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"The Global Race for AI Talent: A Multi-Level Analysis of Workforce Transformation from OECD Trends to Local Realities"

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Declaration of Originality

I hereby declare that I have read and understood the “Anti-plagiarism rules” approved by the Council of the Department of Economics and Management and I am aware of the consequences of making false statements. I declare that this thesis has not been previously submitted – either fully or partially – for fulfilling the requirements of an academic degree, whether in Italy or abroad. Furthermore, I declare that the references used for this work – including the digital materials – have been appropriately cited in the text and in the “References” section.

Signature ....

Abstract

This study investigates the impact of artificial intelligence (AI) on labor markets through a multi-level framework, combining global trends with national data and local insights. The objective is to examine how AI adoption influences job roles, skill requirements, and organizational practices across different contexts. At the global level, data from the OECD.AI Observatory is analyzed to assess AI skills migration, cross-country skill penetration by industry, hiring trends, and gender participation. The national perspective focuses on a dataset of 862 AI/ML job postings in the United States, revealing patterns in job titles, required skills, experience levels, and hiring sectors. The local level presents findings from interviews with five companies in Avezzano, Italy, offering qualitative insights into AI-related transformations within SMEs. The results highlight how AI is reshaping workforce dynamics, accelerating the demand for technical and adaptive skills, and creating new organizational challenges. The research contributes to the literature on innovation and labor by demonstrating the uneven pace of AI integration across sectors and geographies, and by emphasizing the strategic importance of workforce adaptability in managing technological change.

ACKNOWLEDGEMENTS

I would like to express my sincere gratitude to Professor Antonietti for his guidance, critical insights, and steady encouragement throughout the development of this thesis. His support played a key role in helping me shape and refine my ideas with confidence.

To my family and friends, thank you for your unwavering support, understanding, and patience throughout this journey. You reminded me of my strength in moments when I needed it most. This achievement belongs to all of us.

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1. Introduction

1.1 Research Background

The rapid advancement of artificial intelligence (AI) technologies over the past decade has transformed nearly every aspect of the global economy, triggering fundamental shifts in how work is structured, performed, and valued. As AI systems increasingly replicate cognitive capabilities, ranging from language understanding to decision-making, questions surrounding the future of employment, the evolution of required skills, and the distributional impacts of automation have taken center stage in both academic and policy debates.

Unlike previous waves of technological change, the Fourth Industrial Revolution, defined by the convergence of digital, biological, and physical systems, has introduced a new class of general-purpose technologies whose reach transcends traditional industry boundaries (Schwab, 2016). AI is not only enhancing productivity in tech-intensive sectors but also redefining professional roles in education, healthcare, marketing, and public services. This has created both optimism about job creation and concerns over displacement, inequality, and institutional unpreparedness.

As the OECD and other international bodies emphasize, the diffusion of AI is highly uneven across countries, regions, and economic sectors. While some economies benefit from concentrated digital infrastructure and talent pipelines, others, particularly in Southern Europe, struggle with fragmented industrial strategies and insufficient educational adaptation. This unevenness raises critical questions about the inclusiveness and sustainability of the AI transition.

1.2 Problem Statement

Most research on AI and work is either macro-level and generic or micro-level and sector-specific. Few studies bridge the two perspectives to show how global trends translate into concrete labour-market signals, such as job postings, and how local organisations perceive and act upon them. Peripheral regions like Abruzzo (Italy) remain under-represented, even though they face acute structural transitions. This study responds to that gap through a multi-scalar design that triangulates global datasets, U.S. job-posting analytics, and firm-level interviews in Avezzano.

1.3 Research Questions

This study is guided by the following research questions:

- RQ1 – Global AI Skill Dynamics: How have AI-related skill demands evolved across OECD economies between 2015 and 2025?
- RQ2 – Occupational Signals in the U.S.: Which new occupational clusters and soft-versus-hard skill mixes emerge in AI-intensive U.S. job postings?
- RQ3 – Local SME Perspective: How do small and medium-sized enterprises (SMEs) in Avezzano interpret and respond to AI-driven workforce transformation?

1.4 Objectives

The main objectives of this study are to:

1. Analyze the global AI skills landscape using OECD datasets.
2. Identify emerging job titles and skill demands from a dataset of 862 AI-related job postings in the United States.
3. Understand the perceptions, readiness, and constraints of local firms in Avezzano regarding AI integration.
4. Bridge theoretical insights with practical realities through a multi-level research design.

1.5 Significance of the Study

By combining data analytics with qualitative inquiry, this study contributes to a more nuanced understanding of how AI adoption is shaping labor dynamics. The study provides value not only to academic discussions on technological change and employment but also to policymakers seeking to design inclusive AI strategies and to educational institutions aiming to modernize curricula in response to evolving labor needs.

Furthermore, the focus on a peripheral European region introduces a much-needed geographic diversification in AI and labor studies, which are often dominated by data from major tech hubs.

1.6 Structure of the Study

The study is organized into five chapters. Following this introduction, Chapter 2 reviews the literature on industrial transformation, AI labor impacts, skill demands, and policy frameworks. Chapter 3 details the research design and methodology, including the datasets used and the analytical approach. Chapter 4 presents the key findings and discusses them in relation to the existing literature. Chapter 5 concludes the study by summarizing the main contributions, reflecting on limitations, and offering directions for future research.

2. Literature Review

2.1 Historical Background: From Industrial Revolutions to AI

The transformation of work has historically followed the rhythm of technological progress. Each industrial revolution, mechanical (Industry 1.0), electrical (Industry 2.0), digital (Industry 3.0), and now cyber-physical and AI-driven (Industry 4.0), has triggered shifts in production modes, skill requirements, and labor relations (Rifkin, 2011; Schwab, 2016). In particular, the Fourth Industrial Revolution, as conceptualized by Klaus Schwab, marks a phase of intensified automation, characterized not only by technological acceleration but also by the convergence of digital, biological, and physical systems.

Historians such as Hobsbawm and Mokyr emphasize that each wave of industrialization reshaped economic institutions and altered the class composition of societies. Labor alienation, structural unemployment, and skill mismatches have been recurring outcomes of technological transitions. Turkish academic works (e.g., OPUS and Atlas Ulusal Sosyal Bilimler Dergisi) and Italian policy studies such as DIPE0025 reinforce these insights by reflecting on the socio-economic consequences of past industrial transformations in regional contexts.

The notion of "technological displacement" is not new. From the Luddite protests of the 19th century to the deskilling debates of the late 20th century, fears surrounding labor redundancy have accompanied most waves of automation. Yet, each technological leap has also created new forms of employment, reorganized sectors, and pushed education systems toward adaptation.

The current AI era both echoes and exceeds these historical patterns. Unlike past revolutions that replaced physical tasks with machines, AI replaces cognitive tasks, challenging knowledge-based work and managerial functions. As Rifkin (2011) warned, the "end of work" narrative looms larger as artificial intelligence decouples labor from productivity.

Understanding this historical lineage provides essential context for interpreting AI's current and future impact on workforce dynamics. The structural and societal transformations described in this section will guide how global trends, job posting data, and local interviews are analyzed in subsequent chapters.

2.2 AI as a Disruptive Technology: Definitions and Frameworks

Artificial intelligence (AI) refers broadly to machines and systems capable of performing tasks that typically require human intelligence, such as learning, decision-making, problem-solving, and pattern recognition (OECD, 2024). Within academic and policy literature, AI is increasingly defined not just as a set of technologies, but as a socio-technical system that reshapes labor processes, institutional structures, and the distribution of economic power (Acemoglu & Restrepo, 2018; Schwab, 2016).

Disruptive technologies, by definition, significantly alter or displace existing systems. AI meets this criterion due to its potential to automate both routine physical and non-routine cognitive tasks (Frey & Osborne, 2013). Unlike earlier waves of automation which primarily affected manufacturing and manual labor, AI is penetrating knowledge-intensive sectors such as finance, healthcare, law, education, and creative industries.

OECD studies conducted in the United Kingdom and Canada (OECD, 2024) further emphasize that AI should not be treated as a singular innovation but as a "general-purpose technology", one that spreads across multiple domains, continuously evolves, and triggers complementary innovations. These characteristics render AI not only a tool for productivity but a catalyst for systemic change.

Moreover, scholars have pointed out that AI differs from previous digital technologies due to its self-improving capabilities (e.g., machine learning and generative AI) and its potential to operate autonomously, raising concerns about accountability, explainability, and human control (TTC/EC/CEA, 2022).

Understanding AI as a general-purpose and disruptive technology is essential for analyzing how it interacts with labor markets. This perspective frames the analysis of both job displacement and job creation in the following sections, as well as the interpretation of AI adoption levels in global and local data.

2.3 Job Displacement and the Substitution Effect

The displacement effect refers to the substitution of human labor with machines or algorithms, often resulting in job losses or deskilling. This concept gained renewed attention with the rise of AI and machine learning, which now extend automation beyond physical tasks into the cognitive domain (Acemoglu & Restrepo, 2021).

Frey and Osborne (2013), in their landmark study, estimated that nearly 47% of U.S. jobs are at high risk of being computerized. They identified occupations involving routine and predictable tasks, such as clerks, telemarketers, and some categories of administrative staff, as most vulnerable. This framework has since influenced both academic discourse and public policy debates.

More recent studies reinforce this view with real-world data. Damioli et al. (2021; 2023) analyzed firm-level adoption of AI and found a negative impact on employment in sectors with high exposure to automation technologies, particularly among low- and mid-skilled workers. Gries and Naudé (2021) emphasize that substitution pressures are not evenly distributed but are shaped by demand constraints and institutional factors, such as labor regulations and collective bargaining systems.

Sector-specific research has also confirmed that manufacturing, transportation, and administrative services face disproportionate displacement risks (Cirillo et al., 2021). These findings are particularly relevant when comparing global trends in AI skills penetration across industries, as presented in the OECD data explored in Chapter 3.

In addition to economic risk, some studies highlight psychological and social dimensions of displacement. Job insecurity, role obsolescence, and reduced autonomy have been linked to deteriorating job quality in AI-intensive environments (IBM, 2023).

This body of literature provides the foundation for assessing which sectors and roles may be most threatened by AI, validating the indicators used in our OECD dataset analysis and informing the challenges expressed in interviews with local companies in Avezzano.

2.4 Sectoral and Regional Asymmetries

The adoption of AI technologies does not proceed evenly across sectors or regions. A growing body of literature highlights that industry-specific structures, capital intensity, and digital readiness significantly influence how and where AI is deployed (OECD, 2024; Martinelli et al., 2021). For instance, sectors like finance, IT, and advanced manufacturing are early adopters, whereas education, agriculture, and public administration often lag due to institutional inertia and budgetary constraints.

Cirillo et al. (2021) emphasize that in Italy's Industry 4.0 transition, technology diffusion has been highly uneven even within the manufacturing sector, with northern regions and large firms adapting faster than southern SMEs. This reflects broader patterns observed globally, where digital transformation tends to concentrate in innovation hubs, reinforcing regional economic disparities.

TTC/EC/CEA (2022) and IBM (2023) underline the role of infrastructural gaps and workforce maturity in determining a region's AI absorption capacity. Countries with stronger investment in R&D, data infrastructure, and lifelong learning programs show more inclusive AI diffusion, while others risk being left behind in what some scholars call a "twin transition divide", digital and green.

Additionally, cultural factors such as risk aversion, labor union strength, and regulatory environments shape AI deployment. For example, the uptake of AI in public health in the UK contrasts with resistance in similar institutions across Southern Europe, reflecting differing institutional capacities and policy environments (OECD, 2024).

