the flexible regex matching patterns classified ME occupation while maintaining good precision.

Table 4.6: ME Performance Evaluation (n=100)

Type	Positive	Negative
Positive	80	80
Negative	3	7

Table 4.7: ME Classification Performance

Accuracy	Precision	Recall	F1 Score
0.8788	0.8989	0.9639	0.9302

As presented in Table 4.7, the model reached 88% accuracy in overall predictions. With a precision of 90%, the model proved highly reliable in avoiding false positives, and its recall of 96% demonstrates excellent coverage of true positive cases. The resulting F1 score of 93% reflects the harmonious balance between precision and recall, confirming the model's strong and consistent performance in the classification task within the job posting data.

Table 4.8 O*NET-SOC Mapped Data, Reclassified Postings Complete Postings (No NaN Degrees) for CE/EE/ME

Discipline	O*NET-SOC Mapped Data	Reclassified Postings	Complete Postings (No NaN Degrees)
Civil Engineering	973,451	766,288	621,131
Electrical Engineering	1,317,338	1,223,953	949,648
Mechanical Engineering	1,199,302	876,133	697,810
Total	3,490,091	2,866,374	2,268,589

Table 4.8 summarizes the impact of applying pattern-based text classification and flexible regex matching to job postings initially mapped by the O*NET-SOC taxonomy. The number of postings decreased from 973,451 to 766,288 for CE, from 1,317,338 to 1,223,953 for Electrical EE, and from 1,199,302 to 876,133 for Mechanical Engineering (ME) following reclassification. The classification system's emphasis on precision and recall, as validated by confusion matrix evaluations, where CE, EE, and ME achieved high F1 scores (94%, 92%, and 93%, respectively). The strong performance across accuracy, precision, recall, and F1-score confirm that the reclassification more effectively isolates discipline-specific postings while reducing false positives. As a result, the refined dataset provides a more reliable foundation for labor market analysis. When further filtered to include only postings with complete degree information (no NaN values), the totals declined to 621,131 for CE, 949,648 for EE, and 697,810 for ME resulting in a total of 2,268,589 postings that were used for the analysis. This additional filtering step was applied to ensure effective analysis of educational level and skills trends across CE/EE/ME

Table 4.9 Yearly Distribution of For Non-CE/EE/ME Classified Job Ads

Year	non-civil-major	non-electrical-major	non-mechanical-major
2010	6,106	2,867	14,043
2011	8,146	3,339	18,012
2012	8,918	3,558	18,962
2013	13,928	6,757	21,648
2014	15,234	6,832	21,204
2015	17,293	7,513	24,331
2016	15,148	7,149	21,861
2017	15,662	6,912	22,899
2018	19,586	8,425	31,911
2019	20,804	9,161	31,192
2020	17,533	7,791	23,703
2021	19,855	9,554	26,675
2022	28,966	13,547	46,744
Total	207,179	93,405	323,185
Total Non-CE/EE/ME	623,769		
Original Non-CE/EE/ME	623,717		
Total of NaN Dates	52		

Table 4.9 presents the yearly distribution of Non-CE/EE/ME job advertisements classified as non-CE, non-EE, and non-ME from 2010 to 2022. The total counts across all years indicate that there were 207,179 non-civil-major, 93,405 non-electrical-major, and 323,185 non-mechanical-major postings, culminating in an aggregated total of 623,769 job ads classified outside these primary engineering fields. A small discrepancy between the calculated total and the originally recorded total (623,717) and the presence of 52 records with missing or unclassified dates are noted.

4.5 Degree Distribution for CE/EE/ME

Table 4.10 Distribution of Degrees For CE/EE/ME Classified Job Ads (No NaN Degrees)

Degrees	CE (N)	%	EE (N)	%	ME (N)	%
Bachelor's	595,766	95.92%	904220	95.22%	662121	94.89%
Master's	23,075	3.71%	35982	3.79%	26822	3.84%
Doctoral	2,290	0.37%	9446	0.99%	8867	1.27%
Total	621,131	100%	949648	100%	697810	100%
Total	2,268,589					

Table 4.10 shows that jobs requiring at least a bachelor's degree dominate the CE job advertisement database, accounting for 595,766 (95.92%) of the 621,131 degrees recorded. Jobs requiring at least a master's degree comprise 23,075 (3.71%), and jobs requiring a doctoral degree represent the smallest

proportion at 2,290 (0.37%). In EE, jobs requiring a bachelor's degree account for 904,220 (95.22%) of the 949,648 degrees recorded. Master's degree requirements make up 35,982 (3.79%), while doctoral-level postings total 9,446 (0.99%). Similarly, in ME, 662,121 (94.89%) of the 697,810 postings require a bachelor's degree. Jobs requiring a master's degree comprise 26,822 (3.84%), and 8,867 (1.27%) require a doctoral degree.

4.4 Job Posting Skill Analysis

Table 4.11: Average Skills Per Year Across CE/EE/ME in Job Advertisement (2010–2022)

Year	CE (Avg Skills)	EE (Avg Skills)	ME (Avg Skills)
2010	6.49	7.43	6.93
2011	7.35	7.86	7.47
2012	7.12	7.86	7.48
2013	7.21	7.99	7.36
2014	7.40	8.27	7.75
2015	7.53	8.57	7.94
2016	7.66	8.70	8.08
2017	7.91	8.90	8.22
2018	8.16	9.04	8.61
2019	7.80	9.01	8.76
2020	7.79	9.02	8.96
2021	8.31	9.79	9.27
2022	8.85	10.30	9.62

Table 4.11 presents the average skills per year from 2010 to 2022, highlighting a steady increase in the number of skills listed within each job advertisement across Civil, Electrical, and Mechanical engineering. EE job advertisements consistently had a greater number of skills, with skills rising from 7.43 in 2010 to 10.30 in 2022, marking a 38.6% increase. This is followed by Mechanical Engineering, which grew from 6.93 to 9.62 skills (38.7%). While growing more slowly, CE increased from 6.49 to 8.85 skills (36.2%), reflecting steady but more traditional skill demand, as indicated by job advertisements. The analysis indicates that job advertisements in all three fields—Civil, Electrical, and Mechanical Engineering—have become more complex and listed more skills between 2010 and 2022. The results cannot speak with certainty as to whether the jobs themselves required a higher number of skills.

The sections that follow step through each engineering discipline separately, beginning with civil engineering, followed by electrical engineering, and then mechanical engineering. Each section works through the research questions as relevant to that discipline.

4.5 Examining Civil Engineering Skills by Proportion and Trends

Table 4.12 shows that jobs requiring at least a bachelor's degree dominate the CE job advertisement database, accounting for 595,766 (95.92%) of the 621,131 degrees recorded. Jobs requiring at least a master's degree comprise 23,075 (3.71%), and jobs requiring a Doctoral degree represent the smallest proportion at 2,290 (0.37%).

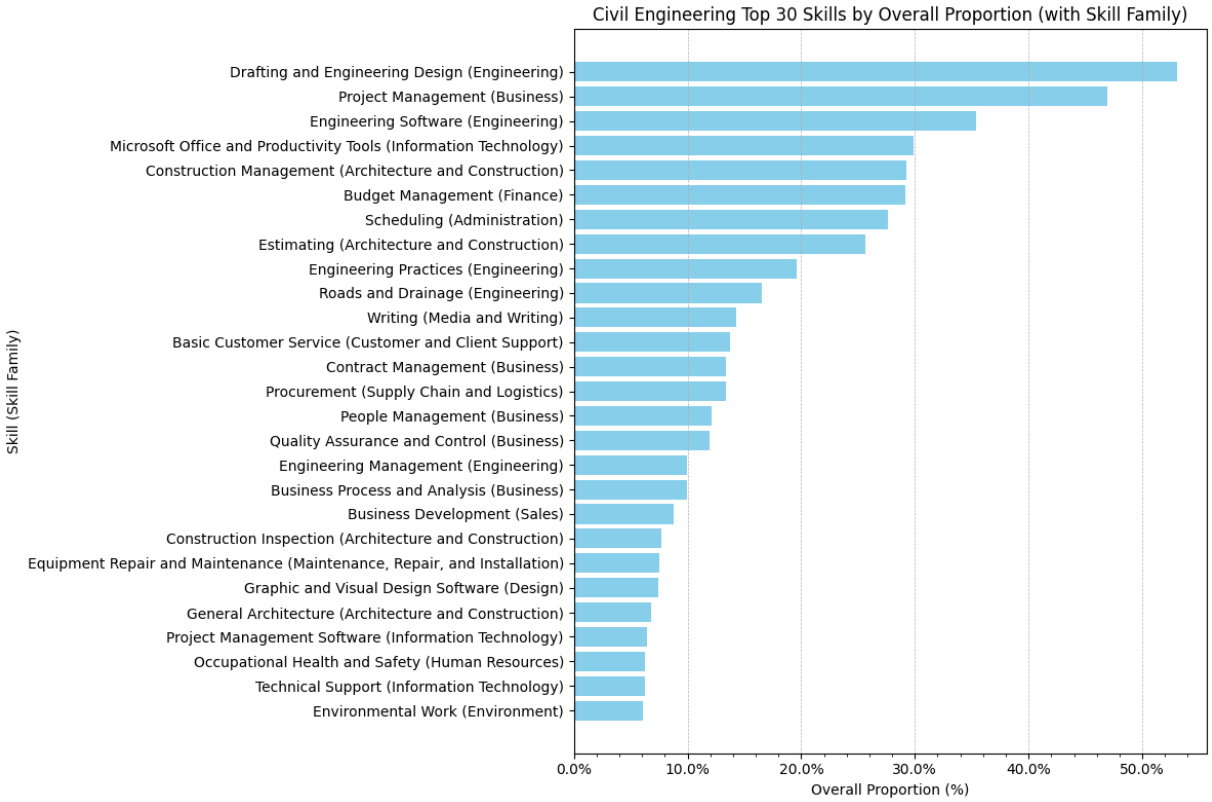
Table 4.12: CE Degree Distribution

CE Degrees	Degree (N)	Percentage
Bachelor's	595,766	95.92%
Master's	23,075	3.71%
Doctoral	2,290	0.37%
Total	621,131	100%

4.5.1 CE Top 30 Skills by Overall Proportions

Figure 4.1 highlights the top 30 skills in CE based on their overall proportions across various skill families (note: the skill family is shown in parentheses). The proportion of CE job advertisements included a particular skill as a requirement. Drafting and Engineering Design stands out as the most prevalent skills in CE job advertisements, followed closely by Project Management and Engineering Software, underscoring their foundational roles in CE projects. Skills such as Microsoft Office, Productivity Tools, and Construction Management rank highly, emphasizing the importance of digital tools. Budget management and scheduling are also prominent, reflecting the need for financial planning and project coordination.

Figure 4.1: Civil Engineering Top 30 Skills by Overall Proportions

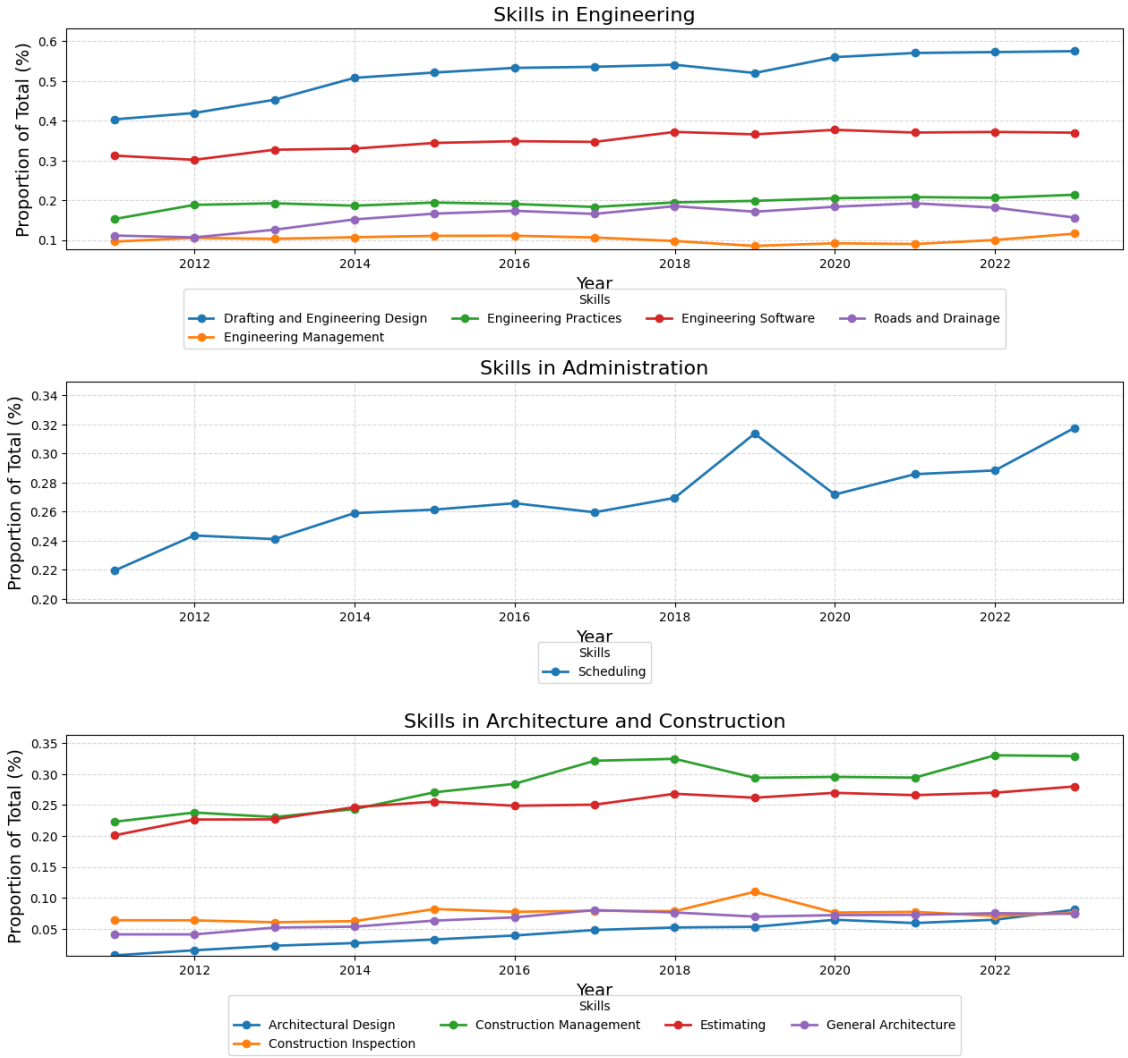


Lower-ranked but notable skills include Writing, Basic Customer Service, and Procurement, which point to the importance of communication, client relations, and supply chain management in CE practices. Specialized skills such as Graphic and Visual Design Software, Occupational Health and Safety, and Environmental Work, while less represented, demonstrate their importance in specific contexts like safety, sustainability, and innovative design. This distribution showcases the multidisciplinary nature of civil engineering, with a balance between technical expertise, managerial skills, and supporting competencies essential for success in modern projects. Next, I closely examine how these skills have evolved from 2010 to 2022, shedding light on trends and shifts in CE priorities and practices.

Next, I present each of these skills from a temporal perspective across multiple plots grouped by skills family. From 2010 to 2022, the trends in skill proportions across three categories: Engineering, Administration, and Architecture and Construction which reflect the evolving needs in CE. Drafting and engineering design dominate the engineering category, with other skills like engineering management, engineering practices, and engineering software showing stable trends. Roads and Drainage demonstrate a gradual increase, highlighting its growing relevance. In Administration, Scheduling shows an upward trend, emphasizing the increasing importance of project planning and coordination in CE projects. In Architecture and Construction, Construction Management and General Architecture maintain prominence, while Architectural Design shows

steady growth over time. Specialized skills like construction inspection and estimation increase gradually, indicating their importance in CE.

Figure 4.2: Trend of Top 30 Skill (Engineering, Administration, Architecture and Construction) 2010-2012

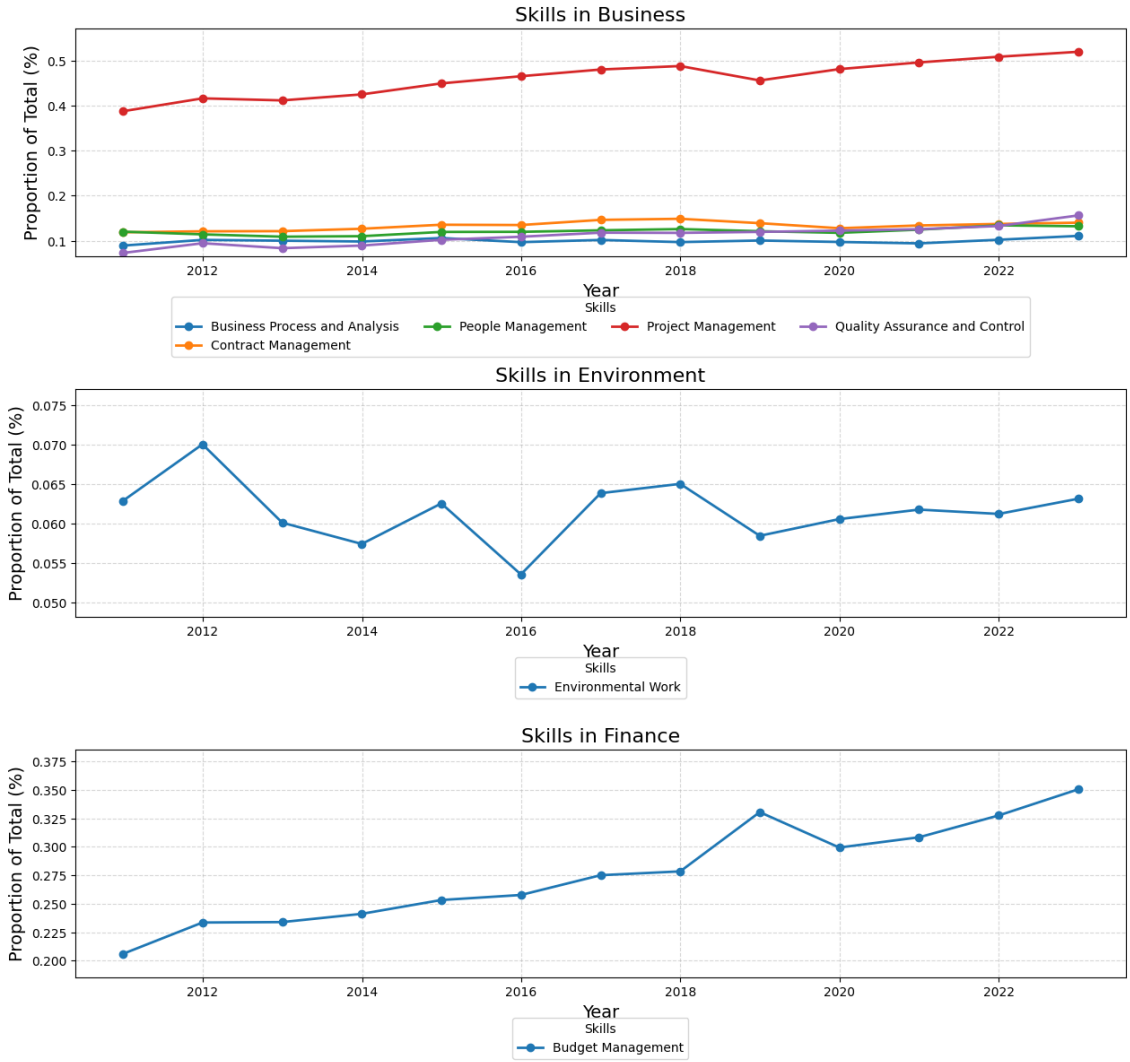


Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

In figure 4.3, over the past decade, the trends in skill proportions across three categories: Business, Environment, and finance have displayed the shifting demands of civil engineering. In the business category, project management consistently dominates and has become even more prevalent in job ads, reflecting its critical role in CE positions. Other skills, such as People Management and Quality Assurance and Control, maintain lower proportions but gradually increase, indicating their growing importance in managing teams and ensuring quality standards. In the Environment category, Environmental Work displays fluctuating trends, with periods of decline followed by recovery in recent years, reflecting its variable emphasis depending on

environmental and regulatory priorities. Budget Management shows a steady upward trajectory in Finance, highlighting its increasing significance as cost control and financial planning become more critical in managing large-scale CE projects.

Figure 4.3: Trend of CE Top 30 Skill (Business, Environment, and Finance) 2010-2012

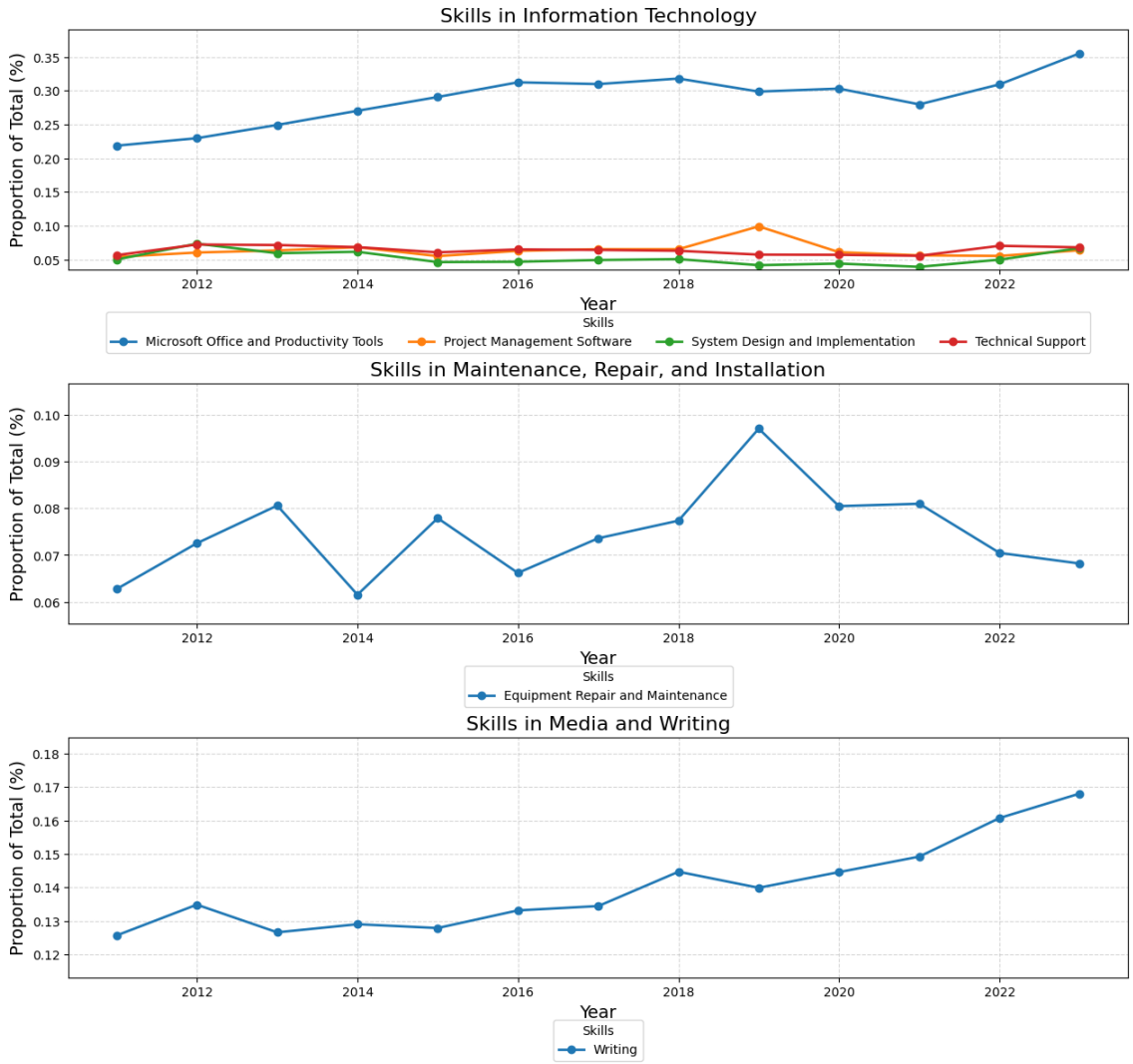


Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

In figure 4.4, over the past decade, trends in skill proportions across three categories: Information Technology, Maintenance, Repair, and Installation, and Media and Writing which reflect shifts in skill demands within CE (note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots). In the Information Technology category, Microsoft Office and Productivity Tools consistently dominate, highlighting their essential role in engineering workflows. Other skills, such as Project Management Software and System Design and Implementation, maintain smaller proportions with limited but steady growth, indicating their importance in specific technical and managerial contexts. In the Maintenance, Repair, and

Installation category, Equipment Repair and Maintenance shows variability, peaking around 2018 before declining in recent years. This trend suggests periodic demand, potentially influenced by technological advancements and equipment life cycles or availability of certain kinds of jobs at any given time. Writing exhibits a clear upward trend in the Media and Writing category, reflecting an increasing emphasis on documentation, reporting, and communication within CE projects.

Figure 4.4: Trend of CE Top 30 Skill (Information Technology, Maintenance, Repair and Installation, and Media and Writing) 2010-2012



Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

In figure 4.5, over the past 10 years, trends in skill proportions across three categories: Science and Research, Supply Chain and Logistics, and Design which reflect changes in demand of these skills within CE see Figure 4.5. In the Science and Research category, Earth and Space Science peaked around 2018, with a decline in recent years. This pattern suggests periodic emphasis on research-driven initiatives potentially influenced by environmental and technological

factors. Procurement has gradually grown over time in the Supply Chain and Logistics category, with a notable spike in 2018. Its recent upward trend reflects the increasing importance of effective resource management in CE projects. Graphic and visual design software has steadily risen in the design category, particularly in the last few years, highlighting its growing relevance in integrating visual tools for engineering design and communication.

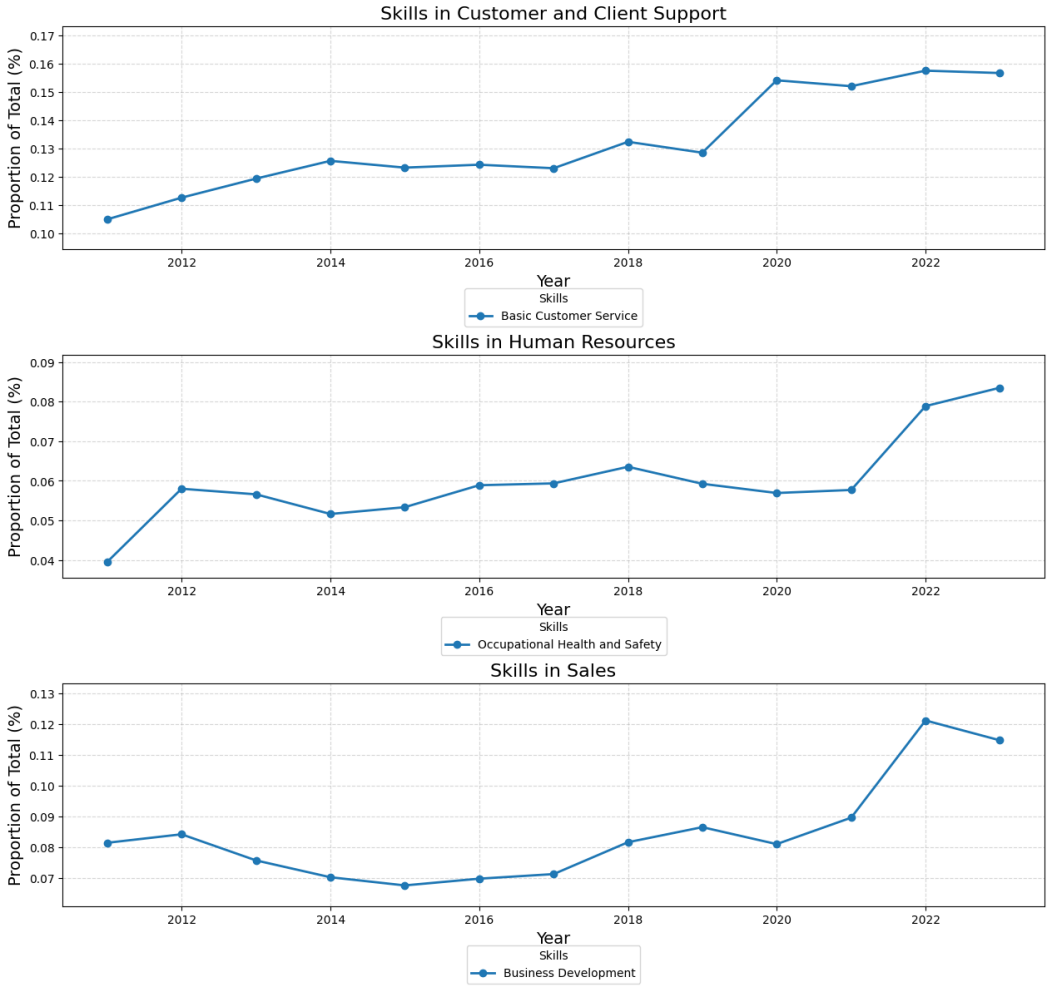
Figure 4.5: Trend of CE Top 30 Skill (Science and Research, Supply Chain and Logistics and Design) 2010-2012

Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

Figure 4.6 shows that from 2010 to 2022, the trends in skill proportions across three categories: Customer and Client Support, Human Resources, and Sales which reflect evolving priorities in civil engineering. Basic Customer Service demonstrates a steady upward trend in the Customer and Client Support category, plateauing in recent years. This increase underscores the growing importance of client engagement and support in project management and service delivery.

In the Human Resources category, Occupational Health and Safety has shown growth, particularly after 2020. This trend highlights an increasing focus on workplace safety and compliance, likely driven by stricter regulations and heightened awareness of health standards. Business Development exhibits notable variability in the Sales category, with a sharp increase peaking around 2020, followed by a slight decline. This suggests a growing emphasis on strategic growth and business opportunities in civil engineering, influenced by market expansion and competition.

Figure 4.6: Trend of CE Top 30 Skill Customer and Client Support, Human Resources and Sales) 2010-2012



Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

Figure 4.7 presents the top Engineering skills in CE by proportion within the engineering skill family (note: analyses presented above did not only focus on the engineering skills family). Drafting and Engineering Design stand out as the most dominant skills, followed by Engineering Software, Engineering Practices, and Roads and Drainage. This reflects their critical importance in CE projects and workflows. Moderately represented skills include Surveying, Simulation, and Process Engineering. In contrast, skills such as Optical Engineering, Radio Frequency Equipment,

and Hardware Description Languages appear less frequently, indicating their more specialized nature within civil engineering. This distribution highlights the essential technical competencies within CE that could cut across more jobs or also reflect the kinds of jobs within CE that tend to be more predominant, with a strong emphasis on design, software, and practical engineering practices that are fundamental to the profession.

Figure 4.7: Top CE Skills in Engineering Family Skill

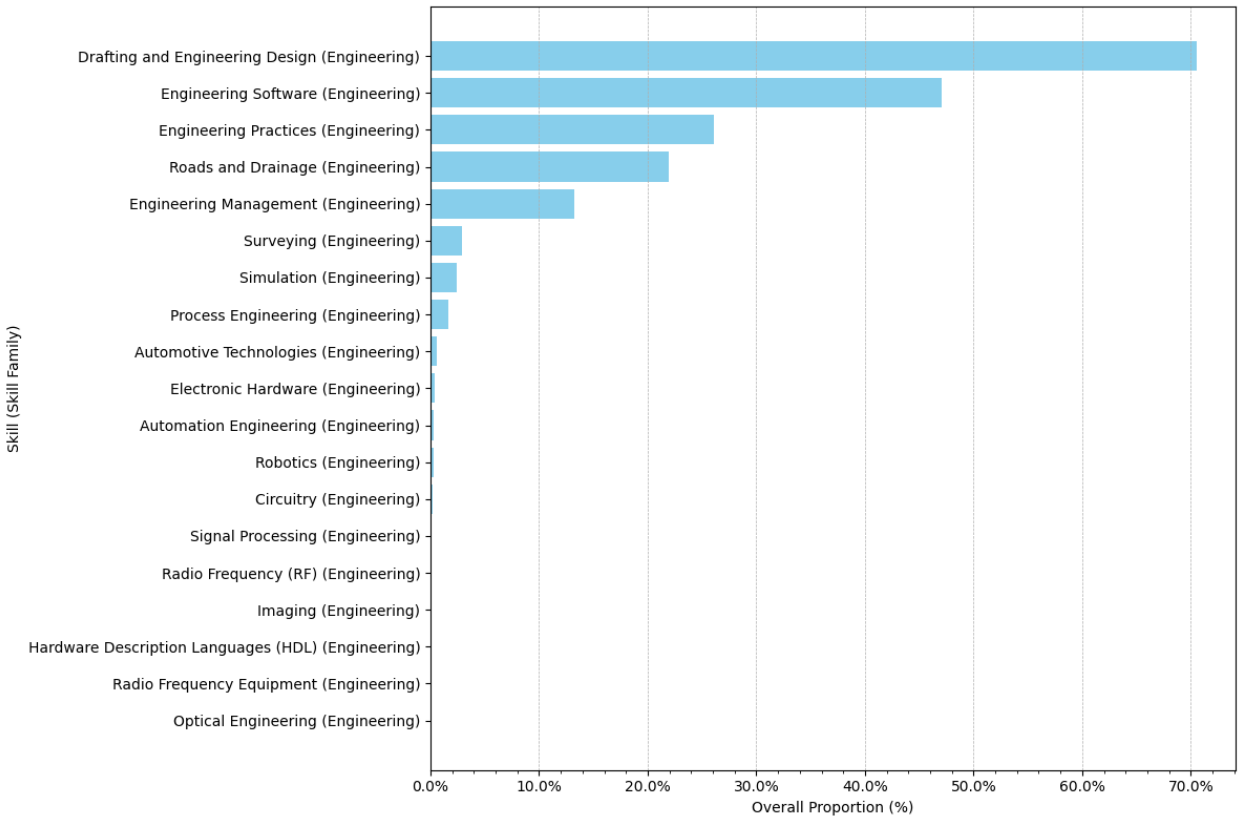
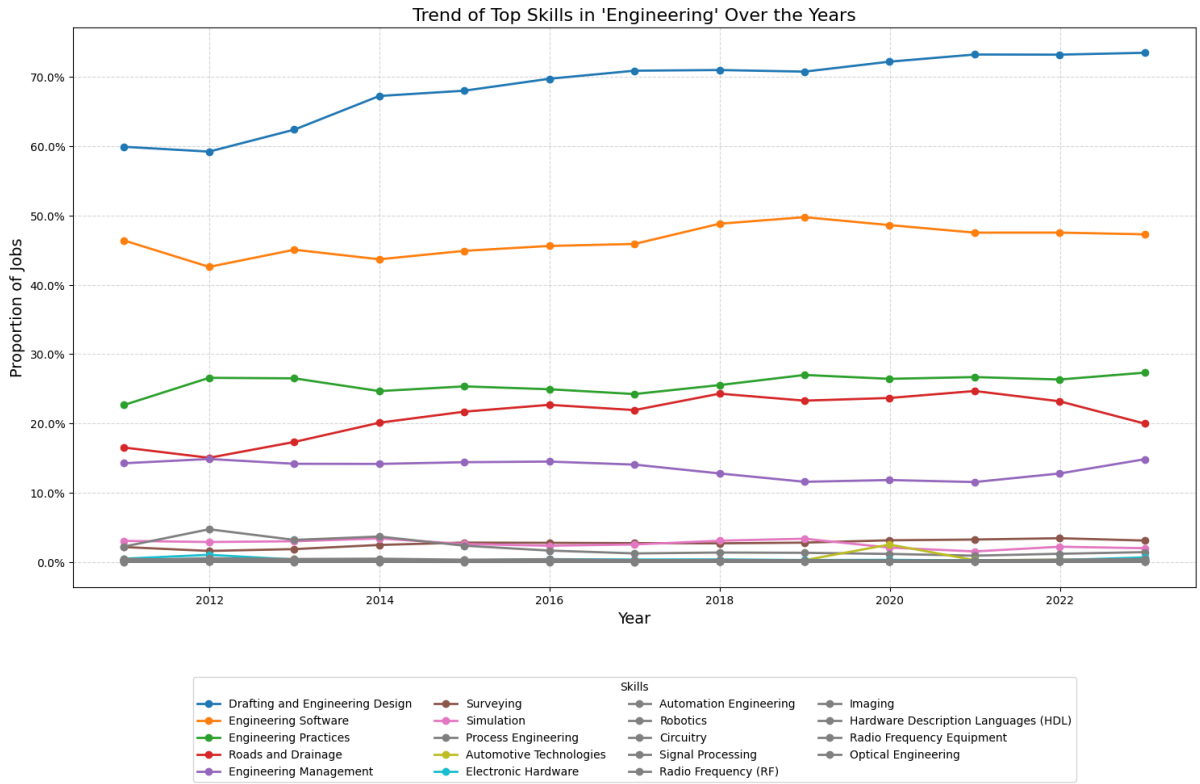


Figure 4.8: Top CE Skills in Engineering Family Skill Across Time (2010-2022)



Note: Skills shown in gray have a maximum proportion of 1% and below.

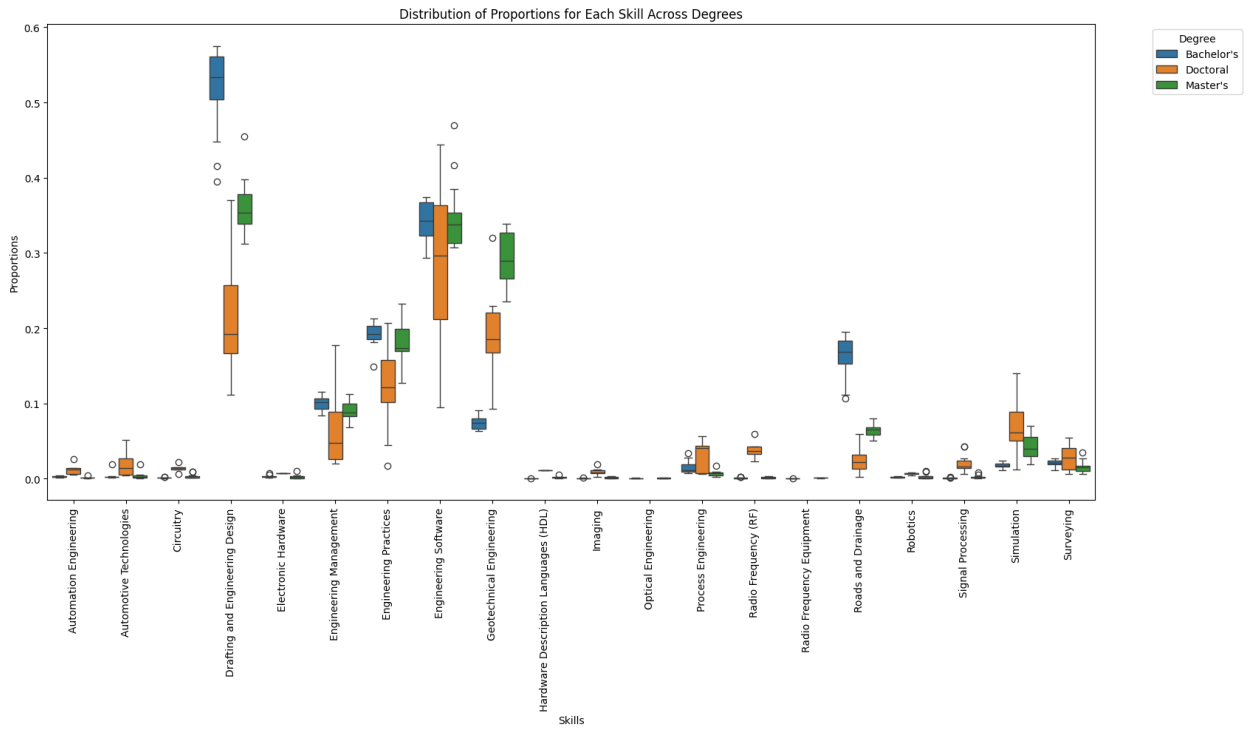
Figure 4.8 presents the trends in key engineering skills in CE job postings over time (2010–2022). Drafting and Engineering Design stands out as the most dominant skills, consistently increasing in prevalence and surpassing 70% by 2022. This highlights their foundational importance in the field. Engineering Software follows with a stable proportion, reflecting the ongoing demand for technological proficiency in engineering projects.

