*Corresponding Author's Email: Maayan.Nakash@biu.ac.il
Proceedings of the International Conference on Research in Business, Management and Finance
Vol. 2, Issue. 1, 2025, pp. 9-20
DOI: https://doi.org/10.33422/icrbmf.v2i1.1178

ISSN: 3030-1106 online

From Junior to Senior: Skill Requirements for AI Professionals Across Career Stages

Or Peretz[1,2], Maayan Nakash[1]*

[1*]Department of Management, Bar-Ilan University, Ramat Gan, Israel

[2] School of Industrial Engineering and Management, Shenkar College, Ramat Gan, Israel

Abstract

Artificial intelligence (AI) experts play a pivotal role in driving technological innovation; however, the literature offers limited insights into the specific skills required for various AI roles across different levels of experience. To address this gap, we manually collected data from 18,497 AI job postings on LinkedIn throughout 2024. Using advanced analytical techniques, including exploratory data analysis and natural language processing, we examined the distribution of job postings by experience level—junior vs. senior—and analyzed the prevalence of specific skills within each category. The preliminary findings presented in this paper reveal notable differences in skill expectations across position levels in the AI job market. The results indicate that junior AI roles, representing 32.6% of the postings, predominantly prioritize foundational technical skills, such as Python, machine learning, and SQL. In contrast, senior AI roles, accounting for 67.4% of the postings, require not only advanced technical expertise (e.g., Git, AWS, Scala) but also emphasize the strategic importance of communication, leadership, and marketing skills. These findings underscore the need for early-career AI professionals to develop a strong technical foundation while progressively cultivating soft skills to transition into senior roles. The evolving landscape of AI employment highlights the necessity of a balanced approach to skill development, integrating technical proficiency with interpersonal capabilities. Such a balance is essential for fostering technological innovation and leveraging learning technologies to effectively advance AI competencies.

Keywords: Skill Requirements, Artificial Intelligence, Labor Market, AI Professionals, Workforce Development

1 Introduction

Recent studies have highlighted the rapid growth of the global artificial intelligence (AI) job market, with a significant demand for roles such as machine learning engineers, data scientists, and AI research scientists (Acemoglu et al., 2022; Alekseeva et al., 2021; Meesters et al., 2022). These trends underscore the necessity for professionals who can not only master current technologies but also adapt to advancements in AI tools and methodologies through continuous learning (Fenlon & Fitzgerald, 2019; Meesters et al., 2022; Nakash, 2024; Poquet & De Laat, 2021).

LinkedIn has emerged as a leading platform for job searches and professional networking, offering real-time insights into labor market dynamics (Dinath, 2021; Wang et al., 2019). With over 1 billion registered members, LinkedIn provides a vast network for professionals to connect, share knowledge, and explore career opportunities (Li et al., 2020). By leveraging its extensive database of job postings and professional profiles, LinkedIn can offer valuable insights into the evolving demands for AI roles (Bäck et al., 2021; Khaouja et al., 2021).

Understanding how skill requirements change at different career stages is crucial for individuals entering or advancing in this field, as well as for educators and employers aiming to develop a robust AI talent pool. The growing significance of AI expertise is widely recognized (Acemoglu et al., 2022; Alekseeva et al., 2021). Nevertheless, companies continue to face challenges in recruiting for AI-related roles, while many new graduates struggle to secure employment—suggesting a potential skills gap or a misalignment between graduates' competencies and industry requirements (Rigley et al., 2024). Despite this, there is a notable gap in the literature regarding how skill requirements differ between junior and senior AI roles.

This paper presents preliminary insights from an exploratory study we conducted, involving manual data collection from LinkedIn throughout the year 2024. A total of 18,947 AI job postings were analyzed, mapping the evolving landscape of AI skills across different levels of experience, using text analysis and natural language processing (NLP) techniques.

2 Related Works

As AI continues to reshape the global economy, understanding its implications for workforce skills has become a central concern for researchers and policymakers alike. The rapid advancement of AI technologies has fundamentally reshaped numerous industries, driving technological innovation, efficiency, and new business models (Rashid & Kausik, 2024). As AI technologies evolve, they create substantial economic impacts and increase the demand for specialized skills across sectors such as healthcare, finance, manufacturing, and retail (Badet, 2021; Reis et al., 2020; Squicciarini & Nachtigall, 2021).