This literature is essential to interpret the sector-specific skills penetration visualized in the OECD dataset (Chapter 3.2) and to contextualize the heterogeneous AI adoption patterns expressed by firms in the Avezzano interviews (Chapter 3.4). It also helps frame Italy's structural position within the global AI labor economy.

2.5 Skills, Education and Workforce Readiness

The diffusion of AI across labor markets has revealed a widening gap between the skills demanded by employers and those supplied by education systems. Numerous studies argue that traditional training models, particularly in Europe, are ill-equipped to keep pace with the accelerating demands of digital transformation (Schwab, 2016; Acemoglu et al., 2022).

OECD data from countries like Canada and the UK (OECD, 2024) confirm a growing premium on AI literacy, even in non-technical roles. The UK report shows that professionals in sectors such as marketing, education, and public services are now increasingly expected to possess basic AI understanding, while the Canadian data links AI penetration with greater reskilling and cross-functional career mobility.

However, Italy remains among the countries with the lowest AI skills penetration in Europe, especially in the education and public administration sectors. TTC/EC/CEA (2022) emphasize that without significant national upskilling policies, countries like Italy risk falling behind not only in productivity but also in workforce inclusivity. Similarly, IBM (2023) finds that employers worldwide cite "insufficient internal digital skills" as the most significant barrier to AI implementation.

Martinelli et al. (2021) and Damioli et al. (2023) offer a more granular view, highlighting how even within high-tech sectors, companies struggle to define the right skill mix, often needing both technical fluency (e.g., Python, ML frameworks) and soft skills (e.g., critical thinking, adaptability, ethics).

These findings align with the emerging view that AI readiness is not simply about coding skills, but about rethinking curricula, lifelong learning structures, and institutional responsiveness. Education systems that prioritize interdisciplinary thinking and real-time industry alignment are seen as key enablers of resilient labor markets.

This literature directly supports the analysis of skill demands in the U.S. job postings dataset (Chapter 3.3) and reinforces the skill shortage narratives found in the Avezzano interviews (Chapter 3.4). It also offers a framework for interpreting the country-level differences in AI penetration discussed in Chapter 3.2.

2.6 Governance, Ethics, and Regulatory Perspectives

The acceleration of AI development has raised critical concerns about governance, transparency, and the ethical use of intelligent systems. As AI begins to shape decisions in hiring, lending, surveillance, and healthcare, questions of accountability and regulatory control become increasingly central to the socio-economic discourse (TTC/EC/CEA, 2022; DIPE0025).

The European Union's Artificial Intelligence Act (2021) is the most ambitious attempt to build a legal framework around AI. It classifies AI systems by risk level (unacceptable, high, limited, minimal) and requires companies to meet transparency, data governance, and human oversight standards for high-risk applications. While it aims to ensure "human-centric" AI deployment, critics argue that enforcement capacity remains uneven across member states, especially in contexts with weaker digital infrastructure.

National-level political economy perspectives also suggest that AI may amplify existing labor inequalities. The DIPE0025 report emphasizes that countries with limited state capacity or fragmented industrial strategies may struggle to ensure that AI adoption aligns with social equity goals. In this context, AI becomes not just a technological issue, but a governance dilemma, intertwined with public trust, policy legitimacy, and long-term institutional resilience.

Scholars warn that without cohesive regulation, the benefits of AI could become concentrated among a few large firms or digitally advanced regions, exacerbating what TTC/EC/CEA (2022) term a "dual-speed AI Europe." This scenario risks leaving behind rural areas, SMEs, and lower-skilled workers.

This governance-focused literature provides an essential frame for interpreting country-level differences in AI adoption as seen in the OECD data (Chapter 3.2), and explains the policy concerns raised by small businesses in Avezzano (Chapter 3.4) regarding AI implementation barriers and institutional support.

2.7 Methodological Contributions and Link to This Study

The literature reviewed throughout this chapter reveals not only the conceptual and empirical evolution of AI and labor studies but also the diversity of methodological approaches used to analyze the phenomenon. Two dominant traditions emerge:

1. Quantitative empirical research, using large-scale datasets such as online job postings, labor statistics, or employer surveys (e.g., Acemoglu et al., 2022; Engberg et al., 2024; OECD, 2024), and
2. Qualitative-historical analysis, focusing on political economy, labor theory, and socio-technical systems (e.g., Hobsbawm, Schwab, Rifkin, DIPE0025).

This study consciously integrates both perspectives. By combining:

- OECD global AI skills datasets (macroeconomic level),
- A dataset of 862 U.S. job postings focused on AI/ML roles (meso level), and
- Primary interviews with SMEs in Avezzano (micro level),

the research adopts a multi-level mixed-methods approach designed to bridge top-down structural analysis with bottom-up experiential insight.

Furthermore, the methodological choices reflect a theoretical alignment with the literature's key themes:

- The job postings analysis responds directly to studies using vacancy data to track AI's labor demand (e.g., Acemoglu, Damioli, Engberg).
- The OECD data interpretation is grounded in cross-country AI skills penetration metrics used by international policy institutions.
- The qualitative findings from Avezzano align with calls for more grounded, context-sensitive understanding of AI's impact on underrepresented geographies and sectors (Cirillo et al., TTC/EC/CEA).

In this sense, the literature not only defines the scope of inquiry but also shapes the methodological architecture of this study. The following chapter operationalizes this framework to investigate how AI is transforming labor markets from global structures to local realities.

3. Methodology and Data Analysis

3.1 Research Design

This study adopts a mixed-methods research design to comprehensively investigate the impact of artificial intelligence (AI) on workforce dynamics, skill demands, and sectoral transformations. The methodology integrates secondary data analysis of global and national datasets with primary qualitative data collected through interviews with local companies. This multi-layered approach enables the study to move from a general global perspective to a specific local context, offering both breadth and depth in the analysis.

The research is organized into three sequential components:

1. Global Perspective: OECD.AI Jobs and Skills Data

The first phase analyzes live data from OECD.AI, sourced from LinkedIn's Economic Graph. This dataset provides a comprehensive overview of global AI workforce dynamics, including between-country skills migration, AI skills penetration across countries and industries, hiring trends over time, gender participation rates, and top emerging AI skills. By examining these global patterns, the study establishes a foundational understanding of how AI is reshaping labor markets worldwide and identifies the international benchmarks against which national and local findings can be compared.

2. National Perspective: United States AI/ML Job Postings Dataset

The second phase focuses on a detailed exploratory data analysis of 862 AI/ML-related job postings collected from a U.S.-based dataset (sourced from Kaggle). This dataset offers insights into job title distributions, geographical concentration of hiring, top recruiting companies, nature of employment contracts, required experience levels, sectoral hiring trends, and key skill demands. The national-level analysis provides a rich and specific view of how AI talent is being absorbed in one of the most advanced AI economies globally, setting a crucial reference point for understanding broader labor market transformations.

3. Local Perspective: Primary Data Collection in Avezzano, Italy

The third phase narrows the focus to a local case study based on semi-structured interviews with five companies in Avezzano, Italy, spanning sectors such as IT, fashion, education, and import/export. These interviews explore companies' current levels of AI adoption, the resulting impacts on workforce structure, key challenges encountered, and perceived opportunities for growth through AI integration. This primary data collection captures the nuanced, localized experiences of small- and medium-sized enterprises (SMEs) navigating AI transformations in a non-metropolitan setting.

Justification for Mixed-Methods Approach

The integration of global, national, and local datasets is essential for capturing the full complexity of AI's influence on labor markets. The global analysis identifies macro-level patterns and competitive dynamics; the national analysis details occupational shifts and employer demands within a leading economy; and the local analysis provides contextualized insights into how AI adoption manifests at the company level. Together, these complementary perspectives offer a multi-scalar understanding of AI's transformative role in the workforce, ensuring both generalizability and specificity in the study's findings.

3.2 Global Perspective: OECD.AI Jobs and Skills Data

In order to situate national and local findings within a broader international context, this section begins by analyzing secondary data sourced from the OECD.AI platform. The data is based on LinkedIn's Economic Graph and reflects real-time insights into AI workforce dynamics across countries. Each subsection includes visualizations and metrics illustrating global trends in AI skills migration, workforce penetration, hiring growth, gender participation, and skills development.

Source: OECD.AI (2025), data from LinkedIn Economic Graph, last updated 2025-04-07, accessed on 2025-04-25, https://oecd.ai/

3.2.1 Between-Country AI Skills Migration

Artificial intelligence is not only transforming industries but also reshaping global migration patterns for high-skilled labor. Countries today are not merely competing for markets or technological supremacy but for the human capital that drives AI innovation. Figure 1 presents the net migration flows of LinkedIn members possessing AI skills between 2019 and 2023. Countries with positive net inflows are successfully attracting AI talent, while countries with negative net flows are losing such professionals to more competitive environments.

Figure 1 Net Migration Flows of AI-Skilled Professionals (2019–2023)

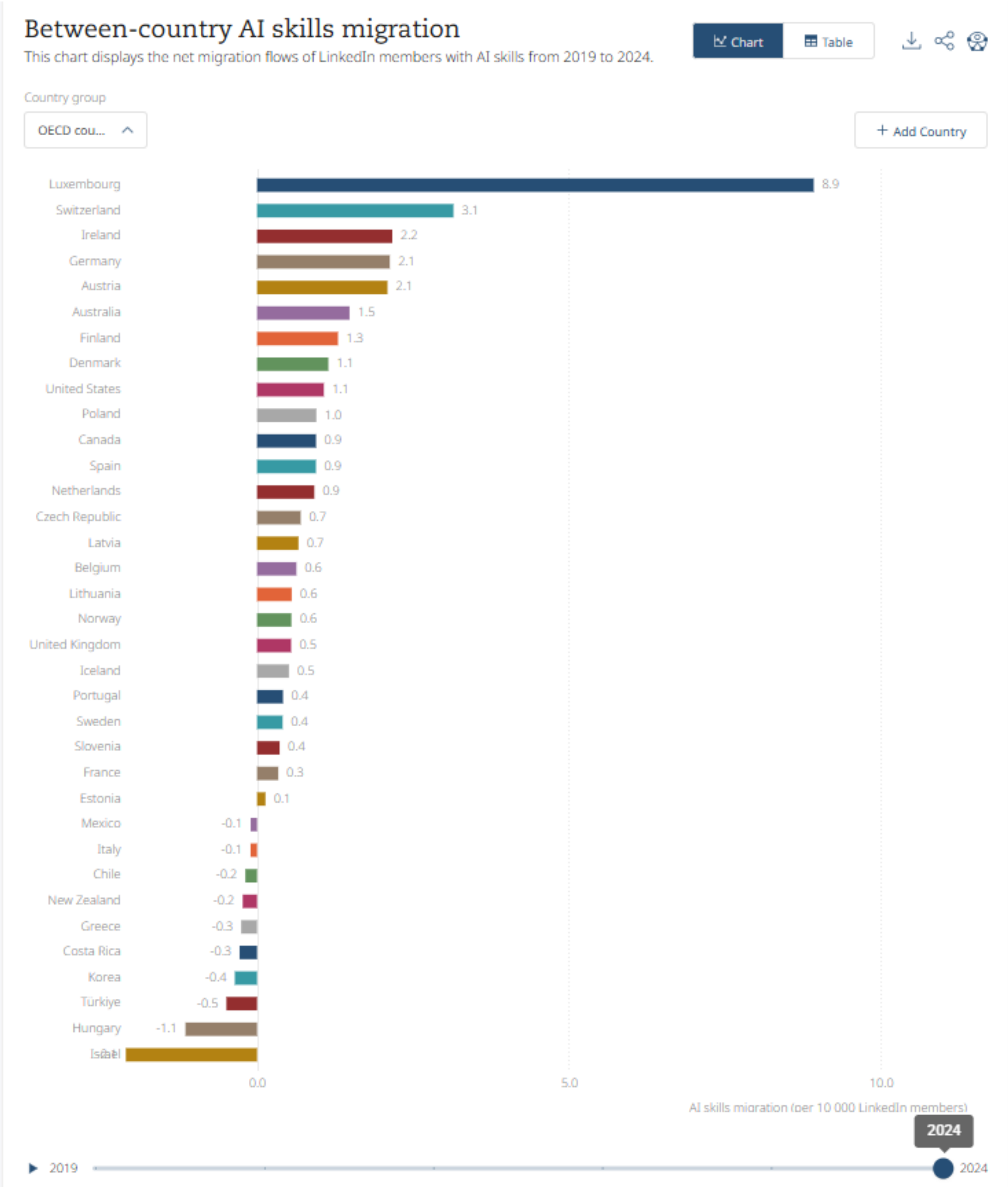

Figure 1 Net Migration Flows of AI-Skilled Professionals (2019–2023)

Source: OECD.AI (2025), data from LinkedIn Economic Graph, last updated 2025-04-07, accessed on 2025-04-25, https://oecd.ai/

The data reveals that Luxembourg, Switzerland, and Ireland recorded the highest net AI talent gains during this period. Luxembourg's leadership position is particularly notable given its small size; the country's strong financial sector, multilingual environment, and supportive innovation policies likely contribute to its attractiveness for AI-skilled migrants. Similarly, Switzerland benefits from its world-class universities, high R&D investment, and thriving healthcare and fintech sectors. Ireland's position reflects its growing role as a European technology hub, fueled by foreign direct investment from global tech giants such as Google, Facebook, and Amazon.