Moderately represented skills include Engineering Practices, Roads and Drainage, and Engineering Management, which show steady trends, emphasizing their critical roles in project execution and infrastructure development. In contrast, skills such as Optical Engineering, Radio Frequency Equipment, and Hardware Description Languages appear less frequently, pointing to their specialized applications within civil engineering. This distribution highlights the essential technical competencies in civil engineering, strongly emphasizing design, software, and practical engineering practices. These trends reflect the evolving priorities of the profession, shaped by advancements in technology and the demands of modern infrastructure projects.

The next part of the analysis examines how CE skills differ across education levels. For illustration, the box plot displays a selected sample of skills distributed across bachelor's, master's, and doctoral degrees. Each box and whisker represent the range of skill proportions over the period of record for each skill-education level combination. Foundational skills like Drafting and

Engineering Design show consistently higher proportions in jobs requiring bachelor's degrees, underscoring their importance in entry-level roles. For jobs requiring master's degrees, the data reveals greater variability in skills such as engineering management and geotechnical engineering, which may reflect the broader scope and specialization options available at this level. At the Doctoral level, while the overall proportion of jobs is lower, there is noticeable variation in advanced skills like simulation, process engineering, and surveying—highlighting the specialized and research-oriented nature of these roles. This analysis aims to highlight both the proportion and variability of skills across education levels to address how educational attainment shapes skill demand in civil engineering.

Figure 4.9: Distribution of Skill Proportions Across Degree Levels in CE



Results presented in Table 4.13 provide an overview of the differences in CE and related engineering skills across various degree levels (bachelor's, Master's, and doctoral). Significant F-values with corresponding p-values less than 0.05 indicate that the differences among the degree groups are statistically significant for most of the analyzed skills. For example, skills such as Geotechnical Engineering ($F(2, 36) = 108.51$, $p < 0.001$) and Roads and Drainage ($F(2, 35) = 160.12$, $p < 0.001$) exhibited substantial variation across degree levels. These results suggest that jobs requiring different education attainment levels emphasize skills. However, for a few skills, such as Surveying ($F(2, 30) = 2.81$, $p = 0.076$), the p-value exceeds the 0.05 threshold, indicating no statistically significant difference among the groups for these skills. Cohen's D tests were further investigated to determine the magnitude and direction of these differences. These tests

quantified the effect sizes between specific degree pairs (e.g., bachelor's vs. master's) and identified which degree level demonstrated the highest proficiency in each skill category.

Table 4.13: ANOVA for CE and Engineering Skills Across Degree Levels

Skill	F	df	p	Significant
Automation Engineering	20.8	2, 24	0	Yes
Automotive Technologies	7.47	2, 27	0.003	Yes
Circuitry	44	2, 28	0	Yes
Drafting and Engineering Design	84.73	2, 36	0	Yes
Electronic Hardware	3.95	2, 24	0.033	Yes
Engineering Management	6.59	2, 36	0.004	Yes
Engineering Practices	16.5	2, 36	0	Yes
Engineering Software	4.13	2, 36	0.024	Yes
Geotechnical Engineering	108.51	2, 36	0	Yes
Hardware Description Languages	66.3	2, 18	0	Yes
Imaging	28.72	2, 26	0	Yes
Optical Engineering	8.74	1, 14	0.01	Yes
Process Engineering	9.5	2, 28	0.001	Yes
Radio Frequency (RF)	81.81	2, 23	0	Yes
Radio Frequency Equipment	17.73	1, 13	0.001	Yes
Roads and Drainage	160.12	2, 35	0	Yes
Robotics	6.39	2, 23	0.006	Yes
Signal Processing	31.2	2, 33	0	Yes
Simulation	16.66	2, 36	0	Yes
Surveying	2.81	2, 30	0.076	No

Table 4.14: **Cohen's Effect Sizes for CE and Engineering Skills Across Degree Levels**

Skill	Degree Pair	Cohen's d	Effect Size	Larger Group
Automation Engineering	Bachelor's vs Doctoral	2.546	Large	Bachelor's Large
Automation Engineering	Bachelor's vs Master's	1.075	Large	Bachelor's Large
Automation Engineering	Doctoral vs Master's	2.398	Large	Doctoral Large
Automotive Technologies	Bachelor's vs Master's	0.063	Small	Master's Large
Automotive Technologies	Bachelor's vs Doctoral	1.573	Large	Doctoral Large
Automotive Technologies	Master's vs Doctoral	1.499	Large	Master's Large
Circuitry	Bachelor's vs Doctoral	4.636	Large	Doctoral Large
Circuitry	Bachelor's vs Master's	0.923	Large	Master's Large
Circuitry	Doctoral vs Master's	2.93	Large	Doctoral Large
Drafting and Engineering Design	Bachelor's vs Doctoral	4.503	Large	Bachelor's Large
Drafting and Engineering Design	Bachelor's vs Master's	3.054	Large	Bachelor's Large
Drafting and Engineering Design	Doctoral vs Master's	2.508	Large	Master's Large
Electronic Hardware	Bachelor's vs Doctoral	2.834	Large	Bachelor's Large
Electronic Hardware	Bachelor's vs Master's	0.158	Small	Bachelor's Large
Electronic Hardware	Doctoral vs Master's	1.747	Large	Master's Large
Engineering Management	Bachelor's vs Doctoral	1.158	Large	Bachelor's Large
Engineering Management	Bachelor's vs Master's	0.843	Large	Bachelor's Large
Engineering Management	Doctoral vs Master's	0.855	Large	Master's Large
Engineering Practices	Bachelor's vs Doctoral	1.861	Large	Bachelor's Large
Engineering Practices	Bachelor's vs Master's	0.419	Medium	Bachelor's Large
Engineering Practices	Doctoral vs Master's	1.532	Large	Master's Large
Engineering Software	Bachelor's vs Doctoral	0.83	Large	Bachelor's Large
Engineering Software	Bachelor's vs Master's	0.171	Small	Bachelor's Large
Engineering Software	Doctoral vs Master's	0.86	Large	Master's Large
Geotechnical Engineering	Bachelor's vs Doctoral	3.07	Large	Doctoral Large
Geotechnical Engineering	Bachelor's vs Master's	8.387	Large	Master's Large
Geotechnical Engineering	Doctoral vs Master's	2.158	Large	Doctoral Large
Hardware Description Languages	Bachelor's vs Doctoral	NaN	Large	Doctoral Large

Table 4.14: Continued

Hardware Description Languages	Bachelor's vs Master's	1.757	Large	Master's Large
Hardware Description Languages	Doctoral vs Master's	NaN	Large	Master's Large
Imaging	Bachelor's vs Master's	1.643	Large	Master's Large
Imaging	Bachelor's vs Doctoral	2.985	Large	Doctoral Large
Imaging	Master's vs Doctoral	2.376	Large	Doctoral Large
Optical Engineering	Bachelor's vs Master's	1.893	Large	Bachelor's Large
Process Engineering	Bachelor's vs Master's	1.277	Large	Bachelor's Large
Process Engineering	Bachelor's vs Doctoral	1.159	Large	Bachelor's Large
Process Engineering	Master's vs Doctoral	2.022	Large	Master's Large
Radio Frequency (RF)	Bachelor's vs Master's	0.645	Medium	Master's Large
Radio Frequency (RF)	Bachelor's vs Doctoral	5.677	Large	Doctoral Large
Radio Frequency (RF)	Master's vs Doctoral	4.792	Large	Master's Large
Radio Frequency Equipment	Bachelor's vs Master's	3.198	Large	Master's Large
Roads and Drainage	Bachelor's vs Doctoral	5.811	Large	Doctoral Large
Roads and Drainage	Bachelor's vs Master's	4.489	Large	Bachelor's Large
Roads and Drainage	Doctoral vs Master's	3.266	Large	Master's Large
Robotics	Bachelor's vs Doctoral	4.705	Large	Bachelor's Large
Robotics	Bachelor's vs Master's	0.463	Medium	Bachelor's Large
Robotics	Doctoral vs Master's	0.979	Large	Doctoral Large
Signal Processing	Bachelor's vs Master's	0.886	Large	Master's Large
Signal Processing	Bachelor's vs Doctoral	2.463	Large	Doctoral Large
Signal Processing	Master's vs Doctoral	2.263	Large	Doctoral Large
Simulation	Bachelor's vs Doctoral	2.043	Large	Doctoral Large
Simulation	Bachelor's vs Master's	1.965	Large	Master's Large
Simulation	Doctoral vs Master's	0.993	Large	Doctoral Large
Surveying	Bachelor's vs Master's	0.593	Medium	Master's Large
Surveying	Bachelor's vs Doctoral	0.654	Medium	Doctoral Large
Surveying	Master's vs Doctoral	0.897	Large	Master's Large

Cohen's d effect sizes CE and related engineering skills across degree pairings (bachelor’s, master’s, and doctoral) highlight substantial differences in skill proportions between educational levels. Skills such as Circuitry (Bachelor's vs Doctoral: Cohen's d = 4.636, large effect) and Roads and Drainage (Bachelor's vs Doctoral: Cohen's d = 5.811, large effect) exhibit large effect sizes, indicating that jobs requiring Doctoral degrees include this skill in job advertisements proportionally more frequently than jobs requiring a bachelor’s degree. Similarly, skills like Drafting and Engineering Design (Bachelor's vs Master's: Cohen's d = 3.054, significant effect) and Radio Frequency Equipment (Bachelor's vs Master's: Cohen's d = 3.198, significant effect) show notable differences in proportions across the degree requirements.

For some skills, the differences are more minor but still notable. For instance, Robotics (Bachelor's vs Master's: Cohen's d = 0.463, medium effect) and Engineering Practices (Bachelor's vs Master's: Cohen's d = 0.419, medium effect) suggest moderate differences for jobs requiring master’s degrees. Conversely, specific skills exhibit minimal differences, such as Automotive Technologies (Bachelor's vs Master's: Cohen's d = 0.063, small effect), where skill proportions are nearly equivalent across the degrees.

4.5.2. Civil Engineering Technical Skills

My analysis also investigated specific technical skills that appeared in job advertisements. Table 4.12 highlights the technical skills required for CE jobs at different degree levels: bachelor’s, master’s, and doctoral. Skills like Excel, CAD, and AutoCAD are consistently in demand across all levels, although the extent varies. For instance, Excel is most required at the doctoral level (49.61%) compared to bachelor’s (48.98%) and master's (48.50%). Advanced skills such as MATLAB and Python are more prevalent in jobs requiring master's (2.76% and 1.71%, respectively) and doctoral degrees (6.24% and 2.75%). On the other hand, practical skills like AutoCAD (31.74%) and Microsoft Office (14.34%) are more prominent in bachelor’s-level job advertisements.

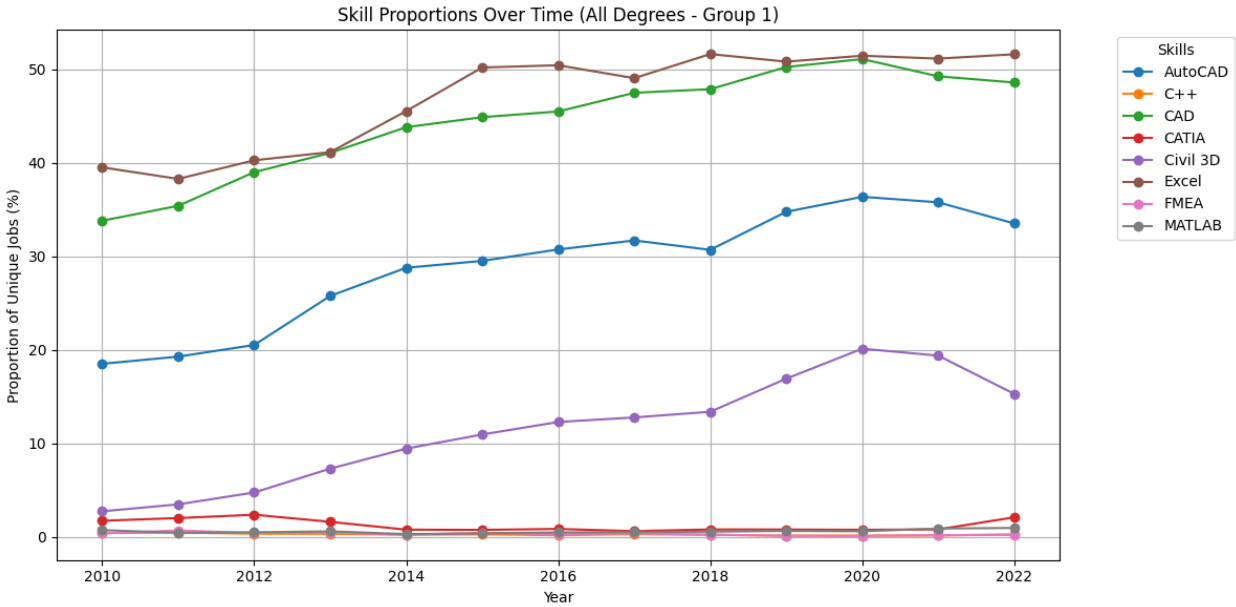
Table 4.15: Technical Skill Proportions in CE Job Ads (2010-2022)

Skill	Bachelor's (%)	Master's (%)	Doctoral (%)
AutoCAD	31.74	20.05	3.93
C++	0.18	1.09	5.41
CAD	47.03	36.62	34.89
CATIA	1.20	0.22	0.09
Civil 3D	13.99	3.89	0.87
Excel	48.98	48.50	49.61
FMEA	0.27	0.29	0.17
MATLAB	0.53	2.76	6.24
Microsoft Office	14.34	9.67	3.32
Microsoft Project	1.96	0.60	0.04
PLC	1.07	1.16	0.26
Python	0.39	1.71	2.75
Revit	5.32	8.87	1.40
SCADA	0.28	0.08	0.00
SQL	0.22	0.57	1.97
SolidWorks	1.10	0.99	0.57

4.5.3 CE Technical Skills Trends (2010-2022)

This section examines the trends in technical skills required in CE job ads from 2010 to 2022. In the upcoming plots, the technical skills presented in Table 4.15 were divided into two groups, with eight skills in each group. This division was made to enhance visualization and ensure that the skill trend lines do not overlap, allowing for a clearer interpretation of the data.

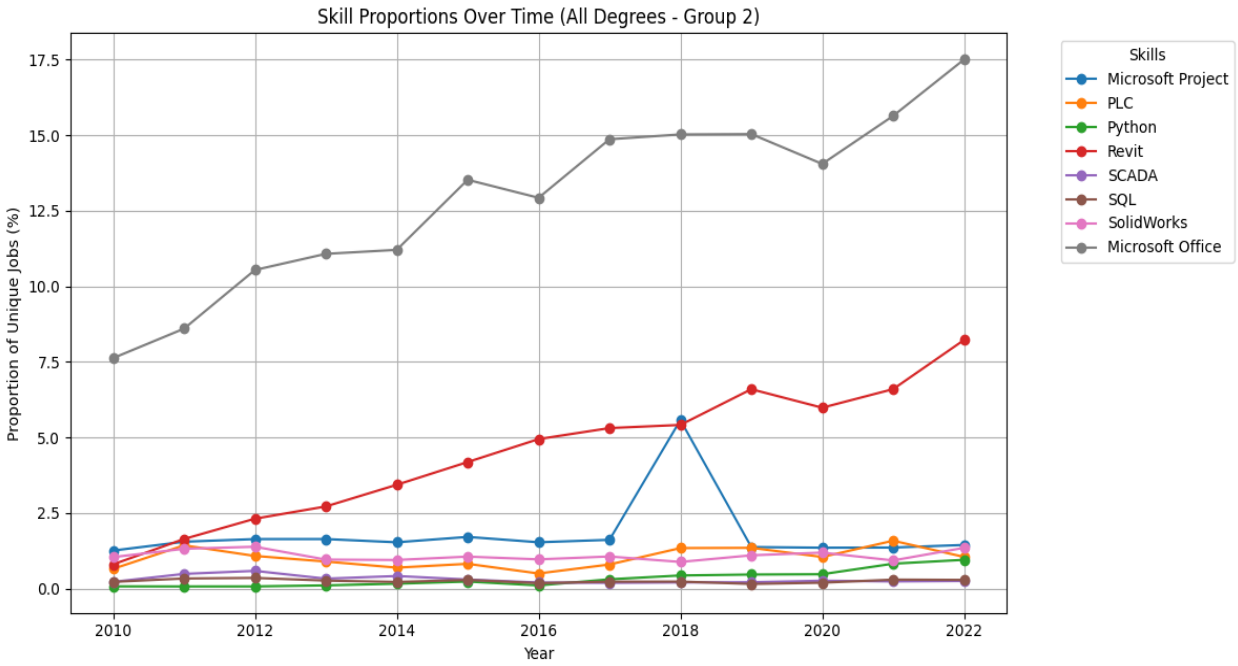
Figure 4.10: Trends in Technical Skill Over Time in CE Job Ads (Group 1)



Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

Figure 4.10 illustrates the trends in the proportions of selected technical skills required in CE job ads over time, combining data for all degree levels (bachelor's, master's, and doctoral). It highlights how specific skills, such as Excel and CAD, consistently dominate the demand across the years, with Excel maintaining the highest proportion. Other skills like AutoCAD and MATLAB show steady but lower trends, indicating their specialized nature in CE roles. Meanwhile, skills such as FMEA, C++, and CATIA remain less prevalent throughout the period.

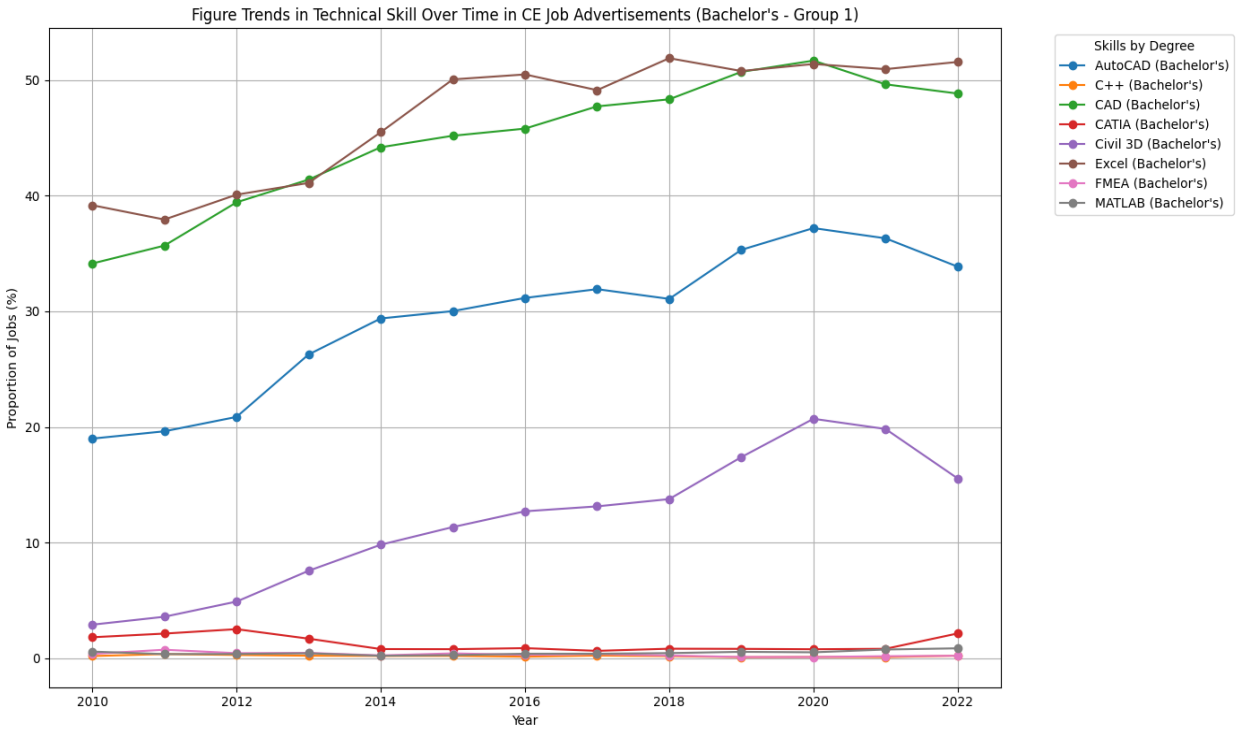
Figure 4.11: Trends in Technical Skill Over Time in CE Job Ads (Group 2)



Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

Figure 4.11 shows the trends in the proportions of additional technical skills required in CE job ads over time, combining data for all degree levels (bachelor's, master's, and doctoral). Microsoft Office was the most frequently appearing technical skill among this group of skills. Skills like Revit show upward trends, reflecting their growing importance in CE roles. Meanwhile, less prevalent skills such as Microsoft Project, SCADA, and PLC remain steady at lower proportions.

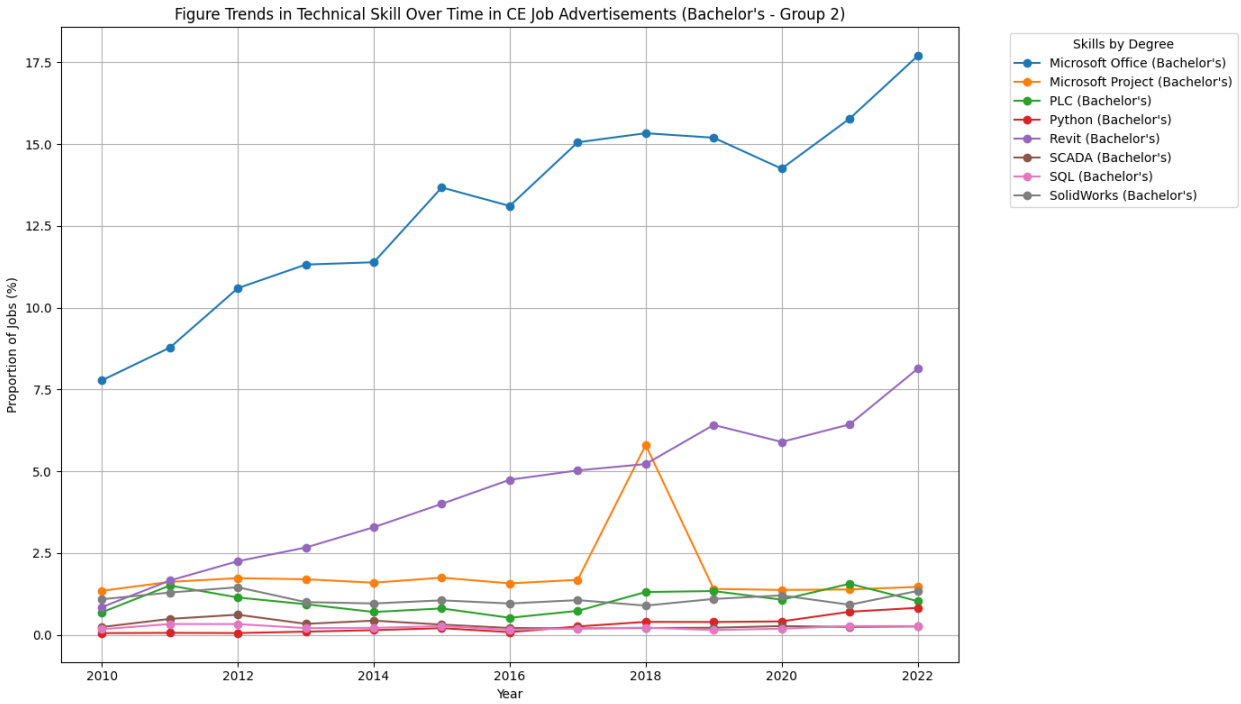
Figure 4.12: Trends in Technical Skill Over Time in CE Job Ads (Bachelor's - Group 1)



Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

Figure 4.12 shows the trends in technical skill proportions for bachelor's-level CE job ads (Group 1) from 2010 to 2022. Skills such as Excel and CAD exhibit the highest and most consistent demand throughout the period. AutoCAD shows a steady trend, maintaining a moderate proportion, while other skills like MATLAB, CATIA, and C++ remain less prominent. The inclusion of FMEA shows minimal demand at the bachelor's level.

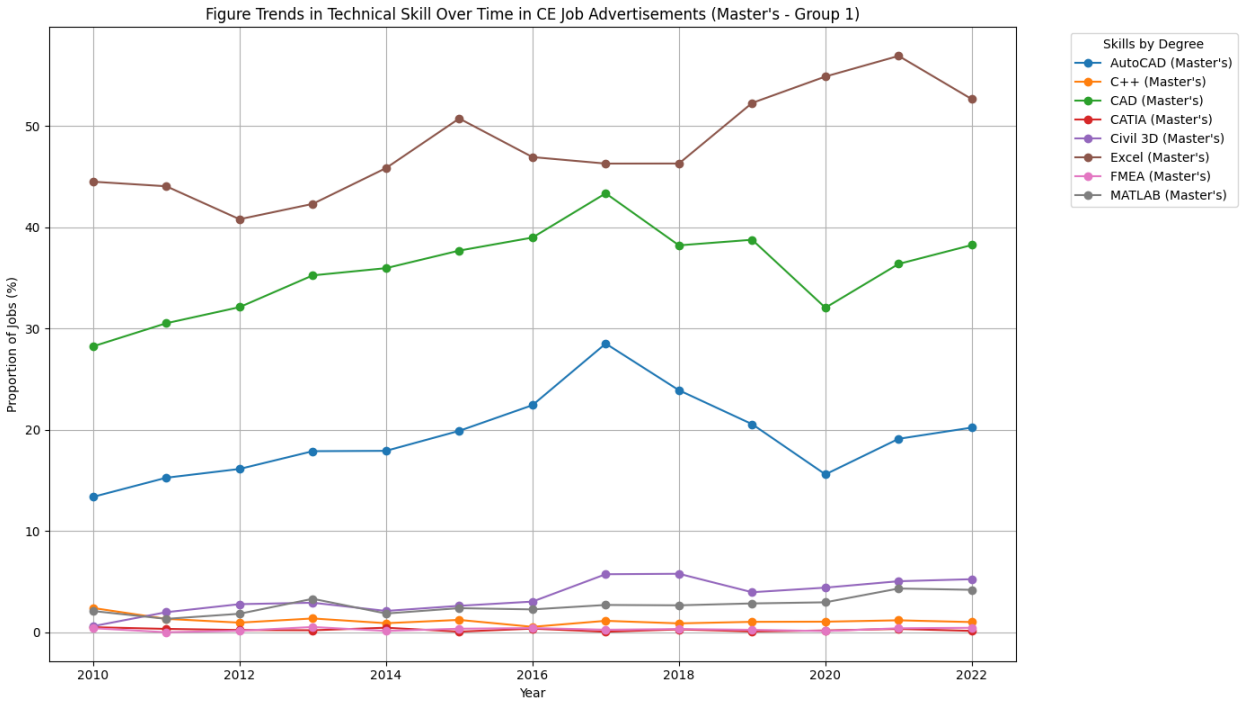
Figure 4.13: Trends in Technical Skill Over Time in CE Job Ads (Bachelor's - Group 2)



Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

Figure 4.13 displays the trends in technical skill proportions for bachelor's-level CE job ads (Group 2) from 2010 to 2022. Microsoft Office shows consistently high demand. Skills like Revit and Python have become more prominent, reflecting the increasing need for specialized software knowledge. Other skills, such as Microsoft Project, SQL, SCADA, and PLC, exhibit steady but lower proportions, indicating their limited application at the bachelor's level.

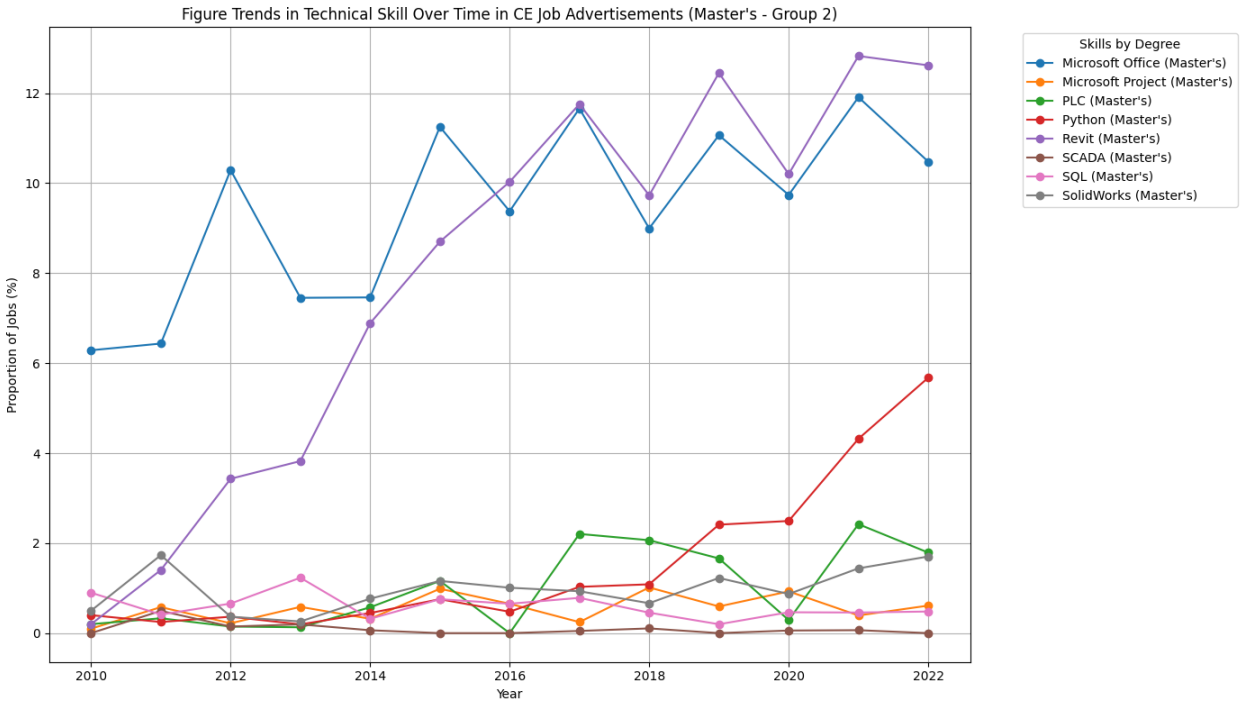
Figure 4.14: Trends in Technical Skill Over Time in CE Job Ads (Master's - Group 1)



Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

Figure 4.14 represents the trends in technical skill proportions for master's-level CE job ads (Group 1) from 2010 to 2022. Excel and CAD demonstrate a consistent presence in the job advertisements, maintaining the highest proportions throughout the years. AutoCAD and CATIA also show steady demand, while MATLAB, C++, and FMEA remain relatively low in proportion, indicating their specialized application in specific roles. The trend suggests that while foundational skills like Excel and CAD continue to be crucial, there is a gradual decline in the demand for other specific technical skills within job advertisements, such as AutoCAD and C++.

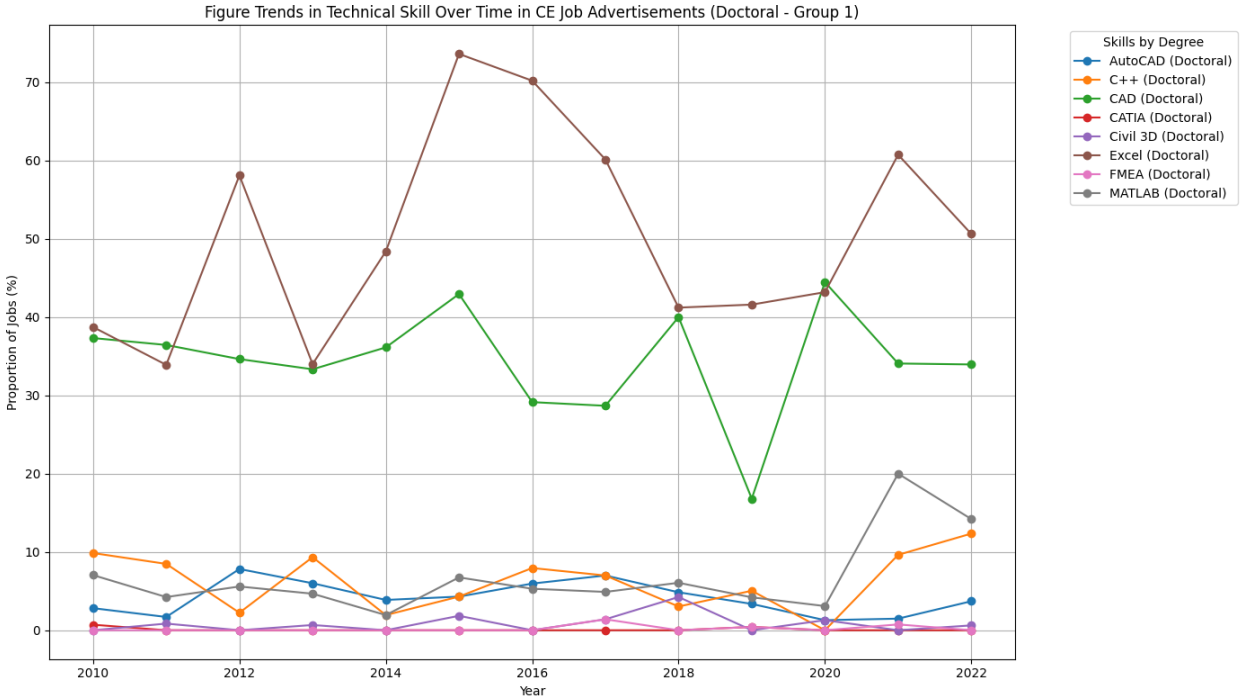
Figure 4.15: Trends in Technical Skill Over Time in CE Job Ads (Master's - Group 2)



Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

Figure 4.15 shows the trends in technical skill proportions for master's-level CE job ads (Group 2) from 2010 to 2022. Microsoft Office shows steady growth, with a notable increase from 2019 onward. Skills like Revit and Python also demonstrate upward trends, reflecting their growing demand in CE roles. Conversely, other skills, such as Microsoft Project, SCADA, and SQL, gradually grow. The data highlights a shift toward more specialized skills in recent years, with some technologies like Revit and Python gaining prominence.

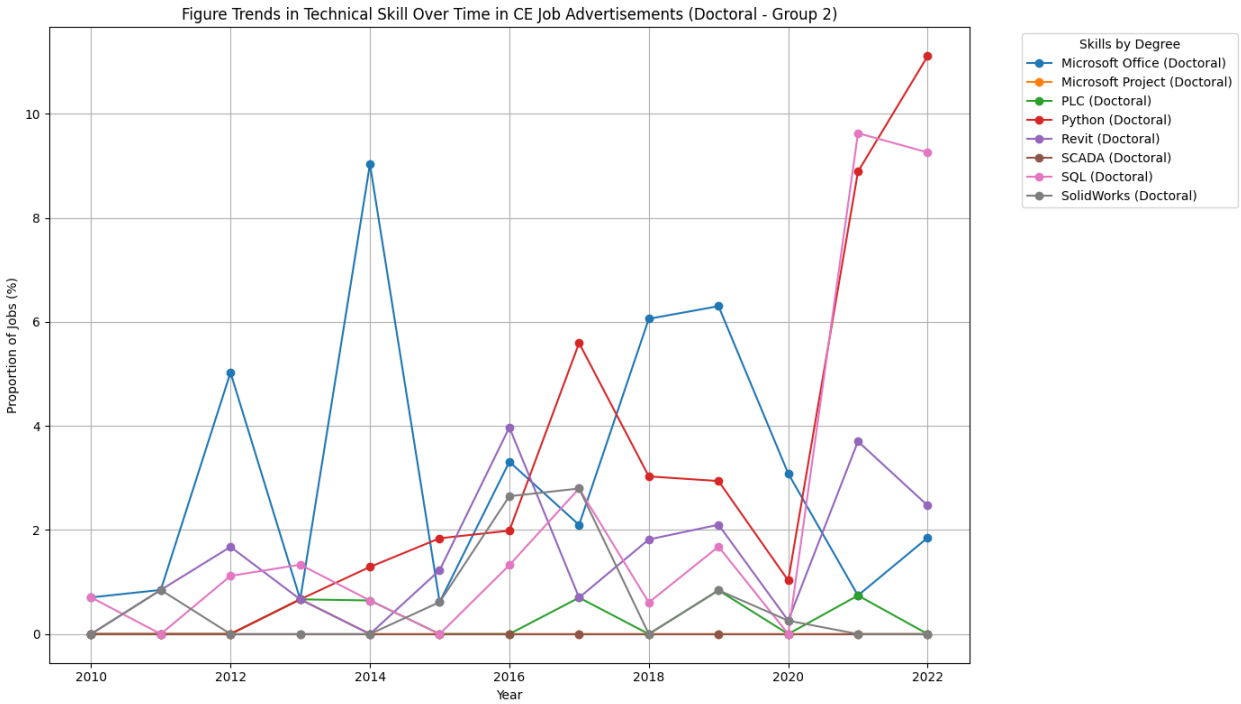
Figure 4.16: Trends in Technical Skill Over Time in CE Job Ads (Doctoral - Group 1)



Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

Figure 4.16 illustrates the trends in technical skill proportions for doctoral-level CE job ads (Group 1) from 2010 to 2022. Excel and CAD consistently dominate the demand, with fluctuations over the years. AutoCAD, MATLAB, and CATIA exhibit moderate proportions, reflecting their specialized use in doctoral-level positions. Skills like C++ and FMEA remain at lower levels, indicating their limited application in these roles. The trends highlight the importance of foundational skills like Excel and CAD while showcasing the steady relevance of specialized tools.