One of the key challenges faced by employers, educators, and workers is planning today for the skills that will be in high demand tomorrow, particularly as the pace of technological change accelerates (Fenlon & Fitzgerald, 2019). Skills refer to the abilities that enable individuals to perform tasks effectively and are often divided into hard and soft skills. Hard skills include technical competencies, typically acquired through formal education, such as programming and data analysis (Balcar, 2016; Heckman & Kautz, 2012). In contrast, soft skills encompass interpersonal abilities like adaptability and leadership. Research shows that both skill types are essential for job performance and innovation, with soft skills sometimes proving as predictive of success as technical skills (Balcar, 2016; Hendarman & Cantner, 2018).

Recruiting for AI roles remains challenging, as many new graduates often lack the specific skills required by employers to effectively perform in AI-focused positions (Fenlon & Fitzgerald, 2019; Shmatko & Volkova, 2020). The integration of AI into the workforce is not only generating entirely new roles but also fundamentally transforming the skill sets required for employment (Gonzalez Ehlinger & Stephany, 2024). This persistent gap between academic preparation and industry expectations necessitates a sufficiently in-depth examination of evolving labor markets and the specific skill sets required within them (Rigley et al., 2024).

As AI integration spreads across industries, a blend of technical and non-technical skills has become increasingly crucial. Alekseeva et al. (2021) observed that AI-related skills often yield a wage premium as companies prioritize technical proficiency alongside essential soft skills like communication and problem-solving. Similarly, Squicciarini and Nachtigall (2021) highlighted a rising need for socio-emotional abilities, such as creativity and teamwork, alongside AI expertise. In the complex labor landscape rapidly transformed by AI, continuous learning, especially in STEM fields, has become essential for adapting to evolving demands (Morikawa, 2017).

In the tech industry, junior and senior roles differ primarily by experience, skills, and responsibilities. Junior positions, often held by recent graduates with 0–3 years of experience, emphasize foundational skill-building under supervision (Floyd & Spencer, 2014). In contrast, senior roles, typically requiring a greater number of years of experience, demand advanced technical skills, project management, and strategic abilities (Matsudaira, 2016). Skill requirements differ accordingly: junior roles focus on basic programming and software development, while senior roles require specialized technical expertise, problem-solving, mentoring, and leadership abilities (Madusanka & Rupasingha, 2022; Maisiri, 2023).

This progression also affects responsibilities. Junior staff primarily handle assigned tasks to build their skills, while senior staff lead projects, mentor others, and make strategic decisions that impact the organization (Floyd & Spencer, 2014; Maisiri, 2023). This tiered structure fosters skill development in junior positions and drives innovation in senior roles. However, advancement from junior to senior is not guaranteed and depends on factors such as skill development, competition, and specialization (Güllich et al., 2023).

3 Methodology

3.1 Data Collection, Preprocessing and Categorization

Due to LinkedIn's (2023) restrictive policy on web scraping, we manually collected data on 18,947 AI job postings throughout 2024, by searching for the keywords "AI" and "Artificial Intelligence." This data collection included job titles and job descriptions. To ensure data quality, we removed duplicates and special characters, converted text to lowercase, and tokenized words (Vijayarani & Janani, 2016). Using NLP, job postings were categorized by experience level (i.e., seniority or position level): junior roles required less than three years of experience, while senior roles required more (Floyd & Spencer, 2014). For skill extraction, we applied regular expressions (regex) to identify common technical skills (Navarro, 2004) and Named Entity Recognition (NER) to pinpoint specific tools and technologies (Li et al., 2020). Additionally, n-gram analysis and collocation detection were used to capture multi-word skill phrases (Subhashini & Kumar, 2010).