In contrast, some larger economies exhibit modest or even negative net flows, suggesting a more competitive or challenging environment for AI talent retention. Although the United States remains a major hub for AI employment, the relative net inflow figure is less dominant than might be expected, reflecting both high domestic supply and increasing global competition for skilled professionals.

Italy, the national focus of this study, does not rank among the top talent-attracting countries. This absence highlights a structural challenge for Italy in becoming a destination for AI professionals. It raises critical questions about the country's digital infrastructure, research investment, regulatory frameworks, and professional development opportunities, factors that will also be visible in the local case study of Avezzano.

The dynamics observed in Figure 1 emphasize the growing importance of international talent mobility as a dimension of AI competitiveness. Countries that succeed in attracting and retaining AI professionals are likely to experience faster innovation cycles and stronger economic growth, while those experiencing net outflows risk falling behind in the global AI race.

3.2.2 Cross-Country AI Skills Penetration

While talent migration provides one dimension of AI workforce dynamics, the extent to which AI skills are embedded within a country's overall labor force offers another critical measure of readiness for the AI economy. Figure 2 presents cross-country AI skills penetration rates from 2016 to 2023, based on LinkedIn member data aggregated by the OECD. A country's AI skills penetration rate indicates how much more (or less) likely its workers are to report AI skills compared to the global average.

Figure 2 Cross-Country AI Skills Penetration (2016–2023)

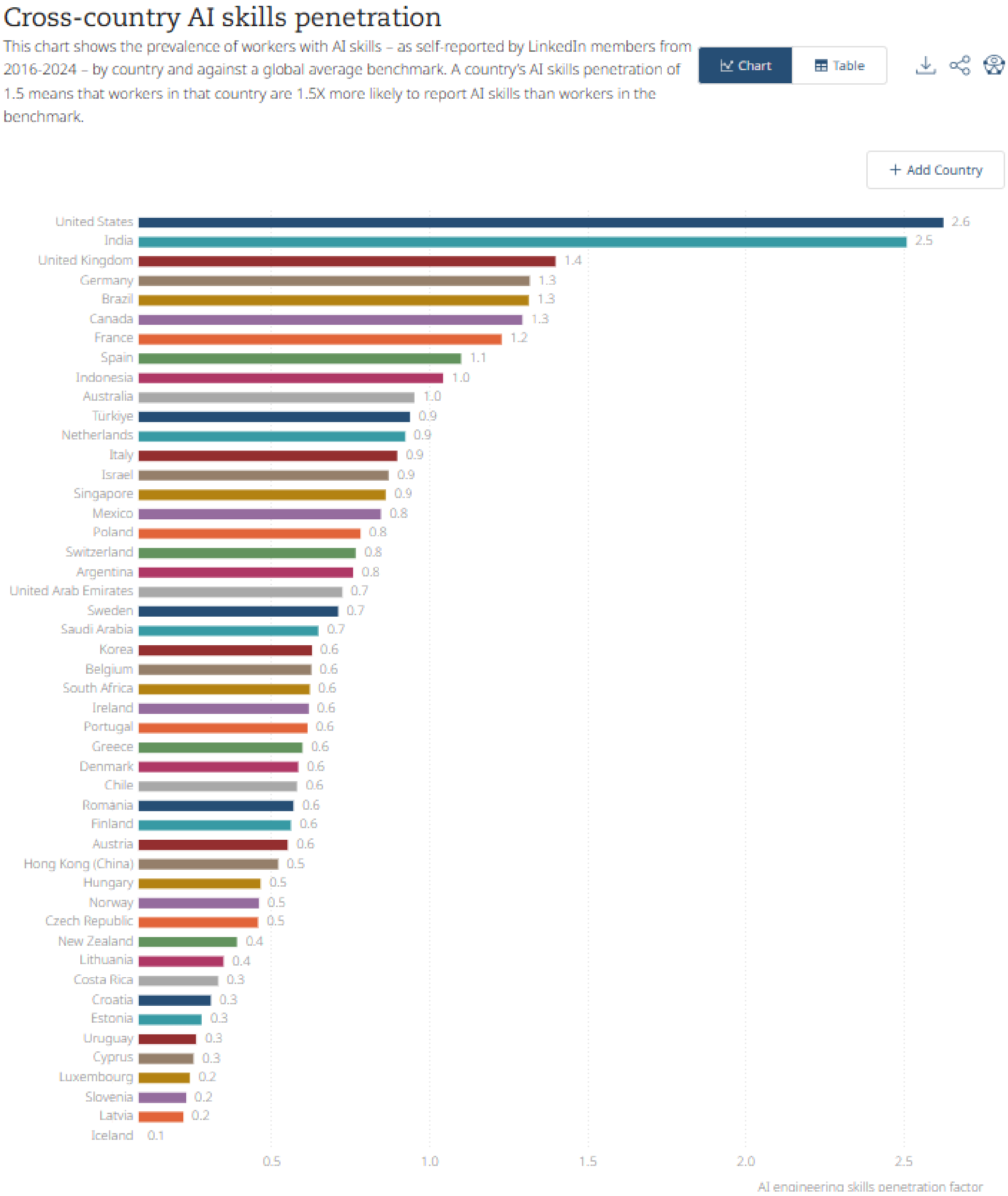

Figure 2 Cross-Country AI Skills Penetration (2016–2023)

Source: OECD.AI (2025), data from LinkedIn Economic Graph, last updated 2025-04-07, accessed on 2025-04-25, https://oecd.ai/

The data reveals that India, the United States, United Kingdom and Germany consistently rank among the countries with the highest AI skills penetration. India's strong showing can be attributed to its vast pool of engineering graduates and its booming IT services sector, where AI competencies are increasingly seen as essential. The United States, home to many leading AI companies and research institutions, maintains a high penetration rate reflecting its advanced digital economy. Germany's performance, meanwhile, underscores the strength of its industrial and manufacturing sectors embracing AI-driven innovation.

Notably, Italy shows a comparatively lower AI skills penetration rate, signaling challenges in integrating AI competencies across its broader workforce. This gap suggests that Italy, while making policy strides in digitalization, still lags behind in embedding AI capabilities into mainstream employment sectors. The slower diffusion of AI skills may have significant implications for national competitiveness, productivity, and the ability to adapt to labor market disruptions caused by automation.

These findings are critical when contextualizing the local-level results from Avezzano. If national-level AI skills penetration remains low, it is unsurprising that SMEs in smaller cities struggle with AI adoption and workforce readiness. The contrast between leading nations and slower adopters like Italy further emphasizes the need for targeted interventions in education, corporate training, and innovation policy to accelerate AI competency development nationwide.

3.2.3 AI Skills Penetration by Industry

While national-level AI skills penetration offers valuable macroeconomic insights, examining sector-specific adoption patterns reveals where AI is most deeply embedded within different segments of the economy. Figures 3 to 7 present the AI skills penetration across selected industries and countries between 2016 and 2024, based on LinkedIn member data compiled by the OECD. The AI skills penetration index shows how much more (or less) likely workers in a specific sector and country are to report AI skills compared to the global average for that same sector. For instance, a penetration score of 2 in Education means that workers in that country's education sector are twice as likely to report AI skills as the global average worker in Education.

Figure 3 AI Skills Penetration in the Education Sector (2016–2024)

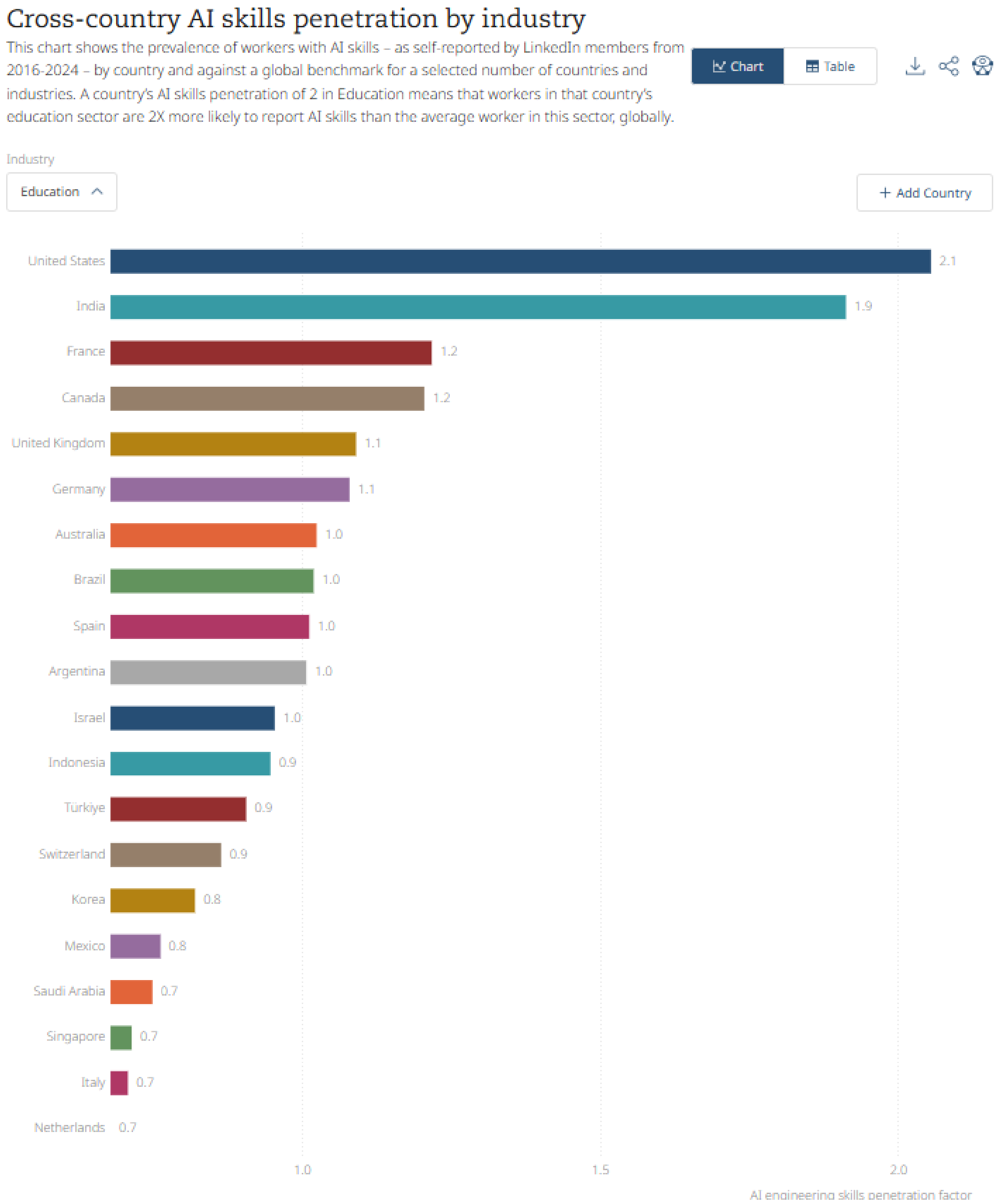

Figure 3 AI Skills Penetration in the Education Sector (2016–2024)

Source: OECD.AI (2025), data from LinkedIn Economic Graph, last updated 2025-04-07, accessed on 2025-04-25, https://oecd.ai/

In the Education sector, the United States (2.1) and India (1.9) lead, meaning their education sector workers report AI skills at approximately double the global average. France (1.2) and Canada (1.2) also show above-average penetration, while Germany (1.1) and the United Kingdom (1.1) maintain moderate levels. Italy, with a score of 0.7, lags significantly, suggesting that AI integration into the educational workforce remains limited compared to leading countries. This pattern reflects slow adoption of adaptive learning technologies and a limited presence of AI-related pedagogy in the Italian education system.