Figure 4.17: Trends in Technical Skill Over Time in CE Job Ads (Doctoral - Group 2)



Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

Figure 4.17 shows the trends in technical skill proportions for doctoral-level CE ads (Group 2) from 2010 to 2022. Microsoft Office and Revit have experienced demand increases, particularly in recent years. SQL and Python have also demonstrated notable growth, reflecting their importance in advanced technical roles. Other skills, such as Microsoft Project, SCADA, and PLC, remain steady at lower proportions. The trends emphasize the growing presence in job advertisements of skills associated with using advanced software tools like Python, SQL, and Revit in jobs requiring a doctorate.

4.5.2 Summary of CE Job Posting Analysis

This section examined the distribution of CE degrees and skill demands across bachelor's, master's, and Doctoral levels from 2010 to 2022. Jobs requiring a bachelor's degree dominate, making up 95.92% of the 621,131 jobs in the dataset, compared to 3.71% for master's and 0.37% for Doctoral degrees. The top 30 skills in CE show that Drafting and Engineering Design, Project Management, and Engineering Software are the most common in CE job advertisements. Other key skills, like Microsoft Office, Construction Management, and Budget Management, emphasize the growing need for digital tools, financial planning, and coordination. Though less common, skills like Writing and Procurement reflect the increasing focus on communication and supply chain management for successful project delivery.

Skill demands differ across educational levels. Bachelor's degrees focus on traditional technical skills like drafting and engineering software, essential for entry-level roles. Master's degrees combine technical knowledge with managerial skills, such as project coordination and strategic planning. Doctoral degrees emphasize research-focused and specialized skills, like Geotechnical Engineering, Circuitry, and Roads and Drainage, requiring advanced expertise. From 2010 to 2022, trends show growth in infrastructure-related skills like Roads and Drainage, increased Scheduling for project coordination, and rising demand for Budget Management in large-scale projects. Additionally, tools like Graphic and Visual Design Software have gained importance.

The analysis of technical skills in CE from 2010 to 2022 shows important trends across degree levels. Foundational skills like Excel, CAD, and AutoCAD are crucial at all levels, with the highest demand at the bachelor's level, reflecting a focus on practical, entry-level roles. Master's-level roles expect at a higher rate advanced tools like Python, MATLAB, and Revit. Doctoral roles emphasize specialized and research-driven skills, with tools like SQL, Python, and Revit gaining importance for advanced analysis and design. Over time, demand for tools like Revit and Python has grown across all levels, signaling a shift toward digital transformation. Managerial skills, such as Project Management and Scheduling, have also increased, reflecting the growing complexity of modern projects. These trends highlight the impact of technology, infrastructure growth, and innovation on the field

4.6 Examining Electrical Engineering Skills by Proportion and Trends

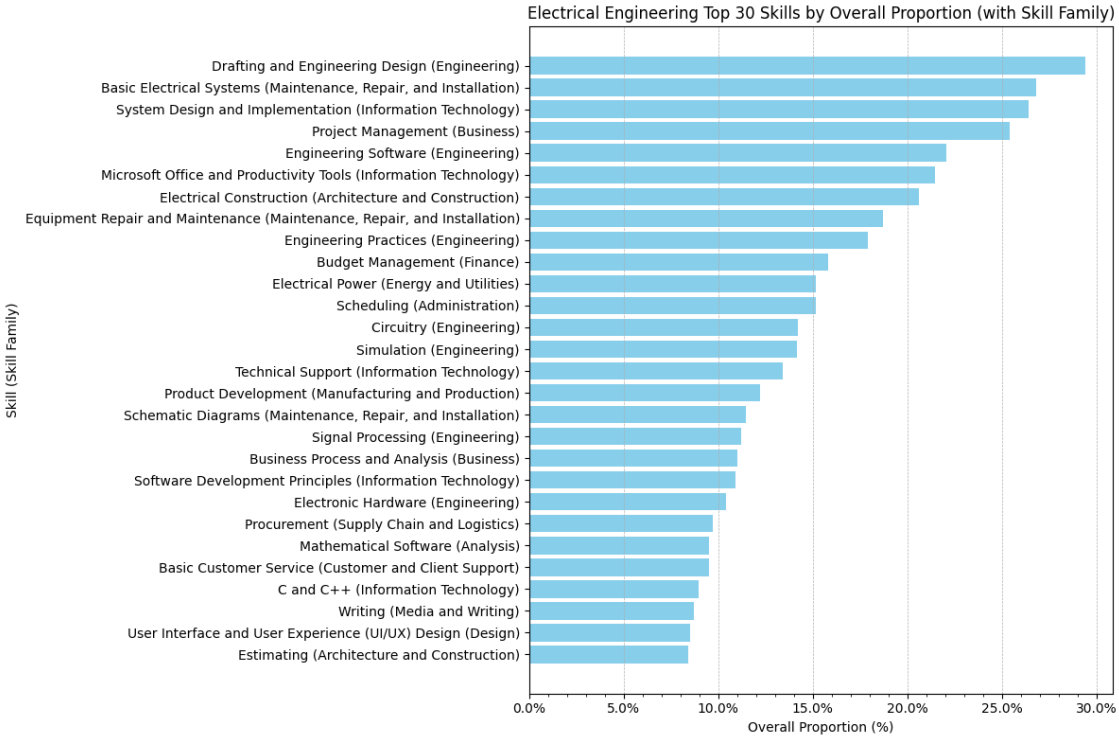
Table 4.16 indicates that jobs with a minimum expectation of a bachelor's degree dominate the EE dataset, accounting for 904,220 (95.22%) of the 949,648 degrees recorded. Jobs requiring master's degrees comprise 35,982 (3.79%), and Doctoral degrees represent a minor proportion at 9,446 (0.99%).

Table 4.16: Distribution of Degrees in EE

EE Degrees	Degree (N)	Percentage
Bachelor's	904220	95.22%
Master's	35982	3.79%
Doctoral	9446	0.99%
Total	949648	100.00%

Figure 4.18 highlights the top 30 EE skills based on their prevalence, with the skills family shown in parentheses. Drafting and Engineering Design and Basic Electrical Systems are the most prominent skills, followed closely by Project Management and Engineering Software, reflecting their foundational roles in technical execution and project oversight. Skills such as Microsoft Office and Productivity Tools, Electrical Construction, and Equipment Repair and Maintenance rank highly, emphasizing the integration of digital tools and hands-on technical expertise. Budget Management and Scheduling are also prominent, underscoring the need for financial planning and operational coordination.

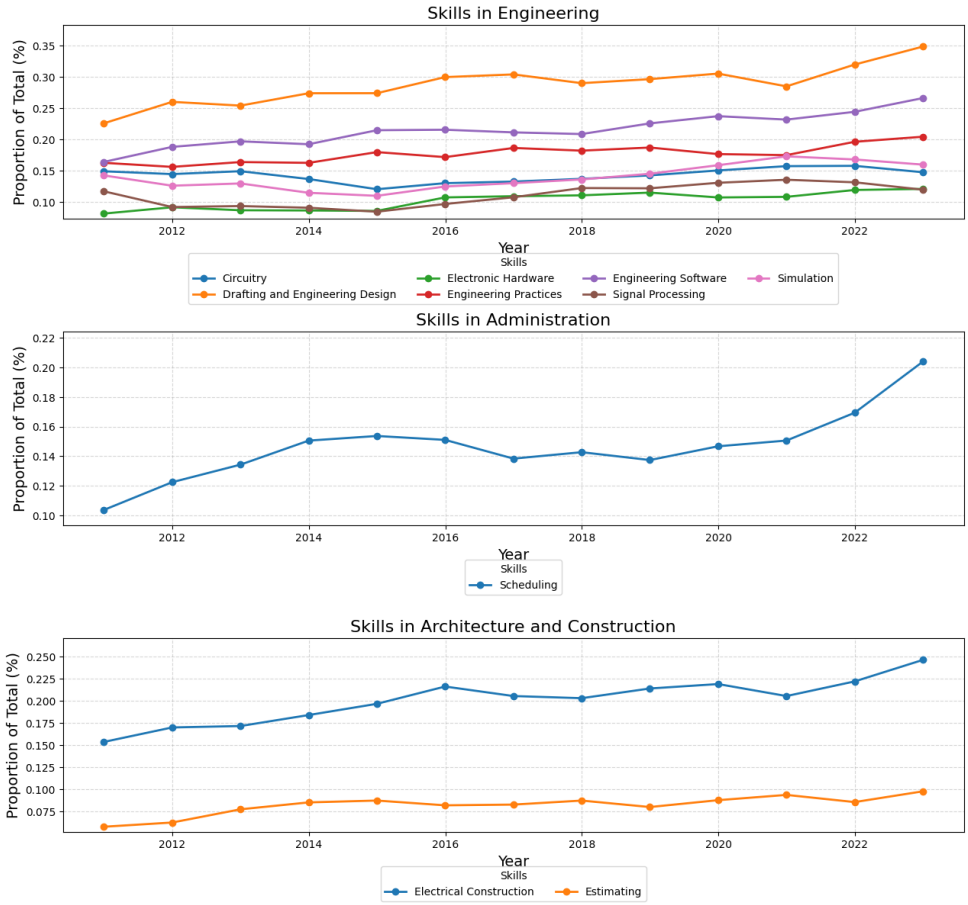
Figure 4.18: EE Top 30 Skill by Overall Proportions



Lower-ranked but notable skills include Writing, Basic Customer Service, and Procurement, highlighting the importance of communication, client interaction, and supply chain management. Though less prevalent, specialized skills such as UI/UX Design and Signal Processing demonstrate their relevance in user-centered innovation and advanced system optimization. This distribution illustrates the multidisciplinary nature of electrical engineering, balancing technical proficiency, managerial competencies, and supporting skills critical for modern industry demands. In the next section, I will examine how these skill proportions have evolved over time, offering insights into shifting trends and future directions in the field.

Figure 4.19 shows from 2012 to 2022 that trends in skill proportions across three categories: Engineering, Administration, and Architecture and Construction, which reflect evolving priorities in EE. Drafting and Engineering Design remain dominant in the Engineering category, while skills such as Circuitry, Signal Processing, and Simulation show stable trends, emphasizing sustained reliance on core technical competencies. Electronic Hardware and Engineering Software exhibit gradual growth, aligning with advancements in hardware integration and digital tool adoption. In Administration, Scheduling displays a steady upward trajectory, highlighting the heightened demand for precise project coordination in complex EE workflows. Within Architecture and Construction, Electrical Construction maintains prominence, complemented by incremental growth in Estimating, underscoring the importance of infrastructure planning and cost management in EE projects. Niche, specialized skills like Simulation and Signal Processing reinforce their critical role in optimizing system performance and fostering innovation.

Figure 4.19: Trend of Top 30 Skill (Engineering, Administration, Architecture and Construction) 2010-2012



Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

Figure 4.20 shows that in the past decade, the trends in skill proportions across three categories: Business, Environment, and finance have displayed the shifting demands of civil engineering. In the business category, project management consistently dominates and has become even more prevalent in job ads, reflecting its critical role in CE positions. Other skills, such as People Management and Quality Assurance and Control, maintain lower proportions but gradually increase, indicating their growing importance in managing teams and ensuring quality standards. In the Environment category, Environmental Work displays fluctuating trends, with periods of decline followed by recovery in recent years, reflecting its variable emphasis depending on environmental and regulatory priorities. Budget Management shows a steady upward trajectory in Finance, highlighting its increasing significance as cost control and financial planning have become more critical in managing large-scale CE projects.

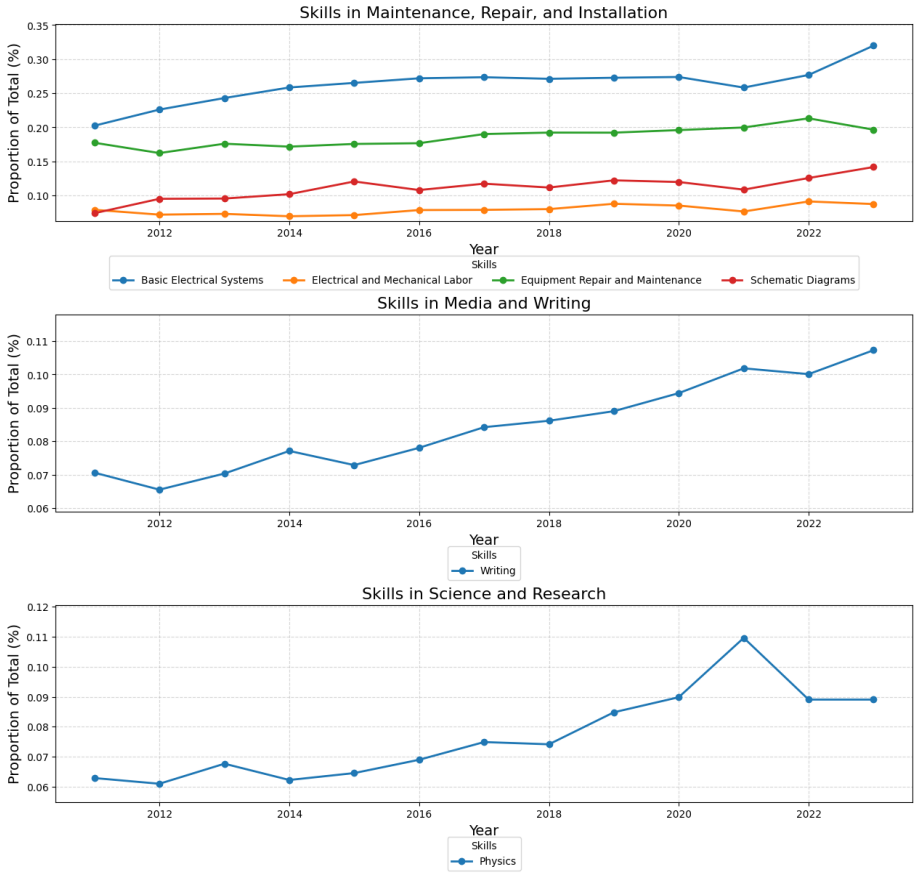
Figure 4.20: Trend of EE Top 30 Skill (Business, Environment, and Information Technology) 2010-2012

Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

Figure 4.21 presents that from 2012 to 2022, trends in skill proportions across three categories: Business, Finance, and Information Technology (IT) which highlight shifting priorities in EE. Additionally, Business category, Project Management and Business Process and Analysis maintain consistent prominence, reflecting the ongoing need for organizational oversight and strategic planning in EE roles. Within Finance, Budget Management remains a critical skill, aligning with industry demands for financial accountability and resource optimization. In IT, System Design and Implementation and Microsoft Office and Productivity Tools dominate, emphasizing the integration of digital proficiency and software-driven workflows. Technical skills such as C and C++ and Software Development Principles show steady relevance, underscoring the growing reliance on programming and IT infrastructure in modern EE applications. While less prominent, specialized competencies like Technical Support highlight the importance of troubleshooting and system maintenance. These trends illustrate the broadening scope of EE,

where technical expertise intersects with business, finance, and IT to address complex, interdisciplinary challenges in the field.

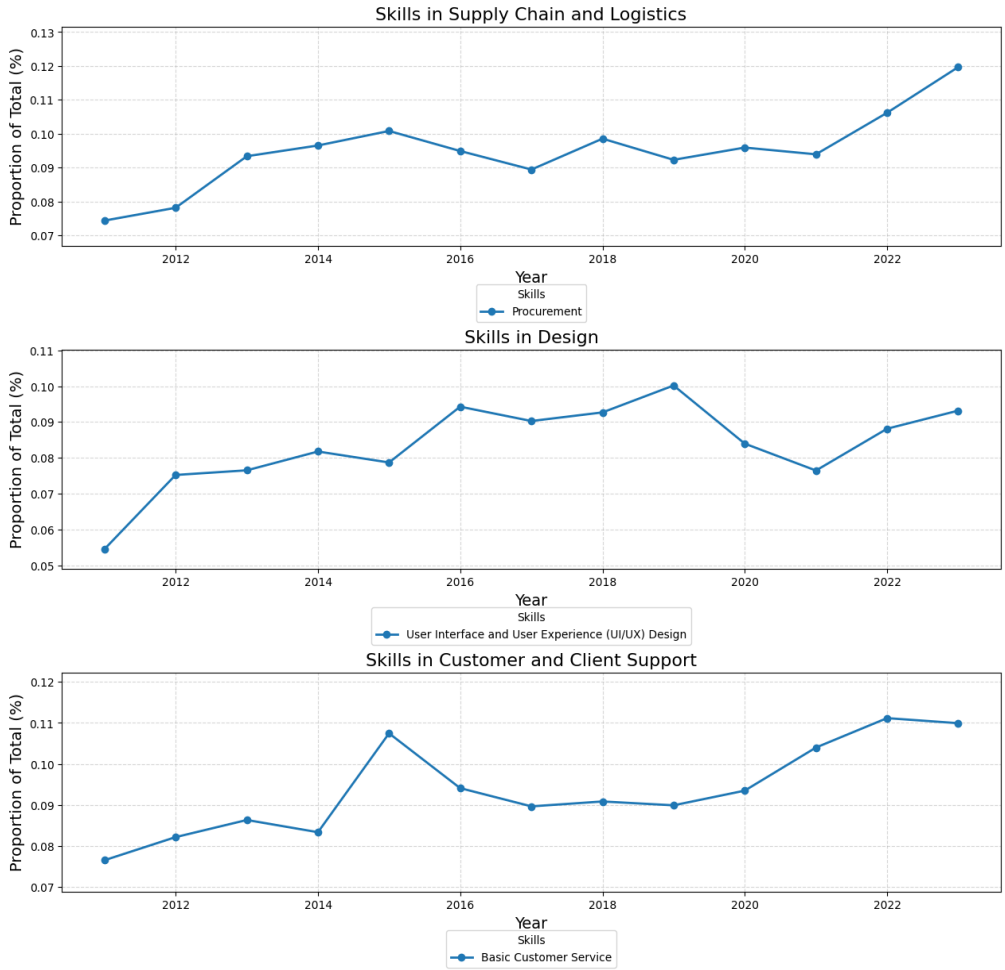
Figure 4.21: Trend of EE Top 30 Skill (Maintenance Repair and Installation, Media and Writing, Science and Research) 2010-2012



Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

Figure 4.22 shows that from 2012 to 2022, skill trends across three categories: Maintenance, Repair, and Installation; Media and Writing; and Science and Research that reveal evolving priorities in EE. Additionally, Maintenance, Repair, and Installation, Basic Electrical Systems and Equipment Repair and Maintenance maintain prominence, reflecting the enduring demand for foundational technical expertise in system upkeep and troubleshooting. Schematic Diagrams show gradual growth, aligning with the need for precise documentation and design interpretation. In Media and Writing, the skill Writing remains increased overtime but in proportion, showing its consistent role in technical communication and reporting. Within Science and Research, Physics exhibits steady relevance, emphasizing its foundational importance in advancing theoretical and applied EE innovations. While these categories represent niche areas compared to core engineering or IT skills.

Figure 4.22: Trend of EE Top 30 Skill (Supply Chain and Logistics, Design, and Customer and Client Support) 2010-2012



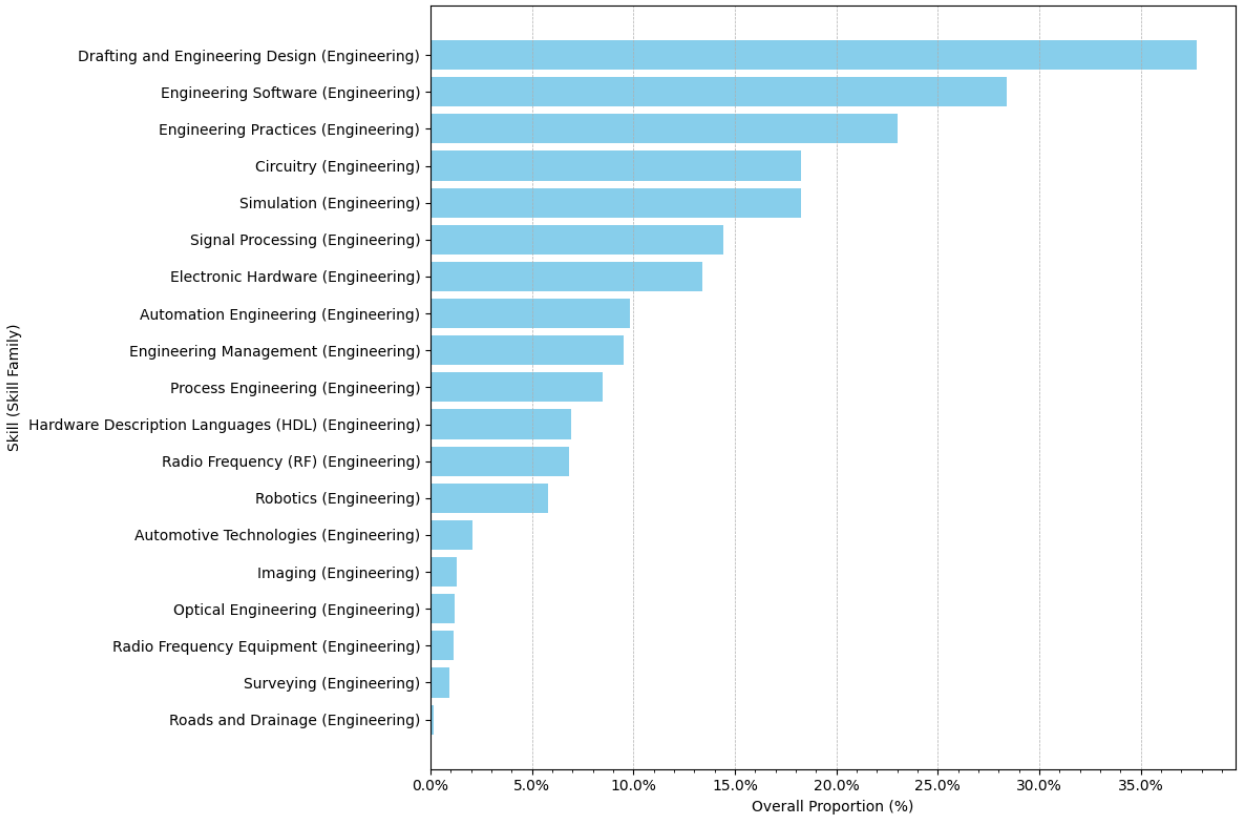
Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

Figure 4.23 presents that from 2012 to 2022, trends in skill proportions across three categories: Supply Chain and Logistics, Design, and Customer and Client Support which reflect nuanced shifts in electrical EE. Also, Supply Chain and Logistics, and Procurement maintains a steady presence, with proportions ranging from 0.07% to 0.13%, emphasizing its consistent role in resource management and operational efficiency. Within Design, User Interface and User Experience (UI/UX) Design shows gradual growth, rising from 0.05% to peak at 0.11%. Basic Customer Service remains stable in Customer and Client Support, hovering between 0.07% and 0.12%.

Next, I analyzed the engineering family of skills, specifically. Figure 4.23 outlines the distribution of core EE skills based on their proportions. Drafting and Engineering Design are the most prevalent skills, reflecting their foundational role in system design and technical execution. Engineering Software, Circuitry, and Simulation are closely followed, underscoring their

importance in digital tool utilization, system analysis, and modeling. Skills like Signal Processing, Electronic Hardware, and Automation Engineering maintain significant representation, aligning with industry demands for hardware integration, automation, and signal optimization.

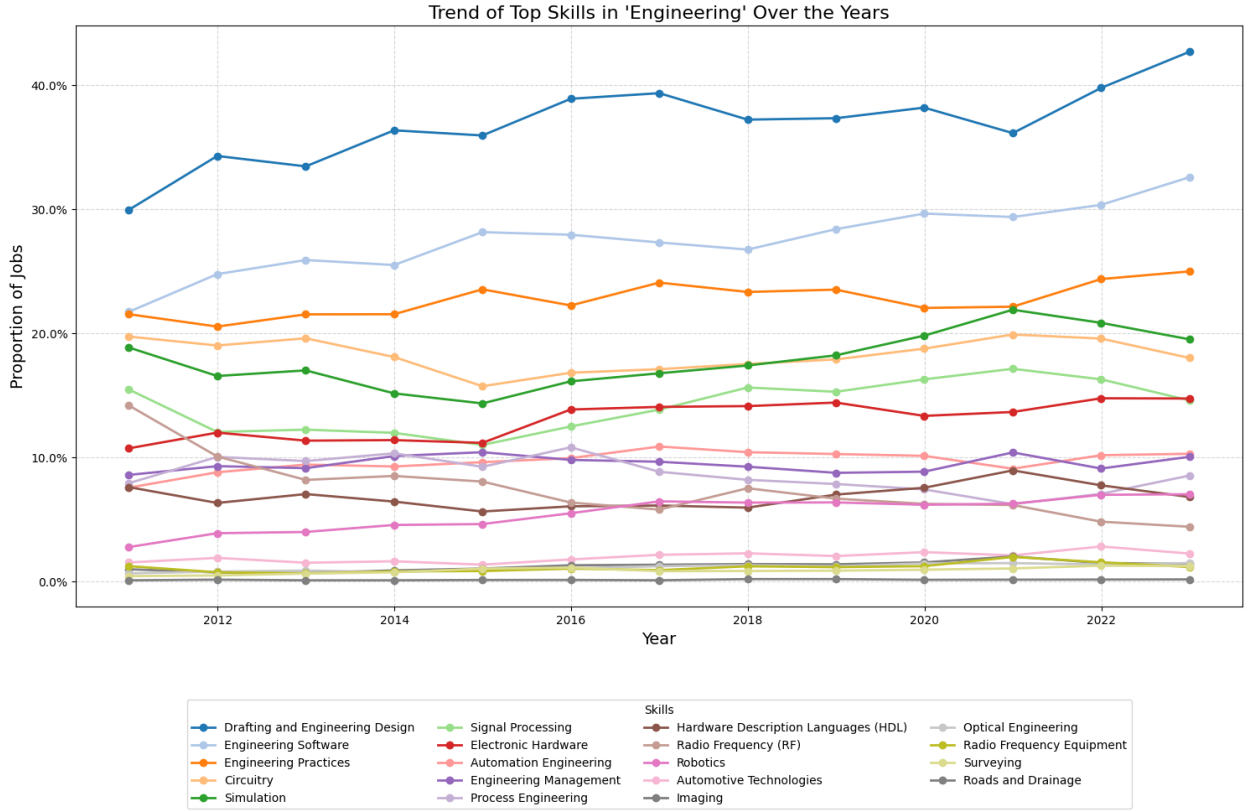
Figure 4.23: Top EE Skills in Engineering Family Skill



Though less dominant, specialized competencies such as Robotics, Automotive Technologies, and Radio Frequency (RF) Engineering highlight niche yet critical areas driving innovation in automation, transportation, and communication systems. While modest in proportion, skills like HDL and Optical Engineering emphasize their relevance in advanced circuit design and photonics. This distribution illustrates the multifaceted nature of EE, where core technical expertise in design, software, and hardware coexists with specialized domains.

Figure 4.24 presents the trends in key skills in EE job postings over time (2010–2022). Drafting and Engineering Design stands out as the most dominant skill, consistently increasing in prevalence and surpassing 40% by 2022. This highlights its foundational importance in system design and technical execution within EE roles. Engineering Software and Circuitry follow with stable and significant proportions, reflecting the sustained demand for digital proficiency and hardware development in engineering projects.

Figure 4.24: Top EE Skills in Engineering Family Skill Across Time (2010-2022)



Note: Skills shown in gray have a maximum proportion of 1% and below.

Moderately represented skills include Signal Processing, Electronic Hardware, and Automation Engineering, which show steady trends, emphasizing their critical roles in system analysis, hardware integration, and process automation. Skills such as Robotics, Automotive Technologies, and Radio Frequency (RF) Engineering appear less frequently but show gradual growth, indicating their continued relevance in specialized areas of EE. In contrast, niche skills like HDL and Optical Engineering maintain lower proportions, pointing to their specialized applications in specific technical domains. This distribution highlights the essential technical competencies in EE, with a strong emphasis on design, software, and hardware practices. These trends reflect the evolving priorities of the profession, shaped by technological advancements and the demands observed in the job market over time.

Table 4.17 summarizes significant differences in EE skill proportions across educational levels. Several skills show strong statistical variation, including Drafting and Engineering Design ($F(2, 36) = 206.25$, $p < 0.001$), Circuitry ($F(2, 36) = 71.75$, $p < 0.001$), and Simulation ($F(2, 36) = 173.97$, $p < 0.001$). Other skills with significant differences include Engineering Management, Signal Processing, Engineering Software, HDL, Engineering Practices, Electronic Hardware,

Automation Engineering, Imaging, Process Engineering, and Optical Engineering (all $p < 0.05$). These findings indicate that many EE-related skills vary meaningfully by degree level, reflecting differences in required technical specialization.

Table 4.17: ANOVA for EE and Engineering Skills Across Degree Levels

Skill	F	df	p	Significant
Automation Engineering	20.92	2, 36	0	Yes
Automotive Technologies	1.53	2, 36	0.231	No
Circuitry	71.75	2, 36	0	Yes
Drafting and Engineering Design	206.25	2, 36	0	Yes
Electronic Hardware	6.56	2, 36	0.004	Yes
Engineering Management	38.74	2, 36	0	Yes
Engineering Practices	72.04	2, 36	0	Yes
Engineering Software	56.67	2, 36	0	Yes
Geotechnical Engineering	1.66	2, 25	0.211	No
Hardware Description Languages	24.81	2, 36	0	Yes
Imaging	17.41	2, 36	0	Yes
Optical Engineering	5.16	2, 34	0.011	Yes
Process Engineering	13.25	2, 36	0	Yes
Radio Frequency (RF)	0.94	2, 36	0.401	No
Radio Frequency Equipment	2.96	2, 36	0.065	No
Roads and Drainage	1.19	1, 20	0.288	No
Robotics	1.37	2, 36	0.267	No
Signal Processing	86.89	2, 36	0	Yes
Simulation	173.97	2, 36	0	Yes
Surveying	1.89	2, 34	0.167	No

However, some skills do not show statistically significant differences across degree levels, as their p-values exceed the 0.05 threshold. These include Automotive Technologies ($F(2, 36) = 1.53$, $p = 0.231$), Geotechnical Engineering ($F(2, 25) = 1.66$, $p = 0.211$), Radio Frequency (RF) ($F(2, 36) = 0.94$, $p = 0.401$), Radio Frequency Equipment ($F(2, 36) = 2.96$, $p = 0.065$), Roads and Drainage ($F(1, 20) = 1.19$, $p = 0.288$), Robotics ($F(2, 36) = 1.37$, $p = 0.267$), and Surveying ($F(2, 34) = 1.89$, $p = 0.167$). These results suggest that these skills are relatively consistent across all degree levels. Further analysis using effect sizes may still reveal meaningful differences in magnitude, helping to clarify which degree levels emphasize these skills most.

Table 4.18: Cohen's Effect Sizes for EE and Engineering Skills Across Degree Levels

Skill	Degree Pair	Cohen's d	Effect Size	Larger Group
Automation Engineering	Bachelor's vs Doctoral	1.984	Large	Bachelor's Larger
Automation Engineering	Bachelor's vs Master's	2.806	Large	Bachelor's Larger
Automation Engineering	Doctoral vs Master's	0.336	Medium	Doctoral Larger
Automotive Technologies	Bachelor's vs Doctoral	0.587	Medium	Doctoral Larger
Automotive Technologies	Bachelor's vs Master's	0.657	Medium	Master's Larger
Automotive Technologies	Doctoral vs Master's	0.219	Medium	Master's Larger
Circuitry	Bachelor's vs Doctoral	4.46	Large	Doctoral Larger
Circuitry	Bachelor's vs Master's	4.76	Large	Master's Larger
Circuitry	Doctoral vs Master's	0.811	Large	Doctoral Larger
Drafting and Engineering Design	Bachelor's vs Doctoral	7.451	Large	Bachelor's Larger
Drafting and Engineering Design	Bachelor's vs Master's	5.769	Large	Bachelor's Larger
Drafting and Engineering Design	Doctoral vs Master's	1.28	Large	Master's Larger
Electronic Hardware	Bachelor's vs Doctoral	1.34	Large	Bachelor's Larger
Electronic Hardware	Bachelor's vs Master's	1.276	Large	Bachelor's Larger
Electronic Hardware	Doctoral vs Master's	0.261	Medium	Master's Larger
Engineering Management	Bachelor's vs Doctoral	3.13	Large	Bachelor's Larger
Engineering Management	Bachelor's vs Master's	3.553	Large	Bachelor's Larger
Engineering Management	Doctoral vs Master's	0.808	Large	Master's Larger
Engineering Practices	Bachelor's vs Doctoral	4.515	Large	Bachelor's Larger
Engineering Practices	Bachelor's vs Master's	3.835	Large	Bachelor's Larger
Engineering Practices	Doctoral vs Master's	1.391	Large	Master's Larger
Engineering Software	Bachelor's vs Doctoral	4.201	Large	Bachelor's Larger
Engineering Software	Bachelor's vs Master's	2.497	Large	Bachelor's Larger

Table 4.18: Continued

Engineering Software	Doctoral vs Master's	1.667	Large	Master's Larger
Geotechnical Engineering	Bachelor's vs Doctoral	1.458	Large	Doctoral Larger
Geotechnical Engineering	Bachelor's vs Master's	0.4	Medium	Master's Larger
Geotechnical Engineering	Doctoral vs Master's	0.601	Medium	Doctoral Larger
Hardware Description Languages	Bachelor's vs Doctoral	2.255	Large	Doctoral Larger
Hardware Description Languages	Bachelor's vs Master's	3.221	Large	Master's Larger
Hardware Description Languages	Doctoral vs Master's	0.328	Medium	Master's Larger
Imaging	Bachelor's vs Doctoral	1.981	Large	Doctoral Larger
Imaging	Bachelor's vs Master's	3.279	Large	Master's Larger
Imaging	Doctoral vs Master's	0.612	Medium	Doctoral Larger
Optical Engineering	Bachelor's vs Doctoral	1.298	Large	Bachelor's Larger
Optical Engineering	Bachelor's vs Master's	0.749	Medium	Bachelor's Larger
Optical Engineering	Doctoral vs Master's	0.582	Medium	Master's Larger
Process Engineering	Bachelor's vs Doctoral	1.754	Large	Bachelor's Larger
Process Engineering	Bachelor's vs Master's	1.796	Large	Bachelor's Larger
Process Engineering	Doctoral vs Master's	0.406	Medium	Master's Larger
Radio Frequency (RF)	Bachelor's vs Doctoral	0.249	Medium	Doctoral Larger
Radio Frequency (RF)	Bachelor's vs Master's	0.56	Medium	Master's Larger
Radio Frequency (RF)	Doctoral vs Master's	0.285	Medium	Master's Larger
Radio Frequency Equipment	Bachelor's vs Doctoral	0.787	Medium	Doctoral Larger
Radio Frequency Equipment	Bachelor's vs Master's	0.961	Large	Master's Larger
Radio Frequency Equipment	Doctoral vs Master's	0.229	Medium	Master's Larger
Roads and Drainage	Bachelor's vs Master's	0.473	Medium	Bachelor's Larger
Robotics	Bachelor's vs Doctoral	0.22	Medium	Bachelor's Larger
Robotics	Bachelor's vs Master's	0.933	Large	Bachelor's Larger
Robotics	Doctoral vs Master's	0.352	Medium	Doctoral Larger
Signal Processing	Bachelor's vs Doctoral	5.345	Large	Doctoral Larger
Signal Processing	Bachelor's vs Master's	4.426	Large	Master's Larger
Signal Processing	Doctoral vs Master's	0.322	Medium	Doctoral Larger
Simulation	Bachelor's vs Doctoral	8.808	Large	Doctoral Larger

Table 4.18: Continued

Simulation	Bachelor's vs Master's	5.65	Large	Master's Larger
Simulation	Doctoral vs Master's	0.492	Medium	Doctoral Larger
Surveying	Bachelor's vs Master's	0.953	Large	Master's Larger
Surveying	Bachelor's vs Doctoral	0.635	Medium	Doctoral Larger
Surveying	Master's vs Doctoral	0.008	Small	Master's Larger

Cohen's d effect sizes for EE skills across degree pairings (bachelor's, master's, and doctoral) highlight substantial differences in skill proportions by educational level. For instance, Drafting and Engineering Design shows a large effect size (Bachelor's vs Doctoral: d = 7.451), with bachelor's jobs having significantly higher proportions indicating its foundational role in entry-level positions. Similarly, Engineering Management (Bachelor's vs Master's: d = 3.553) and Engineering Practices (Bachelor's vs Master's: d = 3.835) also show large effects, with bachelor's-level jobs again having higher proportions, suggesting these skills are emphasized more at the undergraduate level.

Conversely, several advanced technical skills show greater proportions in master's or Doctoral-level jobs. For example, Simulation (Bachelor's vs Doctoral: d = 8.808) and Signal Processing (Bachelor's vs Doctoral: d = 5.345) exhibit large effect sizes, with higher proportions in Doctoral-level jobs, aligning with the technical and research-oriented focus at that level. Similarly, Circuitry (Bachelor's vs Master's: d = 4.76) and Hardware Description Languages (Bachelor's vs Master's: d = 3.221) also appear more prominently in jobs requiring advanced degrees.

However, not all skills follow this trend. For instance, Process Engineering shows a medium effect (Doctoral vs Master's: d = 0.406), with master's-level jobs having higher proportions, contrary to the initial interpretation. Skills like Imaging (Doctoral vs Master's: d = 0.612) and Surveying (Bachelor's vs Master's: d = 0.953) also show medium-to-large differences but vary in which degree level has the higher demand. Some skills, such as Robotics (Bachelor's vs Doctoral: d = 0.22) and Radio Frequency (RF) (Doctoral vs Master's: d = 0.285), show only small to medium differences, indicating relatively similar distributions across degree levels.

4.6.1 Electrical Engineering Technical Skills

Table 4.19 highlights the technical skills required for EE jobs at different degree levels: bachelor's, master's, and doctoral. Skills like Excel, CAD, and AutoCAD are consistently in demand across all levels, though the extent varies. For instance, Excel is most required at the bachelor's level (41.36%) compared to master's (37.16%) and doctoral roles (37.97%). Advanced skills such as MATLAB and Python are more prevalent in master's (24.72% and 11.65%,

respectively) and doctoral roles (30.59% and 14.51%). On the other hand, skills like AutoCAD (15.10%) and PLC (16.24%) are more common in bachelor's-level job advertisements.