3.2 Analytical Analysis

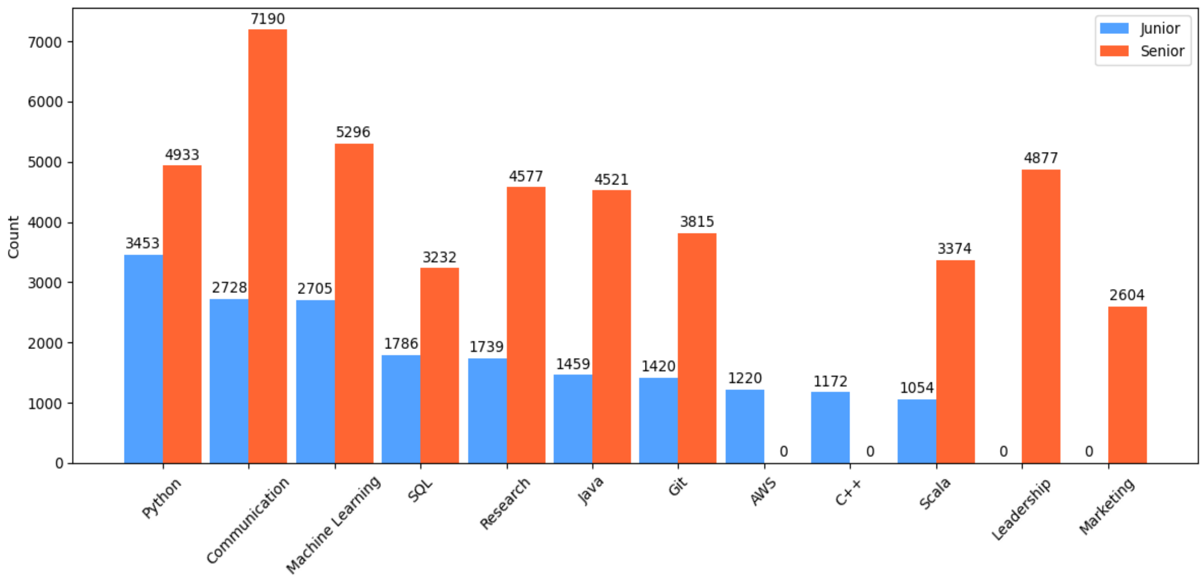
We conducted exploratory data analysis (EDA) to examine the distribution of job postings across different experience levels (Junior vs. Senior) and to analyze the prevalence of specific skills within each category. To further explore the relationship between skills and roles, we applied NLP techniques (Kang et al., 2020). This enabled us to perform correlation analysis, identifying whether certain skills are more strongly associated with junior or senior positions, thus highlighting skill progression in AI roles. Additionally, we created a network of skills for each seniority level using degree centrality analysis (Borgatti et al., 2009; Hevey et al., 2018). Degree centrality, which measures the number of direct connections a node (i.e., skill) has, was used to determine the prominence of specific skills within the network, providing insights into which skills are foundational versus supplementary in AI job roles (Landherr et al., 2010).

4 Results

4.1 Experience Levels and Skill Requirement Differences

Categorizing AI job postings by experience level reveals distinct skill requirements for junior and senior roles, with senior positions comprising 67.4% (12,770 postings) and junior roles 32.6% (6,177 postings). **Figure 1** compares the top skills in demand for both levels.

Figure 1: Comparison of Top Skills in Junior vs. Senior AI Roles



For junior roles, foundational skills such as Python (3,453 mentions), Communication (2,728 mentions), and Machine Learning (2,705 mentions) are the most sought-after. Other essential technical skills include SQL (1,786 mentions) and Git (1,420 mentions), which support data management and version control. Programming languages like Java and C++ appear but are less emphasized, indicating that junior positions prioritize more versatile skills that are widely applicable in AI.

In contrast, senior roles require both advanced technical skills and substantial non-technical competencies. Communication (7,190 mentions), Machine Learning (5,296 mentions), and Python (4,933 mentions) remain essential, but skills in Leadership (4,877 mentions) and Marketing (2,604 mentions) gain prominence, highlighting the managerial and strategic responsibilities in senior AI roles. Specialized tools and platforms, such as AWS (3,815 mentions) and Scala (3,374 mentions), also become more critical, likely due to their relevance in complex, large-scale AI projects.

4.2 Correlation Analysis

We conducted a correlation analysis to explore the relationships between the top skills required in junior and senior roles. The correlation heatmaps for each experience level (**Figures 2 and 3,** respectively) provide insights into how frequently certain skills co-occur in job postings.