Figure 4 AI Skills Penetration in the Financial Services Sector (2016–2024)

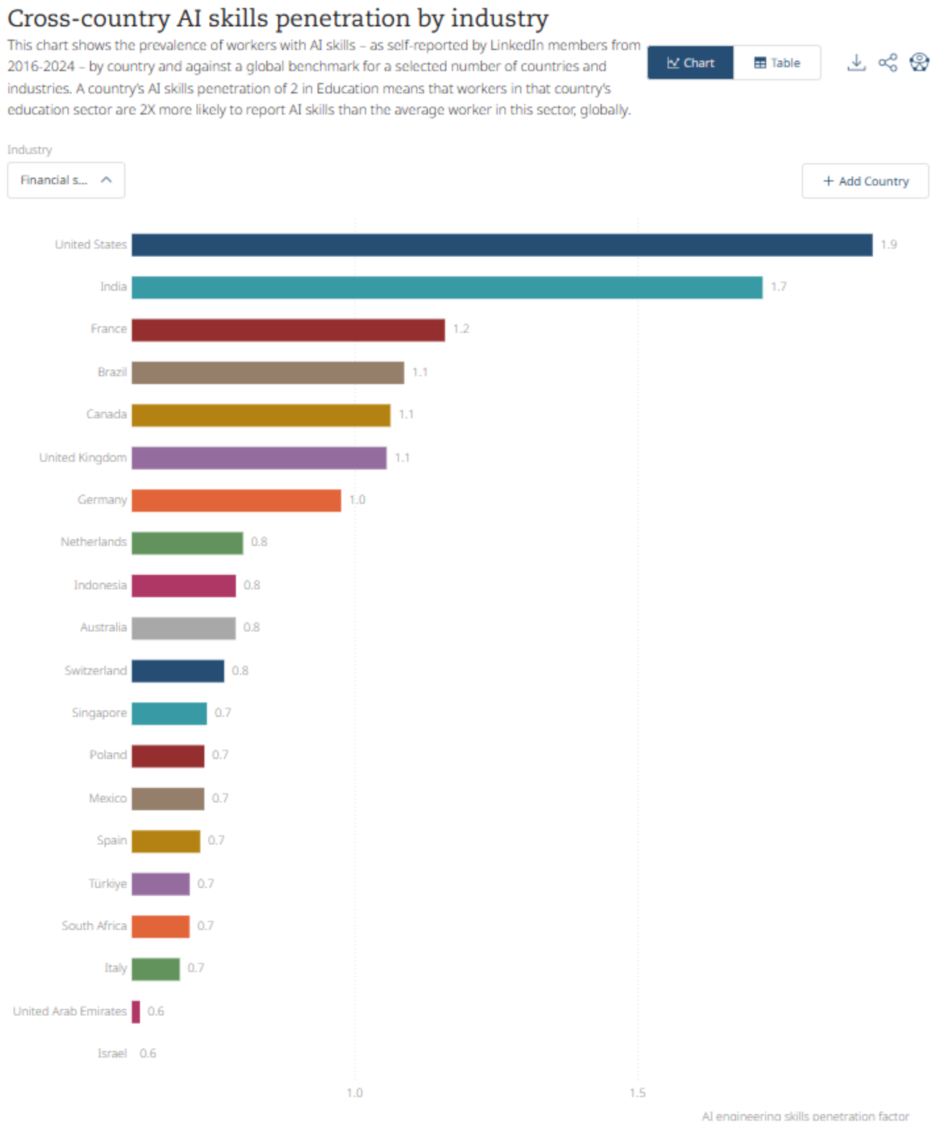

Figure 4 AI Skills Penetration in the Financial Services Sector (2016–2024)

Source: OECD.AI (2025), data from LinkedIn Economic Graph, last updated 2025-04-07, accessed on 2025-04-25, https://oecd.ai/

In Financial Services, the United States (1.9) and India (1.7) again show the highest AI penetration, emphasizing the widespread adoption of AI for algorithmic trading, fraud detection, and personalized finance. Countries like France (1.2), Brazil (1.1), and Canada (1.1) follow. Italy again records 0.7, indicating limited integration of AI in banking, insurance, and fintech sectors, despite Italy's growing digital banking initiatives in urban centers.

Figure 5 AI Skills Penetration in the Manufacturing Sector (2016–2024)

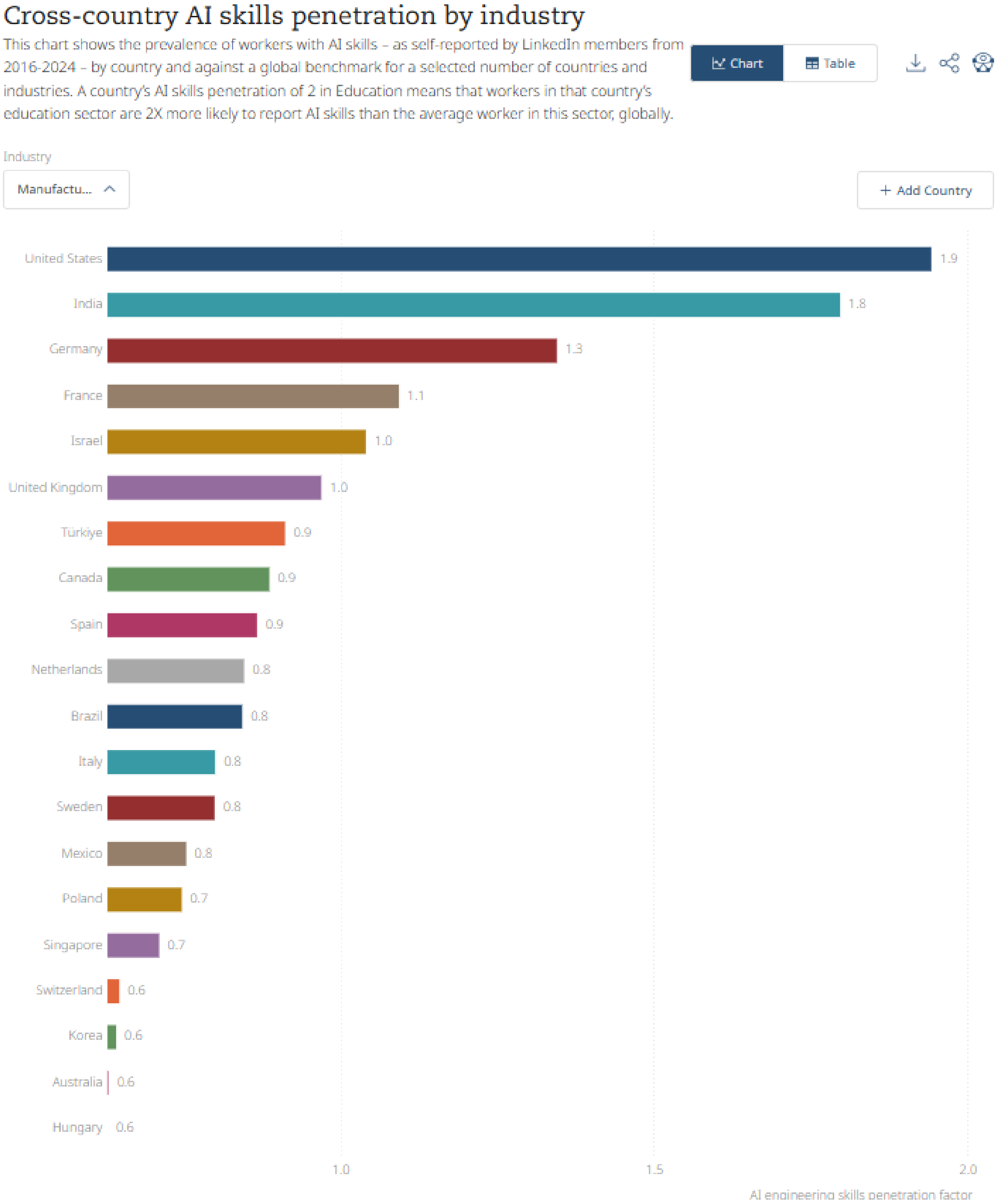

Figure 5 AI Skills Penetration in the Manufacturing Sector (2016–2024)

Source: OECD.AI (2025), data from LinkedIn Economic Graph, last updated 2025-04-07, accessed on 2025-04-25, https://oecd.ai/

In Manufacturing, AI skill penetration remains strong in the United States (1.9) and India (1.8). Germany (1.3) stands out among European countries, leveraging Industry 4.0 frameworks. France (1.1) and Israel (1.0) follow closely. Italy's score of 0.8 is slightly better compared to its Education and Financial sectors but still reflects limited workforce readiness in smart manufacturing, predictive maintenance, and robotics fields.