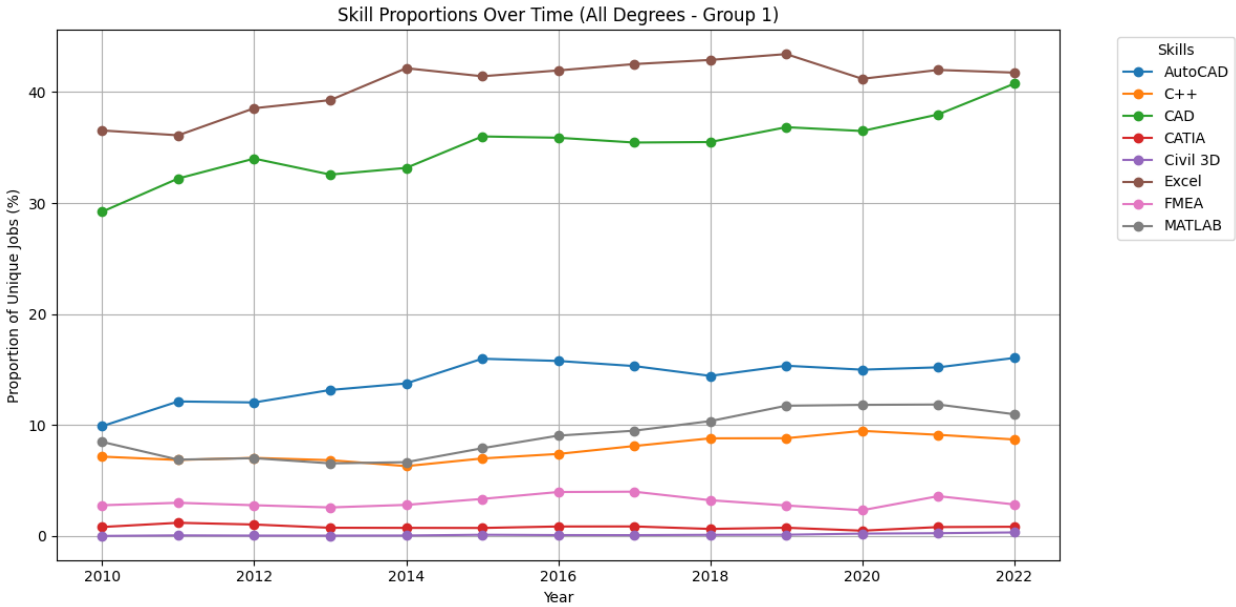
Table 4.19: Technical Skill Proportions in EE Job Ads (2010-2022)

Skill	Bachelor's (%)	Master's (%)	Doctoral (%)
AutoCAD	15.10	3.85	1.41
C++	7.63	15.03	18.42
CAD	36.03	32.64	34.55
CATIA	0.82	0.42	0.10
Civil 3D	0.14	0.02	0.00
Excel	41.36	37.16	37.97
FMEA	3.11	2.65	1.21
MATLAB	8.72	24.72	30.59
Microsoft Office	9.60	3.77	1.96
Microsoft Project	0.89	0.37	0.30
PLC	16.24	4.21	2.37
Python	5.32	11.65	14.51
Revit	4.43	0.71	0.06
SCADA	5.06	1.69	0.56
SQL	2.40	1.47	0.95
SolidWorks	2.20	1.33	0.73

4.6.2 EE Technical Skill Trends (2010-2022)

This research section examines the trends in technical skills required in EE job Ads from 2010 to 2022. Over the past 12 years, the analysis focused on the total demand for technical skills within the EE discipline. Furthermore, the trends were evaluated separately for bachelor's, master's, and doctoral degrees to provide a detailed understanding of skill requirements at each educational level. In the upcoming plots, the technical skills presented in Table 4.18 were divided into two groups, with eight skills in each group. This division was made to enhance visualization and ensure that the skill trend lines do not overlap, allowing for a clearer interpretation of the data.

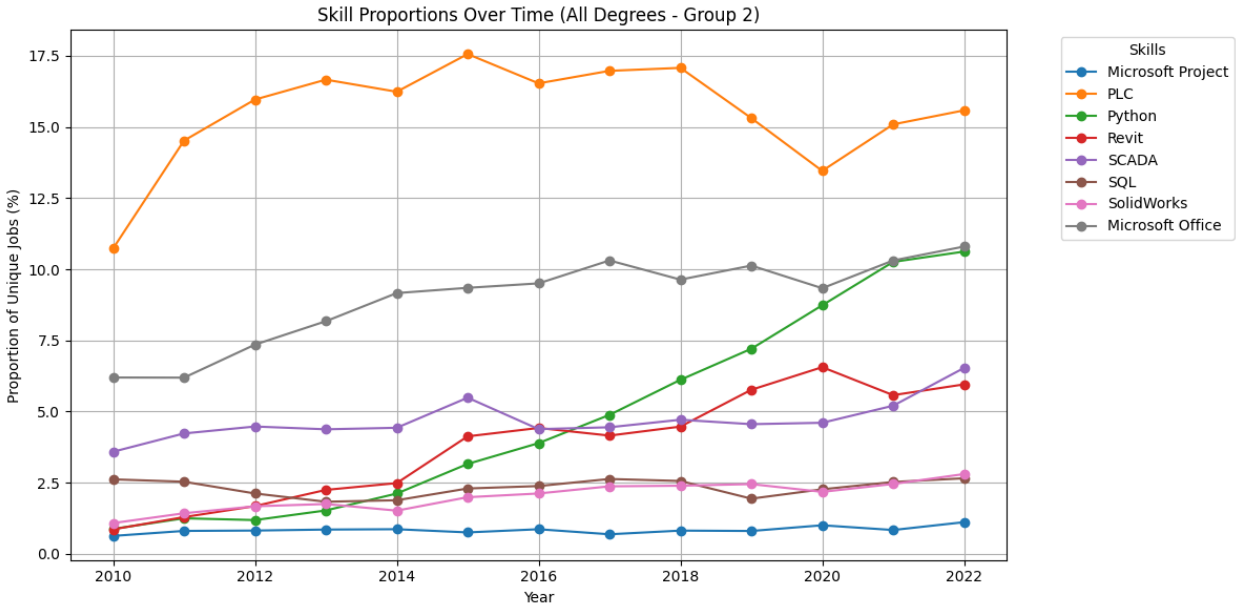
Figure 4.25: Trends in Technical Skills Over Time in EE Job Ads (Group 1)



Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

Figure 4.25 shows the trends in the proportions of selected technical skills required in EE job ads over time, combining data for all degree levels (bachelor's, master's, and doctoral). It highlights how specific skills, such as Excel and CAD, consistently dominate the demand across the years, with Excel maintaining the highest proportion. Other skills like AutoCAD and MATLAB show steady but lower trends, indicating their specialized nature in EE roles. Meanwhile, skills such as FMEA, C++, and CATIA remain less prevalent throughout the period.

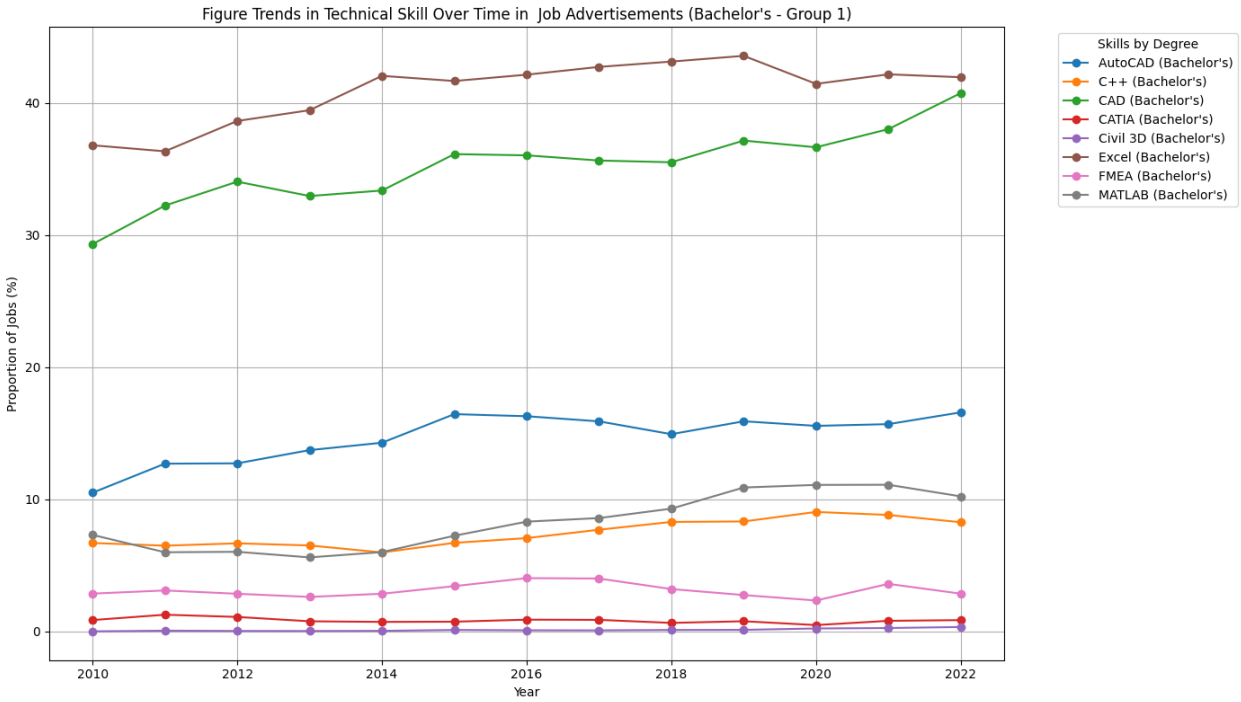
Figure 4.26: Trends in Technical Skills Over Time in EE Job Ads (Group 2)



Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

Figure 4.26 shows the trends in the proportions of selected technical skills required in EE job ads over time, covering all degree levels (bachelor's, master's, and doctoral). Skills like PLC and Microsoft Office consistently show high demand, with PLC having the highest proportion throughout the years. In contrast, skills such as Python and SQL have steadily grown, increasing their importance in programming and data-related tasks. Meanwhile, skills like Microsoft Project, SolidWorks, and SCADA remain less common, reflecting more specialized or niche applications in EE roles.

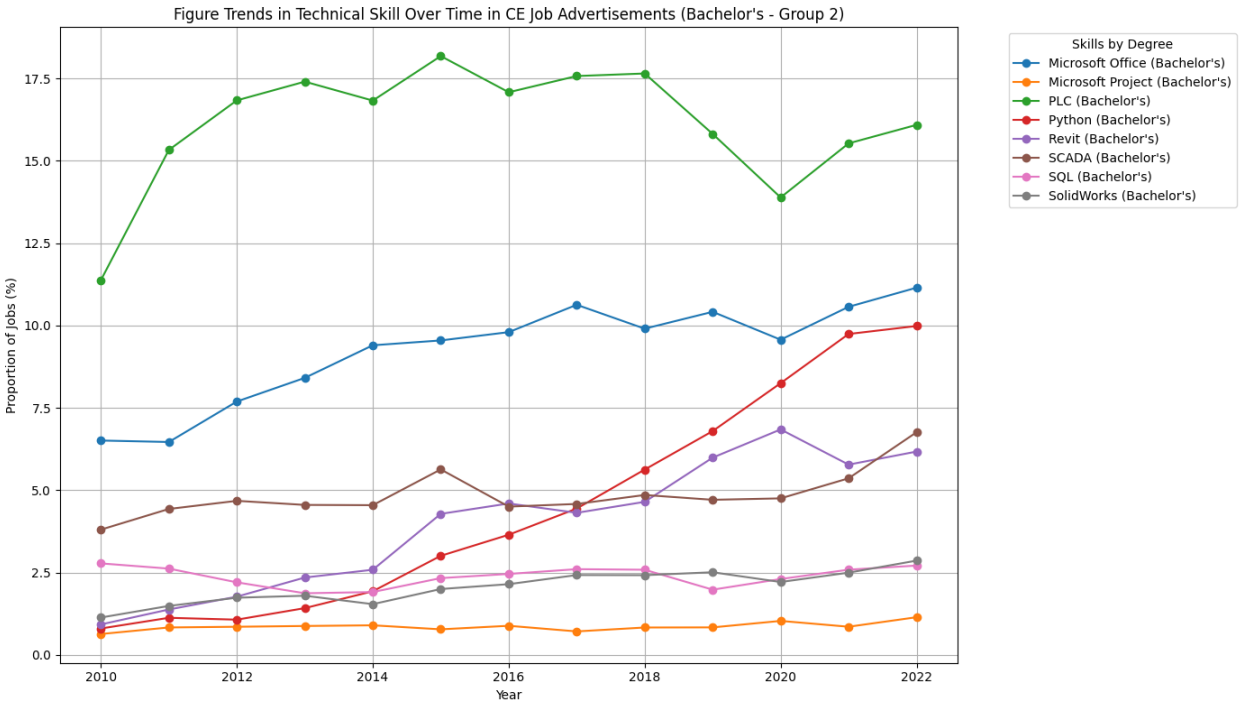
Figure 4.27: Trends in Technical Skills Over Time in EE Job Ads (Bachelor's - Group 1)



Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

Figure 4.27 displays the trends in the proportions of selected technical skills required in EE job advertisements for bachelor's-level positions from 2010 to 2022. Skills like Excel and CAD consistently show high demand, with Excel maintaining the highest proportion throughout the years. AutoCAD also shows steady demand, reflecting its importance in design-related roles. In contrast, skills such as MATLAB, C++, and FMEA have lower proportions, indicating more specialized applications in specific EE tasks. Skills like CATIA and Civil 3D remain the least prevalent, suggesting limited demand in bachelor's-level job postings.

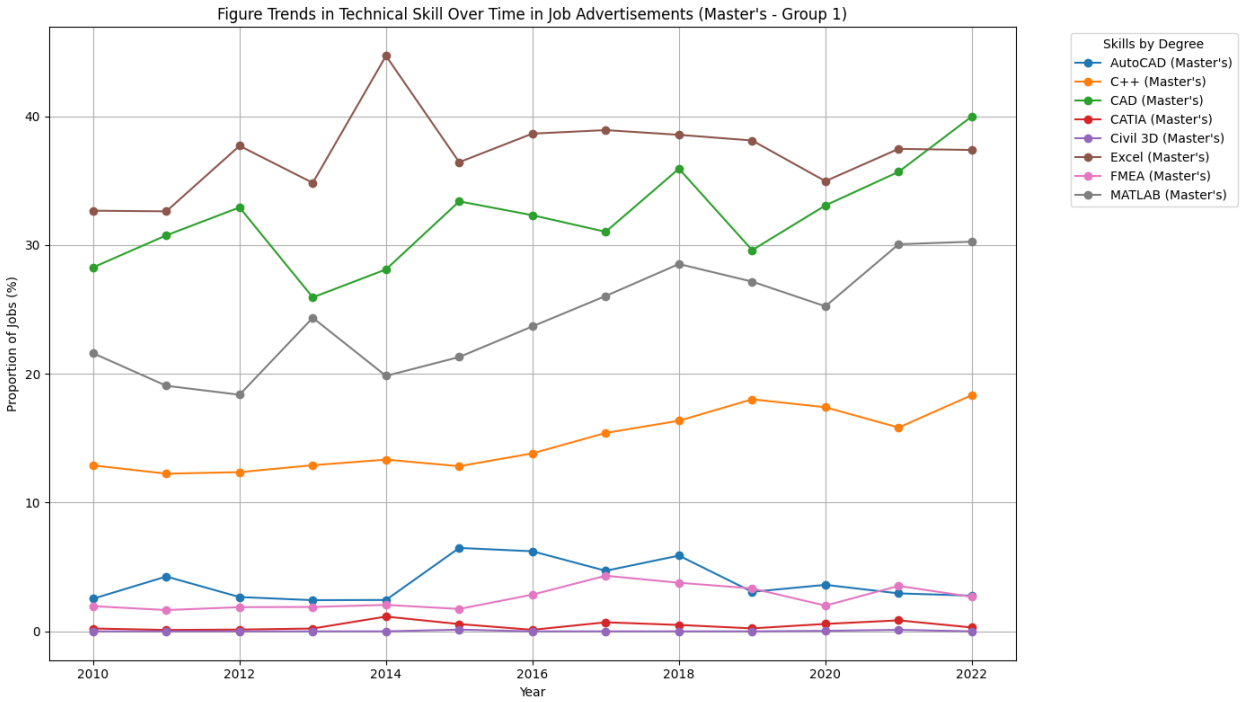
Figure 4.28: Trends in Technical Skills Over Time in EE Job Ads (Bachelor's - Group 2)



Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

Figure 4.28 shows the trends in the proportions of selected technical skills required in EE job advertisements for bachelor's-level positions from 2010 to 2022. Skills like PLC and Microsoft Office consistently show high demand, with PLC maintaining the highest proportion throughout the years. Python and Revit have shown significant growth, reflecting the increasing importance of programming and design tools in EE roles. In contrast, skills such as Microsoft Project, SCADA, and SQL have lower but steady demand, indicating specialized applications. SolidWorks also shows a gradual upward trend, suggesting a growing relevance in specific technical areas.

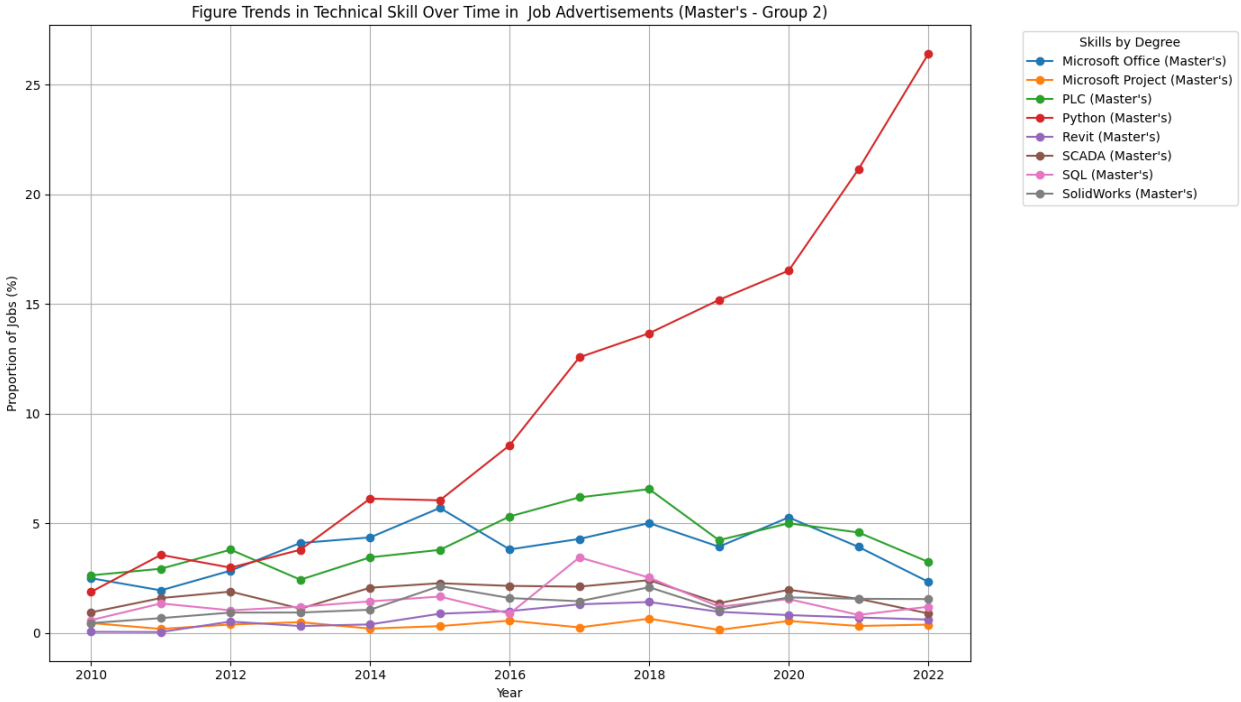
Figure 4.29: Trends in Technical Skills Over Time in EE Job Ads (Master's - Group 1)



Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

Figure 4.29 shows the trends in the proportions of selected technical skills required in EE job advertisements for master's-level positions from 2010 to 2022. Skills like Excel and CAD consistently show high demand, with Excel maintaining the highest proportion throughout the years. MATLAB also demonstrates a strong presence, reflecting its importance in advanced analytical and simulation tasks for master's-level roles. In contrast, skills such as AutoCAD, C++, and FMEA have lower proportions, indicating more specialized or niche applications. Skills like CATIA and Civil 3D remain the least prevalent, suggesting limited demand in master's-level EE job postings.

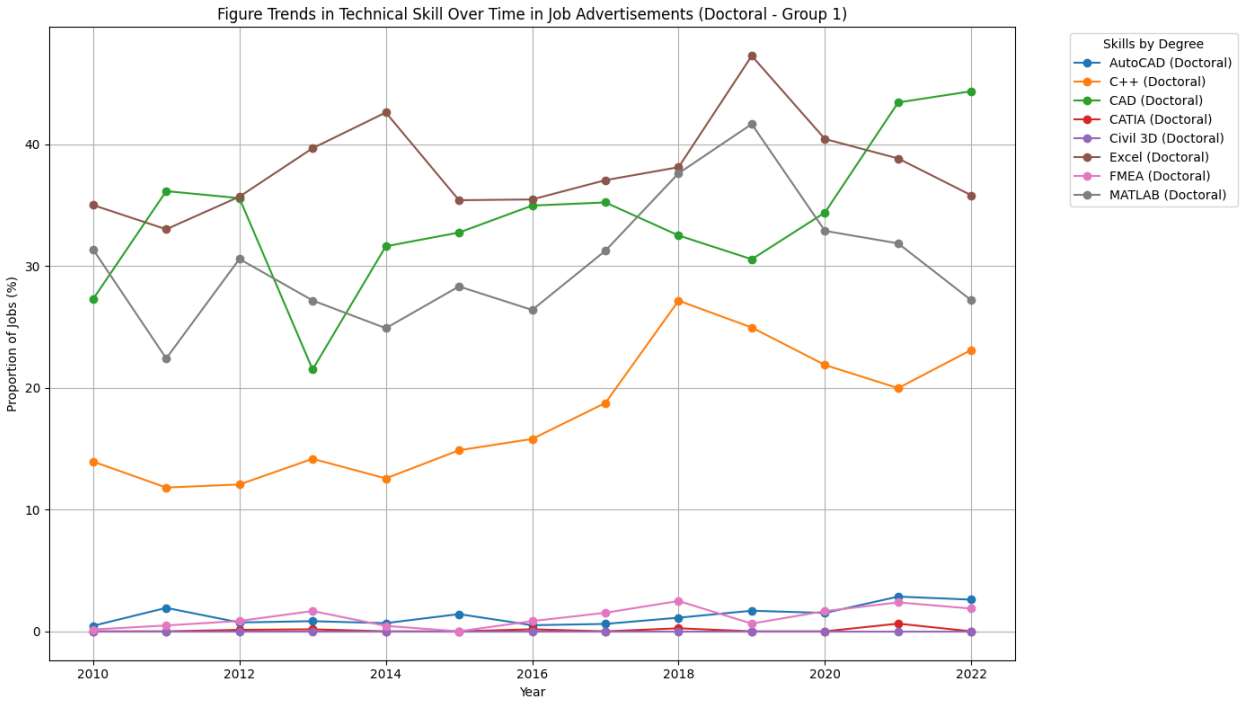
Figure 4.30: Trends in Technical Skills Over Time in EE Job Ads (Master's - Group 2)



Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

Figure 4.30 shows the trends in the proportions of selected technical skills required in EE job advertisements for master's-level positions from 2010 to 2022. Python shows a significant upward trend, reaching the highest proportion by 2022, reflecting its growing importance in programming and data analysis for advanced EE roles. Skills like PLC and Microsoft Office have maintained steady demand throughout the years, indicating their consistent relevance in engineering tasks. In contrast, skills like Microsoft Project, SCADA, SQL, and SolidWorks show lower but stable proportions, suggesting specialized applications within specific EE domains.

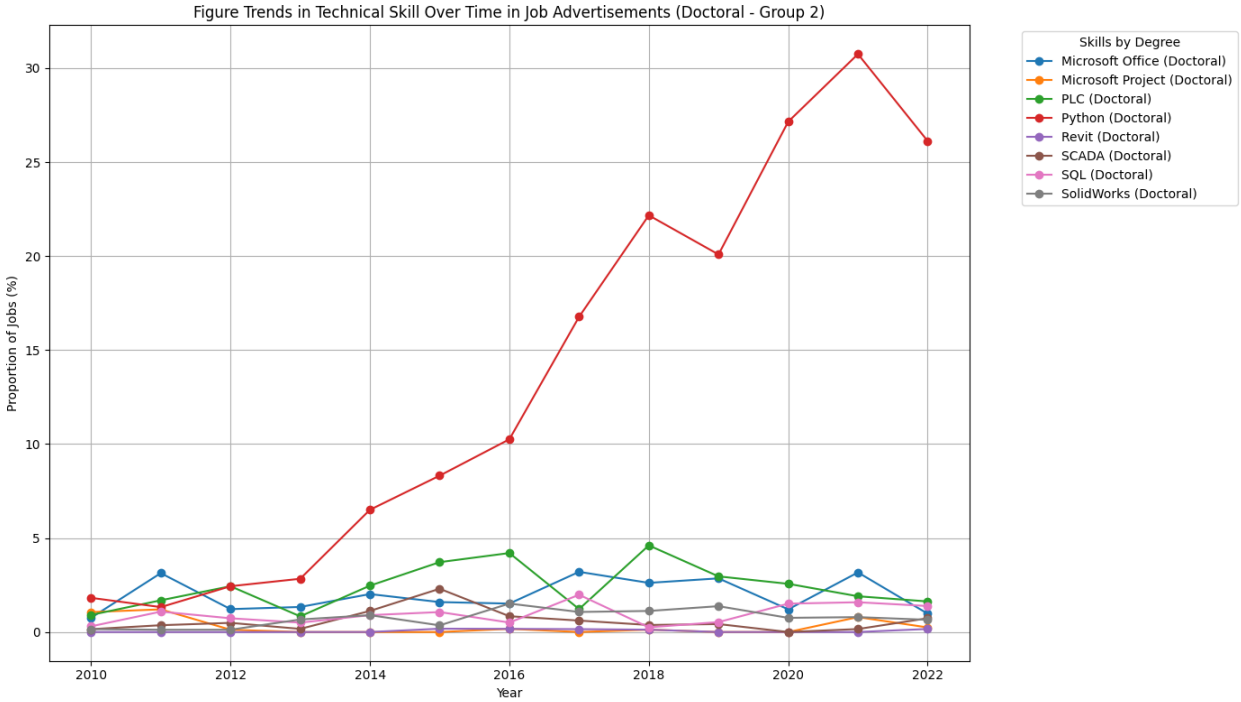
Figure 4.31: Trends in Technical Skills Over Time in EE Job Ads (Doctoral - Group 1)



Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

Figure 4.31 displays the trends in the proportions of selected technical skills required in EE job advertisements for doctoral-level positions from 2010 to 2022. Skills like Excel, MATLAB, and CAD consistently show high demand. Excel and MATLAB maintain the highest proportions throughout the years, reflecting their importance in data analysis, modeling, and design tasks for advanced research roles. C++ also demonstrates a notable upward trend, indicating its relevance in programming-intensive positions. In contrast, skills such as AutoCAD, FMEA, CATIA, and Civil 3D have lower proportions, suggesting more specialized applications within specific EE domains at the doctoral level.

Figure 4.32: Trends in Technical Skills Over Time in EE Job Ads (Doctoral - Group 2)



Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

Figure 4.32 shows the trends in the proportions of selected technical skills required in EE job advertisements for doctoral-level positions from 2010 to 2022. Python exhibits a significant upward trend, reaching the highest proportion by 2022, reflecting its growing importance in programming, data analysis, and research applications. Skills like PLC and Microsoft Office maintain steady demand, indicating their consistent relevance in engineering and administrative tasks. In contrast, skills such as Microsoft Project, SCADA, SQL, and SolidWorks show lower but stable proportions, suggesting specialized applications within specific EE domains at the doctoral level.

4.6.3 Summary of EE Job Posting Analysis

This section examined the distribution of EE degrees and skill demands across bachelor's, master's, and doctoral levels from 2010 to 2022. Jobs requiring a bachelor's degree dominate, accounting for 95.22% of the 949,648 degrees awarded, compared to 3.79% for master's and 0.99% for Doctoral degrees. The top 30 EE skills highlight the dominance of Drafting and Engineering Design, Basic Electrical Systems, Project Management, and Engineering Software, key for technical execution and oversight. Other notable skills, such as Microsoft Office, Electrical Construction, and Equipment Maintenance, reflect the need for digital tools and technical expertise. Less common skills included Writing, Customer Service, and Procurement emphasize communication and supply chain management.

Skill demands vary across educational levels. For entry-level roles, bachelor's degrees focus on technical skills like Drafting, Engineering Software, and PLC. Master's degrees blend technical knowledge with managerial skills like Project Management and advanced tools such as MATLAB and Python. Doctoral degrees prioritize specialized, research-driven skills, including Process Engineering, HDL, and Signal Processing. From 2010 to 2022, skills like Python, Project Management, and MATLAB have grown, reflecting the rise of digital transformation, data analysis, and advanced design technologies in EE.

The analysis of technical skills in EE from 2010 to 2022 highlights essential trends across degree levels. Foundational skills like Excel, CAD, and AutoCAD remain crucial at all levels, with the highest demand at the bachelor's level. Master's-level roles balance technical expertise with leadership, relying more on advanced tools like MATLAB, Python, and Revit. Doctoral roles emphasize specialized and research-driven skills, with tools like Signal Processing, HDL, and SQL gaining importance for advanced analysis and design tasks. Over time, demand for digital tools like Python and MATLAB and managerial skills like Project Management has increased, reflecting the growing influence of technology and project complexity in EE.

4.7 Examining Mechanical Engineering Skills by Proportion and Trends

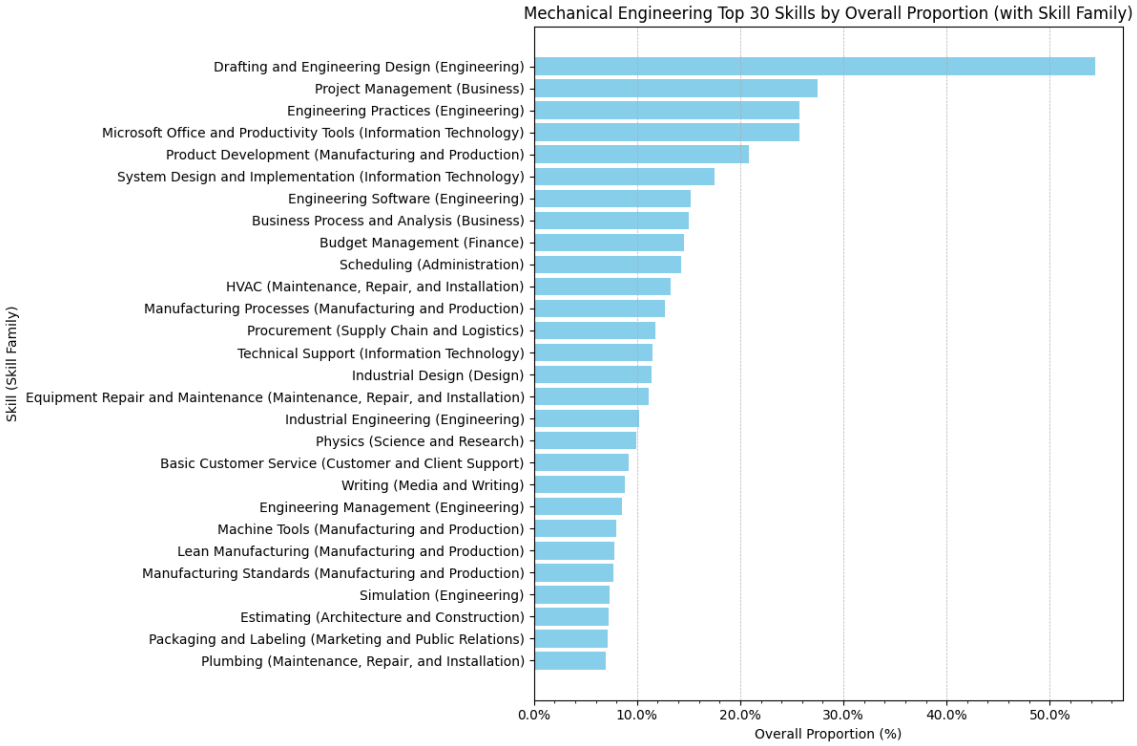
Table 4.20 shows that job advertisements requiring a minimum of a bachelor's degrees dominate the ME education job advertisement database, accounting for 662,121 (94.89%) of the 697,810 degrees recorded. Jobs requiring at minimum master's degrees comprise 26,822 (3.84%), and jobs requiring Doctoral degrees represent a minor proportion at 8,867 (1.27%).

Table 4.20 : ME Degree Distribution

ME Degrees	Degree (N)	Percentage
Bachelor's	662121	94.89%
Master's	26822	3.84%
Doctoral	8867	1.27%
Total	697810	100.00%

Figure 4.33 highlights the top 30 skills in ME based on their overall proportions across various skill families. Drafting and Engineering Design stands out as the most prevalent skill, followed closely by Project Management and Engineering Practices, underscoring their foundational roles in ME projects. Skills such as Microsoft Office, Productivity Tools, and Product Development rank highly, emphasizing the importance of digital tools and manufacturing expertise. Budget Management and Scheduling are also prominent, reflecting the growing need for financial planning and efficient project coordination.

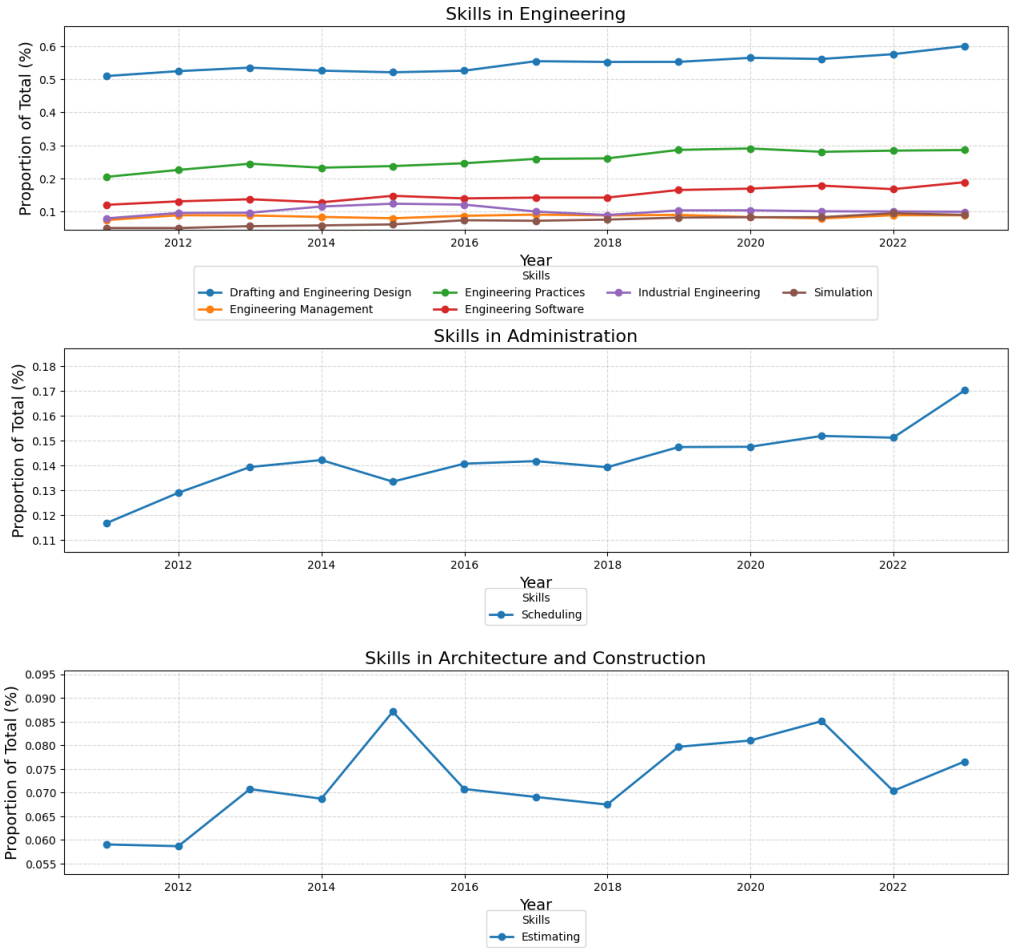
Figure 4.33: ME Top 30 Skill by Overall Proportions



Lower-ranked but notable skills include Writing, Basic Customer Service, and Procurement, which highlight the importance of communication, client relations, and supply chain management in ME practices. Although less represented, specialized skills such as Simulation, Industrial Engineering, and Physics demonstrate their relevance in specific contexts like system modeling, process optimization, and scientific analysis. This distribution showcases the multidisciplinary nature of mechanical engineering, balancing technical expertise, managerial competencies, and supporting skills essential for success in modern engineering environments.

In the next section, I will examine how these skills have evolved from 2010 to 2022, revealing trends and shifts in ME priorities and practices.

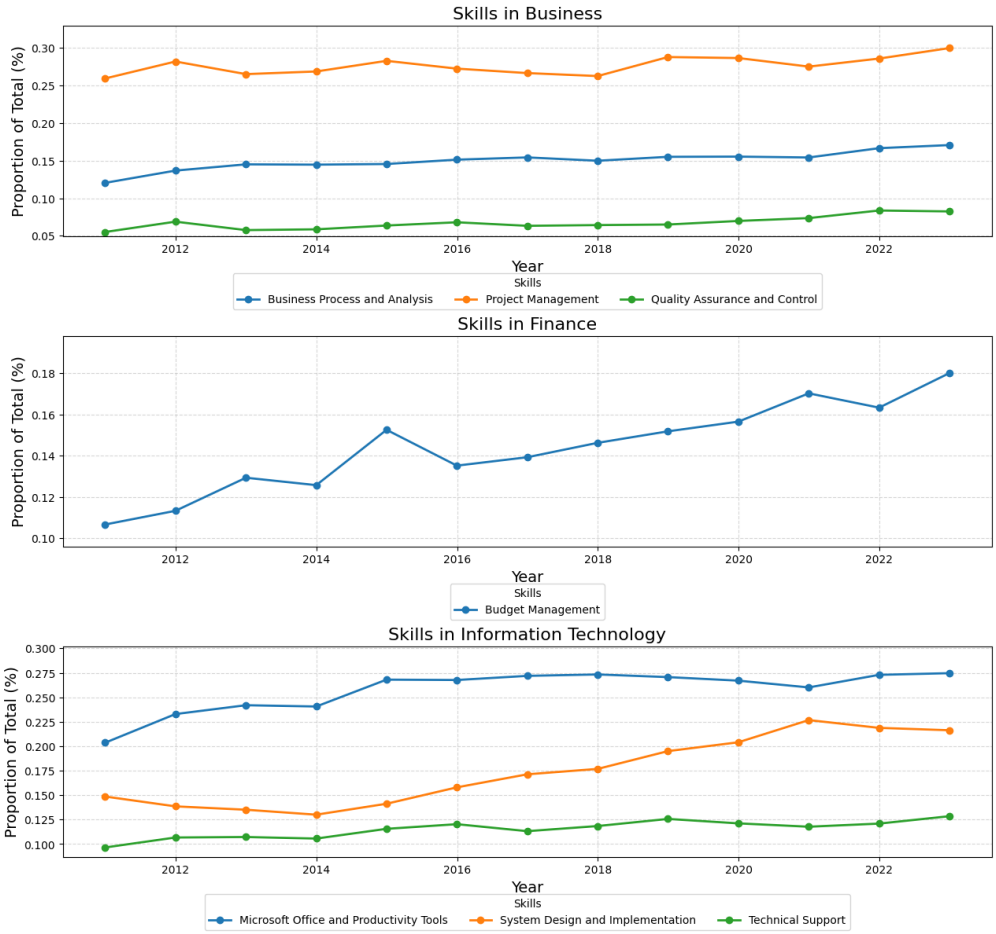
Figure 4.34: Trend of ME Top 30 Skill (Engineering, Administration, Architecture and Construction) 2010-2012



Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

Figure 4.34 shows that from 2010 to 2022, the trends in skill proportions across three categories: Engineering, Administration, and Architecture and Construction, which reflect the evolving priorities in ME. Drafting and Engineering Design dominate the engineering category, with other skills like Engineering Management, Engineering Practices, and Engineering Software showing stable trends. Simulation gradually increases, highlighting its growing relevance in advanced system analysis. In Administration, Scheduling shows an upward trend, emphasizing the increasing importance of project planning and coordination in ME projects. In architecture and construction, estimation maintains steady growth, indicating its importance in cost management and project planning within ME.