Figure 2: Correlation Heatmap of Top Skills for Junior AI Roles

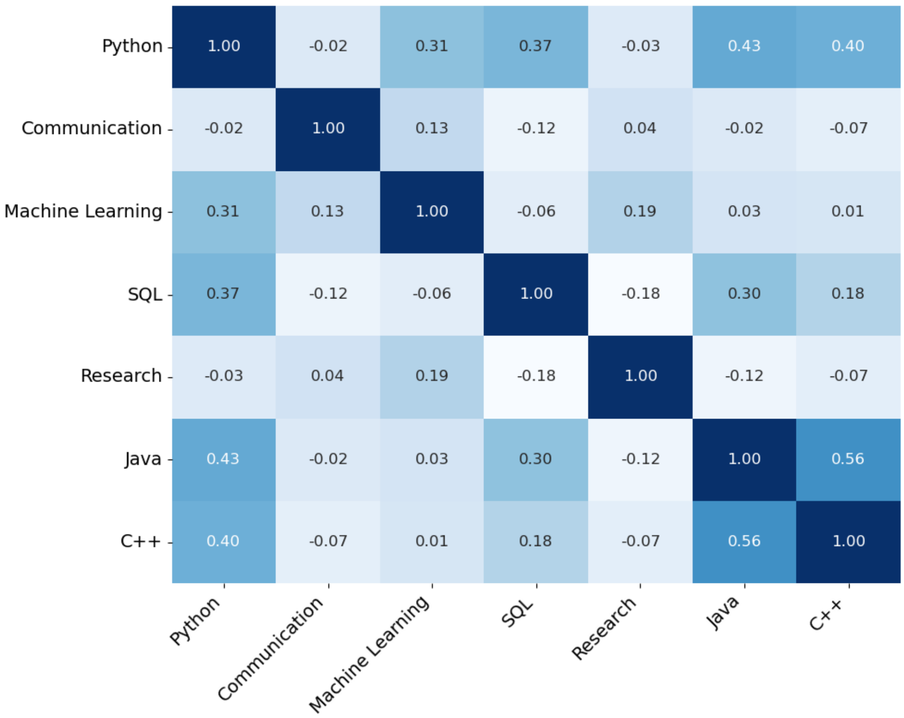
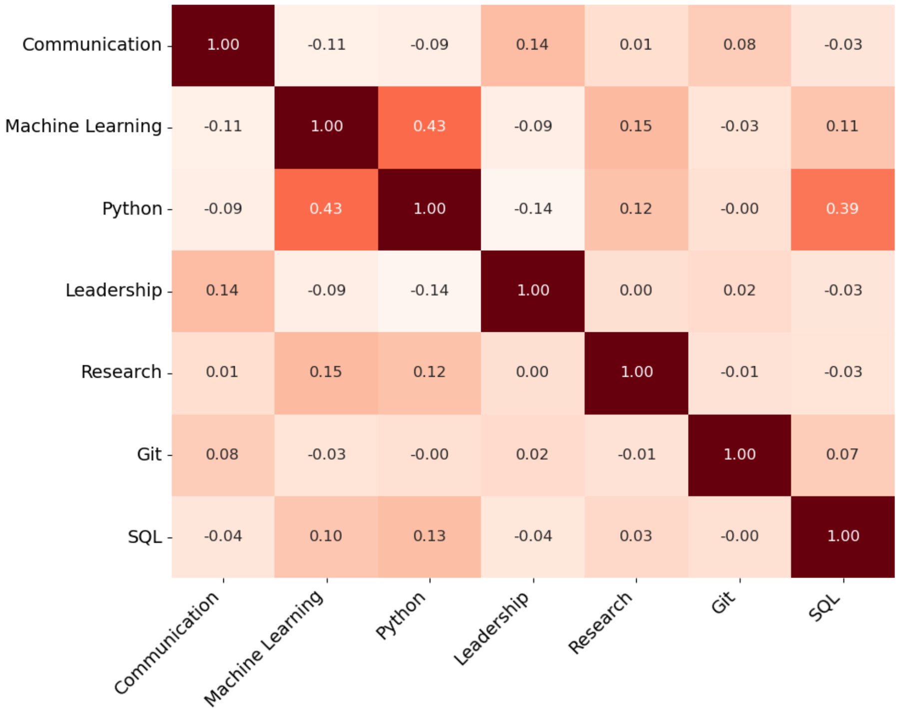


Figure 3: Correlation Heatmap of Top Skills for Senior AI Roles



For junior roles, several interesting correlation patterns emerged. Python and Machine Learning showed a positive correlation (0.31), though less pronounced than expected. The strongest correlations were between programming languages: Java and C++ (0.56), Python and Java (0.43), and Python and C++ (0.40). This suggests that junior AI roles value versatile coding skills for AI diverse projects. Additionally, SQL and Python had a moderate correlation (0.37), highlighting the importance of database skills even at junior level.