Figure 6 AI Skills Penetration in Professional Services Sector (2016–2024)

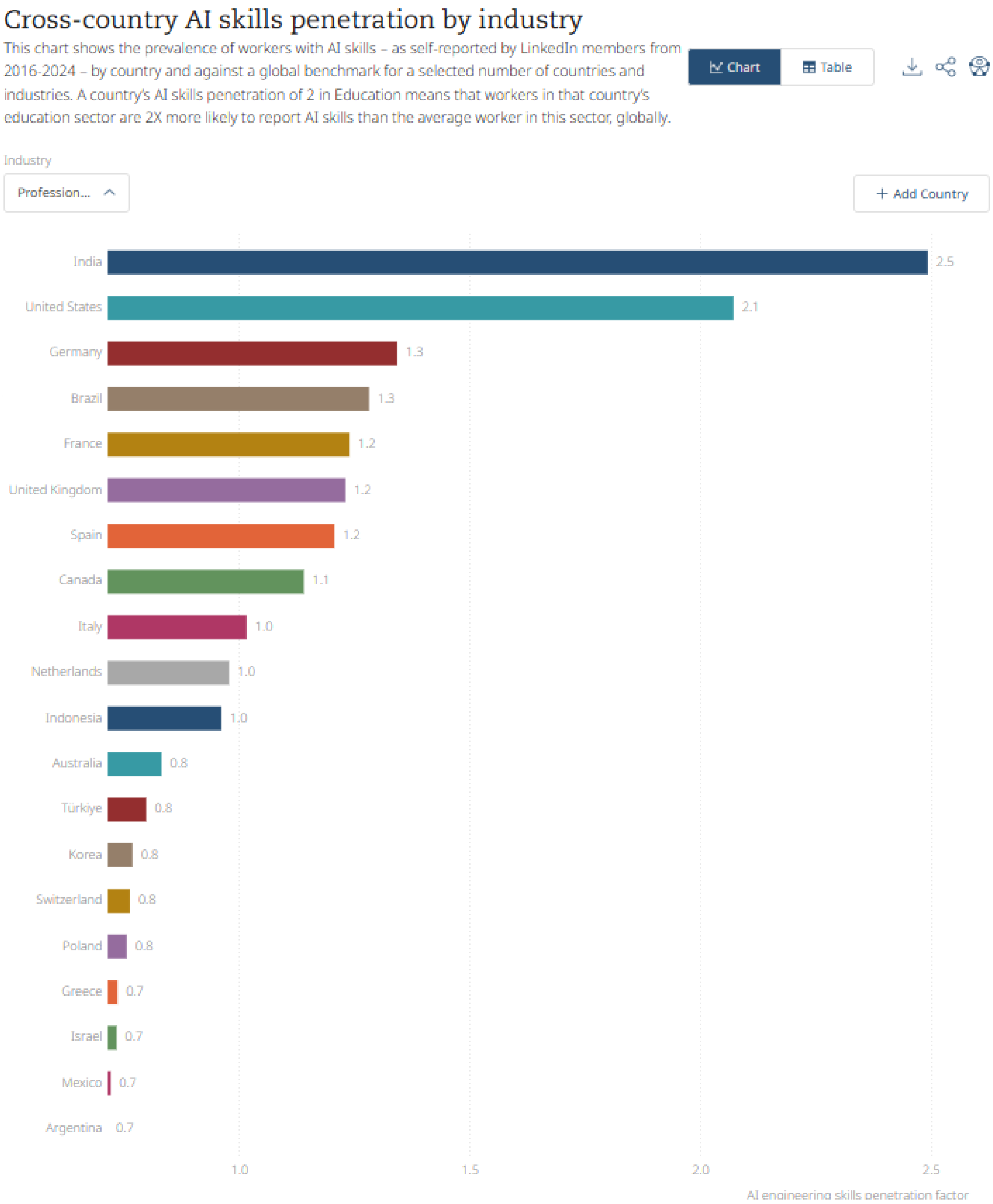

Figure 6 AI Skills Penetration in Professional Services Sector (2016–2024)

Source: OECD.AI (2025), data from LinkedIn Economic Graph, last updated 2025-04-07, accessed on 2025-04-25, https://oecd.ai/

In Professional Services, India (2.5) records the highest AI skills penetration, followed by the United States (2.1). Germany (1.3), France (1.2), and the United Kingdom (1.2) cluster closely behind. Italy, with 1.0, shows a slightly improved position relative to other sectors, suggesting that law firms, consulting agencies, and business services in Italy are more open to AI-driven innovation such as automated research, contract analysis, and client management tools.

Figure 7 AI Skills Penetration in the Technology, Information, and Media Sector (2016–2024)

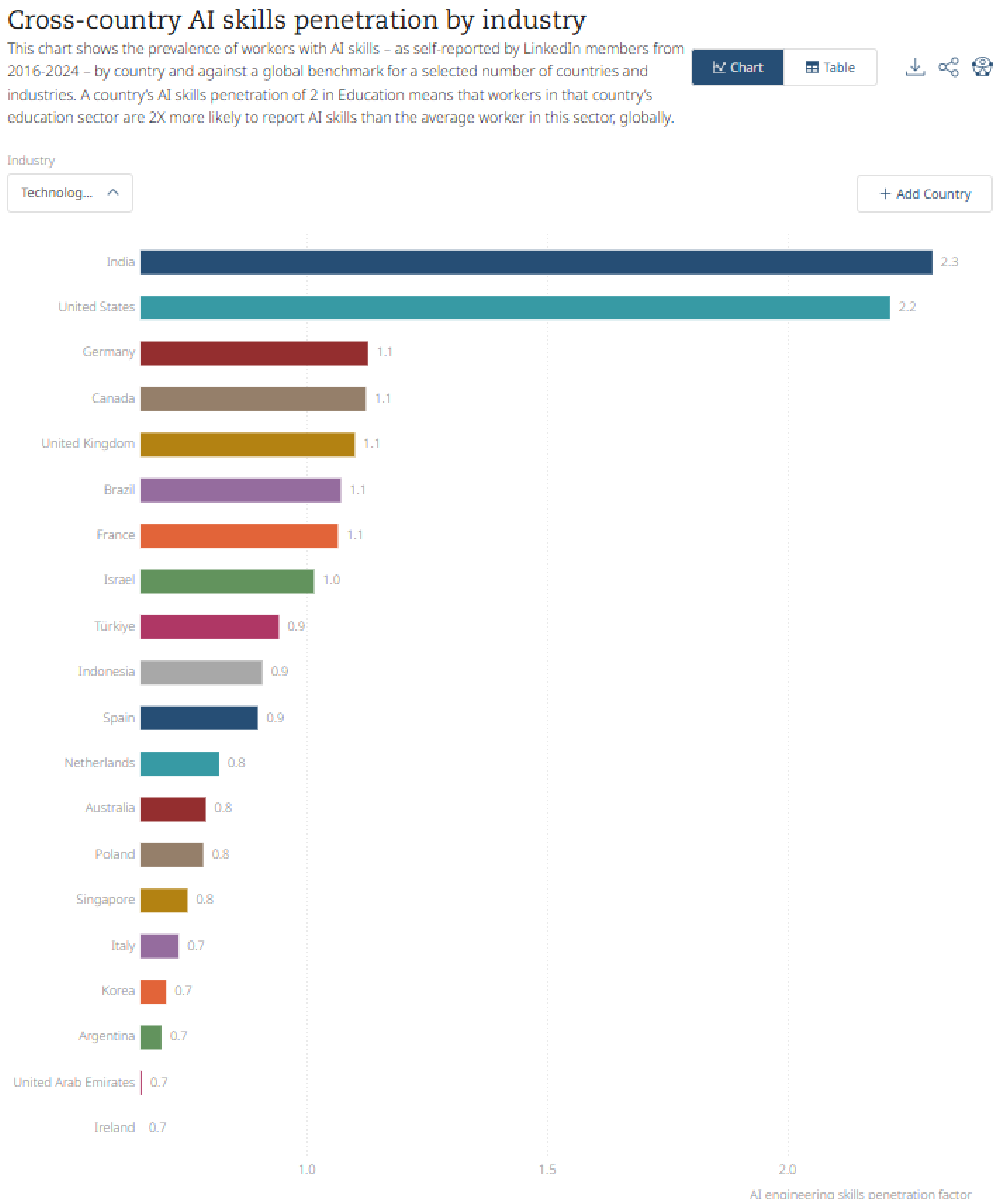

Figure 7 AI Skills Penetration in the Technology, Information, and Media Sector (2016–2024)

Source: OECD.AI (2025), data from LinkedIn Economic Graph, last updated 2025-04-07, accessed on 2025-04-25, https://oecd.ai/

In the Technology, Information, and Media sector, the strongest overall AI skills penetration is recorded. India (2.3) and the United States (2.2) dominate, while Germany (1.1), Canada (1.1), and the United Kingdom (1.1) show solid but lower penetration levels. Italy again scores 0.7, suggesting a significant gap in high-technology industries compared to global AI leaders.

Summary of Sectoral Analysis

Across all sectors, India and the United States consistently demonstrate superior AI skills penetration, indicating strong national ecosystems supporting AI upskilling. Italy, despite its industrial legacy, remains consistently below global averages (0.7–0.8 range across most sectors), signaling structural weaknesses in embedding AI competencies into the workforce.

These findings are critical when considering Italy's national competitiveness in AI and help contextualize the challenges faced by local regions such as Avezzano. Sectors like Education, Import/Export, and even Manufacturing are already globally lagging in AI integration, compounding the local difficulties in workforce transformation and technological adoption.

3.2.4 Global AI Hiring Trends Over Time

Beyond analyzing AI skill penetration, understanding the evolution of hiring trends for AI-skilled professionals offers crucial insight into how rapidly labor markets are absorbing AI talent. Figure 8 presents the growth rate of hiring LinkedIn members with AI skills across 43 countries from December 2016 to December 2023, based on data compiled by the OECD.

The hiring index reflects the relative month-by-month change compared to a baseline period. A higher index value indicates a stronger increase in hiring for AI-skilled workers, capturing both global market expansions and temporary contractions.

Figure 8 Growth of Hiring AI-Skilled Professionals (2016–2023)

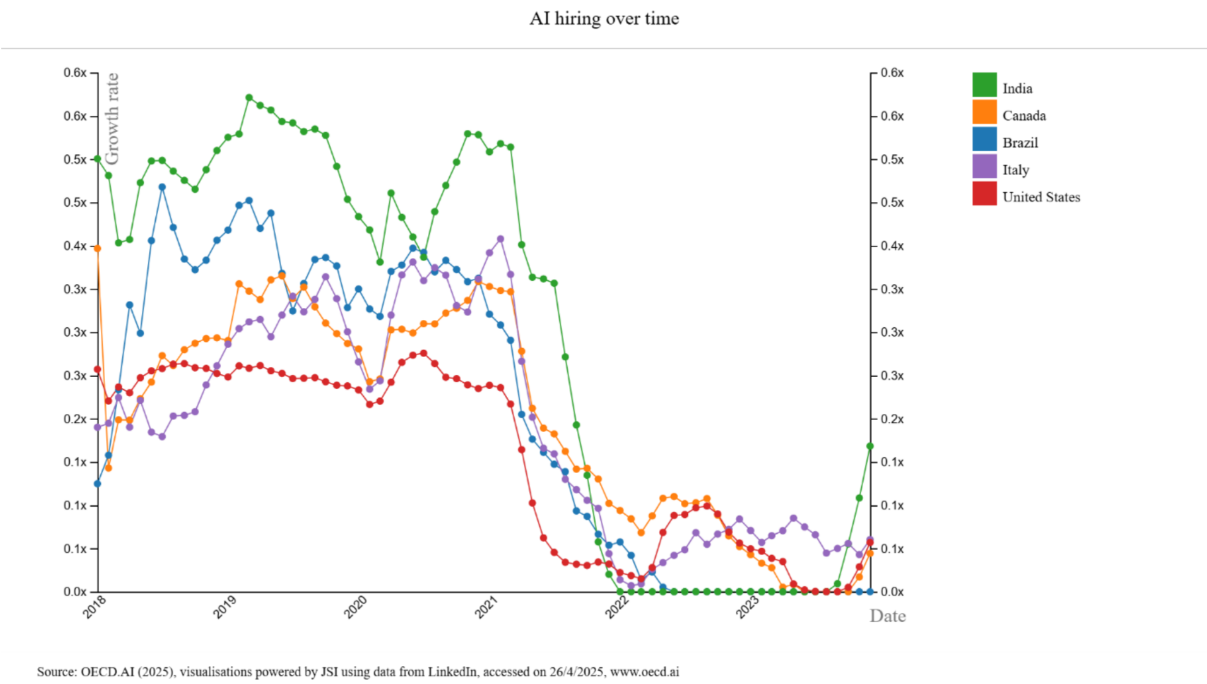

Figure 8 Growth of Hiring AI-Skilled Professionals (2016–2023)

Source: OECD.AI (2025), data from LinkedIn Economic Graph, last updated 2025-04-07, accessed on 2025-04-25, https://oecd.ai/

The graph reveals that India consistently exhibits the highest AI hiring growth rate between 2016 and early 2021, reaching peaks above 0.6x relative to its 2016 baseline. This strong and sustained growth reflects India's robust supply of engineering graduates, expanding IT services sector, and emerging AI startup ecosystem.