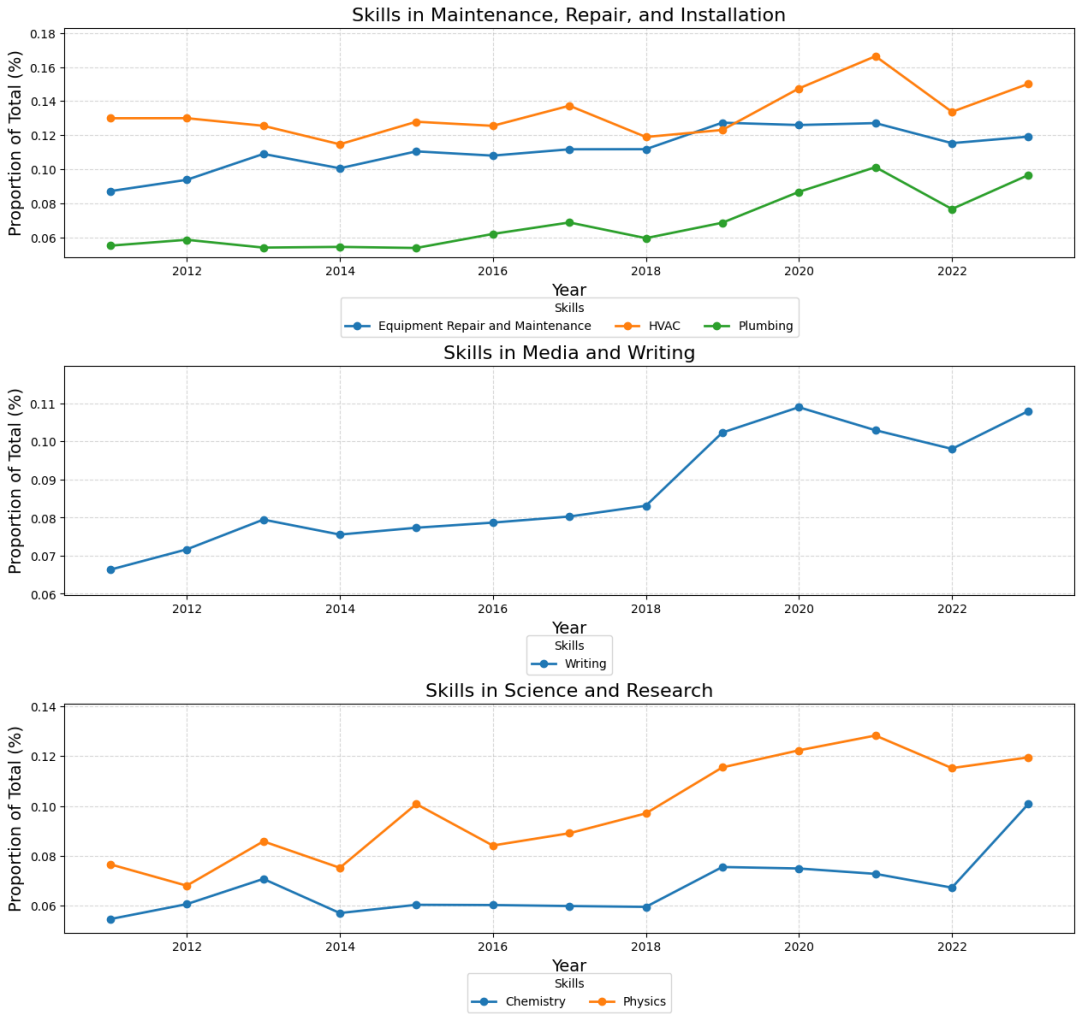
Figure 4.35: Trend of ME Top 30 Skill (Business, Environment, and Information Technology) 2010-2012



Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

Figure 4.35 displays that from 2010 to 2022, the trends in skill proportions across three categories: Business, Finance, and Information Technology, which reflect the shifting priorities, more jobs requiring greater skills and the increased requirements from employers in job ads for ME. In the business category, project management remains dominant, with business process and analysis showing steady growth and emphasizing the importance of strategic planning and process optimization. Quality Assurance and Control demonstrates gradual growth, highlighting its increasing relevance in maintaining engineering standards. Budget Management shows an upward trend in Finance, reflecting the growing need for financial oversight and resource allocation in ME projects. In Information Technology, Microsoft Office and Productivity Tools consistently maintain high demand, while System Design and Implementation exhibit steady growth, underscoring the integration of digital tools in engineering workflows. Technical Support shows moderate growth, indicating its importance in maintaining operational efficiency in ME.

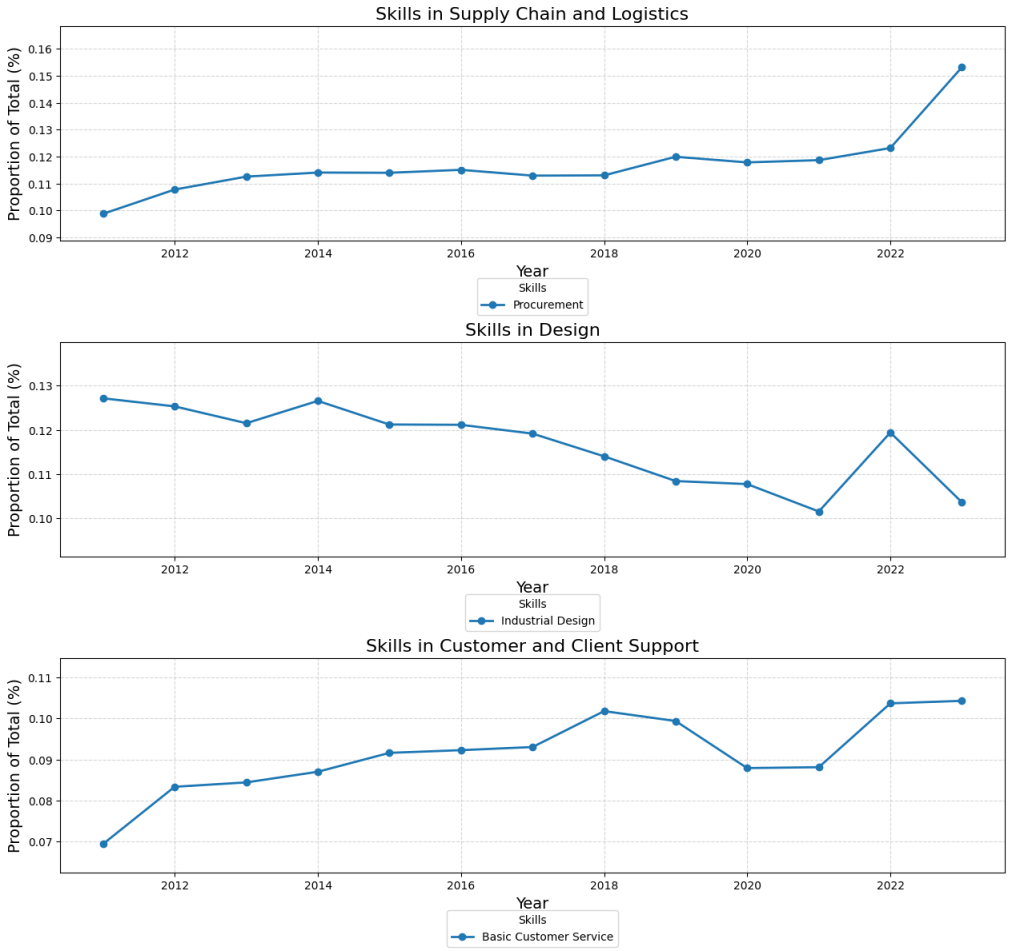
Figure 4.36: Trend ME of Top 30 Skill (Maintenance Repair and Installation, Media and Writing, Science and Research) 2010-2012



Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

Figure 4.36 shows from 2010 to 2022 the trends in skill proportions across three categories: Maintenance, Repair, and Installation; Media and Writing; and Science and Research which reflects that jobs are requiring these skills in ME. In Maintenance, Repair, and Installation, Equipment Repair and Maintenance and HVAC maintain strong demand. HVAC shows gradual growth, highlighting the need for technical expertise in system operations. Plumbing also shows slight growth, indicating its role in specialized maintenance tasks. In Media and Writing, Writing displays a steady upward trend, emphasizing the growing importance of technical communication and documentation in ME projects. In Science and Research, Physics shows consistent growth, reflecting its foundational role in engineering principles, while Chemistry maintains moderate demand, supporting materials science and process-related applications in ME.

Figure 4.37: Trend of ME Top 30 Skill (Supply Chain and Logistics, Design, and Customer and Client Support) 2010-2012



Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

Figure 4.37 presents that from 2010 to 2022, the trends in skill proportions across three categories: Supply Chain and Logistics, Design, and Customer and Client Support which reflect evolving priorities in ME. In Supply Chain and Logistics, Procurement shows a steady upward trend, highlighting its growing importance in resource management and operational efficiency. Industrial design exhibits slight fluctuations with a gradual decline in recent years, suggesting shifts in design priorities within ME projects. Basic Customer Service shows consistent growth in Customer and Client Support, emphasizing the increasing need for effective communication and client interaction in engineering environments.

Figure 4.38 presents the top engineering skills in ME by proportion within the engineering skill family, specifically. Drafting and Engineering Design stands out as the most dominant skill, followed by Engineering Practices, Engineering Software, and Engineering Management. This reflects their critical importance in ME projects and workflows. Moderately represented skills

include Simulation, Process Engineering, and Robotics, highlighting their roles in system modeling and automation. In contrast, skills such as Optical Engineering, Radio Frequency Equipment, and Hardware Description Languages appear less frequently, indicating their more specialized applications within mechanical engineering. This distribution highlights the essential technical competencies within mechanical engineering, emphasizing design, software, and practical engineering practices fundamental to the profession.

Figure 4.38: Top ME Skills in Engineering Family Skill

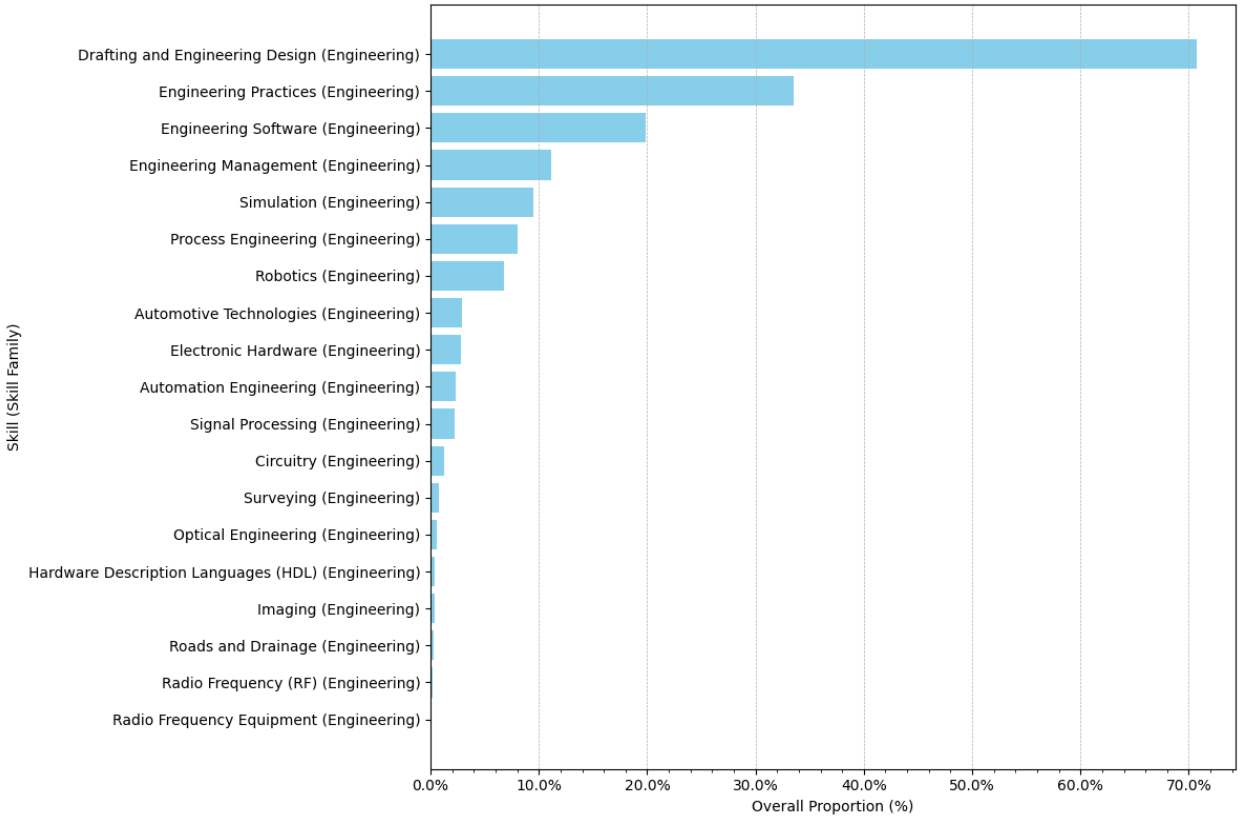
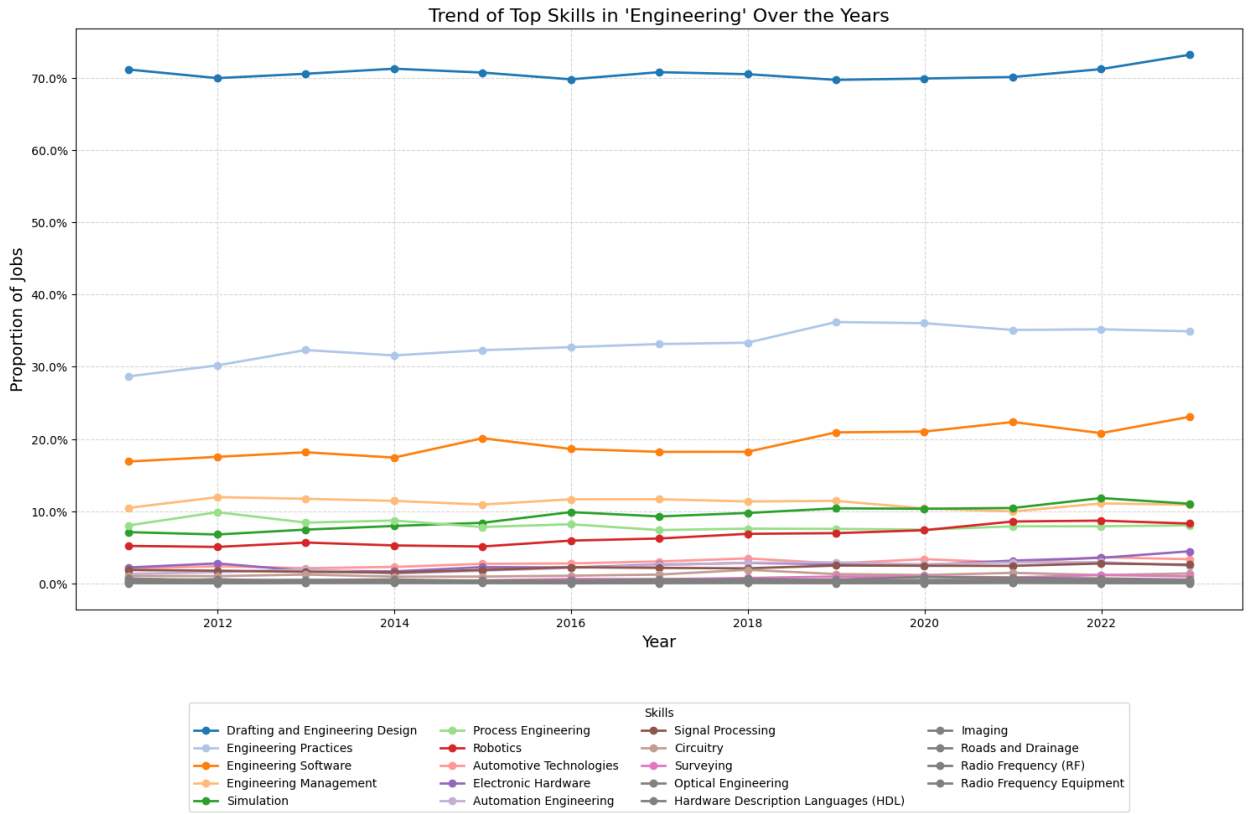


Figure 4.39 : Top ME Skills in Engineering Family Skill Across Time (2010-2022)



Note: Skills shown in gray have a maximum proportion of 1% and below.

Figure 4.39 presents the trends in engineering skills in ME job postings over time (2010–2022). Drafting and Engineering Design stands out as the most dominant skill, consistently increasing in prevalence and surpassing 70% by 2022. This highlights its foundational importance in the field. Engineering Software follows with a stable proportion, reflecting the ongoing demand for technological proficiency in engineering projects.

Skills include Engineering Practices, Engineering Management, and Simulation, which show steady trends, emphasizing their critical roles in system design, project execution, and performance analysis. In contrast, skills such as Optical Engineering, Radio Frequency Equipment, and Hardware Description Languages appear less frequently, pointing to their specialized applications within mechanical engineering. This distribution highlights the essential technical competencies in mechanical engineering, strongly emphasizing design, software, and practical engineering practices. These trends reflect the priorities of the profession, shaped by technological advancements and the demands of modern engineering projects.

Results presented in Table 4.21 provide an overview of the differences in ME and proportional frequency of engineering skills across various degree levels (bachelor's, master's,

and Doctoral). Significant F-values with corresponding p-values less than 0.05 indicate that the differences among the degree groups are statistically significant for many of the analyzed skills. For example, skills such as Drafting and Engineering Design ($F(2, 36) = 375.53$, $p < 0.001$), Engineering Practices ($F(2, 36) = 88.2$, $p < 0.001$), and Engineering Management ($F(2, 36) = 74.69$, $p < 0.001$) exhibited substantial variation across degree levels. These results suggest that jobs with different minimum educational attainment requirements have a different proportional representation of specific skills in ME.

Table 4.21: ANOVA for ME and Engineering Skills Across Degree Levels

Skill	F	df	p	Significant
Automation Engineering	1.44	2, 36	0.251	No
Automotive Technologies	3.47	2, 36	0.042	Yes
Circuitry	7.05	2, 36	0.003	Yes
Drafting and Engineering Design	375.53	2, 36	0	Yes
Electronic Hardware	2.06	2, 36	0.142	No
Engineering Management	74.69	2, 36	0	Yes
Engineering Practices	88.2	2, 36	0	Yes
Engineering Software	12.8	2, 36	0	Yes
Geotechnical Engineering	0.21	2, 24	0.813	No
Hardware Description Languages	48.05	2, 35	0	Yes
Imaging	14.25	2, 36	0	Yes
Optical Engineering	2.05	2, 35	0.144	No
Process Engineering	5.32	2, 36	0.009	Yes
Radio Frequency (RF)	13.64	2, 29	0	Yes
Radio Frequency Equipment	11.15	1, 20	0.003	Yes
Roads and Drainage	4.89	2, 25	0.016	Yes
Robotics	7.26	2, 36	0.002	Yes
Signal Processing	29.06	2, 36	0	Yes
Simulation	113.55	2, 36	0	Yes
Surveying	1.36	2, 32	0.271	No

However, for a few skills, such as Automation Engineering ($F(2, 36) = 1.44$, $p = 0.251$) and Surveying ($F(2, 32) = 1.36$, $p = 0.271$), the p-values exceed the 0.05 threshold, indicating no statistically significant differences among the groups for these skills. This implies that these skills

are consistently included in job advertisements across all degree levels. Cohen's D tests were further conducted to determine the magnitude of these differences, quantifying the effect sizes between specific degree pairs (e.g., bachelor's vs. master's) and identifying which degree level had proportionally higher frequencies of skill over the period of record.

Table 4.22: Cohen's Effect Sizes for ME and Engineering Skills Across Degree Levels

Skill	Degree Pair	Cohen's d	Effect Size	Larger Group
Automation Engineering	Bachelor's vs Doctoral	0.551	Medium	Bachelor's Larger
Automation Engineering	Bachelor's vs Master's	0.127	Small	Master's Larger
Automation Engineering	Doctoral vs Master's	0.587	Medium	Master's Larger
Automotive Technologies	Bachelor's vs Doctoral	0.496	Medium	Doctoral Larger
Automotive Technologies	Bachelor's vs Master's	1.135	Large	Master's Larger
Automotive Technologies	Doctoral vs Master's	0.501	Medium	Master's Larger
Circuitry	Bachelor's vs Doctoral	1.179	Large	Doctoral Larger
Circuitry	Bachelor's vs Master's	2.728	Large	Master's Larger
Circuitry	Doctoral vs Master's	0.172	Small	Doctoral Larger
Drafting and Engineering Design	Bachelor's vs Doctoral	10.385	Large	Bachelor's Larger
Drafting and Engineering Design	Bachelor's vs Master's	5.544	Large	Bachelor's Larger
Drafting and Engineering Design	Doctoral vs Master's	5.418	Large	Master's Larger
Electronic Hardware	Bachelor's vs Doctoral	0.83	Large	Bachelor's Larger
Electronic Hardware	Bachelor's vs Master's	0.233	Medium	Master's Larger
Electronic Hardware	Doctoral vs Master's	0.685	Medium	Master's Larger
Engineering Management	Bachelor's vs Doctoral	5.672	Large	Bachelor's Larger
Engineering Management	Bachelor's vs Master's	2.829	Large	Bachelor's Larger
Engineering Management	Doctoral vs Master's	1.769	Large	Master's Larger
Engineering Practices	Bachelor's vs Doctoral	5.982	Large	Bachelor's Larger
Engineering Practices	Bachelor's vs Master's	1.883	Large	Bachelor's Larger
Engineering Practices	Doctoral vs Master's	3.09	Large	Master's Larger
Engineering Software	Bachelor's vs Doctoral	0.76	Medium	Doctoral Larger
Engineering Software	Bachelor's vs Master's	1.976	Large	Master's Larger

Table 4.22: Continued

Engineering Software	Doctoral vs Master's	1.175	Large	Master's Larger
Geotechnical Engineering	Bachelor's vs Doctoral	0.124	Small	Doctoral Larger
Geotechnical Engineering	Bachelor's vs Master's	0.218	Medium	Bachelor's Larger
Geotechnical Engineering	Doctoral vs Master's	0.306	Medium	Doctoral Larger
Hardware Description Languages	Bachelor's vs Master's	3.491	Large	Master's Larger
Hardware Description Languages	Bachelor's vs Doctoral	0.581	Medium	Doctoral Larger
Hardware Description Languages	Master's vs Doctoral	2.562	Large	Master's Larger
Imaging	Bachelor's vs Doctoral	2.229	Large	Doctoral Larger
Imaging	Bachelor's vs Master's	1.846	Large	Master's Larger
Imaging	Doctoral vs Master's	0.307	Medium	Doctoral Larger
Optical Engineering	Bachelor's vs Master's	0.79	Medium	Master's Larger
Optical Engineering	Bachelor's vs Doctoral	0.216	Medium	Doctoral Larger
Optical Engineering	Master's vs Doctoral	0.492	Medium	Master's Larger
Process Engineering	Bachelor's vs Doctoral	0.63	Medium	Doctoral Larger
Process Engineering	Bachelor's vs Master's	0.932	Large	Bachelor's Larger
Process Engineering	Doctoral vs Master's	1.062	Large	Doctoral Larger
Radio Frequency (RF)	Bachelor's vs Doctoral	1.219	Large	Doctoral Larger
Radio Frequency (RF)	Bachelor's vs Master's	1.981	Large	Master's Larger
Radio Frequency (RF)	Doctoral vs Master's	1.055	Large	Master's Larger
Radio Frequency Equipment	Bachelor's vs Master's	1.448	Large	Master's Larger
Roads and Drainage	Bachelor's vs Master's	1.083	Large	Bachelor's Larger
Roads and Drainage	Bachelor's vs Doctoral	1.052	Large	Doctoral Larger
Roads and Drainage	Master's vs Doctoral	1.506	Large	Doctoral Larger
Robotics	Bachelor's vs Doctoral	1.4	Large	Doctoral Larger
Robotics	Bachelor's vs Master's	0.92	Large	Master's Larger
Robotics	Doctoral vs Master's	0.713	Medium	Doctoral Larger
Signal Processing	Bachelor's vs Doctoral	2.681	Large	Doctoral Larger
Signal Processing	Bachelor's vs Master's	3.359	Large	Master's Larger
Signal Processing	Doctoral vs Master's	0.13	Small	Doctoral Larger
Simulation	Bachelor's vs Doctoral	5.699	Large	Doctoral Larger

Table 4.22: Continued

Simulation	Bachelor's vs Master's	5.391	Large	Master's Larger
Simulation	Doctoral vs Master's	0.302	Medium	Doctoral Larger
Surveying	Bachelor's vs Doctoral	0.243	Medium	Doctoral Larger
Surveying	Bachelor's vs Master's	0.519	Medium	Bachelor's Larger
Surveying	Doctoral vs Master's	0.61	Medium	Doctoral Larger

Cohen's d effect sizes for ME and related engineering skills across degree pairings (bachelor’s, master’s, and doctoral) highlight substantial differences in skill proportionality between job advertisements with different requisite educational levels. Skills such as Drafting and Engineering Design (Bachelor's vs Doctoral: Cohen's d = 10.385, large effect) and Engineering Practices (Bachelor's vs Doctoral: Cohen's d = 5.982, large effect) exhibit significant effect sizes, indicating that job advertisements with bachelor’s degrees as a minimum expectation demonstrate higher proportionality in these foundational areas compared to jobs requiring Doctoral degrees. Similarly, skills like Engineering Management (Bachelor's vs Master's: Cohen's d = 2.829, large effect) and Hardware Description Languages (Bachelor's vs Master's: Cohen's d = 3.491, large effect) show notable differences across degree requirements.

For some skills, the differences are moderate but still meaningful. For example, Process Engineering (Doctoral vs Master's: Cohen's d = 1.062, large effect) and Robotics (Doctoral vs Master's: Cohen's d = 0.713, medium effect) suggest different proportionality for jobs requiring Doctoral degrees. Conversely, specific skills exhibit minimal differences, such as Automation Engineering (Bachelor's vs Master's: Cohen's d = 0.127, small effect) and Circuitry (Doctoral vs Master's: Cohen's d = 0.172, small effect), where skill levels are nearly equivalent across degree levels.

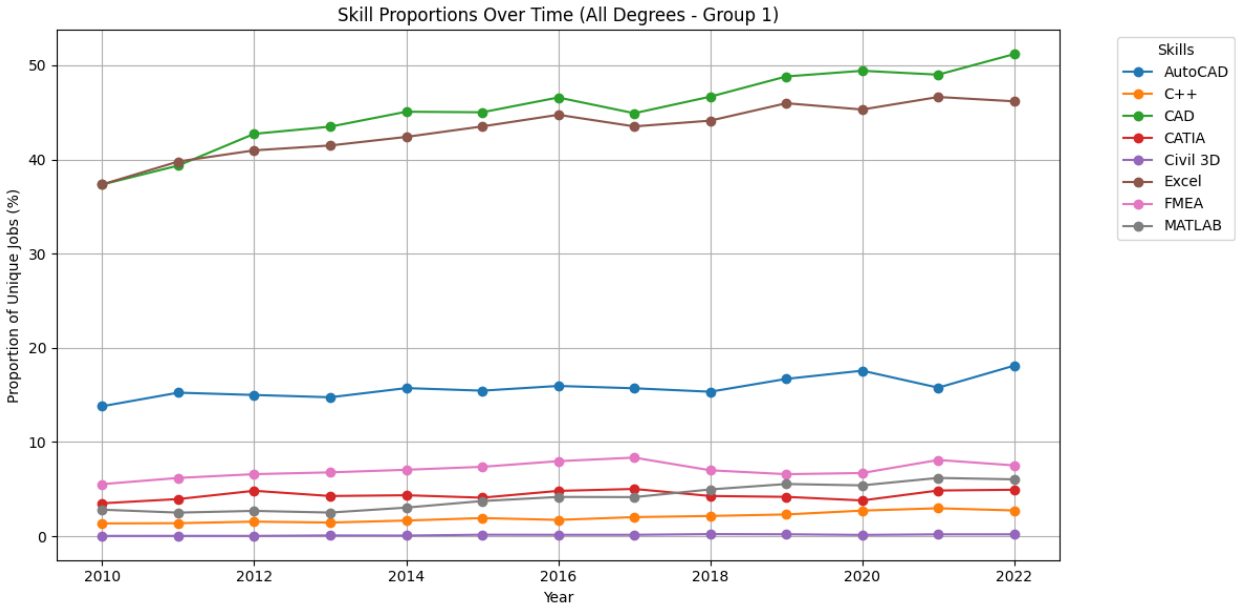
4.7.1 Mechanical Engineering Technical Skills

Table 4.23 highlights the technical skills required for ME jobs at different degree levels: bachelor’s, master’s, and doctoral. Skills like Excel, CAD, and AutoCAD are consistently in demand across all levels, though the extent varies. For instance, Excel is most required at the doctoral level (48.12%) compared to bachelor’s (43.62%) and master’s (41.75%). Advanced skills such as MATLAB and Python are more prevalent in doctoral (14.13% and 8.50%, respectively) and master’s roles (13.72% and 6.35%) compared to bachelor's (3.78% and 1.77%). On the other hand, practical skills like AutoCAD (16.45%) and SolidWorks (18.24%) appear more frequently in bachelor's-level job advertisements, reflecting their importance in bachelor's roles

Table 4.23: Technical Skill Proportions in ME Job Ads (2010-2022)

Skill	Bachelor's (%)	Master's (%)	Doctoral (%)
AutoCAD	16.45	8.07	2.47
C++	1.74	7.38	9.72
CAD	46.31	39.84	37.48
CATIA	4.53	2.91	1.11
Civil 3D	0.14	0.08	0.02
Excel	43.62	41.75	48.12
FMEA	7.18	7.31	2.64
MATLAB	3.78	13.72	14.13
Microsoft Office	11.22	5.36	2.12
Microsoft Project	1.17	0.46	0.45
PLC	2.55	1.63	0.47
Python	1.77	6.35	8.50
Revit	5.14	0.97	0.29
SCADA	0.37	0.18	0.18
SQL	0.68	0.95	1.26
SolidWorks	18.24	15.16	7.44

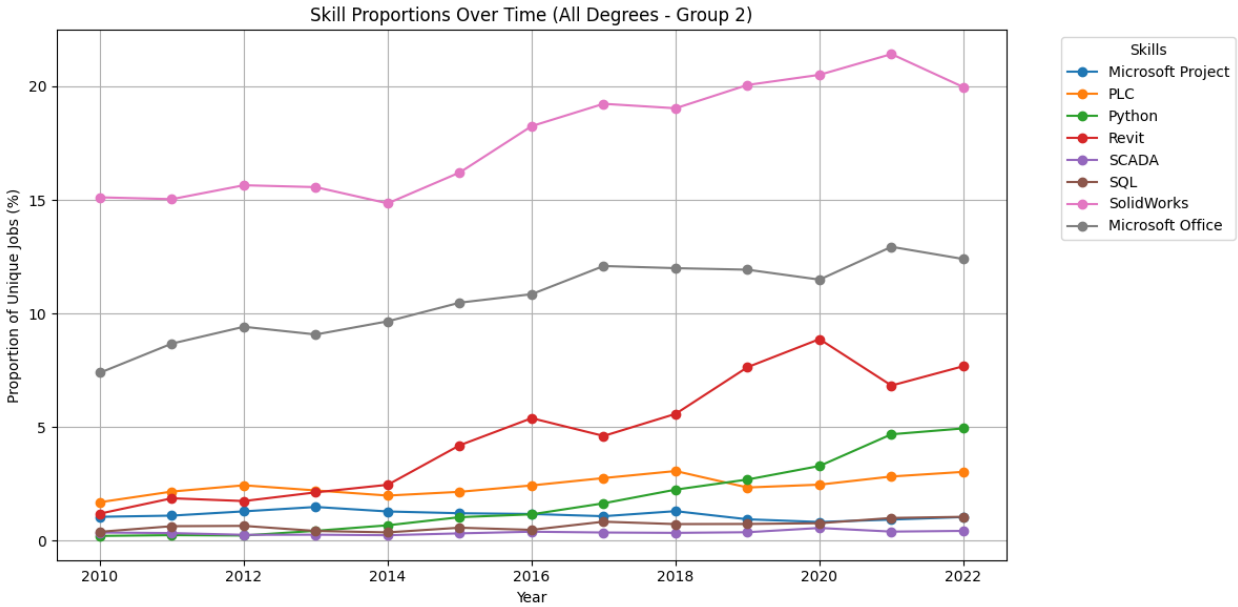
Figure 4.40: Trends in Technical Skills Over Time in ME Job Ads (Group 1)



Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

Figure 4.40 illustrates the trends in the proportions of selected technical skills required in ME job advertisements over time, combining data for all degree levels (bachelor's, master's, and doctoral). It highlights how specific skills, such as Excel and CAD, consistently dominate the demand across the years, with CAD maintaining the highest proportion, followed closely by Excel. Other skills like AutoCAD and MATLAB show steady but lower trends, reflecting their specialized applications in ME roles. Meanwhile, skills such as FMEA, C++, and CATIA remain less prevalent throughout the period, indicating their niche relevance in specific technical contexts.

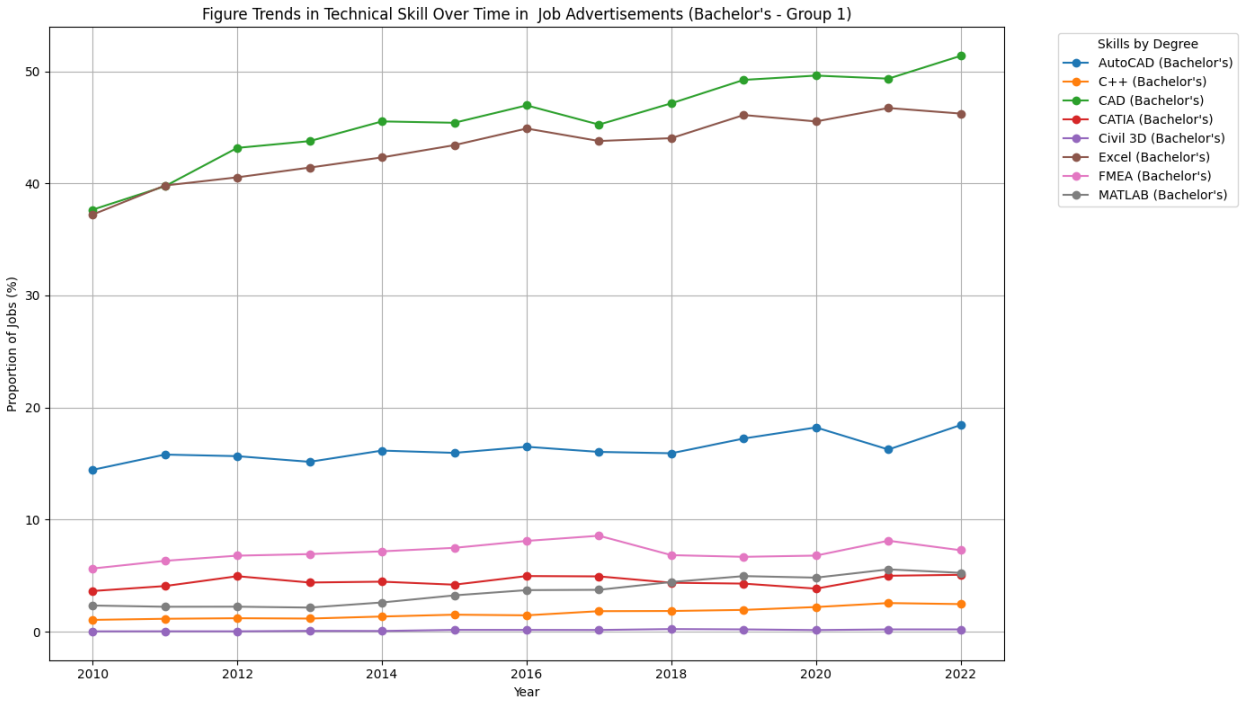
Figure 4.41: Trends in Technical Skills Over Time in ME Job Ads (Group 2)



Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

Figure 4.41 illustrates the trends in the proportions of selected technical skills required in ME job advertisements over time, combining data for all degree levels (bachelor's, master's, and doctoral). It highlights how specific skills, such as SolidWorks and Microsoft Office, consistently dominate the demand across the years, with SolidWorks maintaining the highest proportion. Other skills like Python and Revit show steady growth, reflecting their increasing relevance in ME roles, particularly in design and programming applications. Meanwhile, skills such as PLC, SQL, and SCADA remain less prevalent throughout the period, indicating their specialized nature within ME job requirements.