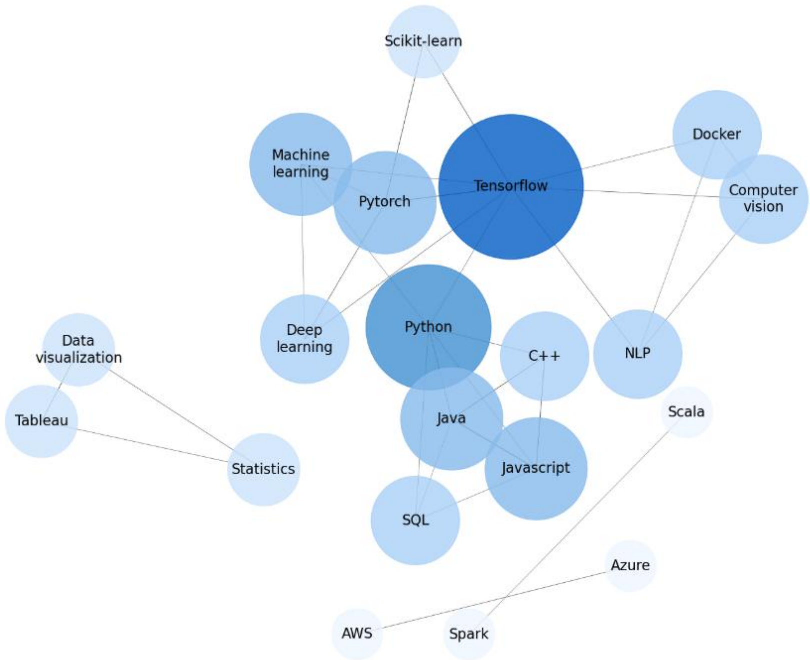
In senior roles, Python and SQL maintained a strong correlation (0.39), indicating that senior AI professionals are expected to be proficient in both data manipulation and advanced programming. Python and Machine Learning exhibited an even stronger correlation (0.43). Another significant finding is the moderate positive correlation between Leadership and Communication (0.14). While this correlation is weaker than that observed for technical skills, it highlights the growing importance of managerial and interpersonal skills for senior professionals.

4.3 Network Analysis

To further explore the relationships between skills, we conducted a network analysis using degree centrality to identify the most connected and influential skills in both junior and senior roles. Degree centrality measures the number of direct connections (edges) a node (skill) has, indicating its prominence within the network. Skills with higher centrality are frequently associated with other skills, underscoring their importance in job postings. In the network visualizations (**Figures 4 and 5**), each node's size reflects its degree centrality, with larger nodes representing more connected skills. Additionally, node colors vary according to centrality: darker shades represent higher centrality, while lighter shades indicate lower centrality, facilitating the identification of the most influential skills.

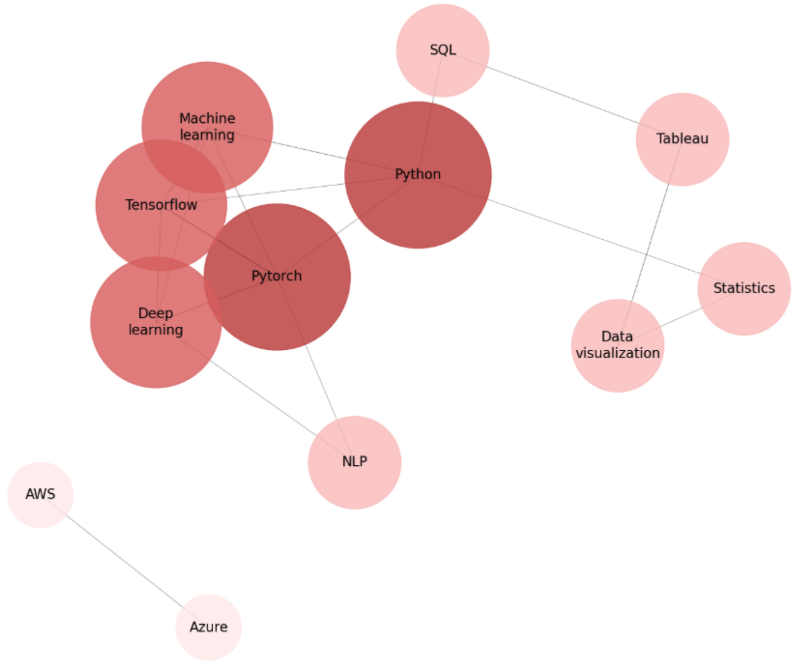
Junior AI Skills Network. The junior skills network comprises 22 nodes and 33 edges, with an average clustering coefficient of 0.5539, indicating a moderately connected skill set. TensorFlow exhibits the highest degree of centrality (0.38), underscoring its pivotal role in entry-level AI positions and reinforcing its dominance as a preferred framework for building machine learning models. Python follows closely with a degree centrality of 0.29, affirming its status as a foundational programming language in AI development. Machine Learning, Java, and JavaScript share the third position, each with a degree centrality of 0.19.