Brazil and Canada also demonstrate significant upward trends, though at lower peaks (around 0.4x for Brazil and 0.3x for Canada by 2020). These countries experience relatively steady increases, indicating gradual integration of AI talent across industries, supported by policy initiatives and digital transformation efforts.

The United States, while still a major AI employer, shows a more moderate hiring growth curve, peaking at around 0.3x before 2020. This flatter trajectory likely reflects a combination of factors: a mature AI labor market with high baseline employment and structural challenges in dramatically scaling new AI hiring rates compared to emerging economies.

Italy, by contrast, consistently exhibits the lowest AI hiring growth rate among the countries shown. Growth remains between 0.1x and 0.2x for most of the period and does not show the sharp upward momentum observed elsewhere. This suggests significant barriers to AI workforce expansion in Italy, such as skills shortages, slower corporate adoption rates, and limited national digital transformation initiatives compared to leading economies.

After early 2021, all countries show a sharp decline in hiring growth, coinciding with broader economic slowdowns and adjustments in post-pandemic recovery strategies. Nevertheless, even in this downturn, India and Brazil maintain comparatively better resilience than Italy and Canada.

Summary of Global Hiring Trends

This comparative analysis highlights a growing divergence between fast-scaling AI economies like India and slower adopters like Italy. Countries that aggressively invest in AI education, infrastructure, and innovation ecosystems see stronger, more resilient growth in AI labor demand.

For Italy, and specifically for regions like Avezzano, these trends suggest potential vulnerabilities in digital workforce competitiveness, unless proactive measures are taken to build AI talent pipelines and stimulate regional adoption.

3.2.5 Gender Participation in the AI Workforce

In addition to skill penetration and hiring growth, the composition of the AI workforce by gender offers important insights into diversity, inclusion, and equitable access to emerging technological opportunities. Figure 9 presents the global gender distribution of AI-skilled professionals based on LinkedIn data compiled by the OECD between 2016 and 2024.

This analysis is critical because AI not only shapes future labor markets but also influences broader societal outcomes. Ensuring gender-balanced participation in AI development is essential for fostering ethical, inclusive, and representative technological systems.

Figure 9 Gender Participation in the Global AI Workforce (2016–2024)

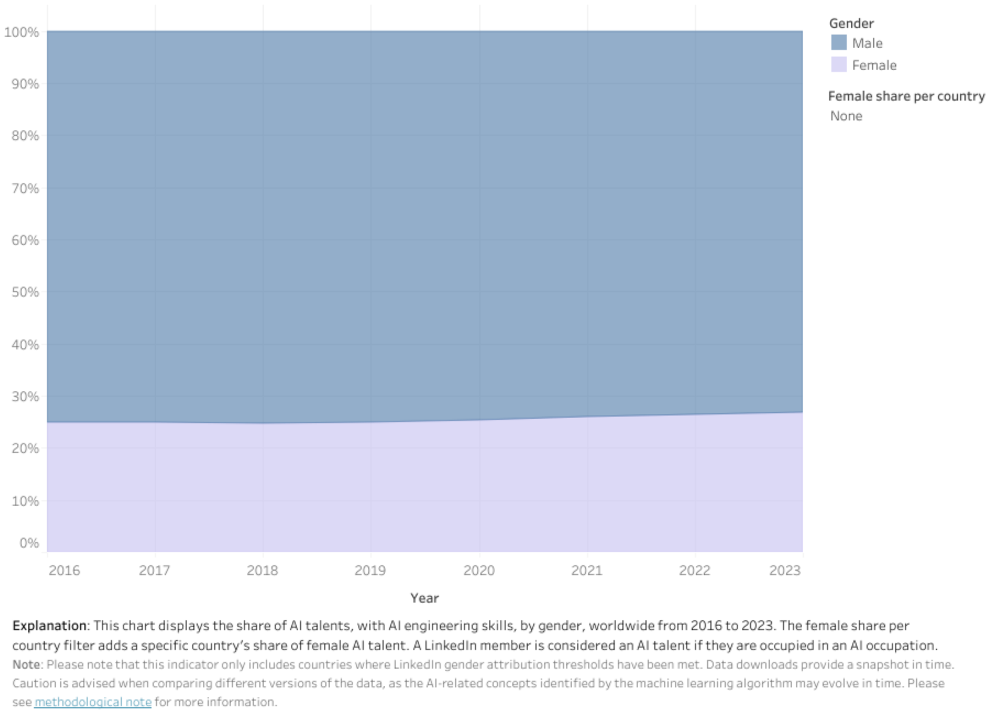

Figure 9 Gender Participation in the Global AI Workforce (2016–2024)

Source: OECD.AI (2025), data from LinkedIn Economic Graph, last updated 2025-04-07, accessed on 2025-04-25, https://oecd.ai/

The data reveals a persistent gender imbalance in the global AI workforce. Across the analyzed period, male professionals dominate AI-skilled roles, comprising approximately 70% to 75% of the total AI talent pool globally. Female participation remains relatively stagnant, hovering between 25% and 30%, with only modest improvements in some countries and sectors over time.

Notably, countries like Canada, Australia, and parts of Europe (e.g., France, Germany) report slightly higher female AI participation rates (closer to 30%), whereas others such as India, Brazil, and even the United States show more pronounced disparities, especially in technical AI engineering roles.

In the case of Italy, female representation in AI-skilled roles mirrors the global average or slightly below, ranging around 24% to 26% depending on the year and sector. This underrepresentation is particularly concerning given Italy's broader structural challenges with female participation in STEM (science, technology, engineering, and mathematics) fields, as documented in Eurostat and OECD education statistics.

The persistent gender gap not only reflects social and educational biases but also risks embedding algorithmic biases into AI systems themselves if the creators of AI lack diverse perspectives. Addressing this imbalance requires coordinated efforts in education reform, targeted mentorship programs, and inclusive hiring policies, especially in emerging AI hubs and innovation sectors.

Summary of Gender Participation Trends

The AI labor market continues to face significant challenges in achieving gender equity. Despite global awareness initiatives, structural barriers to women's full participation in AI careers remain entrenched.

Understanding these disparities is essential for shaping inclusive policy interventions and corporate strategies at both national and regional levels. For Italy and regions like Avezzano, fostering greater gender diversity in AI fields could be a critical lever for broadening talent pools, enhancing innovation capacity, and aligning with global inclusion standards.

3.2.6 Top and Fastest Growing AI Skills

Beyond understanding the scale and composition of AI employment, identifying the specific skills that are most in-demand provides valuable insights into how labor markets are evolving and what competencies are driving the AI economy. Figure 10 presents the top 20 most prevalent AI skills worldwide, based on LinkedIn member data compiled by the OECD between 2015 and 2024.

This skills analysis is critical for aligning education, reskilling, and workforce development initiatives with the actual needs of employers operating in an increasingly AI-driven global market.

Figure 10 Top 20 AI Skills Worldwide (2015–2022)

Figure 10 Top 20 AI Skills Worldwide (2015–2022)

Source: OECD.AI (2025), data from LinkedIn Economic Graph, last updated 2025-04-07, accessed on 2025-04-25, [*https://oecd.ai/*](https://oecd.ai/)

The most commonly reported AI skills globally include:

- Machine Learning (#1)
- Artificial Intelligence (General) (#2)
- Data Structures (#3)
- Deep Learning (#4)
- Pandas (Python Library) (#5)
- Natural Language Processing (NLP) (#6)
- Computer Vision (#7)
- TensorFlow (#8)
- Image Processing (#9)
- Scikit-Learn (#10)

These top 10 skills show that core AI development relies heavily on machine learning algorithms, data manipulation, model building, and software tools supporting deep learning architectures.

In addition, framework-specific expertise is highlighted through skills like PyTorch (#11), Keras (#13), and TensorFlow (#8), emphasizing the industry's demand for proficiency in popular machine learning libraries.

Key underlying AI subfields such as Neural Networks (#12), Artificial Neural Networks (#15), Pattern Recognition (#16), Convolutional Neural Networks (CNNs) (#17), and Reinforcement Learning (#18) reflect the specialized areas where AI applications are advancing rapidly.

Technical skills supporting deployment and scaling such as MS Azure Machine Learning (#19) and Information Retrieval (#20) also feature, indicating that cloud computing and big data integration are increasingly fundamental in modern AI solutions.

Summary of AI Skills Trends

The global demand for AI skills concentrates on a core set of machine learning fundamentals, specialized neural network techniques, and proficiency with mainstream programming libraries.
This pattern suggests that future AI professionals must not only master foundational concepts like supervised learning and data handling but also develop advanced skills in model optimization, deployment, and maintenance frameworks.

For Italy, and particularly for regional labor markets like Avezzano, these findings highlight the critical need to enhance both educational offerings and reskilling programs targeting AI-specific technical competencies.
Failing to align local skill development with these global trends risks widening competitiveness gaps in an increasingly AI-driven economy.

Notably, programming proficiency, particularly in Python, remains a cornerstone of AI-related employment, along with deep familiarity with machine learning frameworks like TensorFlow and PyTorch.

3.3 National Perspective: Analysis of AI/ML Job Postings in the United States

Building upon the global trends identified through the OECD.AI data analysis, this section narrows the focus to the national labor market by examining a dataset of 862 AI/ML job postings collected in the United States.
The purpose is to explore how AI skill demands, hiring patterns, and sectoral distributions observed globally are reflected, or diverge, within one of the world's most advanced and competitive AI economies.

The United States remains a global leader in AI research, commercialization, and workforce development, yet regional differences, sector-specific demands, and emerging trends suggest that the AI labor market is far from homogeneous.
Analyzing real-world job postings provides a practical lens into the actual skills, roles, locations, and sectors driving AI employment growth at the national level.

This dataset, sourced from Kaggle, spans postings primarily between 2022 and 2024, capturing a critical post-pandemic period during which AI hiring rebounded strongly, aligning with global patterns identified in Section 3.2.4.
Moreover, comparing the national dynamics of the United States with the local findings from Avezzano in subsequent sections will offer valuable insights into how global AI trends are filtered through national labor markets and local economic realities.

Data Analysis

The dataset was analyzed using Python for descriptive statistics and visualization. Key analyses included frequency counts for job titles, locations, and hiring companies, as well as word clouds to extract frequently mentioned skills. Data cleaning steps ensured consistency, and visualizations were created to highlight trends. Detailed analysis steps are provided in Appendix.

3.3.1 Data Sources and Processing

To ensure a robust analysis of AI adoption and skill demand trends, multiple datasets were utilized. This section provides a detailed overview of the data sources, processing steps, and tools employed to prepare the data for analysis.

3.3.1.1 Data Sources

1. **United States Dataset**:
   - **Source**: Kaggle platform, specifically the dataset titled "AI and ML Job Listings USA" by Kanchana Wickramasinghe (Kaggle Dataset Link).
   - **Description**: The dataset contains 862 AI/ML job postings in the United States, covering roles, skills, locations, sectors, and experience levels.
   - **Timeframe**: Job postings span from March 2022 to June 2024.
   - **Fields Included**:
     - Job titles, locations, hiring companies, required skills, contract types, and experience levels.
2. **OECD Reports**:
   - **UK**:
     - **Source**: OECD publication on AI skill demand in the United Kingdom.
     - **Focus**: Trends in skill demand, industry-specific AI applications, and occupational shifts.
   - **Canada**:
     - **Source**: OECD publication on AI skill demand in Canada.
     - **Focus**: Digital and social skill integration, as well as industry-wide adoption patterns.
3. **Generative AI Adoption Study**:
   - **Source**: Federal Reserve report on the diffusion and productivity impacts of generative AI in the United States.
   - **Focus**: Rapid adoption rates, productivity contributions, and cross-industry implications.