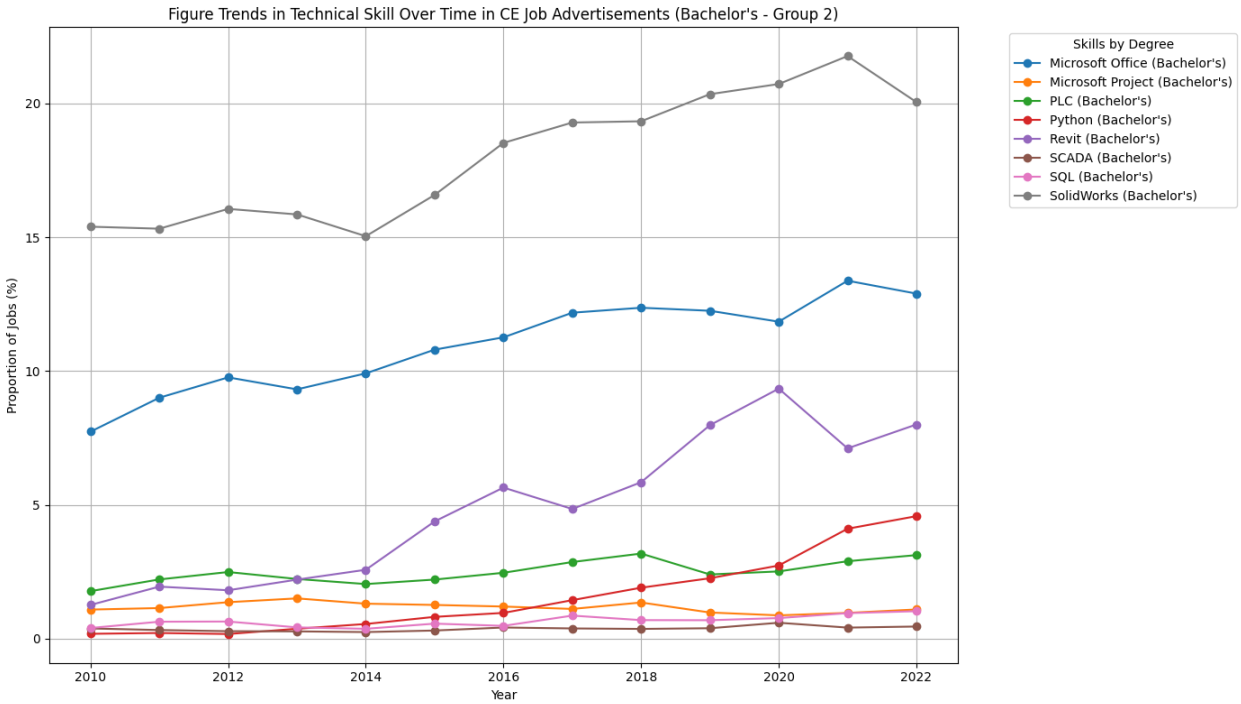
Figure 4.42: Trends in Technical Skills Over Time in ME Job Ads (Bachelor's - Group 1)



Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

Figure 4.42 shows the trends in the proportions of selected technical skills required in ME job advertisements for bachelor's-level positions from 2010 to 2022. Skills like Excel and CAD consistently show high demand, with CAD maintaining the highest proportion throughout the years. AutoCAD also demonstrates steady demand, reflecting its importance in design-related roles. In contrast, skills such as MATLAB, C++, and FMEA have lower proportions, indicating their specialized applications in specific ME tasks. Skills like CATIA and Civil 3D remain the least prevalent, suggesting limited demand in bachelor's-level ME job postings.

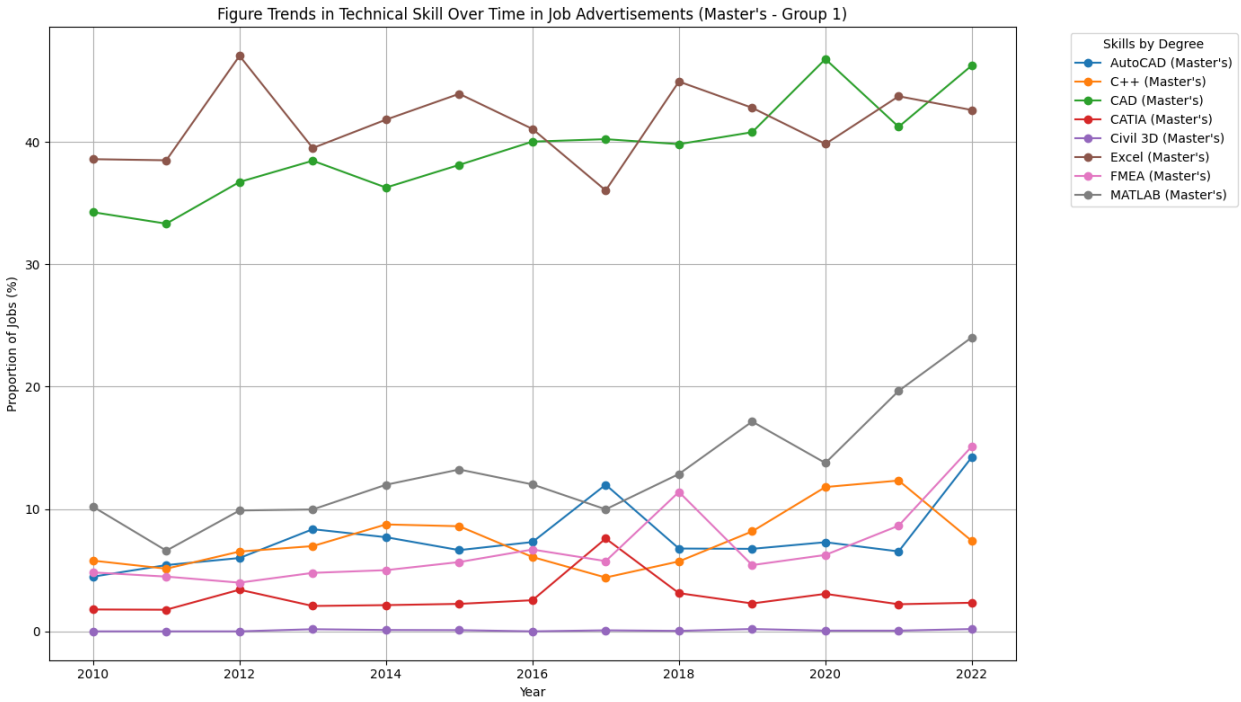
Figure 4.43: Trends in Technical Skills Over Time in ME Job Ads (Bachelor's - Group 2)



Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

Figure 4.43 shows the trends in the proportions of selected technical skills required in ME job advertisements for bachelor's-level positions from 2010 to 2022. Skills like Microsoft Office and SolidWorks consistently show high demand, with SolidWorks maintaining the highest proportion throughout the years. Python and PLC have shown noticeable growth, reflecting the increasing importance of programming and automation tools in ME roles. In contrast, skills such as Microsoft Project, SCADA, and SQL have lower but steady demand, indicating more specialized applications. Revit also shows gradual growth, suggesting its rising relevance in specific technical areas within ME.

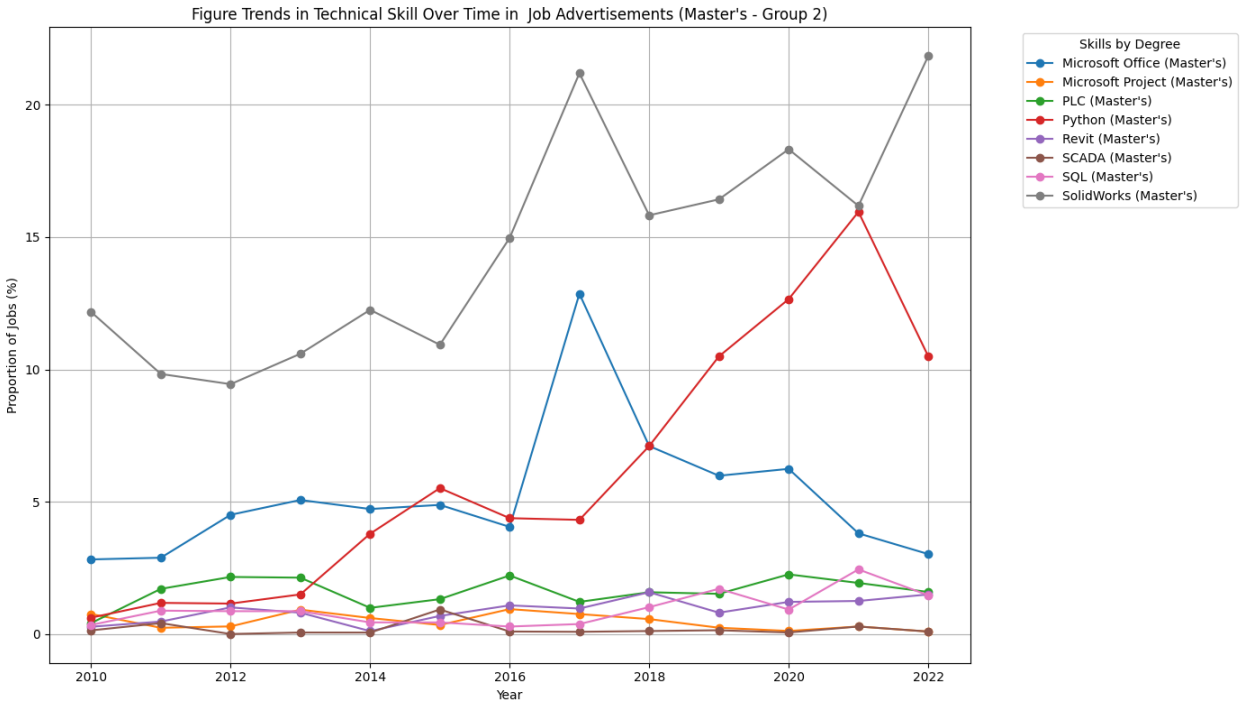
Figure 4.44: Trends in Technical Skills Over Time in ME Job Ads (Master's - Group 1)



Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

Figure 4.44 illustrates the trends in the proportions of selected technical skills required in ME job advertisements for master's-level positions from 2010 to 2022. Skills like Excel and CAD consistently show high demand, with Excel maintaining the highest proportion throughout the years. MATLAB has shown noticeable growth, reflecting its increasing importance in advanced analytical and simulation tasks for master's-level roles. In contrast, skills such as AutoCAD, C++, and FMEA display steady but lower trends, indicating more specialized applications. CATIA and Civil 3D remain the least prevalent, highlighting their limited demand in master-level ME job postings.

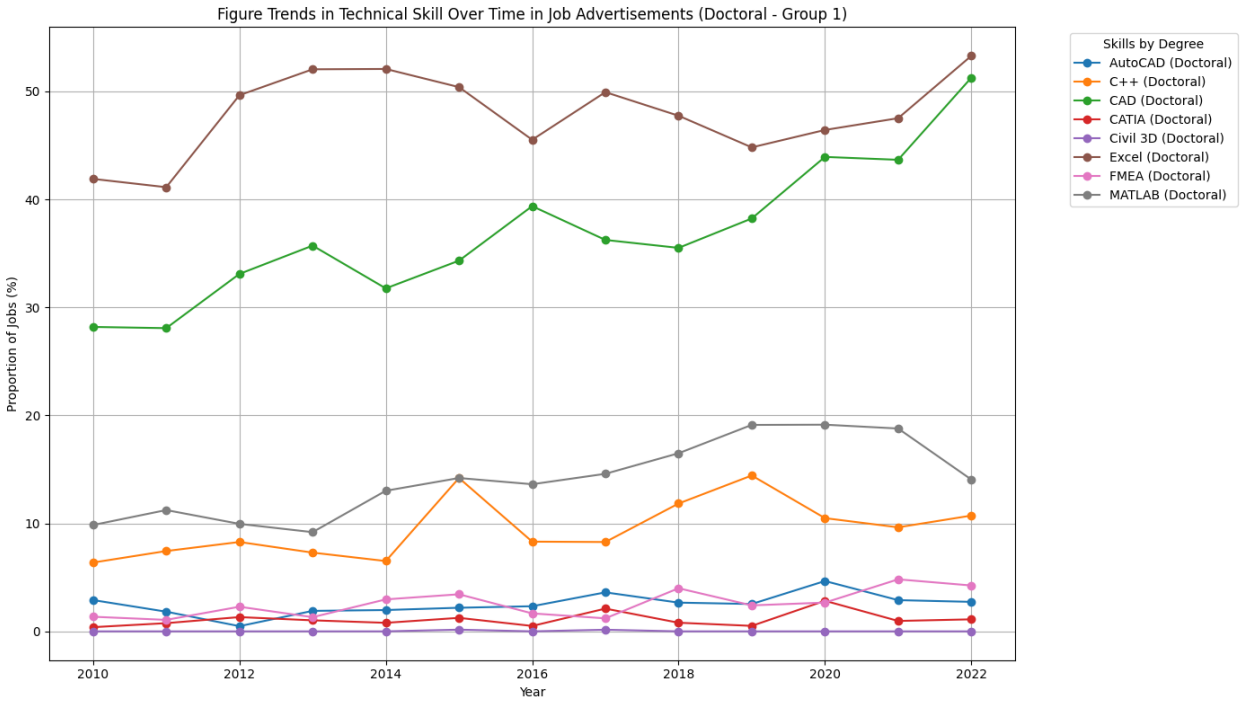
Figure 4.45: Trends in Technical Skills Over Time in ME Job Ads (Master's - Group 2)



Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

Figure 4.45 presents the trends in the proportions of selected technical skills required in ME job advertisements for master's-level positions from 2010 to 2022. SolidWorks and Microsoft Office consistently show strong demand, with SolidWorks experiencing noticeable growth over time. Python has also shown a significant upward trend, reflecting its increasing importance in programming and data analysis for advanced engineering roles. In contrast, skills like Microsoft Project, SCADA, and SQL maintain lower but steady proportions, indicating their specialized applications. PLC and Revit display gradual growth, highlighting their expanding relevance in specific technical domains within ME.

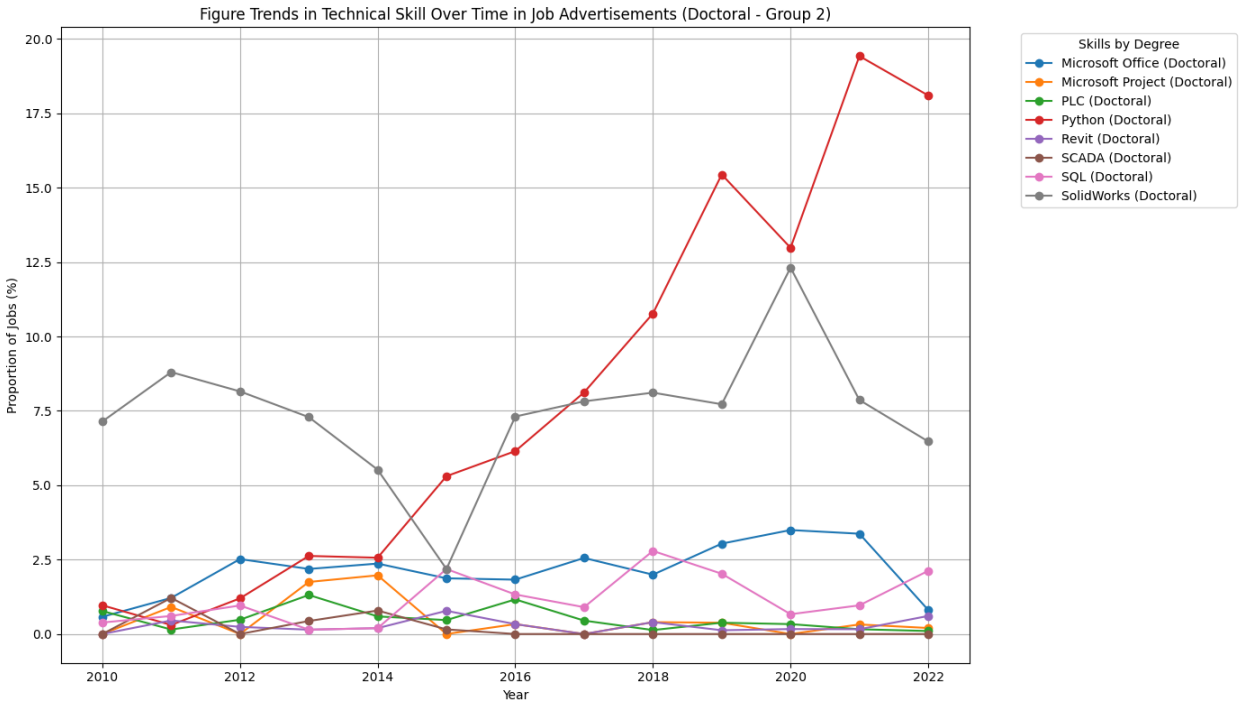
Figure 4.46: Trends in Technical Skills Over Time in ME Job Ads (Doctoral - Group 1)



Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

Figure 4.46 shows the trends in the proportions of selected technical skills required in ME job advertisements for doctoral-level positions from 2010 to 2022. Excel and CAD consistently dominate the demand, maintaining the highest proportion throughout the years, reflecting its critical role in data management and analysis. MATLAB shows a steady upward trend, highlighting its growing significance in advanced modeling and simulation tasks. In contrast, skills like AutoCAD, FMEA, and C++ have moderate and stable trends, indicating their specialized but consistent relevance in doctoral-level ME roles. Meanwhile, skills such as CATIA and Civil 3D remain less prominent, pointing to niche applications within specialized research areas.

Figure 4.47: Trends in Technical Skills Over Time in ME Job Ads (Doctoral - Group 2)



Note: the y-axes of the plots need to be taken into consideration when interpreting changes across plots

Figure 4.47 represents the trends in the proportions of selected technical skills required in ME job advertisements for doctoral-level positions from 2010 to 2022. Python shows a significant upward trend, reflecting its growing importance in data analysis, programming, and research applications. SolidWorks and Microsoft Office maintain steady demand, indicating their continued relevance in design and productivity tasks. In contrast, skills like Microsoft Project, SCADA, and SQL show lower but stable proportions, suggesting specialized applications within specific ME domains. PLC and Revit remain less prominent, indicating their niche roles in advanced engineering projects.

4.7.2 Summary of ME Job Posting Analysis

This section examines the distribution of ME degrees and skill demands across bachelor's, master's, and doctoral levels from 2010 to 2022. Bachelor's degrees dominate the job advertisements, accounting for 662,121 (94.89%) of the 697,810 degrees recorded, compared to 26,822 (3.84%) for master's and 8,867 (1.27%) for Doctoral degrees. The top 30 ME skills highlight the dominance of Drafting and Engineering Design, Project Management, and Engineering Practices, emphasizing their importance in technical execution and project oversight. Other notable skills, such as Microsoft Office, Product Development, and Equipment Maintenance, reflect the need for digital tools, manufacturing expertise, and operational efficiency. Less common skills like Writing, Basic Customer Service, and Procurement underscore the growing emphasis on communication, client relations, and supply chain management.

Skill demands vary across educational levels. For entry-level roles, jobs requiring bachelor's degrees focus on technical skills like Drafting, Engineering Software, and PLC. master's degrees integrate technical knowledge with managerial competencies, including Project Management and advanced tools such as MATLAB and Python. Doctoral degrees emphasize specialized, research-driven skills like Process Engineering, HDL, and Signal Processing, highlighting the need for advanced expertise in theoretical and applied ME domains. From 2010 to 2022, skills like Python, Project Management, and MATLAB have seen notable growth, reflecting the increasing influence of digital transformation, data analysis, and advanced design technologies in ME.

The analysis of technical skills in ME from 2010 to 2022 reveals essential trends across degree levels. Foundational skills such as Excel, CAD, and AutoCAD remain crucial at all levels, with the highest demand at the bachelor's level, reflecting a focus on practical, entry-level competencies. Master's-level roles balance technical expertise with leadership responsibilities, relying more on advanced tools like MATLAB, Python, and Revit. Doctoral roles focus on specialized and research-intensive skills, with tools like Signal Processing, HDL, and SQL becoming increasingly important for advanced analysis and design tasks. Over time, the demand for digital tools such as Python and MATLAB, alongside managerial skills like Project Management, has grown, reflecting the dynamic nature of ME and the increasing complexity of engineering projects.

4.8 Comparative Analysis of Engineering Skills by Degree and Discipline

In this section, I examine differences in BGT engineering skills proficiencies across degree programs in CE/EE/ME engineering fields. To assess these differences, I first applied an analysis of variance (ANOVA) to determine whether significant variations exist across the majors. I then used Cohen's d to quantify the magnitude of the differences. These analyses were conducted separately for bachelor's, master's, and doctoral levels.

4.8.1 Bachelor's Level

ANOVA (Table 4.24) was conducted to examine differences in skill proficiency across Bachelor's degree programs in CE, EE, and ME. The analysis revealed statistically significant differences (all $p < 0.001$) across all 20 skills evaluated, with large effect sizes as indicated by the F-statistics (range: $F = 45.27$ to 1716.34; $df = 2, 36$). Post hoc pairwise comparisons using Cohen's d (Table 4.22) further elucidated the magnitude of differences between majors. Effect sizes were predominantly large ($|d| \geq 0.80$), with exceptions in engineering practices (CE vs. EE: $d = 0.74$, medium) and radio frequency equipment (CE vs. ME: $d = 0.52$, medium). These results show distinct skills across majors, with CE emphasizing civil infrastructure, EE excelling in electronic systems, and ME prioritizing mechanical and automotive applications. The significance of ANOVA outcomes ($p < 0.001$) and the large Cohen's d values highlight robust disciplinary differentiation in skill requirements as appearing in job advertisements across engineering fields.

Table 4.24: ANOVA for Engineering Skill Across CE/EE/ME (Bachelor's Level)

Skill	F	df	p	Significant
Automation Engineering	628.52	2, 36	0	Yes
Automotive Technologies	56.7	2, 36	0	Yes
Circuitry	1716.34	2, 36	0	Yes
Drafting and Engineering Design	139.84	2, 36	0	Yes
Electronic Hardware	450.34	2, 36	0	Yes
Engineering Management	45.27	2, 36	0	Yes
Engineering Practices	54.38	2, 36	0	Yes
Engineering Software	194.7	2, 36	0	Yes
Geotechnical Engineering	898.44	2, 36	0	Yes
Hardware Description Languages	488.67	2, 36	0	Yes
Imaging	68.35	2, 36	0	Yes
Optical Engineering	77.02	2, 36	0	Yes
Process Engineering	172.69	2, 36	0	Yes

Table 4.24: Continued

Radio Frequency (RF)	115.93	2, 36	0	Yes
Radio Frequency Equipment	103.96	2, 36	0	Yes
Roads and Drainage	388.32	2, 36	0	Yes
Robotics	90.58	2, 36	0	Yes
Signal Processing	357.14	2, 36	0	Yes
Simulation	170.8	2, 36	0	Yes
Surveying	82.09	2, 36	0	Yes

Table 4.25: Cohen's d for Engineering Skills in CE/EE/ME (Bachelor's Level)

Skill	Major Pair	Cohen's d	Effect Size	Larger Group
Automation Engineering	CE vs EE	12.95	Large	EE
Automation Engineering	CE vs ME	3.86	Large	ME
Automation Engineering	EE vs ME	8.59	Large	EE
Automotive Technologies	CE vs EE	2.79	Large	EE
Automotive Technologies	CE vs ME	3.77	Large	ME
Automotive Technologies	EE vs ME	1.52	Large	ME
Circuitry	CE vs EE	17.04	Large	EE
Circuitry	CE vs ME	4.63	Large	ME
Circuitry	EE vs ME	15.78	Large	EE
Drafting and Engineering Design	CE vs EE	4.63	Large	CE
Drafting and Engineering Design	CE vs ME	0.74	Medium	ME
Drafting and Engineering Design	EE vs ME	8.57	Large	ME
Electronic Hardware	CE vs EE	9.95	Large	EE
Electronic Hardware	CE vs ME	3.63	Large	ME
Electronic Hardware	EE vs ME	7.45	Large	EE
Engineering Management	CE vs EE	3.38	Large	CE
Engineering Management	CE vs ME	1.8	Large	CE
Engineering Management	EE vs ME	2.33	Large	ME
Engineering Practices	CE vs EE	0.74	Medium	CE
Engineering Practices	CE vs ME	2.88	Large	ME

Table 4.25: Continued

Engineering Practices	EE vs ME	3.45	Large	ME
Engineering Software	CE vs EE	4.65	Large	CE
Engineering Software	CE vs ME	7.86	Large	CE
Engineering Software	EE vs ME	2.82	Large	EE
Geotechnical Engineering	CE vs EE	11.97	Large	CE
Geotechnical Engineering	CE vs ME	11.67	Large	CE
Geotechnical Engineering	EE vs ME	1.56	Large	ME
Hardware Description Languages	CE vs EE	8.91	Large	EE
Hardware Description Languages	CE vs ME	5.43	Large	ME
Hardware Description Languages	EE vs ME	8.44	Large	EE
Imaging	CE vs EE	3.84	Large	EE
Imaging	CE vs ME	2.29	Large	ME
Imaging	EE vs ME	2.74	Large	EE
Optical Engineering	CE vs EE	4.58	Large	EE
Optical Engineering	CE vs ME	3.48	Large	ME
Optical Engineering	EE vs ME	2.22	Large	EE
Process Engineering	CE vs EE	5.71	Large	EE
Process Engineering	CE vs ME	7.01	Large	ME
Process Engineering	EE vs ME	0.74	Medium	EE
Radio Frequency (RF)	CE vs EE	4.26	Large	EE
Radio Frequency (RF)	CE vs ME	0.92	Large	ME
Radio Frequency (RF)	EE vs ME	4.2	Large	EE
Radio Frequency Equipment	CE vs EE	3.99	Large	EE
Radio Frequency Equipment	CE vs ME	0.52	Medium	CE
Radio Frequency Equipment	EE vs ME	4.02	Large	EE
Roads and Drainage	CE vs EE	7.75	Large	CE
Roads and Drainage	CE vs ME	7.71	Large	CE
Roads and Drainage	EE vs ME	1.83	Large	ME
Robotics	CE vs EE	5.04	Large	EE
Robotics	CE vs ME	5.42	Large	ME

Table 4.25: Continued

Robotics	EE vs ME	0.55	Medium	ME
Signal Processing	CE vs EE	8.05	Large	EE
Signal Processing	CE vs ME	5.36	Large	ME
Signal Processing	EE vs ME	6.82	Large	EE
Simulation	CE vs EE	7.29	Large	EE
Simulation	CE vs ME	4.18	Large	ME
Simulation	EE vs ME	3.41	Large	EE
Surveying	CE vs EE	3.71	Large	CE
Surveying	CE vs ME	4.02	Large	CE
Surveying	EE vs ME	0.59	Medium	EE

4.8.2 Master's Level

An ANOVA (Table 4.26) was conducted to examine differences in skills listed in job advertisements across postings requiring a master's degree in CE, EE, and ME. The analysis revealed statistically significant differences (all $p < 0.001$) across 20 skills, with large effect sizes indicated by the F-statistics (range: $F = 3.94$ to 753.50; $df = 2, 21–36$). Post-hoc comparisons using Cohen's d (Table 4.24) further elucidated the magnitude and direction of differences between majors.

Effect sizes were predominantly large ($|d| \geq 0.80$), with exceptions in skills like Engineering Practices (CE vs. ME: $d = 0.53$, medium) and Radio Frequency Equipment (CE vs. ME: $d = 0.42$, medium). These results underscore the distinct skill specializations among engineering disciplines: CE emphasizes civil systems and infrastructure, EE focuses on electronic and signal processing expertise, and ME excels in mechanical and automotive applications. Robust ANOVA outcomes ($p < 0.001$) and large Cohen's d values reflect significant differentiation in skill requirements as apparent in job advertisements across these engineering fields.

Table 4.26: ANOVA for Engineering Skill Across CE/EE/ME (Master's Level)

Skill	F	df	p	Significant
Circuitry	551.08	2, 35	0	Yes
Drafting and Engineering Design	283.49	2, 36	0	Yes
Electronic Hardware	78.76	2, 35	0	Yes
Engineering Management	45.62	2, 36	0	Yes
Engineering Practices	38.08	2, 36	0	Yes
Engineering Software	108.41	2, 36	0	Yes
Geotechnical Engineering	753.5	2, 33	0	Yes
Imaging	63.57	2, 33	0	Yes
Process Engineering	116.51	2, 36	0	Yes
Radio Frequency (RF)	314.19	2, 32	0	Yes
Roads and Drainage	526.31	2, 31	0	Yes
Signal Processing	398.29	2, 36	0	Yes
Simulation	256.57	2, 36	0	Yes
Surveying	12.63	2, 35	0	Yes
Automation Engineering	73.12	2, 32	0	Yes
Automotive Technologies	22.19	2, 35	0	Yes
Hardware Description Languages	166.81	2, 30	0	Yes
Robotics	48.63	2, 31	0	Yes
Optical Engineering	3.94	2, 26	0.032	Yes
Radio Frequency Equipment	16.4	2, 21	0	Yes

Table 4.27: Cohen's d for Engineering Skills in CE/EE/ME (Master's Level)

Skill	Major Pair	Cohen's d	Effect Size	Larger Group
Circuitry	CE vs EE	9.60	Large	EE
Circuitry	CE vs ME	3.81	Large	ME
Circuitry	EE vs ME	9.11	Large	EE
Drafting and Engineering Design	CE vs EE	7.14	Large	CE
Drafting and Engineering Design	CE vs ME	0.97	Large	ME
Drafting and Engineering Design	EE vs ME	9.74	Large	ME
Electronic Hardware	CE vs EE	4.85	Large	EE
Electronic Hardware	CE vs ME	1.77	Large	ME
Electronic Hardware	EE vs ME	2.92	Large	EE
Engineering Management	CE vs EE	3.78	Large	CE
Engineering Management	CE vs ME	2.45	Large	CE
Engineering Management	EE vs ME	1.00	Large	ME
Engineering Practices	CE vs EE	3.06	Large	CE
Engineering Practices	CE vs ME	0.53	Medium	ME
Engineering Practices	EE vs ME	3.09	Large	ME
Engineering Software	CE vs EE	5.07	Large	CE
Engineering Software	CE vs ME	3.84	Large	CE
Engineering Software	EE vs ME	1.77	Large	ME
Geotechnical Engineering	CE vs EE	11.27	Large	CE
Geotechnical Engineering	CE vs ME	10.99	Large	CE
Geotechnical Engineering	EE vs ME	0.65	Medium	ME
Imaging	CE vs EE	4.57	Large	EE
Imaging	CE vs ME	1.98	Large	ME
Imaging	EE vs ME	2.61	Large	EE
Process Engineering	CE vs EE	6.60	Large	EE
Process Engineering	CE vs ME	5.28	Large	ME
Process Engineering	EE vs ME	0.26	Medium	ME
Radio Frequency (RF)	CE vs EE	7.60	Large	EE
Radio Frequency (RF)	CE vs ME	1.91	Large	ME

Table 4.27: Continued

Radio Frequency (RF)	EE vs ME	7.33	Large	EE
Roads and Drainage	CE vs EE	9.25	Large	CE
Roads and Drainage	CE vs ME	9.86	Large	CE
Roads and Drainage	EE vs ME	0.42	Medium	ME
Signal Processing	CE vs EE	9.01	Large	EE
Signal Processing	CE vs ME	4.89	Large	ME
Signal Processing	EE vs ME	6.90	Large	EE
Simulation	CE vs EE	8.38	Large	EE
Simulation	CE vs ME	6.30	Large	ME
Simulation	EE vs ME	3.75	Large	EE
Surveying	CE vs EE	0.83	Large	CE
Surveying	CE vs ME	1.85	Large	CE
Surveying	EE vs ME	1.55	Large	EE
Automation Engineering	CE vs EE	4.66	Large	EE
Automation Engineering	CE vs ME	2.86	Large	ME
Automation Engineering	EE vs ME	2.76	Large	EE
Automotive Technologies	CE vs EE	1.83	Large	EE
Automotive Technologies	CE vs ME	2.86	Large	ME
Automotive Technologies	EE vs ME	0.91	Large	ME
Hardware Description Languages	CE vs EE	5.39	Large	EE
Hardware Description Languages	CE vs ME	3.23	Large	ME
Hardware Description Languages	EE vs ME	5.62	Large	EE
Robotics	CE vs EE	3.00	Large	EE
Robotics	CE vs ME	3.99	Large	ME
Robotics	EE vs ME	2.04	Large	ME
Optical Engineering	CE vs EE	2.12	Large	EE
Optical Engineering	CE vs ME	1.54	Large	ME
Optical Engineering	EE vs ME	0.06	Small	EE
Radio Frequency Equipment	CE vs EE	1.82	Large	EE
Radio Frequency Equipment	CE vs ME	0.42	Medium	CE
Radio Frequency Equipment	EE vs ME	2.30	Large	EE

4.8.3 Doctoral Level

Finally, an ANOVA (Table 4.28) was conducted to examine differences in skill proficiency across job postings that require a doctorate for CE, EE, and ME jobs. Statistically significant differences were found across 16 of the 20 skills evaluated (all $p < 0.05$), with large effect sizes as indicated by the F-statistics (range: $F = 6.01$ to 354.34; df = 2, 36). Then, Cohen's d (Table 4.26) revealed notable differences in the magnitude and direction of skill proficiency among the majors. Effect sizes were predominantly large ($|d| \geq 0.80$), with a few medium effects observed, such as Imaging (CE vs. ME: $d = 0.44$) and Automotive Technologies (EE vs. ME: $d = 0.69$). These findings underscore the distinct skill specializations across doctoral programs, with EE excelling in electronic and automation domains, CE emphasizing infrastructure and geotechnical expertise, and ME focusing on manufacturing and mechanical applications.

Table 4.28: ANOVA for Engineering Skill Across CE/EE/ME (Doctoral Level)

Skill	F	df	p	Significant
Circuitry	247.08	2, 29	0	Yes
Drafting and Engineering Design	32.67	2, 36	0	Yes
Electronic Hardware	29.74	2, 25	0	Yes
Engineering Management	3.06	2, 36	0.059	No
Engineering Practices	6.35	2, 36	0.004	Yes
Engineering Software	29.38	2, 36	0	Yes
Geotechnical Engineering	34.07	2, 16	0	Yes
Roads and Drainage	6.01	1, 13	0.029	Yes
Robotics	18.73	2, 28	0	Yes
Simulation	266.97	2, 36	0	Yes
Automation Engineering	40.92	2, 28	0	Yes
Signal Processing	354.34	2, 33	0	Yes
Hardware Description Languages	63.39	2, 23	0	Yes
Process Engineering	10.98	2, 28	0	Yes
Imaging	14.1	2, 29	0	Yes
Surveying	8.74	2, 25	0.001	Yes
Automotive Technologies	1.2	2, 28	0.317	No
Radio Frequency (RF)	33.01	2, 20	0	Yes
Optical Engineering	0.01	1, 21	0.927	No

Table 4.29: Cohen's d for Engineering Skills in CE/EE/ME (Doctoral Level)

Skill	Major Pair	Cohen's d	Effect Size	Larger Group
Circuitry	CE vs EE	6.52	Large	EE
Circuitry	CE vs ME	0.59	Medium	ME
Circuitry	EE vs ME	7.22	Large	EE
Drafting and Engineering Design	CE vs EE	2.37	Large	CE
Drafting and Engineering Design	CE vs ME	0.15	Small	ME
Drafting and Engineering Design	EE vs ME	4.70	Large	ME
Electronic Hardware	CE vs EE	2.41	Large	EE
Electronic Hardware	CE vs ME	1.23	Large	ME
Electronic Hardware	EE vs ME	2.81	Large	EE
Engineering Management	CE vs EE	0.72	Medium	CE
Engineering Management	CE vs ME	0.71	Medium	CE
Engineering Management	EE vs ME	0.07	Small	ME
Engineering Practices	CE vs EE	1.10	Large	CE
Engineering Practices	CE vs ME	0.16	Small	CE
Engineering Practices	EE vs ME	1.60	Large	ME
Engineering Software	CE vs EE	2.51	Large	CE
Engineering Software	CE vs ME	1.58	Large	CE
Engineering Software	EE vs ME	2.46	Large	ME
Geotechnical Engineering	CE vs EE	3.82	Large	CE
Geotechnical Engineering	CE vs ME	3.80	Large	CE
Geotechnical Engineering	EE vs ME	0.82	Large	ME
Roads and Drainage	CE vs ME	1.58	Large	CE
Robotics	CE vs EE	1.55	Large	EE
Robotics	CE vs ME	2.83	Large	ME
Robotics	EE vs ME	1.58	Large	ME
Simulation	CE vs EE	8.74	Large	EE
Simulation	CE vs ME	3.95	Large	ME
Simulation	EE vs ME	5.38	Large	EE
Automation Engineering	CE vs EE	2.74	Large	EE
Automation Engineering	CE vs ME	0.22	Medium	ME
Automation Engineering	EE vs ME	3.12	Large	EE

Table 4.29: Continued

Signal Processing	CE vs EE	8.82	Large	EE
Signal Processing	CE vs ME	1.75	Large	ME
Signal Processing	EE vs ME	7.73	Large	EE
Hardware Description Languages	CE vs EE	NaN	Large	EE
Hardware Description Languages	CE vs ME	NaN	Large	CE
Hardware Description Languages	EE vs ME	4.44	Large	EE
Process Engineering	CE vs EE	0.91	Large	EE
Process Engineering	CE vs ME	1.95	Large	ME
Process Engineering	EE vs ME	1.44	Large	ME
Imaging	CE vs EE	1.62	Large	EE
Imaging	CE vs ME	0.44	Medium	ME
Imaging	EE vs ME	1.71	Large	EE
Surveying	CE vs EE	1.32	Large	CE
Surveying	CE vs ME	1.72	Large	CE
Surveying	EE vs ME	0.63	Medium	EE
Automotive Technologies	CE vs EE	0.14	Small	CE
Automotive Technologies	CE vs ME	0.38	Medium	ME
Automotive Technologies	EE vs ME	0.69	Medium	ME
Radio Frequency (RF)	CE vs EE	1.33	Large	EE
Radio Frequency (RF)	CE vs ME	3.84	Large	CE
Radio Frequency (RF)	EE vs ME	4.03	Large	EE
Optical Engineering	EE vs ME	0.04	Small	EE

4.8.4 Summary of the Comparative Analysis

This study examined differences in engineering skill proficiencies across Civil (CE), Electrical (EE), and Mechanical (ME) Engineering programs at bachelor's, master's, and doctoral levels using ANOVA and Cohen's d analyses. Results revealed robust disciplinary specialization patterns, with statistically significant differences ($p < 0.001$ at bachelor's/master's; $p < 0.05$ for 16/20 skills at doctoral) and predominantly large effect sizes (Cohen's $d \geq 0.8$), showing distinct skill acquisition as apparent in job advertisements aligned with each discipline's focus. These findings show that CE, EE, and ME cultivate distinct expertise hierarchies that reflect their respective industrial and academic priorities. Such differentiation shows the need for tailored curricula to address evolving workforce demands while preserving core disciplinary identities

Chapter Five: Discussion and Conclusion

5.0 Introduction

This research aims to illuminate evolving workforce demands by systematically analyzing skill demands appearing in online job postings. Curriculum leaders could then use the findings to consider alignment or misalignment with engineering curricula. Thus, my research contributes to conversations regarding challenges in aligning skills learned in higher education with rapid technological advancements and shifting employer expectations (Fiore et al., 2017; Mitchell et al., 2021). To achieve this goal, the study first employed a Natural Language Processing (NLP) classification system designed to resolve inconsistencies in occupational coding (e.g., SOC code in BGT dataset) within large-scale datasets. This system utilized pattern-based text analysis and regex matching to enhance the precision of skill mapping across engineering disciplines, including civil, electrical, and mechanical engineering, thereby improving the quality of the dataset used in this research and generating detailed insights into employer priorities.