Figure 4: Junior AI Skill Network



Senior AI Skills Network. The senior skills network, consisting of 13 nodes and 19 edges, has a lower average clustering coefficient of 0.3641, suggesting a more loosely connected skill set compared to junior roles. In this network, Python, PyTorch, and Deep Learning share the top position with a degree centrality of 0.42, indicating that senior AI roles demand balanced expertise. Machine Learning and TensorFlow rank second with a degree centrality of 0.33, highlighting their continued relevance in senior roles.

Figure 5: Senior AI Skill Network



Comparative Overview. The senior skills network emphasizes advanced deep learning frameworks (e.g., PyTorch, TensorFlow), whereas the junior network underscores a broader foundation in programming languages (e.g., Java, JavaScript). This shift underscores the increasing specialization and technical depth required in senior AI roles. Comparing the junior and senior networks reveals clear trends in skill progression: while TensorFlow dominates in junior roles, PyTorch and Deep Learning gain prominence in senior positions, reflecting the need for specialized tools at higher levels. Python remains a central skill across all experience levels, illustrating its widespread applicability.

5 Discussion

The analytical analysis reveals that the surveyed AI job postings contain 2.07 times more positions for AI experts compared to entry-level roles. The distinction between junior and senior AI roles reflects a classic trajectory in technological learning, where foundational skills are built at entry levels, gradually evolving into more complex and specialized knowledge. For junior roles, the emphasis on versatile, foundational skills like Python, SQL, and Machine Learning underscores the need for adaptable competencies that form the basis of AI work, aligning with Floyd and Spencer's (2014) description of entry-level positions focusing on skill-building under supervision. Such skills are instrumental in creating a workforce that can swiftly engage in AI tasks, while the broader programming proficiency observed (e.g., familiarity with Java and C++) prepares junior AI professionals to work in diverse project environments.

At the senior level, the shift toward specialized skills such as deep learning frameworks (e.g., PyTorch) and advanced platforms (e.g., AWS) mirrors the growing complexity and sophistication required in AI applications. Senior professionals are expected to handle large-scale, advanced AI solutions, and these skills reflect the need for both technical depth and strategic acumen. The prominence of management and interpersonal skills, such as Leadership and Communication, indicates that senior AI roles are integral not only to technical implementation but also to guiding technological innovation and fostering a collaborative work environment. This aligns with the recognition in the literature that soft skills are as important as hard skills, even in roles with a strong technological orientation (Hendarman & Cantner, 2018; Balcar, 2016; Li et al.,2020; Nakash, 2024; Squicciarini & Nachtigall, 2021).

The skill trajectory observed in AI roles provides valuable insights for designing learning programs in technology education. For instance, junior-level programs should focus on versatile, foundational skills that allow graduates to adapt to various technological settings, while senior-level programs can emphasize specialization and strategic skills development. The correlation between foundational skills like Python and SQL at both experience levels suggests a continuous emphasis on data handling and programming fluency, indicating that these should remain core components of any AI learning curriculum.

6 Conclusion

In conclusion, the analysis of AI job postings provides preliminary insights into the evolving trajectory of skill development across different career stages. These initial findings indicate that foundational technical skills dominate entry-level roles, while specialized technical expertise and managerial competencies gain prominence at more advanced levels. This trajectory underscores the need for adaptive educational strategies to meet the dynamic demands of the AI field. By cultivating both technical depth and strategic acumen, organizations and educational institutions can better prepare AI professionals to drive technological innovation and effectively deploy AI solutions in complex, large-scale environments. This approach holds promise not only for advancing individual career development but also for fostering sustained progress in the broader field of AI.