3.3.1.2 Data Processing

1. **Data Cleaning**:
   - Handled missing values by imputing, removing, or categorizing them as necessary.
   - Normalized location names and job titles to ensure consistency across entries.
2. **Filtering and Categorization**:
   - **US Dataset**: Filtered job postings to focus on AI-related roles using keywords such as "Artificial Intelligence," "Machine Learning," and "Deep Learning."
   - **OECD Reports**: Extracted key insights related to skill demand and workforce dynamics.
   - **Federal Reserve Study**: Focused on adoption metrics and productivity implications.
3. **Visualization Preparation**:
   - Developed graphs and tables using Python libraries, including Matplotlib and WordCloud.
   - Included visualizations such as bar charts (e.g., top job titles, locations), word clouds (e.g., skill demand), and heatmaps (e.g., challenges across companies).

Tools Used

- **Programming Language**: Python.
- **Libraries**:
  - **Pandas**: Data manipulation and cleaning.
  - **Matplotlib/Seaborn**: Visualization of data trends.
  - **WordCloud**: Creation of skill-demand visualizations.

Data Collection Process

- **Timeframe**: The dataset includes job postings from March 24, 2022, to June 1, 2024, providing insights into recent and ongoing trends in the AI/ML job market.
- **Source**: The dataset was obtained from Kaggle, an online platform hosting datasets for various domains, at the following link: AI and ML Job Listings USA.

- **Platforms**: The dataset aggregates information from multiple online job posting platforms, ensuring relevance and up-to-date information.
- **Keyword Selection**: A comprehensive set of AI-related keywords, including "Artificial Intelligence," "Machine Learning," "Deep Learning," and "Natural Language Processing," was used to filter job postings.
- **Scope**: The dataset focuses solely on job postings in the United States, aligning with the primary geographical scope of this study.

3.3.1.3 Ethical Considerations

- **Privacy Compliance**: All data used were publicly available, and no personal or sensitive information was included.
- **Transparency**: The data collection and processing steps are outlined clearly to ensure replicability.

3.3.2 Exploratory Data Analysis (EDA)

Objective

The EDA aimed to uncover trends and patterns in the AI/ML job market in the United States by examining job titles, locations, hiring companies, required skills, contract types, and experience levels.

3.3.2.1 Job Titles:

- **Most Common Roles**: "Machine Learning Engineer" emerged as the top job title, accounting for 17% of postings.
- **Diversity in Roles**: Titles ranged from AI/ML Engineers to specialized roles such as AI Ethics Specialists and Prompt Engineers.

Figure 11 Top 10 Job Titles in AI/ML Job Postings

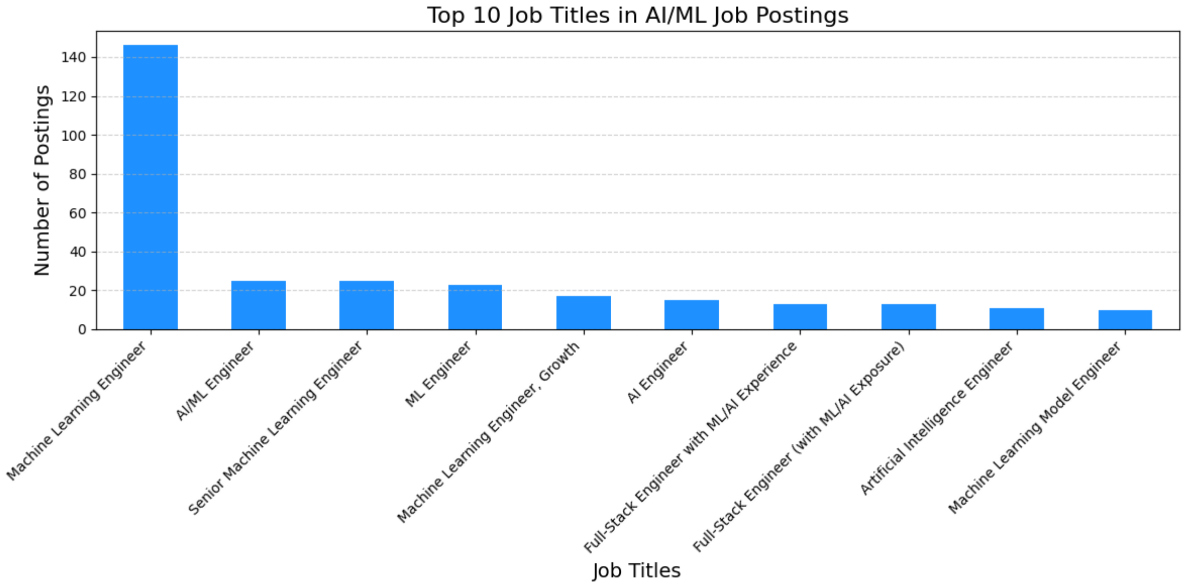

Figure 11 Top 10 Job Titles in AI/ML Job Postings

- Figure 11 presents a bar chart depicting the top 10 job titles appearing in AI and machine learning (ML) job postings across the United States, based on a dataset of 862 listings from March 2022 to June 2024. Bar charts are ideal for highlighting frequency comparisons, and in this figure, the vertical bars reflect how often each job title appeared, offering a clear overview of the most in-demand AI-related roles in the contemporary labor market.

3.3.2.2 Geographical Concentration:

- **Geographical Concentration**: Major hiring cities included San Francisco, New York, and Seattle, with California being the most active state.
- **Emerging Hubs**: Cities like Mountain View and Austin showed notable activity.

Figure 12 Top 10 Locations for AI/ML Job Postings

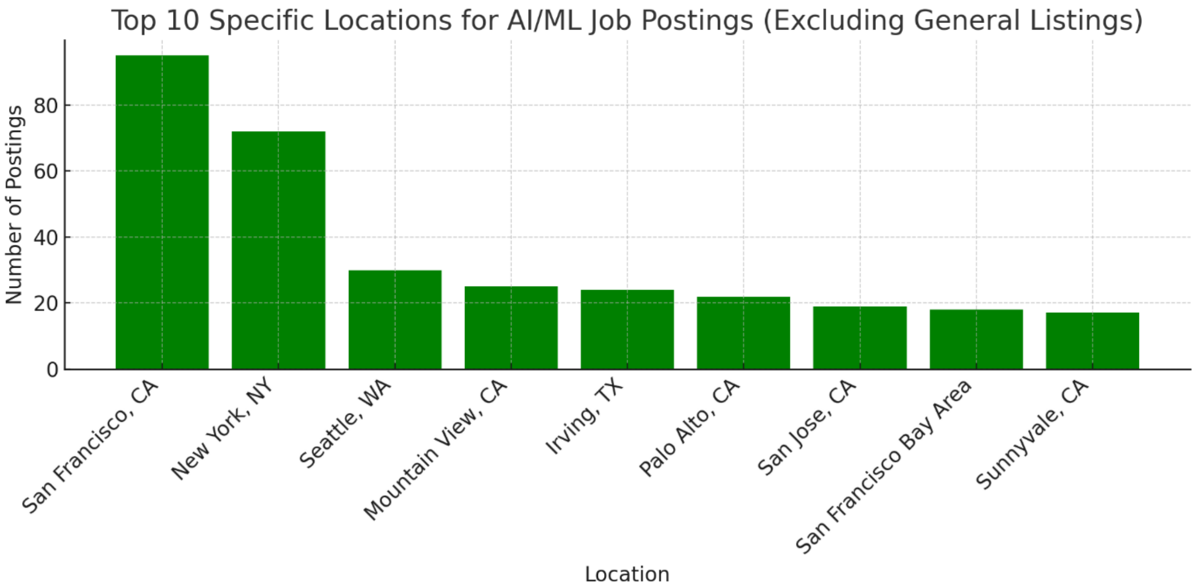

Figure 12 Top 10 Locations for AI/ML Job Postings

- Figure 12 presents a bar chart showcasing the top 10 U.S. cities with the highest number of AI and machine learning (ML) job postings between March 2022 and June 2024. The chart provides a spatial view of employment concentration, revealing where AI-related labor demand is most prominent. The data clearly identifies San Francisco, New York, and Seattle as the leading hubs for AI/ML job opportunities, followed by emerging technology centers such as Austin, Mountain View, and Boston.
- The dominance of San Francisco is unsurprising, given its central role in the Silicon Valley ecosystem, home to many leading AI companies, startups, and research institutions. Similarly, New York stands out as a major financial and commercial hub, where AI is heavily applied in fintech, algorithmic trading, and customer analytics. Seattle's strong showing reflects the presence of major technology firms like Amazon and Microsoft, both of which have aggressively expanded their AI capabilities.
- Beyond the top three, the presence of Mountain View and Palo Alto reinforces the concentration of AI hiring within California, while Austin's emergence demonstrates the growing decentralization of tech innovation due to its favorable business climate and cost of living. Boston's placement highlights its strength in healthcare AI and university-linked research environments.
- This figure underscores the geographic clustering of AI opportunities, which reflects not only the locations of major tech employers but also the availability of highly skilled labor, investment capital, and innovation ecosystems. For job seekers, educators, and

policymakers, understanding this spatial distribution is key to developing responsive strategies for workforce development, talent mobility, and regional innovation policy.

3.3.2.3 Hiring Companies:

- **Top Employers**: Companies such as Unreal Staffing, DoorDash, and Grammarly had the highest number of postings.
- **Sector Trends**: The technology and software development sectors dominated the hiring landscape.

Figure 13 Top 10 Companies Hiring for AI/ML Roles

Figure 13 Top 10 Companies Hiring for AI/ML Roles

- Figure 13 presents a bar chart illustrating the ten companies with the highest number of AI/ML job postings in the analyzed dataset. Interestingly, the top recruiter is Unreal Staffing, Inc., which accounts for over 40 postings, substantially more than any other company in the list. This suggests a significant role played by staffing and recruitment firms in the AI talent ecosystem. Rather than hiring for in-house roles, such companies often serve as intermediaries, sourcing AI professionals for a wide range of client organizations, particularly in consulting, healthcare, fintech, and tech sectors.
- Doordash ranks second, reflecting its growing reliance on AI for delivery route optimization, dynamic pricing, and customer behavior modeling. Other notable companies include Grammarly, known for its AI-driven writing assistant tools, and Samsung Electronics America, likely expanding its AI teams in areas like computer vision, speech recognition, and mobile device intelligence.

- This chart reveals a notable blend of platform companies, service providers, and recruitment firms, illustrating how AI-related hiring is not confined to "big tech" but extends into support services, digital platforms, and specialized outsourcing channels. It suggests that job seekers may benefit not only from targeting brand-name tech companies but also by exploring roles in consulting firms and intermediaries, which serve as key nodes in the AI hiring network.
- *Unreal Staffing, Inc. is primarily a staffing and recruitment agency specializing in connecting talent with opportunities in the gaming industry, with a strong focus on Unreal Engine-related roles. They recruit for roles that support the creation of Unreal Engine-based games by other companies.*

  Examples of Games Using Unreal Engine:

  - *Fortnite (Epic Games): A massively popular battle royale game that heavily utilizes Unreal Engine, with ongoing development requiring the kind of talent Unreal Staffing recruits.*
  - *Hogwarts Legacy (Portkey Games/Avalanche Software): A 2023 action RPG set in the Harry Potter universe, showcasing Unreal Engine's capabilities in open-world design.*
  - *Final Fantasy VII Remake (Square Enix): A critically acclaimed remake that uses Unreal Engine for its stunning visuals and gameplay.*
  - *PUBG: Battlegrounds (Krafton): Another battle royale giant leveraging Unreal Engine for its expansive environments.*

3.3.2.4 Contract Types:

- **Employment Distribution**: Full-time roles constituted 86% of the postings, followed by contract roles at 12%.