Guided by the SABER-WfD conceptual framework (Tan et al., 2013), this dissertation provides an understanding of the demand side of workforce development by examining over a decade of job postings (2010–2022). While prior studies have predominantly focused on educational supply-side factors like curricular content (Hadgraft & Kolmos, 2020; Seely, 2005), this work shifts attention to employer-driven skill requirements, operationalized through Burning Glass Technologies (BGT) data. This approach identifies critical technical skills (e.g., Python) and engineering skills (e.g., BGT defined Engineering Management, Simulation) while revealing how skill prioritization varies across disciplines and degree levels over time. For example, SolidWorks is prioritized more in ME than in EE or CE, with its emphasis varying across ME degree levels in terms of proportional appearance in job advertisements. The findings in this study provide insights for curriculum designers and engineering program leaders to bridge the gap between academic preparation and workplace needs.

The significance of this work lies in its integration of big data analytics with the SABER-WfD conceptual framework, combined with an NLP classification framework that provides a replicable model for categorizing fields using pre-classified data, such as the BGT job posting dataset. According to Fleming et al. (2024), systematically categorizing in-demand skills in online job postings provides one window into understanding the specific skill employers seek. The findings of this research can support research, practice, and curricular alignment with workforce demands.

5.0.1 Chapter Overview

As presented in the previous chapter, the analysis was divided into two parts. The first part addressed the initial research question: "*RQ1: How well can pattern-based text classification and flexible regex matching be used to categorize job postings into engineering disciplines (e.g., civil, electrical, and mechanical engineering)?*" Addressing this research question involved evaluating the performance of the NLP classification framework using a confusion matrix to assess its ability to distinguish relevant fields (e.g., CE, EE, and ME) from non-relevant ones. Specifically, the framework determined whether a job posting belonged to one of these three engineering disciplines or not. This step was critical to ensure the dataset's reliability and readiness for the second part of the analysis–using the BGT data set's disciplinary categorization would have included erroneous job postings.

The evaluation provided key performance metrics, including precision, recall, and F1-score, to quantify the effectiveness of the classification. The results were highly promising, with the framework achieving an F1-score of 94.19% for CE, 91.67% for EE, and 93.02% for ME when applied to the SOC pre-classified BGT dataset. According to existing research, an F1-score above 0.9 is generally considered excellent for text classification tasks, as it reflects a strong balance between precision and recall, with minimal false positives and false negatives (CITE). These outcomes demonstrate that the pattern-based text classification and flexible regex matching approach is highly effective in distinguishing if a job post belongs to CE, EE, and ME disciplines, even when applied to a large and complex dataset like the BGT job postings.

This classification framework laid the foundation for addressing RQ2 and RQ3, which explored the evolving skill requirements across CE, EE, and ME disciplines and their variations across different educational levels over time

- Research Question 2 (RQ2): How do the proportions of different skills required for engineering jobs, as indicated in job postings, vary across levels of requisite education (i.e., bachelor's, master's, doctoral) and engineering disciplines (i.e., Civil, Electrical, and Mechanical Engineering)?
- Research Question 3 (RQ3): How have the proportions of different skills required for engineering jobs, as indicated in job postings, changed across the period of 2010-2022, considering both levels of requisite education and the specific disciplines of Civil, Electrical, and Mechanical Engineering?

This chapter discusses my findings for each of the three research questions related to literature.

5.1 Research Question One:

How well can pattern-based text classification and flexible regex matching be used to categorize job postings into engineering disciplines (e.g., civil, electrical, and mechanical engineering)?

Improving the accuracy of job classifications within large, pre-classified datasets such as BGT is important to ensure high-quality data that can be used for further exploration in this research. Previous studies (Dawson et al., 2019, 2020; Forsythe et al., 2020; Squicciarini & Nachtigall, 2021) show the value of BGT's extensive historical job postings for labor market analysis, yet they also highlight notable inconsistencies in occupation coding. Carnevale et al. (2014), for instance, found that only 73% of BGT's job postings were accurately mapped to SOCs, revealing the need for more reliable, automated classification approaches. Given the significant advancements in data collection and processing technologies since that study, addressing the first research question made a contribution in this space.

A central component of my classification approach is the use of regular expressions (regex), which have long been fundamental in text analysis because of their simplicity and adaptability (Pillar et al., 2022) In my research, the classification process employed NLP techniques that utilize regex for matching engineering-related terms within job postings, ensuring flexible and case-insensitive identification. Although deep learning and other advanced statistical methods have become popular for text classification tasks, regex-driven techniques remain appealing because they demand minimal training data and produce transparent, rule-based outputs (Ningrum et al., 2020). Such transparency enables domain experts to fine-tune classification rules with ease, ensuring that the resulting system aligns with online job advertisements' terminology. The Office for National Statistics in the UK similarly used standardized frameworks including O*NET to extract and analyze skills in job advertisements (Vassilev et al., 2021). Thus, in this study, I ensured alignment with recognized occupational standards by incorporating O*NET job title terms for CE, EE, and ME and refining classification rules based on O*NET job title terminology.

However, variations in job titles can occur. To better account for these differences, the study tested regex patterns designed to capture variation in engineering job titles that showed in CE, EE, and ME. For example, **Chapter 3 Table 3.4** illustrates several patterns used to identify "electrical engineer" roles, including "electrical engineer," "electricalengineer," "electrical-engineer," and "electrical engineers." All these terms were successfully matched within the regex-based framework, reducing the risk of missing relevant postings due to minor spelling or formatting differences. The results demonstrate that integrating standardized O*NET terminology with regex-based pattern matching effectively improves data quality and reliability, offering a scalable and interpretable solution for managing high-volume labor market data. This approach

could be adopted by other researchers using similar data sets and represents a contribution of my work.

This research expands the application of regex-based text classification to a large dataset of job advertisements from January 2010 to December 2022. Using SOC mappings, the NLP classification system initially processed 3.49 million postings labeled CE, EE, and ME. After filtering and reclassification, more than 2.86 million postings were above 80% relevant to these three engineering disciplines, as shown in Table 5.1 Had I not incorporated this method, I would have included erroneous job postings in addressing the second and third research questions.

Table 5.1 O*NET-SOC Mapped Data and Reclassified Postings Across CE/EE/ME

Discipline	O*NET-SOC Mapped Data	Reclassified Postings
Civil Engineering	973,451	766,288
Electrical Engineering	1,317,338	1,223,953
Mechanical Engineering	1,199,302	876,133
Total	3,490,091	2,866,374

** *Reclassified Postings are the job advertisements that were filtered using the NLP method*.

Multiple studies emphasize that carefully crafted regular regex can still achieve strong and interpretable results in online job advertisements. For example, Pillar et al., (2022) demonstrated that regex-based methods remain highly effective for identifying explicit indicators of age discrimination using the Job Digger dataset, which comprises 1.2 million Dutch job advertisements. Their findings suggest that when specific classes or patterns are closely tied to relevant keywords or phrases, regex techniques can provide transparency and reliable performance without requiring extensive training data. Building on this perspective, the present research applies pattern-based text classification to engineering job postings. As illustrated in the Results chapter, performance metrics indicate that the model was good in classifying job advertisement for CE/EE/ME. These findings are consistent with the work of Ningrum et al., (2020), who combined n-grams and regex to classify job advertisements for discrimination detection. In their study of 8,969 online job postings. The authors emphasized that explicitly modeling word order and employing fixed pattern templates make regex-based methods effective at filtering and categorizing the complex language found in job postings. Similarly, my research applied multiple regex patterns to capture variations of CE, EE, and ME job titles (see Appendix A all of which were successfully identified by the regex-based framework). Collectively, these findings demonstrate the effectiveness of a regex-driven approach, utilizing tailored O*NET terminology, in accurately classifying engineering jobs within a large dataset (N=3,490,091). This method achieves a high accuracy rate by balancing recall and precision, thereby minimizing the risk of overlooking relevant positions (low false negatives) or misclassifying unrelated ones (low false

positives). Moreover, the transparency of regex allows domain experts to easily review and refine classification rules, which is advantageous when analyzing extensive online job advertisements

5.1.2 Advantages, Limitations, and Conclusion of the NLP Classification System

One of the key advantages of regex-based classification is its transparency and interpretability. Since the rules are explicitly defined, domain experts can easily understand and modify them without requiring extensive computational expertise. Additionally, this approach requires minimal training data, making it ideal for rapid deployment in data-scarce environments. Regex rules are also highly adaptable. They can be quickly updated to accommodate new terminology, spelling variations, and plural or hyphenated job titles, ensuring flexibility in capturing diverse role descriptions. Furthermore, aligning regex patterns with recognized occupational standards such as O*NET enhances the system's replicability, enabling large-scale labor market analyses across different sectors and regions.

However, there are limitations to consider. First, effective regex design relies on domain expertise. Without sufficient knowledge of industry-specific terminology, key keywords or spelling variations may be overlooked. Second, the system struggles with novel or emerging job titles, as predefined rules cannot automatically capture unfamiliar terms unless regularly updated. Third, rather than applying regex classification to all job postings, the system was first tested on a sample labeled postings to refine the rules test performance before scaling to the full dataset. While this ensured good classification accuracy, it also means that the approach was dependent on the initial labeled subset, which may introduce bias or limit generalizability. Finally, as the number of targeted job titles increases, managing and validating complex rule sets becomes more challenging. If not optimized, an extensive rule set can also slow down the classification process.

In summary, while modern approaches such as deep learning offer powerful tools for text classification, regex-based methods remain highly relevant in scenarios where interpretability and ease of manual refinement are paramount. When clear, rule-based patterns exist (as is often the case with job advertisements), regex matching provides a straightforward yet effective means to extract structured information and categorize engineering fields using a set of rules such as O*NET job title terminology.

5.2 Discussion of Research Questions 2 and 3

Research Questions 2 and 3 are inherently interconnected, as both examine variations in the proportions of different skills required for engineering jobs. While RQ2 focuses on how these skill proportions differ across levels of requisite education (bachelor's, master's, and doctoral) and engineering disciplines (Civil, Electrical, and Mechanical Engineering), RQ3 extends this analysis over time, investigating how these proportions have evolved from 2010 to 2022. Given this overlap, it is beneficial to discuss these research questions holistically rather than in isolation. A combined discussion allows for a more cohesive interpretation of trends, ensuring that the analysis

remains digestible and well-aligned with the broader objectives of this study. Therefore, considering the findings from both questions together, we can better understand how educational requirements and disciplinary distinctions shape skill demand over time, providing a more comprehensive picture of workforce trends in engineering.

5.3.0 Civil Engineering

In this section, I discussed the topmost in-demand skills across Civil Engineering, which include the top in-demand skills, engineering skills, and technical skills. This section identifies the most proportionally critical skills from 2010 to 2022, highlighting trends, technological shifts, and industry expectations for CE. Please refer to the figures in chapter four, which serve as a reference for understanding how skill demand has evolved, reflecting broader industry transformations and the increasing reliance on digital tools, automation, and interdisciplinary competencies.

5.3.1 Most In-Demand CE Skills

The analysis of CE job advertisements from 2010 to 2022 highlights evolving skill demands that align with broader industry shifts. These changes reflect not only shifting employer priorities but also the ongoing challenge of aligning engineering education with market needs. Scholars have noted that engineering curricula often lag behind technological advancements and industry demands (Hadgraft & Kolmos, 2020; Walkington, 2002). The findings presented here identify the most in-demand skills, providing visibility into key competencies that CE programs could emphasize to better prepare graduates for emerging industry expectations. The analysis of CE job postings highlights the growing demand for Drafting and Engineering Design, Project Management, and Engineering Software as foundational skills, as indicated in the proportion of job advertisements that include those skills. Among these, Drafting and Engineering Design ranks as the most in-demand skill, increasing from appearing in 40% of job advertisements in 2010 to 58% in 2022. This shift likely reflects the industry's transition from manual drafting to digital modeling, driven by advancements in Building Information Modeling (BIM) and simulation technologies. The adoption of BIM has played a transformative role by enhancing collaboration, reducing design clashes, and improving project execution (Borrmann et al., 2018; Hemmerling & Bähre, 2020) . Additionally, BIM’s integration with Artificial Intelligence (AI), the Internet of Things (IoT), and Extended Reality (XR) has expanded its capabilities, enabling predictive analytics and real-time feedback for complex infrastructure projects (Izbash & Babayev, 2024). This trend aligns with Industry 4.0 principles, where sectors increasingly incorporate AI, IoT, and XR to drive automation, data-driven insights, and digital transformation (Javaid et al., 2022; J. Lee et al., 2018).

These findings align with previous research emphasizing the growing reliance on digital tools to improve accuracy, efficiency, and interdisciplinary collaboration in construction projects (Eastman et al., 2008; Izbash & Babayev, 2024; Kelly et al., 2018). (Eastman et al., 2008; Izbash

& Babayev, 2024; Kelly et al., 2018) Construction Management demand as a skill increased from appearing in 23% of job postings in 2010 to 34% in 2022, reflecting industry trends and regulatory support that mandate BIM adoption for improving project efficiency, sustainability, and cost-effectiveness (Bevanda & Andreea, 2022; Li et al., 2024). While regulatory support and industry initiatives have encouraged the adoption of technologies such as BIM, the direct connection between BIM and this observed increase in Construction Management demand requires further investigation. Similarly, Scheduling skills demand grew from 22% to 32% over the record period, highlighting the industry's focus on streamlining project timelines and coordination.

Additionally, Project Management and Construction Management rank highly, emphasizing the need for professionals to oversee complex, multi-stakeholder projects. CE requires cross-disciplinary collaboration, making effective schedule control, quality management, and cost efficiency essential (Liu, 2023; Luo, 2024). The increase of Project Management skill (40% to 50%) reaffirms its centrality in large-scale infrastructure initiatives, confirming research that calls for greater emphasis on project-based learning and professional competencies in engineering curricula (Moore & Voltmer, 2003; Paretti, 2008). Incorporating project management earlier and more explicitly in coursework may help reduce the mismatch between graduates' qualifications and employers' needs.

The demand for Estimating skills increased from 20% in 2010 to 29% in 2022, reinforcing the industry's focus on accurate cost assessment and resource planning, aligning with calls to introduce financial literacy and resource management in engineering education (Brent & Ward, 2018; Farrell, 2002; Hussain et al., 2018). The prominence of Budget Management and Scheduling further highlights the economic and logistical challenges in CE, where maintaining cost-effectiveness and timely project completion is critical (Xie, 2023). These trends align with projections from the Bureau of Labor Statistics (2021), which predicts steady growth in construction and extraction occupations, reinforcing the demand for technical expertise and managerial competence. The findings reflect this trend, showing from 2010 to 2022 growth in:

- Estimating (20% to 28%)
- Scheduling (22% to 32%)
- Project Management (40% to 50%)
- Budget Management (20% to 37%)
- Microsoft Office Tools (23% to 35%)

Furthermore, innovative management models that integrate advanced technologies and resource scheduling optimization enhance project quality control, risk reduction, and overall efficiency (Xie, 2023).

Moreover, Microsoft Office and Productivity Tools play a crucial role in CE communication, documentation, and collaboration. Microsoft Project aids in planning and scheduling, helping engineers manage task sequences and dependencies—essential not only for

construction projects like road and bridge rehabilitation but also for large-scale infrastructure initiatives in transportation, water resources, environmental, and structural engineering (Bhatele & Saxena, 2019). These tools facilitate resource management, ensuring efficient allocation of labor, equipment, and materials to prevent cost overruns and delays across diverse CE domains (Bhatele & Saxena, 2019). Additionally, Excel automation streamlines calculations and workflows, enhancing efficiency in project planning and data analysis across multiple CE specializations (Lluch, 2012). These findings highlight the increasing reliance on digital tools intertwined with estimating, scheduling, project management, and budget management skills—reinforcing the expectation that civil engineers possess both technical expertise and digital proficiency to contribute to project success across various subfields effectively.

The analysis of CE job advertisements from 2010 to 2022 reveals a dynamic shift in the skills employers seek, with clear distinctions emerging across different education levels. Overall, the ANOVA results confirm that the proportion of various skills mentioned in job postings differ significantly by degree requirement. In practical terms, these differences are often substantial: Cohen's d effect sizes indicate medium-to-large differences in skill emphasis between bachelor's-, master's-, and doctoral-level positions. A notable trend is the contrast between fundamental technical skills and advanced competencies as degree requirements increase. Bachelor's-level positions primarily emphasize core engineering skills, such as drafting, computer-aided design (CAD), and general design principles, which frequently appear in job postings for new graduates. Employers consistently expect B.S. candidates to be proficient in these foundational areas, and data show a high prevalence of such skills in job ads. Aligning with prior research highlighting design as a foundational skill in engineering (Dym et al., 2005; Jiang & Pang, 2023).

Certain technical tools remain essential at all levels. For instance, proficiency in industry-standard software like Microsoft Office and CAD programs ranks among the most sought-after technical skills in CE job ads (Fleming et al., 2024). This reinforces the idea that a strong grasp of fundamental engineering tools and practices is necessary, regardless of degree level. Since they are universally valued, the gap between a bachelor's and a Ph.D. posting for a skill like "engineering design" may be statistically small. This broad emphasis on fundamentals highlights their role as the "common language" of civil engineering.

However, as job requirements shift to the master's and Doctoral levels, the skill profile expands to include more advanced and specialized competencies, often alongside a greater emphasis on managerial and leadership abilities (Xu, 2024). Master's-level job postings frequently combine technical expertise with project oversight responsibilities. The research analysis found that while some skills, such as Automotive Technologies, show only minor variation between degree levels, other specialized areas like Geotechnical Engineering demonstrate very large effect sizes. These patterns underline the importance of program flexibility and adaptability, ensuring that undergraduate offerings provide a strong foundation while coursework deepens knowledge in specialized areas (Furman & Weissman, 2020). Additionally, the literature suggests that industry-

driven demands for advanced competencies reinforce the need to consistently update curricula to reflect emerging technologies and practices (Hadgraft & Kolmos, 2020; Kaushal & Vaghela, 2023). This is particularly critical as CE roles intersect more frequently with broader trends in automation, digitalization, and sustainability (Kamaruzaman et al., 2019).

Doctoral-level positions, however, often follow a different trajectory. Some PhD focused roles, particularly in industry R&D or specialized consulting, prioritize deep technical research over management. Others, such as high-level consulting or leadership in innovation teams, blend both skill sets. The data show that Ph.D.-level postings frequently emphasize cutting-edge technical expertise such as advanced modeling, simulation, and signal processing at significantly higher rates. In contrast, project management-related skills show only moderate differences between M.S. and Ph.D. postings, suggesting that while managerial competencies are valued at the doctoral level, they do not define the primary expectations for these roles. In other words, the Ph.D. path often leads to niche expert positions where technical leadership, driven by innovation and specialized knowledge (Newton et al., 2019), outweighs traditional managerial duties (H. Lee et al., 2010).

5.3.2 CE Software Skills on the Rise

Alongside the core skills, the 2010–2022 period witnessed growing emphasis on specialized software and programming abilities in CE roles. In recent years, job advertisements have increasingly emphasized expertise in advanced digital tools such as Building Information Modeling (BIM) software (e.g., Autodesk Revit) and programming or data analysis languages (e.g., Python and SQL). This trend is particularly evident in roles requiring graduate education or specialized technical expertise. The research found that, although Python is mentioned in relatively small proportions within Civil Engineering, its adoption is on an upward trajectory, particularly at the PhD level. This trend signals the expanding role of computational methods in tasks such as project optimization and big-data-driven decision-making (Rahmani et al., 2021). This shift reflects the industry's transition toward more data-driven and model-based practices and aligns with calls in the literature for engineering curricula to integrate advanced digital tools to meet Industry 4.0 demands (Khanna & Kumar, 2020; Ustundag et al., 2018)

For example, Fleming et al. (2024) found that although programming languages were not as frequently listed as Office or CAD skills, job postings that did request languages like Python or MATLAB tended to offer significantly higher salaries. This premium on coding skills suggests that employers value these tools' advanced analytical capabilities, often expecting master's and Ph.D.-level engineers to bring such expertise. Similarly, BIM proficiency has become far more common in job requirements over the last decade, as civil projects adopt 3D modeling and integrated project delivery methods. Open-source research confirms a "growing demand for BIM" skills in the construction industry (Li et al., 2024), with platforms like Revit now mainstream for design and collaboration. In short, CE employers are seeking candidates who can leverage

specialized software for complex analysis, simulation, and information management. This trend is especially pronounced at the higher education levels, where roles often involve advanced design, research, or management tasks that benefit from these tools. In sum, digital fluency has evolved from a niche bonus into a mainstream expectation, particularly for engineers with postgraduate training who are presumed to drive innovation.

5.4.0 Electrical Engineering

In this section, I discussed the most in-demand skills in Electrical Engineering, including core engineering, technical, and specialized skills. Skill demand shifts reflect broader industry transformations, increasing reliance on digital tools, automation, and the growing need for EE skills.

5.4.1 Most In-Demand EE Skills

The analysis of EE job advertisements from 2010 to 2022 highlights significant shifts in skill demands that align with broader industry trends. These changes reflect not only the technological advancements shaping EE but also the increasing interdisciplinary nature of the field, integrating competencies from business, information technology, and customer engagement.

The high demand for Drafting and Engineering Design skills in EE highlights the discipline's focus on technical precision and systematic planning. This demand reflects broader economic recovery, particularly within semiconductor and telecommunications industries, and shows an increased need for quality and control engineers (Patel, 2014). These findings align with the NACE report, emphasizing employer expectations for engineering graduates to possess competencies in troubleshooting, quality assurance, equipment maintenance, and effective technical management (National Academies of Sciences, Engineering, and Medicine, 2017).

The prominence of drafting and engineering design skills in EE has notably increased, rising from appearing in 25% of job advertisements in 2010 to 35% in 2022. This growth is driven primarily by the industry's shift from traditional drafting toward advanced digital modeling and simulation tools, such as computer-aided design (CAD) and specialized engineering software, reflecting broader digitalization trends across engineering industries (Patel, 2014). Despite this increased emphasis on sophisticated technical skills, the educational requirements remain predominantly at the bachelor's degree level. Specifically, my analysis indicates that only limited job postings explicitly require advanced degrees beyond the bachelor's degree with minimal explicit demand for master's or doctoral qualifications (Degree demand: master's 3.85%, doctoral 1.41%). Despite the growing shift toward automation and AI, these core technical competencies remain essential. Recent research by Kecman et al. (2023) reinforces this perspective, indicating that EE tasks, although vulnerable to AI disruption, will likely undergo transformation rather than full displacement. Consequently, engineering curricula must adapt to these technological advancements, emphasizing skills that complement emerging AI-driven practices (Kecman et al., 2023).

Engineering software, and simulation techniques reflect broader digitalization trends across industries, emphasizing data-driven optimization and sophisticated system simulations (Patel, 2014). My findings suggest that tasks involving advanced data-driven optimization and complex system simulations show a greater demand for graduate-level qualifications, indicating that these advanced technical competencies align closely with master's and doctoral-level education rather than undergraduate preparation alone.

The observed stability or incremental growth in Simulation, Electronic Hardware, and Engineering Software skills over the study period (2010-2022) highlights the sustained significance of these competencies in modern EE practice. This study found that Electronic Hardware skills increased from appearing in 2% of job advertisements in 2010 to 13% in 2022, whereas software skills increased from 16% in 2010 to 27% in 2022 and simulation skills had a slight increase from 14% in 2010 to 16% in 2022 These findings align with previous work demonstrating that foundational EE knowledge, specifically Circuitry and Signal Processing, remains pivotal for the design, analysis, and optimization of complex systems (Montoya et al., 2020; Rodriguez-Sanchez et al., 2020) (Montoya et al., 2020; Rodriguez-Sanchez et al., 2020). Indeed, the increased integration of advanced hardware solutions and digital simulation tools within engineering curricula reflects broader initiatives aimed at enhancing learning, efficiency, and reliability (Milczarek, 2019; Montoya et al., 2020).

Moreover, the observed growth in Electronic Hardware and Simulation skills resonates with efforts to implement real-time simulation and hardware-in-the-loop (HIL) methods, which have been reported to accelerate technology validation and improve education (Chernikova et al., 2020; Milczarek, 2019; Montoya et al., 2020). Notably, the adoption of open-source tools and collaborative projects across international educational settings has further supported motivation and learning outcomes, indicating the crucial role that digital simulation and shared software resources play in contemporary engineering education (Chernikova et al., 2020; Hajirasouli et al., 2023; Rodriguez-Sanchez et al., 2020). Collectively, these findings reinforce the idea that continued emphasis on these core technical skills not only aligns with emerging industry demands but also reflects a pedagogical shift toward experiential, technology-enhanced, and globally collaborative learning environments (Chernikova et al., 2020).

As EE projects continue to grow in complexity and scale, the demand for administrative competencies, particularly in scheduling and project oversight, has become increasingly critical. Effective project management necessitates a combination of leadership, communication, and management skills to address key challenges related to cost, time, and scope (Khattak & Mustafa, 2019). Scheduling, as a fundamental component of project management, ensures that projects adhere to planned timelines and budgets, reducing risks associated with delays and cost overruns (Carvalho et al., 2015). The findings from this study further reinforce the growing importance of administrative skills in electrical engineering. The prevalence of scheduling as a required

competency increased from appearing in 10% of EE job advertisements in 2010 to 22% in 2022, while the demand for project management skills rose from 23% to approximately 30% over the same period. Additionally, budget management saw a notable increase, from appearing in 11% of job advertisements in 2010 to 21% in 2022. These trends indicate a significant shift in the responsibilities of electrical engineers, extending beyond technical execution to include project oversight and strategic financial planning, aligning with literature (Brent & Ward, 2018; Farrell, 2002; Hussain et al., 2018).

The growing complexity of engineering projects, along with the expansion of digital communication and global collaboration, has made strong writing skills essential for engineers (Du, 2020). My study found that the demand for writing in EE job advertisements peaked at 11% in 2021 from 7% in 2010 before declining to 9% in 2022. This shift aligns with research emphasizing the evolving nature of engineering work, where professionals are expected to engage in extensive documentation, report writing, and interdisciplinary communication (Du, 2020). As engineering becomes more collaborative and data-driven, writing plays an essential role in ensuring that technical information is conveyed accurately and efficiently across diverse teams.

Studies indicate that engineers spend a significant portion of their work hours on communication-related tasks, with writing accounting for 32% of their total work time (Tenopir & King, 2004). The widespread use of personal computers, enterprise networks, and the internet has transformed communication in engineering workplaces. As Du (2020) notes,

> "Because of widely used personal computers, enterprise network and internet, emails, or online instant messaging or even online meeting had become the most widely used mediums for engineers to share and update information. Because of emails, engineers must write more, and more has to be documented" (p. 12).

The growing reliance on written communication stems from remote collaboration, digital project management, and the need for clear documentation in complex, multi-stakeholder projects. As a result, the increasing demand for writing skills in job ads highlights their recognition as a core engineering competency rather than a secondary requirement.

The analysis of variance (ANOVA) results presented in the Results chapter reveal significant differences across different educational attainment levels. Notably, competencies such as Drafting and Engineering Design, Circuitry, Signal Processing, and Simulation show substantial differences, emphasizing the critical role of advanced education in mastering these specialized domains. These findings align with previous research indicating that higher education plays a crucial role in developing deep technical expertise in fields requiring advanced theoretical knowledge and computational techniques (Lyon & J. Magana, 2020; Stevens et al., 2024). Advanced degrees provide greater exposure to research methodologies, design optimization, and complex system modeling, explaining the higher demand for these skills in job advertisements (Fleming et al., 2024).

Conversely, certain skills such as Automotive Technologies and Radio Frequency (RF) exhibit no significant variation across degree levels, suggesting that foundational competencies in these domains can be developed at the undergraduate level. This aligns with industry findings that while these technical skills remain essential, they do not necessarily require advanced theoretical training or a substantial research component, as they rely more on practical, hands-on experience. According to Passow & Passow, (2017) "Actual engineering practice does not match the emphasis in engineering curricula." (p. 483). Instead, these competencies are often acquired through industry certifications, apprenticeships, or professional training programs, rather than through graduate education (Kaushal & Vaghela, 2023).

Furthermore, the strong presence of Engineering Management skills across both bachelor's and master's levels highlights the growing industry demand for professionals with project oversight, resource coordination, and leadership capabilities. This aligns with earlier discussion as these skills are in demand as was discussed in section 5.4.0. This finding supports research advocating for the integration of project management, communication, and leadership training into engineering curricula, recognizing that technical expertise alone is insufficient for navigating modern engineering workplaces (Atkinson, 1990; Komarek et al., 2021; Moore & Voltmer, 2003). Engineering graduates who receive formal management training are better positioned to transition into leadership roles, a trend widely recognized in engineering education reforms (Martin et al., 2005; National Science Board, National Science Foundation, 2024).

Finally, these findings emphasize the importance of differentiated educational strategies, where undergraduate programs focus on broad-based fundamentals and hands-on technical skills, while graduate education delves into advanced methodologies, research, and management competencies (Hadgraft & Kolmos, 2020; Martin et al., 2005). This distinction ensures that engineering education aligns with workforce demands, equipping graduates with the necessary skills for both specialized technical roles and leadership positions in an increasingly complex engineering landscape (Mitchell et al., 2021; Sargent Jr, 2017).

5.4.2 EE Software Skills on the Rise

At the bachelor's level, proficiency in foundational tools such as Microsoft Excel and computer-aided design (CAD) software has remained consistently high, showing their essential role in EE tasks. However, a notable shift has emerged with an increasing demand for programming skills, particularly in Python. Job postings requiring Python proficiency have risen from 2% in 2010 to 8% in 2022, reflecting a growing expectation for entry-level engineers to engage with automation, data analysis, and computational problem-solving. This trend aligns with the industry's transition toward data-driven decision-making and the integration of scripting capabilities in engineering roles. The heightened emphasis on programming skills is corroborated by studies indicating that coding proficiency is becoming essential for modern engineers as they

also increase salary (Fleming et al., 2024). The growing demand for programming skills aligns with research emphasizing the critical need for coding proficiency as engineers adapt to Industry 4.0-driven workplace transformations (Alhloul & Kiss, 2022).

For master's degree holders, the demand for advanced software skills is even more pronounced. MATLAB, a tool widely used for modeling and simulation, has seen its demand rise from 15% in 2010 to 28% in 2022. Similarly, Python has experienced a significant increase, with job postings citing it as a requirement growing from 5% to 14% over the same period. This trend reflects the industry's need for professionals capable of handling complex simulations and data analyses, essential for developing and optimizing sophisticated electrical systems. The integration of such advanced tools is crucial for addressing the challenges posed by Industry 4.0 technologies (Saniuk et al., 2022).

At the doctoral level, specialized software skills are increasingly essential, reflecting the advanced analytical and computational demands of research and development. MATLAB remains a key requirement, with job postings citing it more frequently, rising from 20% in 2010 to 35% in 2022, showing its role in simulation, modeling, and algorithm development. Similarly, Python's demand grew from 3% to 12%, highlighting its expanding use in machine learning, artificial intelligence, and data-driven engineering. This trend aligns with research emphasizing the need for engineers to continuously adapt to evolving Industry 4.0 technologies (Miah et al., 2024).

5.5.0 Mechanical Engineering

This section explores the most in-demand skills in Mechanical Engineering, covering core engineering, technical, and specialized competencies. Changes in skill demand highlight broader industry shifts, the increasing adoption of digital tools, automation, and core ME skills

5.5.1 Most In-Demand ME Skills

A prominent finding in this study is the sustained demand for Drafting and Engineering Design, reflecting the discipline's persistent focus on precision and systematic planning. Over the 12-year span, these skills consistently appeared in a substantial proportion of job postings (57%), aligning with prior research highlighting design as a foundational element in engineering education (Dym et al., 2005; C. Jiang & Pang, 2023). This ongoing emphasis also parallels industry trends, wherein engineers increasingly rely on advanced digital modeling, prototyping, and simulation tools (Khanna & Kumar, 2020). However, the proportion of industrial design skill in job postings declined gradually from 13% in 2010 to 10.5% in 2022, reflecting a broader trend in the industrial design field. However, according to the U.S. Bureau of Labor Statistics Occupational Hand Book, employment of industrial designers is projected to grow 3% from 2023 to 2033 (Bureau of Labor Statistics, U.S & U.S. Department of Labor, 2024).

Shifts in administrative competencies also stand out. For instance, Scheduling requirements rose from appearing in just under 12% of postings in 2010 to 17% by 2022, highlighting the growing need for engineers to balance technical responsibilities with comprehensive project oversight. Meanwhile, Budget Management grew from 11% to 18%, highlighting the imperative for financially literate engineers who can manage resource allocation and maintain cost efficiency (Brent & Ward, 2018; Farrell, 2002; Hussain et al., 2018). These findings indicate an industry-wide recognition that mechanical engineers should possess both technical mastery and the organizational proficiencies necessary to guide projects.

In addition, as evidenced by the job advertisement data, project management skills increased in proportional frequency in the job advertisements over time. This finding aligns with recent research, including Prabhakar (2024), which emphasizes the pivotal role of project management proficiency in mechanical engineering. Meanwhile, Business Process and Analysis, though second in prominence, exhibits a steady upward trajectory. Quality Assurance and Control, while initially the least emphasized among the observed skills, "Quality is a virtue in engineering design and management, and achieving high-quality standards is mandatory for effective project implementation and execution." (Fakhravar & Ouabira, 2021, p. 84). Thus, this trend highlights the growing emphasis on streamlined workflows and data-driven decision-making as integral to modern mechanical engineering. As industry demands evolve, technical expertise increasingly requires complementary managerial, analytical, and quality-focused skills, reinforcing the need for interdisciplinary training in engineering education and professional development.

Beyond technical execution, the rising demand for writing skills, increasing from appearing explicitly in 6.5% of job advertisements in 2010 to 11% in 2022, underscores the growing importance of communication in engineering. As digital collaboration and documentation need expand, engineers must convey technical information clearly across teams (Du, 2020). This shift reflects the evolving nature of mechanical engineering, where technical expertise in design and simulation remains crucial, but proficiency in management, finance, and communication is equally vital. As workplaces become more interdisciplinary, engineers must integrate core engineering principles with project management and business strategy.

The ANOVA results reveal significant differences in engineering skills across degree levels in ME job postings. Drafting and Engineering Design, Engineering Practices, and Simulation are more common in roles requiring higher qualifications. However, Drafting and Engineering Design are most prevalent in bachelor’s-level positions, underscoring their foundational importance and the industry's emphasis on CAD proficiency and design methodologies. Research reinforces this trend by highlighting how ME programs emphasize design skills at the undergraduate level through curriculum innovations (Borrego et al., 2010). Their findings suggest that industry expectations drive the integration of these foundational competencies early in education, aligning with the skill distribution observed in job postings.

My study also found advanced degrees are more aligned with complex skills such as Simulation, Hardware Description Languages, and Signal Processing, emphasizing the role of graduate education in fostering analytical and computational expertise. In contrast, niche skills like Optical Engineering and Radio Frequency Equipment appear less frequently across all degree levels, suggesting their relevance to specialized industries such as aerospace and telecommunications. Meanwhile, Engineering Software remains consistently represented, underscoring its broad applicability across all educational levels.

The findings indicate that Engineering Management skills are significantly more prevalent at the bachelor's level, with continued importance at the master's level, reflecting industry demand for engineers with leadership and project coordination capabilities. This trend aligns with educational shifts advocating for the integration of management training into engineering curricula, recognizing that technical expertise alone is insufficient for career advancement (Jamieson & Donald, 2020; Kotha et al., 2024).

Ultimately, these findings emphasize the importance of differentiated educational pathways in mechanical engineering. Undergraduate programs focus on fundamental design, software, and practical engineering skills, while graduate education enhances expertise in advanced methodologies, simulation, and management. This distinction ensures alignment with workforce needs, preparing graduates for both specialized technical roles and leadership positions in an increasingly complex engineering landscape.

5.5.2 ME Software Skills on the Rise

At the bachelor's Level, foundational tools like Microsoft Excel and CAD are essential in ME education and practice. Job market analyses confirm that proficiency in these tools is among the most sought-after technical skills for mechanical engineers (Fleming et al., 2024). Nearly half of entry-level job postings now require CAD proficiency, with specific platforms gaining prominence. For example, SolidWorks appeared in about 15% of postings in 2010 but rose to 20% by 2022, while mentions of Autodesk Revit grew from 2% to 8% over the period of record, reflecting the increasing role of 3D modeling and design collaboration. Expectations for Microsoft Office proficiency have also risen, with job postings requiring these skills increasing from 7% to 16% over the period of recording, aligning with the growing need for documentation and presentation tasks (Du, 2020). In contrast, programming remains less emphasized at the bachelor's level. While MATLAB is used in coursework, job postings indicate relatively low demand, with only 3–7% mentioning it, suggesting that entry-level mechanical roles still prioritize CAD and office tools over programming skills.

However, learning programming offers significant advantages, particularly as industries adopt Industry 4.0 technologies, such as automation, digital twins, and smart manufacturing (Alhloul & Kiss, 2022; Miah et al., 2024). Programming skills enable engineers to automate repetitive tasks, analyze large datasets, and develop custom simulations, enhancing efficiency and

problem-solving capabilities. Additionally, programming proficiency fosters adaptability, allowing engineers to integrate emerging technologies like machine learning and IoT into learning (Kamaruzaman et al., 2019; Khanna & Kumar, 2020; Ustundag et al., 2018). While entry-level roles may not heavily emphasize programming, the increasing reliance on data-driven decision-making and advanced simulations suggests that engineers with coding expertise will have a competitive edge in the evolving job market with a salary premium (Fleming et al., 2024).

At the master's level, proficiency in Excel and CAD remains critical, appearing in job postings as frequently as, or even more often than, at the bachelor's level. My research found that Excel was required in nearly 45% of master's-level ME positions, up from approximately 38% a decade ago. Beyond these core tools, programming and data analysis skills have seen notable growth. Python, for example, was rarely mentioned in job postings a decade ago but now appears in approximately 11% of listings in 2020, however, it peaked at 16% in 2021. This shift mirrors the industry's increasing focus on automation, data analytics, and machine learning. Similarly, MATLAB references in job postings grew from about 10% in 2010 to 25% by 2022, reflecting the rising need for simulation and large-scale computational capabilities in master's-level roles. The demand for programming skills at this level is associated with a skill premium salary increase (Fleming et al., 2024).

For Ph.D. holders in mechanical engineering, job postings place greater emphasis on advanced analytical and simulation skills. Proficiency in programming environments such as MATLAB and Python is significantly more valued at this level. Over the past decade, the percentage of Ph.D.-level job postings mentioning MATLAB has risen from approximately 10% to 25%, while Python has increased from just 1% to 18% by 2022. Watson and Lyons (2011) emphasize that expertise in modern programming languages, numerical methods, and modeling software provides Ph.D. graduates with a competitive advantage, particularly in computational research. These trends highlight the importance of integrating coding and computational thinking into graduate engineering curricula at both the master's and doctoral levels. This shift aligns with industry expectations, where Ph.D. graduates are often required to conduct advanced simulations, modeling, and data analysis for research and development roles (Watson & Lyons, 2011).