From a practical perspective, the findings may offer useful insights for various stakeholders. Higher education institutions could consider aligning curricula more closely with emerging industry needs by emphasizing both foundational and specialized skills. Employers might draw on these insights to refine recruitment strategies and explore targeted upskilling initiatives that support smoother transitions between junior and senior roles. Additionally, policymakers may find value in this evidence when shaping workforce development programs that promote a balanced integration of technical and soft skills—contributing to the cultivation of a more adaptable and future-oriented AI workforce.

As this paper offers an initial exploration, future research is needed to delve deeper into the nuances of AI job postings. Areas for further investigation could include sector-specific skill requirements, regional variations, and the rising importance of soft skills, such as ethical reasoning and cross-disciplinary collaboration. These additional dimensions would enrich our understanding of the evolving AI job market and guide the creation of more targeted educational and professional development programs.

References

Acemoglu, D., Autor, D., Hazell, J., & Restrepo, P. (2022). Artificial intelligence and jobs: Evidence from online vacancies. *Journal of Labor Economics*, *40*(S1), S293-S340. https://doi.org/10.1086/718327

Alekseeva, L., Azar, J., Giné, M., Samila, S., & Taska, B. (2021). The demand for AI skills in the labor market. *Labour economics*, *71*, 102002. https://doi.org/10.1016/j.labeco.2021.102002

Bäck, A., Hajikhani, A., & Suominen, A. (2021). Text mining on job advertisement data: Systematic process for detecting artificial intelligence related jobs. In *AI+ Informetrics* (pp.111-124).

Badet, J. (2021). AI, automation and new jobs. *Open journal of business and management*, *9*(5), 2452-2463. https://doi.org/10.4236/ojbm.2021.95132

Balcar, J. (2016). Is it better to invest in hard or soft skills?. *The Economic and Labour Relations Review*, *27*(4), 453-470. https://doi.org/10.1177/1035304616674613

Borgatti, S.P., Mehra, A., Brass, D.J., & Labianca, G. (2009). Network analysis in the social sciences. *science*, *323*(5916), 892-895. https://doi.org/10.1126/science.1165821

Dinath, W. (2021). Linkedin: a link to the knowledge economy. In *ECKM 2021 22nd European Conference on Knowledge Management. Academic Conferences Limited* (pp.253-259).

Fenlon, M.J., & Fitzgerald, B.K. (2019). Reskilling–a solution for the digital skills gap. In *Business Higher Education Forum*.

Floyd, R.E., & Spencer, R.H. (2014). Career paths: Technical or management?. *IEEE Potentials*, *33*(3), 25-26. https://doi.org/10.1109/MPOT.2012.2195341

Gonzalez Ehlinger, E., & Stephany, F. (2024). Skills or degree? The rise of skill-based hiring for AI and green jobs. *The Rise of Skill-Based Hiring for AI and Green Jobs (February 25, 2024)*. https://doi.org/10.2139/ssrn.4743968

Güllich, A., Barth, M., Macnamara, B.N., & Hambrick, D.Z. (2023). Quantifying the extent to which successful juniors and successful seniors are two disparate populations: a systematic review and synthesis of findings. *Sports Medicine*, *53*(6), 1201-1217. https://doi.org/10.1007/s40279-023-01840-1

Heckman, J.J., & Kautz, T. (2012). Hard evidence on soft skills. *Labour economics*, *19*(4), 451-464. https://doi.org/10.1016/j.labeco.2012.05.014

Hendarman, A.F., & Cantner, U. (2018). Soft skills, hard skills, and individual innovativeness. *Eurasian Business Review*, *8*, 139-169. https://doi.org/10.1007/s40821-017-0076-6

Hevey, D. (2018). Network analysis: a brief overview and tutorial. *Health psychology and behavioral medicine*, *6*(1), 301-328. https://doi.org/10.1080/21642850.2018.1521283

Kang, Y., Cai, Z., Tan, C. W., Huang, Q., & Liu, H. (2020). Natural language processing (NLP) in management research: A literature review. *Journal of Management Analytics*, *7*(2), 139-172. https://doi.org/10.1080/23270012.2020.1756939

Khaouja, I., Kassou, I., & Ghogho, M. (2021). A survey on skill identification from online job ads. *IEEE Access*, *9*, 118134-118153. https://doi.org/10.1109/ACCESS.2021.3106120

Landherr, A., Friedl, B., & Heidemann, J. (2010). A critical review of centrality measures in social networks. *Business & Information Systems Engineering*, *2*, 371-385. https://doi.org/10.1007/s12599-010-0127-3

Li, J., Sun, A., Han, J., & Li, C. (2020). A survey on deep learning for named entity recognition. *IEEE transactions on knowledge and data engineering*, *34*(1), 50-70. https://doi.org/10.1109/TKDE.2020.2981314

LinkedIn. (2023). Prohibited software and extensions. LinkedIn Help. Retrieved from https://www.linkedin.com/help/linkedin/answer/a1341387

Madusanka, H.A.G., & Rupasingha, R.A.H.M. (2022). The Relationship between Job Skills and the Level of Job Availability in the Information Technology Industry: An Analysis of Information Technology Job Market. *Journal of Business and Technology*, *6*(2). https://doi.org/10.4038/jbt.v6i2.91

Maisiri, W., & van Niekerk, W. (2023). Transfer of knowledge and skills from junior to senior years: Getting the fundamentals right. In *Conference of the South African Society for Engineering Education* (p.136).

Matsudaira, K. (2016). Delegation as Art: Be someone who makes everyone else better. *Queue*, *14*(1), 10-15. https://doi.org/10.1145/2898442.2926696

Meesters, M., Heck, P., & Serebrenik, A. (2022). What is an AI engineer? An empirical analysis of job ads in The Netherlands. In *Proceedings of the 1st International Conference on AI Engineering: Software Engineering for AI* (pp.136-144). https://doi.org/10.1145/3522664.3528594

Morikawa, M. (2017). *Who are afraid of losing their jobs to artificial intelligence and robots? Evidence from a survey* (No.71). GLO Discussion Paper.

Nakash, M. (2024). Reskilling and Upskilling the Workforce: Text Mining to Identify Patterns and Trends in Research. In *Proceedings of the International Conference on Research in Human Resource Management,* *1*(1), 1-10. https://doi.org/10.33422/icrhrm.v1i1.169

Navarro, G. (2004). Pattern matching. *Journal of Applied Statistics*, *31*(8), 925-949. https://doi.org/10.1080/0266476042000270527

Poquet, O., & De Laat, M. (2021). Developing capabilities: Lifelong learning in the age of AI. *British Journal of Educational Technology*, *52*(4), 1695-1708. https://doi.org/10.1111/bjet.13123

Rashid, A. B., & Kausik, A. K. (2024). AI revolutionizing industries worldwide: A comprehensive overview of its diverse applications. *Hybrid Advances*, 100277. https://doi.org/10.1016/j.hybadv.2024.100277

Reis, C., Ruivo, P., Oliveira, T., & Faroleiro, P. (2020). Assessing the drivers of machine learning business value. *Journal of Business Research*, *117*, 232-243. https://doi.org/10.1016/j.jbusres.2020.05.053

Rigley, E., Bentley, C., Krook, J., & Ramchurn, S.D. (2024). Evaluating international AI skills policy: A systematic review of AI skills policy in seven countries. *Global policy*, *15*(1), 204-217. https://doi.org/10.1111/1758-5899.13299

Shmatko, N., & Volkova, G. (2020). Bridging the skill gap in robotics: Global and national environment. *Sage Open*, *10*(3). https://doi.org/10.1177/2158244020958736

Squicciarini, M., & Nachtigall, H. (2021). Demand for AI skills in jobs: Evidence from online job postings.

Subhashini, R., & Kumar, V.J.S. (2010). Shallow NLP techniques for noun phrase extraction. In *Trendz in information sciences & computing (tisc2010)* (pp.73-77). IEEE. https://doi.org/10.1109/TISC.2010.5714612

Vijayarani, S., & Janani, R. (2016). Text mining: open source tokenization tools-an analysis. *Advanced Computational Intelligence: An International Journal (ACII)*, *3*(1), 37-47. https://doi.org/10.5121/acii.2016.3104

Wang, Q., Liu, X., & Huang, K. (2019). Displaced or Augmented? How does Artificial Intelligence Affect Our Jobs: Evidence from LinkedIn. In *ICIS*.