5.6.0 Implications

The findings of this research have significant implications across multiple dimensions of the engineering workforce ecosystem, influencing educational institutions, policy and regulatory bodies, industry stakeholders, engineering students, career services, and economic development initiatives. By analyzing evolving skill demands in job postings, this study provides insights that can inform strategic decisions and foster greater alignment between education and industry needs.

5.6.1 Educational Institutions

Higher education institutions, including universities and technical schools, stand to benefit from these findings by refining curricula to better align with industry requirements. The identification of high-demand technical skills across CE/EE/ME disciplines presents an opportunity for curriculum designers to integrate these competencies more intentionally. Specifically, the findings suggest that foundational engineering skills should remain a priority at the undergraduate level, while graduate education should emphasize advanced technical expertise, interdisciplinary collaboration, and emerging technologies such as programming and simulation. This strategic realignment ensures that graduates enter the workforce with the necessary skill set to meet employer expectations and contribute meaningfully to engineering practice.

5.6.2 Policy and Regulatory Bodies

Government agencies responsible for workforce planning and development can leverage these insights to shape policies that address existing and emerging skill gaps. By utilizing data-driven approaches to workforce forecasting, agencies such as the U.S. Department of Labor and the Federal Communications Commission can design targeted initiatives that support engineering education and training programs. Additionally, regional economic development agencies can integrate these findings into strategic planning efforts to ensure that investments in engineering talent development align with the evolving demands of the labor market. A well-informed policy framework that bridges the gap between educational institutions and industry needs will ultimately enhance workforce preparedness and economic growth. Findings from this dissertation should be particularly informative for accrediting bodies such as ABET, whose mission explicitly aims to align educational experiences with workforce needs.

5.6.3 Industry Stakeholders

Employers, human resources professionals, and engineering professional organizations—including the Institute of Electrical and Electronics Engineers (IEEE), the American Society of Mechanical Engineers (ASME), and the American Society for Engineering Education (ASEE)—can apply these findings to optimize recruitment and training strategies. Understanding the shifting landscape of engineering skills enables organizations to develop more targeted hiring practices, ensuring that their workforce possesses the technical competencies required to drive innovation. Moreover, engineering firms can strengthen collaborations with universities by aligning internship programs and industry partnerships with the most relevant technical and managerial skills. This alignment will help bridge the transition from academic training to professional practice, ultimately improving workforce readiness and long-term career success for engineering graduates.

5.6.4 Engineering Students and Career Services

For engineering students, these findings offer valuable guidance in selecting educational pathways that maximize career opportunities. By identifying the skills most frequently emphasized

in job postings, students can make more informed decisions about coursework, specialization, and professional development activities. Career services offices within universities can also use these insights to enhance advising services, ensuring that students receive evidence-based recommendations regarding industry trends and employment prospects. By proactively aligning academic experiences with labor market expectations, students will be better positioned for successful entry into the engineering workforce.

5.6.5 Research Community

From a research perspective, this study contributes to the ongoing discourse on engineering workforce development by integrating big data analytics and Natural Language Processing (NLP) techniques to analyze labor market trends. It also provides a replicable framework to classify job ads into major or discipline fields. My research operationalized SABER-WfD conceptual framework, this dissertation provides an understanding of the demand side of workforce development by examining big data a decade of job postings from 2010 to 2022. Future research could build upon these findings by further exploring the intersection of technological advancement, skill evolution, and career outcomes in engineering disciplines. Also, exploring more advanced machine learning techniques such as: decision trees, random forests, support vector machines, or transformer-based models to compare their performance which it could help identify the most effective approach for job advertisement classification. Additionally, longitudinal studies examining the impact of curriculum changes on graduate employability could provide further insights into the effectiveness of educational interventions in addressing industry needs. Expanding on this work, researchers can continue to refine strategies that enhance workforce readiness and support sustainable career growth in engineering.

5.6.6 Diverse Educational Training Models

In addition to informing traditional academic curricula, the findings of this study can support a broader range of educational and workforce development models. The identified trends in skill demands may guide the design of micro-credentialing programs and short-term certificates tailored to emerging industry needs. Similarly, employers may use these insights to shape internal upskilling initiatives or on-the-job training programs. Recognizing that skill acquisition increasingly occurs outside formal education, this study supports a more flexible and responsive approach to workforce preparation that aligns with real-time labor market demand.

5.7 Future Research

This study provides a foundation for further exploration into engineering workforce development, particularly in understanding how skill demands evolve in response to technological advancements and industry needs. While this research highlights employer expectations as evidenced in job advertisements, further research should expand on these findings to ensure engineering education remains responsive to workforce demands. A key next step is to conduct longitudinal analyses to track skill demand trends over time. While this study identifies shifts in demand from 2010 to 2022, future research should explore how skill requirements continue to evolve with emerging technologies, economic fluctuations, and policy changes, particularly in this extremely dynamic period with the broad adoption of AI across sectors. A deeper understanding of sector-specific skill evolution would also help industries such as energy, manufacturing, and software engineering adapt to technological disruptions rather than the broader disciplinary focus in my work.

Expanding the analysis to additional engineering disciplines is another critical avenue. Fields like Computer, Biomedical, Aerospace, and Environmental Engineering are experiencing rapid innovation, and their workforce demands may differ significantly from engineering roles that were investigated in this study. A comparative study across multiple disciplines could identify interdisciplinary trends and transferable competencies, informing curriculum adjustments that better prepare graduates for a changing job market. Industry 4.0 and artificial intelligence (AI) are reshaping engineering job roles, involving research on how automation, AI-driven tools, and digital transformation influence skill requirements. Investigating whether AI are applied at the workplace would provide insights into how engineering education should integrate these technologies.

Further studies should also evaluate the effectiveness of educational interventions aimed at bridging the gap between employer expectations and academic training. Longitudinal research tracking engineering graduates' career trajectories could determine whether curriculum modifications improve employability and career advancement. Additionally, research on micro-credentialing and competency-based education could assess whether short-term certification programs targeted at the skills identified in analyses of job advertisements effectively supplement traditional engineering degrees and enhance workforce readiness. Finally, future research should explore employer perspectives more deeply through qualitative studies involving hiring managers and industry leaders. Although job postings provide valuable insights into skill demand, direct engagement with employers could reveal additional gaps in technical and professional competencies. Understanding expectations regarding emerging skills, such as sustainability engineering, data analytics, and Programming languages, or other in-demand skills can help prepare students for the workforce. A future study design could use my findings as an artifact grounding such interview-based data collection.

Furthermore, future research should consider incorporating years of experience to better distinguish between entry-level and advanced job requirements, offering a more nuanced view of how skills evolve across career stages. Additionally, linking job ad trends with macroeconomic indicators such as unemployment rates, automation adoption, or government policy. These shifts could clarify how external factors drive changes in employer demand over time.

5.8 Author's Final Thought: Education, Workplace and Lifelong Learning

Education plays an important role in building foundational knowledge and critical thinking skills, but it cannot always prepare students for the exact demands of a specific job. As the labor market continues to evolve, much of the learning needed to stay relevant will happen beyond the classroom. Training in the workplace through upskilling, reskilling, and hands-on experience has become an essential part of preparing individuals for the realities of today's work. This highlights the importance of embracing a lifelong learning approach, where formal education and workplace training work together to support continuous growth throughout a person's career.

5.9 Limitations

As a researcher, I recognize the importance of acknowledging the limitations of this study. Although job descriptions provide a useful baseline for analysis, they do not always reflect the full scope of workplace dynamics, as job roles and responsibilities can evolve significantly in practice. These changes may not always be captured in formal job postings, which could impact the accuracy and relevance of the data used in this research (Titor, 2022). For instance, aspects like company culture, teamwork, and interpersonal skills are often underrepresented in job ads but play a significant role in job performance. Also, job ads online often reflect ideal candidate profiles rather than the essential day-to-day skills needed for the role (Banfi & Villena-Roldán, 2019).

Furthermore, this dataset was developed by The Burning Glass Institute, and I have provided sufficient information about its development and the technology used to achieve it. For more detailed information, please refer to their report titled "A Machine Learning Approach to Classify Skills in Burning Glass Technologies Data." This report offers an in-depth look at the methodology and tools employed to create their dataset. A key limitation of this study is the balance between covering a wide range of data and providing detailed insights. While the study focuses on analyzing a large dataset to identify broader trends, it does not look deeply into specific jobs or industries. This study's approach offers a big-picture view but may overlook detailed insights that a more focused analysis could uncover. Understanding this trade-off clarifies the study's limitations and how its findings relate to the job market.

Using a large dataset helps identify trends, patterns, and shifts in skill demands over time, enabling conversations regarding the future development of more targeted and effective educational curricula that better align with industry needs. However, since the analysis relies exclusively on

data collected by BGT, I have limited control over the accuracy and completeness of the information. This dependence introduces challenges, as the pre-labeled SOC data may not always be accurate due to the complexities of categorizing large numbers of job descriptions and technological change over time.

Another limitation is that while my classification framework improves accuracy by filtering out misclassified postings, it does not evaluate all job postings to identify potential discipline misclassifications by BGT. This means that while incorrect postings labeled as CE, EE, or ME were removed, the study did not assess whether certain CE jobs were mistakenly categorized under other fields such as Industrial and System Engineering (ISE). Although this does not affect the primary findings, acknowledging this constraint clarifies the scope of the analysis.

As a result, I developed a classification framework aimed at enhancing the accuracy of pre-labeled SOC-coded data. Although some classification errors may still occur, the framework improves the dependability of using pre-labeled SOC data for researchers. Despite achieving a strong accuracy score of 0.85, the classification system may occasionally misidentify engineering positions (false positives), potentially categorizing non-CE/EE/ME jobs as CE/EE/ME positions or vice versa. Additionally, the analysis may overlook engineering jobs that fall outside traditional classifications by O*NET (17-200) code, potentially missing roles that are evolving or emerging in the field. It also mainly depends on existing skill classifications rather than developing a new, customized set of skills that better reflects changes in the job market.

Nonetheless, many researchers in the field have successfully used BGT data to understand job market dynamics (Alipour et al., 2021; Dawson et al., 2019, 2020; D. J. Deming & Noray, 2020), and the findings provide meaningful insights into shifts in engineering job demands and skill requirements. Additionally, this analysis does not directly account for broader external or economic factors that influence shifts in skill demand. Factors such as technological disruptions, policy changes, labor shortages, or macroeconomic trends like recessions or industry booms can significantly shape employer preferences in job advertisements. While these factors likely influence the patterns observed, they are not explicitly modeled in this study and should be interpreted as part of the larger labor market context. Finally, this study does not account for the required years of work experience across job postings. As a result, trends identified in skill demand may reflect a blend of expectations for entry, junior, and senior positions.

5.10 Conclusion

Conceptualized using the SABER-Workforce Development (SABER-WfD) framework (Tan et al., 2013), this study has provided a comprehensive analysis of the evolving skill demands in engineering job postings from 2010 to 2022, with a focus on three major disciplines: Civil Engineering (CE), Electrical Engineering (EE), and Mechanical Engineering (ME). By leveraging Natural Language Processing (NLP) classification techniques and pattern-based text analysis, this study improved the precision of job classification within large-scale occupational datasets such as Burning Glass Technologies (BGT). This new classification framework demonstrated a high level of accuracy in distinguishing job postings relevant to CE, EE, and ME, ensuring that subsequent skill demand analyses were based on reliable and well-defined data. The findings contribute to ongoing discussions on the alignment between engineering education and workforce requirements, offering valuable insights for curriculum designers, industry stakeholders, and policymakers.

The first research question (RQ1) addressed the effectiveness of regex-based text classification in categorizing engineering job postings. The results indicated that this method provided high precision and recall rates, with F1-scores exceeding 90% for each engineering discipline. This finding supports the viability of regex-based classification as an efficient and transparent approach for refining pre-classified datasets, particularly in cases where job title variations and inconsistencies pose challenges to traditional SOC-based categorization.

The second research question (RQ2) explored how skill demands vary across educational levels (bachelo's, master's, and doctoral) and engineering disciplines. The results revealed significant differences in skill prioritization based on education level, with undergraduate job postings emphasizing fundamental engineering competencies such as drafting, engineering design, and project management. In contrast, master's and doctoral-level positions exhibited greater demand for advanced technical skills such as simulation, signal processing, and engineering software proficiency. These findings suggest that higher education curricula should continue to differentiate learning objectives based on degree level, ensuring that students acquire both foundational and specialized competencies aligned with workforce needs.

The third research question (RQ3) examined how skill demands evolved over time. The longitudinal analysis highlighted notable shifts in employer priorities, with increasing emphasis on digital tools, automation, and programming competencies. For instance, Python and MATLAB have become more prevalent in engineering job postings, reflecting the growing intersection of engineering with data analytics and computational modeling. Additionally, demand for software-based design tools such as SolidWorks, Autodesk Revit, and Building Information Modeling (BIM) applications has risen, underscoring the importance of digital literacy in modern engineering practice. These trends indicate that engineering education must adapt to emerging technologies by integrating relevant software training and computational problem-solving techniques into curricula.

Beyond technical skills, the findings also emphasized the rising importance of non-technical competencies such as project management, budgeting, and communication. Employers increasingly seek engineers who can navigate complex, interdisciplinary projects, demonstrating both technical expertise and leadership capabilities. This shift reinforces the need for engineering programs to incorporate project-based learning, interdisciplinary collaboration, and industry partnerships to better prepare graduates for the realities of the workforce. Additionally, this dissertation highlights the critical intersection between engineering education and labor market demands. As technology continues to reshape the engineering landscape, higher education institutions must remain agile in adapting curricula to equip graduates with the skills necessary for success. This research contributes to bridging the gap between academia and industry, fostering a workforce that is both technically proficient and adaptable to the challenges of the future.

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Appendix A

All of Burning Glass Skills Taxonomy

Skill Family	**Individual Skill**
Sales	Company Product and Service Knowledge
Sales	General Sales
Sales	General Sales Practices
Sales	Salesmanship
Sales	Outside Sales
Sales	Merchandising
Sales	Business Development
Sales	Account Management
Sales	Solution Sales Engineering
Sales	Sales Analysis
Sales	Retail Sales
Sales	Technical Sales
Sales	E-Commerce
Sales	Prospecting and Qualification
Sales	Insurance Sales
Sales	Telemarketing
Sales	Business-to-Business (B2B) Sales
Sales	Trade Shows
Sales	Sales Management
Sales	Inside Sales
Sales	Technical Demonstrations
Sales	Specialized Sales
Sales	Online Sales
Administration	Memoranda Preparation
Administration	Dictation
Administration	Telephone Skills

Administration	Administrative Support
Administration	Office Management
Administration	General Administrative and Clerical Tasks
Administration	Office Machines
Administration	Scheduling
Manufacturing and Production	Lean Manufacturing
Manufacturing and Production	Machine Tools
Manufacturing and Production	Manufacturing Processes
Manufacturing and Production	Brazing and Soldering
Manufacturing and Production	Computer-aided manufacturing
Manufacturing and Production	Product Development
Manufacturing and Production	Materials Science
Manufacturing and Production	Micro Manufacturing
Manufacturing and Production	Metal Fabrication
Manufacturing and Production	Welding
Manufacturing and Production	Manufacturing Standards
Manufacturing and Production	Manufacturing Design
Manufacturing and Production	Machinery
Manufacturing and Production	Computer-Aided Manufacturing
Manufacturing and Production	Materials Process
Manufacturing and Production	Product Inspection
Supply Chain and Logistics	Material Handling
Supply Chain and Logistics	Supply Chain Management
Supply Chain and Logistics	Procurement
Supply Chain and Logistics	Transportation Operation and Management
Supply Chain and Logistics	TSA Regulation
Supply Chain and Logistics	Supplier Relationship Management
Supply Chain and Logistics	Warehouse Management
Supply Chain and Logistics	Inventory Management
Supply Chain and Logistics	Transportation Operations

Supply Chain and Logistics	General Shipping and Receiving
Supply Chain and Logistics	Store Management
Supply Chain and Logistics	Retail Store Operations
Supply Chain and Logistics	Transportation Operations Management
Supply Chain and Logistics	Logistics
Supply Chain and Logistics	Facility Management and Maintenance
Supply Chain and Logistics	Operations Analysis
Supply Chain and Logistics	Supply Chain Planning
Supply Chain and Logistics	Inventory Maintenance
Supply Chain and Logistics	Air Transport
Marketing and Public Relations	Concept Development
Marketing and Public Relations	Fundraising
Marketing and Public Relations	Promotions and Campaigns
Marketing and Public Relations	Brand Management
Marketing and Public Relations	Online Marketing
Marketing and Public Relations	Market Analysis
Marketing and Public Relations	Web Analytics
Marketing and Public Relations	Promotional Materials
Marketing and Public Relations	Advertising
Marketing and Public Relations	Investor Relations
Marketing and Public Relations	Corporate Communications
Marketing and Public Relations	Social Media
Marketing and Public Relations	General Marketing
Marketing and Public Relations	Media Strategy and Planning
Marketing and Public Relations	Marketing Strategy
Marketing and Public Relations	Marketing Management
Marketing and Public Relations	Grant Applications
Marketing and Public Relations	Marketing Software
Marketing and Public Relations	Online Advertising
Marketing and Public Relations	Public Relations

Marketing and Public Relations	Customer Relationship Management (CRM)
Marketing and Public Relations	Packaging and Labeling
Engineering	Simulation
Engineering	Civil and Architectural Engineering
Engineering	Optical Engineering
Engineering	Industrial Engineering
Engineering	Hardware Description Languages (HDL)
Engineering	Automation Engineering
Engineering	Electronic Hardware
Engineering	Chemical Engineering
Engineering	Aerospace Engineering
Engineering	Automotive Technologies
Engineering	Signal Processing
Engineering	Process Engineering
Engineering	Circuitry
Engineering	Drafting and Engineering Design
Engineering	Engineering Management
Engineering	Engineering Software
Engineering	Engineering Practices
Engineering	Electrical and Computer Engineering
Engineering	Geotechnical Engineering
Engineering	Mechanical Engineering
Engineering	Robotics
Engineering	Radio Frequency (RF)
Engineering	Surveying
Engineering	Imaging
Engineering	Radio Frequency Equipment
Engineering	Roads and Drainage
Architecture and Construction	Roofing
Architecture and Construction	Architectural Design

Architecture and Construction	Drywall
Architecture and Construction	Construction Inspection
Architecture and Construction	Estimating
Architecture and Construction	Masonry
Architecture and Construction	Carpentry
Architecture and Construction	Green Architecture
Architecture and Construction	Electrical Construction
Architecture and Construction	Insulation
Architecture and Construction	Construction Management
Architecture and Construction	Construction Painting
Architecture and Construction	Construction Labor
Architecture and Construction	General Architecture
Architecture and Construction	Conduits
Architecture and Construction	Road and Bridge Construction
Industry Knowledge	Electrical Engineering Industry Knowledge
Industry Knowledge	Local Government Industry Knowledge
Industry Knowledge	Allied Health Care Industry Knowledge
Industry Knowledge	Industrial Engineering Industry Knowledge
Industry Knowledge	Employment Services Industry Knowledge
Industry Knowledge	Telecommunications Industry Knowledge
Industry Knowledge	Insurance Industry Knowledge
Industry Knowledge	Civil Engineering Industry Knowledge
Industry Knowledge	Biologics Industry Knowledge
Industry Knowledge	Supply Chain and Logistics Industry Knowledge
Industry Knowledge	Apparel Industry Knowledge
Industry Knowledge	Financial Services Industry Knowledge
Industry Knowledge	Automotive Industry Knowledge
Information Technology	Application Programming Interface (API)
Information Technology	Mainframe Technologies
Information Technology	Internet Security

Information Technology	Mobile development
Information Technology	Microsoft Office and Productivity Tools
Information Technology	IT Management
Information Technology	Cloud Computing
Information Technology	Extraction, Transformation, and Loading (ETL)
Information Technology	Software Development Tools
Information Technology	Mobile Development
Information Technology	Database Administration
Information Technology	Data Storage
Information Technology	Advanced Microsoft Excel
Information Technology	cybersecurity
Information Technology	Application Security
Information Technology	Distributed Computing
Information Technology	NoSQL Databases
Information Technology	General Networking
Information Technology	Basic Computer Knowledge
Information Technology	Extensible Languages
Information Technology	Telecommunications
Information Technology	IT Hardware
Information Technology	JavaScript and jQuery
Information Technology	Software Development Principles
Information Technology	Cloud Storage
Information Technology	PHP Web
Information Technology	Network Security
Information Technology	Web Content
Information Technology	Wiki
Information Technology	System Design and Implementation
Information Technology	Health Checks
Information Technology	Systems Administration
Information Technology	Networking Hardware

Information Technology	Network Configuration
Information Technology	Web Servers
Information Technology	Enterprise Content Management (ECM)
Information Technology	Software Quality Assurance
Information Technology	Scripting
Information Technology	Help Desk Support
Information Technology	Programming Principles
Information Technology	Virtual Machines (VM)
Information Technology	Android Development
Information Technology	Test Automation
Information Technology	Integrated Development Environments (IDEs)
Information Technology	Management Information System (MIS)
Information Technology	Application Development
Information Technology	Anti-Malware Software
Information Technology	Cloud Solutions
Information Technology	Artificial Intelligence
Information Technology	cloud solutions
Information Technology	Other Programming Languages
Information Technology	Geographic Information System (GIS) Software
Information Technology	Web Development
Information Technology	SAP
Information Technology	Operating Systems
Information Technology	Microsoft Windows
Information Technology	Web Design
Information Technology	Data Warehousing
Information Technology	Oracle
Information Technology	database administration
Information Technology	Productivity Software
Information Technology	Internet of Things (IoT)
Information Technology	Data Management

Information Technology	Java
Information Technology	Computer Hardware
Information Technology	Technical Support
Information Technology	Augumented Reality / Virtual Reality (AR / VR)
Information Technology	Project Management Software
Information Technology	Enterprise Messaging
Information Technology	Version Control
Information Technology	Information Security
Information Technology	Document Management Systems
Information Technology	iOS Stack
Information Technology	Network File System (NFS)
Information Technology	Microsoft SQL Extensions
Information Technology	Middleware
Information Technology	Big Data
Information Technology	IT Automation
Information Technology	Network Protocols
Information Technology	Software Development Methodologies
Information Technology	C and C++
Information Technology	Microsoft Development Tools
Information Technology	SQL Databases and Programming
Information Technology	Scripting Languages
Information Technology	JavaScript and Jquery
Information Technology	Cybersecurity
Information Technology	Enterprise Resource Planning (ERP)
Maintenance, Repair, and Installation	Basic Electrical Systems
Maintenance, Repair, and Installation	Schematic Diagrams
Maintenance, Repair, and Installation	Power Tools
Maintenance, Repair, and Installation	Bike Repair
Maintenance, Repair, and Installation	Vehicle Repair and Maintenance
Maintenance, Repair, and Installation	HVAC

Maintenance, Repair, and Installation	Equipment Operation
Maintenance, Repair, and Installation	Painting
Maintenance, Repair, and Installation	Tailoring and Sewing
Maintenance, Repair, and Installation	Plumbing
Maintenance, Repair, and Installation	Hand Tools
Maintenance, Repair, and Installation	Hazard Identification
Maintenance, Repair, and Installation	electrical and mechanical labor
Maintenance, Repair, and Installation	Equipment Repair and Maintenance
Maintenance, Repair, and Installation	Heavy Equipment
Maintenance, Repair, and Installation	Appliance Repair and Maintenance
Maintenance, Repair, and Installation	Electrical and Mechanical Labor
Business	Internal Controls
Business	Business Consulting
Business	Business Communications
Business	Due Diligence
Business	Pricing Analysis
Business	Business Strategy
Business	Property Management
Business	Project Management
Business	Quality Assurance and Control
Business	Performance Management
Business	Business Solutions
Business	Knowledge Management
Business	Key Performance Indicators
Business	Event Planning and Management
Business	Category Management
Business	Contract Management
Business	risk management
Business	Risk Management
Business	Order Management

Business	Product Management
Business	People Management
Business	Business Management
Business	Process Improvement
Business	Real Estate and Rental
Business	Benefits Analysis
Business	Business Process and Analysis
Business	Technical Assistance
Business	Optimization
Business	Operations Management
Finance	Corporate Accounting
Finance	General Lending
Finance	Mortgage Lending
Finance	Financial Reporting
Finance	Financial Aid Counseling
Finance	Cash Management
Finance	Accounts Payable and Receivable
Finance	Tax
Finance	Financial Trading
Finance	Financial Regulations
Finance	Financial Analysis
Finance	Cost Accounting
Finance	Financial Advisement
Finance	Specialized Accounting
Finance	Billing and Invoicing
Finance	Financial Accounting
Finance	Investment Management
Finance	Banking Services
Finance	Commodities
Finance	Costing

Finance	Financial Management
Finance	General Accounting
Finance	Accounting and Finance Software
Finance	Commercial Lending
Finance	Lending Assessment
Finance	Auditing
Finance	Mergers and Acquisitions
Finance	Underwriting
Finance	Budget Management
Science and Research	Cellular Biology
Science and Research	Research Methodology
Science and Research	Chemical Analysis
Science and Research	Physics
Science and Research	Biology
Science and Research	Genetics
Science and Research	Chemistry
Science and Research	Drug Development
Science and Research	Earth and Space Science
Science and Research	Neuroscience
Science and Research	Laboratory Research
Science and Research	Molecular Biology
Science and Research	Surveys
Science and Research	Biopharmaceutical Manufacturing
Energy and Utilities	Oil Well Intervention
Energy and Utilities	Clean Energy
Energy and Utilities	Energy Efficiency
Energy and Utilities	Electrical Power
Energy and Utilities	Petroleum Science
Energy and Utilities	Solar Energy
Energy and Utilities	Oil Refining

Energy and Utilities	Energy Solutions
Energy and Utilities	Nuclear Energy
Energy and Utilities	Power Generation
Energy and Utilities	Oil Wells
Energy and Utilities	Hydraulic Fracturing
Energy and Utilities	Power Plant
Energy and Utilities	Energy Management
Energy and Utilities	Natural Gas
Energy and Utilities	Water Supply
Energy and Utilities	Water Energy
Energy and Utilities	Gas Drilling
Energy and Utilities	Oil Drilling
Energy and Utilities	Oil Reservoirs
Energy and Utilities	Wind Energy
Public Safety and National Security	Fire Inspection
Public Safety and National Security	Surveillance
Public Safety and National Security	Intelligence Collection and Analysis
Public Safety and National Security	Government Clearance and Security Standards
Public Safety and National Security	Loss Prevention
Public Safety and National Security	Physical Security
Public Safety and National Security	Emergency Services
Public Safety and National Security	Transportation Security
Legal	Federal Acquisition
Legal	Intellectual Property
Legal	Labor Compliance
Legal	Regulation and Law Compliance
Legal	Law Enforcement and Criminal Justice
Legal	Litigation
Legal	Legal Research
Legal	Forensics

Health Care	Medical Support
Health Care	Radiology
Health Care	Physical Abilities
Health Care	First Aid
Health Care	Medical Billing and Coding
Health Care	Advanced Patient Care
Health Care	Nephrology
Health Care	Medical Procedure and Regulation
Health Care	Hematology
Health Care	Eye Care
Health Care	Geriatrics
Health Care	Patient Reception
Health Care	Basic Patient Care
Health Care	Infectious Diseases
Health Care	Obstetrics and Gynecology (OBGYN)
Health Care	Animal Health and Veterinary Medicine
Health Care	Speech Language Pathology
Health Care	Orthopedics
Health Care	Oncology
Health Care	Neurology
Health Care	Health Care Procedure and Regulation
Health Care	Patient Education and Support
Health Care	General Medicine
Health Care	Dermatology
Health Care	Health Information Management and Security
Health Care	Physical Therapy
Health Care	Mental and Behavioral Health Specialties
Health Care	Endocrinology
Health Care	Public Health and Disease Prevention
Health Care	Ear, Nose, and Throat

Health Care	Basic Living Activities Support
Health Care	Mental Health Therapies
Health Care	Emergency and Intensive Care
Health Care	Clinical Informatics
Health Care	Medical Records
Health Care	Cardiology
Health Care	Social Work
Health Care	Urology
Health Care	Injury Treatment
Health Care	Pediatrics
Health Care	Routine Examination Tests and Procedures
Health Care	Pharmacy
Health Care	Clinical Data Management
Health Care	Rehab Therapy
Health Care	Clinical Research
Health Care	Patient Physical Measurements
Health Care	Nuclear Medicine
Health Care	Alternative Therapy
Health Care	Nutrition and Diet
Health Care	Surgery
Health Care	Mobility Assistance
Health Care	Allergies
Health Care	Medical Documentation and Abstraction
Health Care	Gastroenterology
Health Care	Anesthesiology
Health Care	General Medical Tests and Procedures
Health Care	Rehabilitation
Health Care	Dental Care
Health Care	Medical Research
Health Care	Mental Health Diseases and Disorders

Health Care	Blood Collection
Health Care	Pathology
Health Care	Pulmonology
Economics, Policy, and Social Studies	Economics
Economics, Policy, and Social Studies	Economic Development
Economics, Policy, and Social Studies	Policy Analysis
Economics, Policy, and Social Studies	Social Studies
Economics, Policy, and Social Studies	Urban Planning
Analysis	Natural Language Processing (NLP)
Analysis	Mathematical Software
Analysis	Data Visualization
Analysis	Data Analysis
Analysis	Validation
Analysis	Machine Learning
Analysis	Data Techniques
Analysis	Data Science
Analysis	Mathematics
Analysis	Business Intelligence Software
Analysis	Ad Hoc Analysis and Reporting
Analysis	Business Intelligence
Analysis	Mathematical Modeling
Analysis	Data Mining
Analysis	Statistics
Analysis	Statistical Software
Human Resources	Employee Relations
Human Resources	Deductions
Human Resources	Occupational Health and Safety
Human Resources	Recruitment
Human Resources	Human Resource Management Systems
Human Resources	Employee Training

Human Resources	Payroll
Human Resources	Compensation and Benefits
Human Resources	Talent Management
Human Resources	Human Resource Management and Planning
Education and Training	Peer Review
Education and Training	Training Programs
Education and Training	Archiving
Education and Training	Education Administration
Education and Training	Interpretations and Translations
Education and Training	Childhood Education and Development
Education and Training	Learning Management Systems
Education and Training	Teaching
Education and Training	Exercise Training
Education and Training	Library and Cataloging
Education and Training	Instructional and Curriculum Design
Education and Training	Instruction
Education and Training	Higher Education
Education and Training	Program Management
Education and Training	Coaching and Athletic Training
Education and Training	Child Development
Education and Training	Test Administration
Design	Creative Design
Design	Animation and Game Design
Design	Art and Illustration
Design	Industrial Design
Design	Graphic and Visual Design Software
Design	Digital Design
Design	Presentation Design
Design	User Interface and User Experience (UI/UX) Design
Design	Graphic and Visual Design

Media and Writing	Audio Production
Media and Writing	Visual Design Production
Media and Writing	Music
Media and Writing	Media Production
Media and Writing	Content Development and Management
Media and Writing	Writing
Media and Writing	Journalism
Media and Writing	Multimedia
Environment	Waste Management
Environment	Water Testing and Treatment
Environment	Environmental Work
Environment	Emissions Management
Environment	Hazardous Waste Management
Environment	Ecology
Environment	Resource Management and Restoration
Environment	Ethanol
Environment	Air Quality
Environment	Forestry
Environment	Environmental Geology
Environment	Environmental Regulations
Environment	Conservation
Customer and Client Support	Advanced Customer Service
Customer and Client Support	Claims Processing
Customer and Client Support	Basic Customer Service
Customer and Client Support	Cash Register Operation
Customer and Client Support	Payment Processing and Collection
Personal Care and Services	Child Care
Personal Care and Services	Personal Care
Personal Care and Services	Food and Beverage Service
Personal Care and Services	Animal Care

Personal Care and Services	Housekeeping
Agriculture, Horticulture, and the Outdoors	Landscaping and Yard Care
Agriculture, Horticulture, and the Outdoors	Agricultural Research
Agriculture, Horticulture, and the Outdoors	Agronomy and Farming
Religion	Ministry

Appendix B

Dataset Full Range of Variables

Variable	Description	Use in Analysis
JobDate	Date when the job was posted	Yes
ConsolidatedO*NET	Consolidated O*NET occupation code	Yes
CanonSkillClusters	Skill clusters associated with the job posting	Yes
CanonMaximumDegree	Maximum educational degree required	Yes
CanonMinimumDegree	Minimum educational degree required	Yes
CanonOtherDegrees	Other acceptable degrees	Yes
CanonPreferredDegrees	Preferred educational degrees	Yes
CanonRequiredDegrees	Required educational degrees	Yes
Major	Specific major fields required	Yes
JobID	Unique identifier for each job posting	Yes
CleanJobTitle	Standardized job title	Yes
MaxExperience	Maximum years of experience required	No
MinExperience	Minimum years of experience required	No
YearsOfExperience	Years of experience required	No
CanonYearsOfExperienceLevel	Standardized level of years of experience required	No
ConsolidatedDegreeLevels	Consolidated degree levels required	No
MaxDegreeLevel	Maximum degree level required	No
MinDegreeLevel	Minimum degree level required	No
JobDomain	Domain or field of the job	No
CanonCity	Standardized city of the job location	No
CanonCountry	Standardized country of the job location	No
CanonState	Standardized state of the job location	No
JobText	Full text of the job posting	No
JobURL	URL of the job posting	No
PostingHTML	HTML content of the job posting	No

Source	Source from which the job posting was obtained	No
JobReferenceID	Reference ID for the job posting	No
Email	Contact email for the job posting	No
CanonEmployer	Standardized name of the employer	No
Latitude	Latitude of the job location	No
Longitude	Longitude of the job location	No
CanonIntermediary	Intermediary organization (if any)	No
Telephone	Contact telephone number for the job posting	No
CanonJobTitle	Standardized job title	No
CanonCounty	Standardized county of the job location	No
DivisionCode	Division code of the job location	No
MSA	Metropolitan Statistical Area	No
LMA	Labor Market Area	No
InternshipFlag	Indicator if the job is an internship	No
CanonCertification	Required certifications	No
CanonSkills	Specific skills required for the job (empty values)	No
IsDuplicate	Indicator if the job posting is a duplicate	No
IsDuplicateOf	Reference to the original job posting if it is a duplicate	No
CIPCode	Classification of Instructional Programs code	No
StandardMajor	Standardized major field of study	No
ConsolidatedInferredNAICS	Inferred NAICS code for industry classification	No
BGTOcc	Burning Glass occupational code	No
MaxAnnualSalary	Maximum annual salary offered	No
MaxHourlySalary	Maximum hourly salary offered	No
MinAnnualSalary	Minimum annual salary offered	No
MinHourlySalary	Minimum hourly salary offered	No
CanonJobHours	Job hours (e.g., full-time, part-time)	No
CanonJobType	Job type (e.g., permanent, temporary)	No
CanonPostalCode	Postal code of the job location	No

ConsolidatedTitle	Consolidated job title	No
Language	Language requirements	No
BGTSubOcc	Burning Glass sub-occupation code	No

O*NET Job Title and Its Synonyms For Civil Engineering

O*NET Job Title	Synonyms
City Engineer	Municipal Engineer, Urban Infrastructure Engineer, Public Works Engineer
Civil Engineer	Infrastructure Engineer, Structural Civil Engineer, Construction Engineer, Road Engineer
County Engineer	District Engineer, Regional Engineer, Public Works Engineer
Design Engineer	Civil Design Engineer, Structural Designer, Project Design Engineer
Engineer	Professional Engineer, Licensed Engineer, Project Engineer, Technical Engineer
Geotechnical Engineer	Soil Engineer, Geo-Environmental Engineer, Ground Engineer, Foundation Engineer
Licensed Engineer	Registered Professional Engineer, Certified Engineer, Chartered Engineer, Licensed Civil Engineer
Project Engineer	Project Manager Engineer, Engineering Project Manager, Technical Project Engineer
Railroad Design Consultant	Railroad Engineer, Rail Systems Designer, Transportation Engineer
Structural Engineer	Building Engineer, Structural Designer, Bridge Engineer, Infrastructure Engineer

O*NET Job Titles and its Synonyms For Electrical Engineering

O*NET Job Title	Synonyms
Circuits Engineer	Circuit Design Engineer, Electrical Circuit Engineer, Electronic Engineer, PCB Engineer
Design Engineer	Electrical Design Engineer, Product Design Engineer, CAD Engineer, Systems Design Engineer
Electrical Controls Engineer	Controls Engineer, Automation Engineer, Control Systems Engineer, PLC Engineer
Electrical Design Engineer	Circuit Design Engineer, Power Systems Engineer, Electrical Systems

	Designer, Hardware Design Engineer
Electrical Engineer	Power Engineer, Electronic Engineer, Electrical Systems Engineer, Power Distribution Engineer
Electrical Project Engineer	Project Electrical Engineer, Electrical Engineering Project Manager, Electrical Design Engineer
Engineer	Professional Engineer, Licensed Engineer, Technical Engineer, Systems Engineer
Instrumentation and Electrical Reliability Engineer	Instrumentation Engineer, Reliability Engineer, Electrical Maintenance Engineer, Automation and Instrumentation Engineer
Project Engineer	Engineering Project Manager, Technical Project Engineer, Electrical Project Manager
Test Engineer	Validation Engineer, QA Engineer, Test Automation Engineer, Quality Engineer

O*NET Job Titles and its Synonyms For Mechanical Engineering

Job Title	Synonyms
Application Engineer	Applications Engineer, Technical Engineer, Field Application Engineer
Design Engineer	Mechanical Design Engineer, CAD Engineer, Product Designer
Equipment Engineer	Plant Engineer, Maintenance Engineer, Tooling Engineer
Mechanical Design Engineer	Mechanical Engineer, Product Design Engineer, CAD Mechanical Engineer
Mechanical Designer	CAD Designer, Mechanical Draftsperson, Technical Designer
Mechanical Engineer	Mechanical Systems Engineer, Mechanical Specialist, Design Engineer
Product Development Engineer	R&D Engineer, New Product Engineer, Innovation Engineer
Product Engineer	Production Engineer, Manufacturing Engineer, Process Engineer
Project Engineer	Engineering Project Manager, Technical Project Engineer, Site Project Engineer
Test Engineer	QA Engineer, Quality Engineer, Validation Engineer

Exclusion Terms for CE/EE/ME

Discipline	Exclusion Terms
Civil Engineering	Electrical eningeering/engineer, Aerospace eningeering/engineer, Mechanical eningeering/engineer, Combat eningeering/engineer
Electrical Engineering	Mechanical eningeering/engineer, Civil eningeering/engineer, Aerospace eningeering/engineer, Combat eningeering/engineer, Water resource, Construction eningeering/engineer
Mechanical Engineering	Electrical eningeering/engineer, Aerospace eningeering/engineer, Civil eningeering/engineer, Combat eningeering/engineer, Water resource, Construction eningeering/engineer