Figure 14 Distribution of Contract Types in AI/ML Job Postings

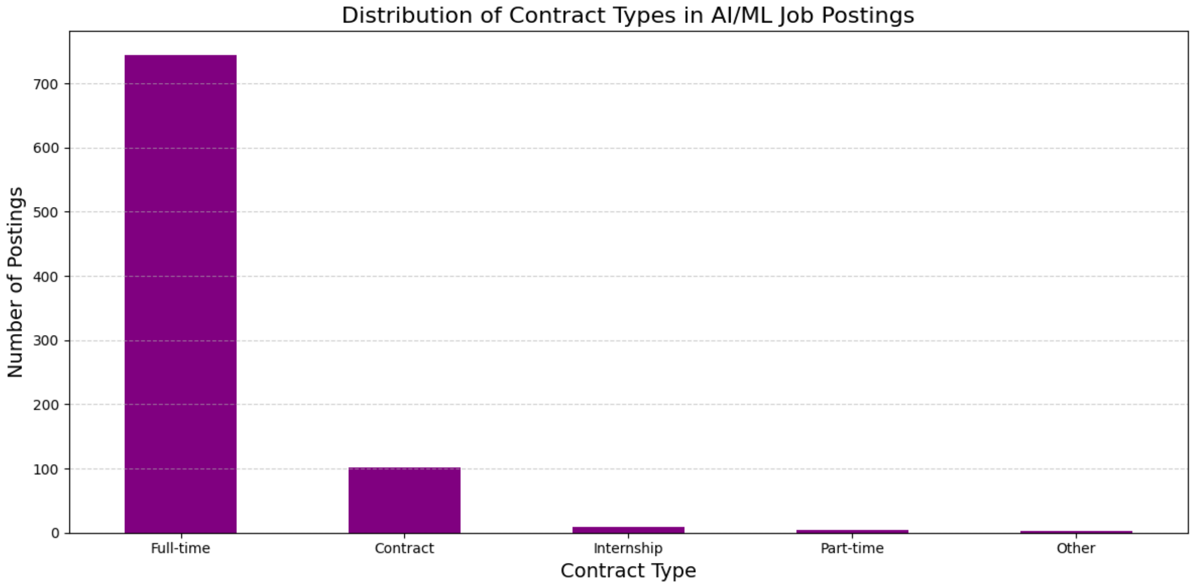

Figure 14 Distribution of Contract Types in AI/ML Job Postings

Figure 14 presents the distribution of contract types among AI and machine learning job postings, offering insight into the nature and stability of AI-related employment in the contemporary U.S. labor market. The data shows that a large majority of positions (approximately 86%) are full-time roles, indicating that employers generally view AI roles as long-term strategic investments rather than temporary or project-based needs. This trend suggests that companies hiring AI talent seek to build and retain in-house expertise, reflecting the integral role of AI in ongoing product development, data infrastructure, and decision-making processes.

Contract-based and part-time positions, while present, constitute a much smaller proportion of the postings. Contract roles are often associated with specialized, short-term AI consulting or implementation projects, while part-time roles may appear in research settings or startups with limited resources. The scarcity of internships and freelance roles suggests that companies prioritize candidates with existing professional experience and expect them to contribute to advanced systems from the outset.

This employment structure supports the thesis argument that AI is not only reshaping the demand for certain job titles and skills but is also redefining the employment model itself, favoring stability and long-term integration. It reflects how AI expertise has transitioned from experimental or outsourced work to a core business function requiring dedicated internal capacity. Moreover, the dominance of full-time roles may also signal a growing maturity in **AI** adoption, where organizations are investing in workforce continuity to maintain competitive advantage in data-driven innovation.

3.3.2.5 Experience Levels:

- **Demand for Seniority**: Mid-senior level roles dominated (47%), followed by entry-level positions (39%).

Figure 15 Experience Level Distribution in AI/ML Job Postings

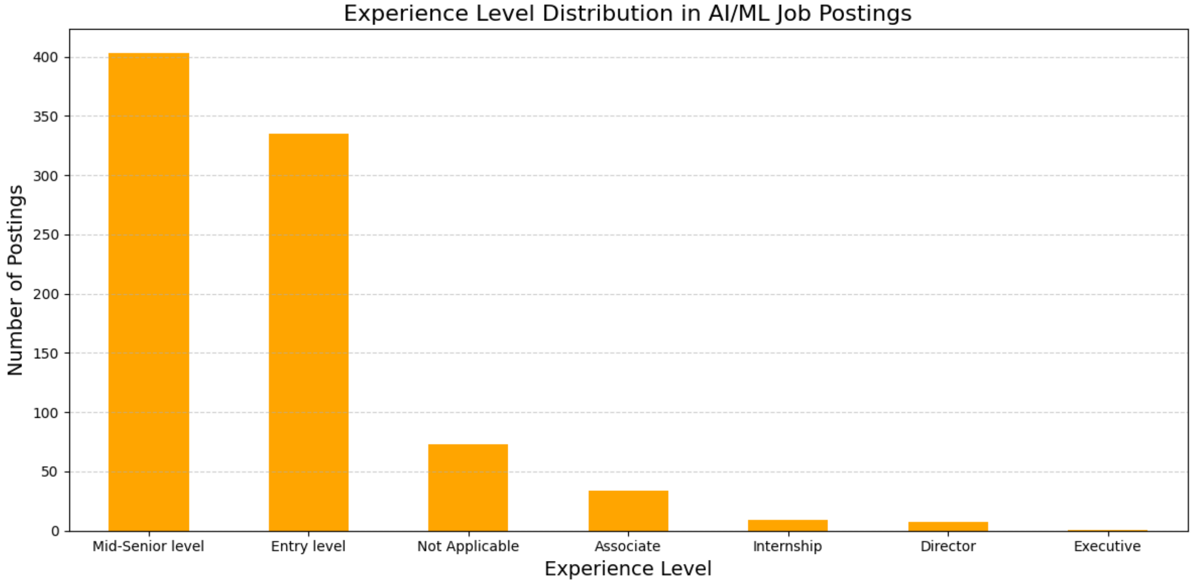

Figure 15 Experience Level Distribution in AI/ML Job Postings

Figure 15 displays the distribution of experience levels required in AI and machine learning job postings across the United States, providing valuable insight into employer expectations and entry thresholds in the AI job market. The data reveals that mid-senior level positions dominate the landscape, accounting for approximately 47% of postings. This trend indicates that employers are seeking professionals who not only possess technical expertise but also have proven experience in deploying AI models, managing projects, and contributing to strategic decision-making. AI's complexity and business-critical nature mean that firms often prioritize candidates capable of leading initiatives with minimal supervision.

Entry-level roles constitute about 39% of postings, which, while significantly lower than mid-level, still represent a substantial opportunity for recent graduates and early-career professionals. These roles typically involve supporting data preparation, writing code under supervision, or maintaining models. Their presence suggests that although the field is competitive, there is an openness to nurturing emerging talent, particularly among companies with mentorship capacity or academic collaborations.

Senior and executive-level positions, including AI directors and lead researchers, make up a smaller share of the dataset. Their limited presence aligns with organizational structures where fewer top-level roles exist but are highly strategic and compensated accordingly.

Overall, this figure underscores the fact that AI is a skill-intensive field with a steep learning curve, and employers tend to favor individuals with demonstrated experience. However, the meaningful share of entry-level roles also reflects growing institutional investment in AI talent pipelines, emphasizing the importance of education, internships, and continuous learning. For policymakers and academic institutions, this distribution highlights the need to support early-stage talent while also facilitating upskilling pathways for mid-career professionals aiming to transition into AI roles.

3.3.2.6 Job Descriptions:

- **Skill Demand**: Python, TensorFlow, and PyTorch were the most frequently mentioned technical skills.
- **Emerging Trends**: Focus on ethical AI practices and generative AI technologies.

Figure 16 Word Cloud of Job Descriptions

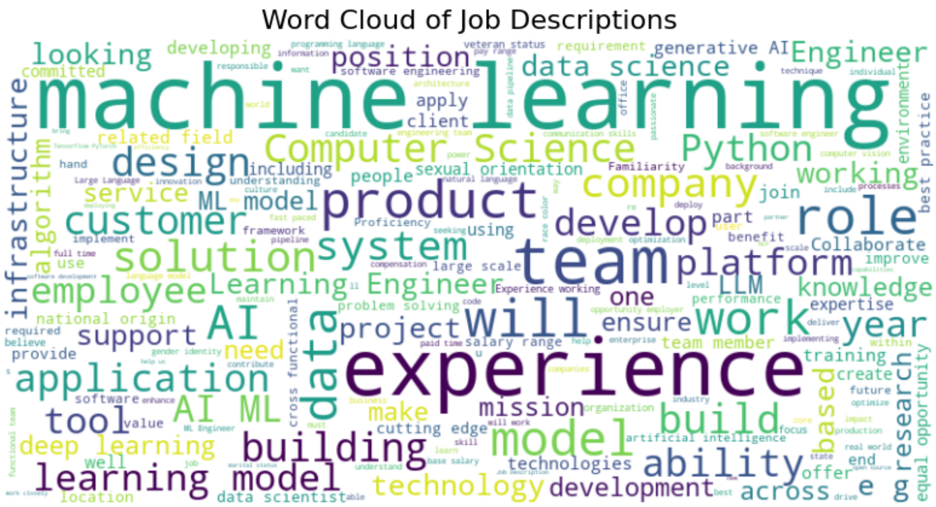

Figure 16 Word Cloud of Job Descriptions

Figure 16 presents a word cloud generated from the textual content of AI/ML job descriptions collected in the dataset. A word cloud is a text mining visualization tool that highlights the most frequently occurring words within a body of text, with font size indicating word frequency. This method offers an immediate and intuitive understanding of what employers prioritize when advertising AI/ML positions.

The word cloud reveals that technical competencies dominate the AI job landscape. Key terms such as *Python*, *TensorFlow*, *PyTorch*, *machine learning*, *data*, and *model* appear most prominently, indicating the centrality of programming and model development in AI roles. These tools are essential for tasks such as building and training neural networks, processing large datasets, and deploying AI-driven applications, functions that form the backbone of modern AI systems.

In addition to technical skills, the presence of terms like *team*, *communication*, and *collaboration* suggests that AI work is rarely isolated. Even highly technical roles demand strong interpersonal skills, as cross-functional collaboration between engineers, product managers, and data scientists is often required to ensure that AI systems align with business goals and are ethically implemented.

The prominence of *research*, *optimization*, and *production* further highlights the balance employers seek between innovation (e.g., developing new models) and practical application (e.g., deploying models into real-world systems). The word cloud also reflects growing attention to *ethics*, *bias*, and *interpretability*, signaling that responsible AI development is becoming a mainstream concern.

Altogether, this visualization encapsulates the interdisciplinary nature of AI roles, blending deep technical expertise with problem-solving, creativity, and communication. It reinforces the need for AI professionals to be both technically proficient and context-aware, able to work within teams and across departments to deliver scalable, ethical, and high-impact AI solutions.

3.3.2.7 Hiring Sectors:

- **Dominant Industries**: Software development, IT services, and engineering were the leading sectors.

Figure 17 Top 10 Hiring Sectors for AI/ML Roles

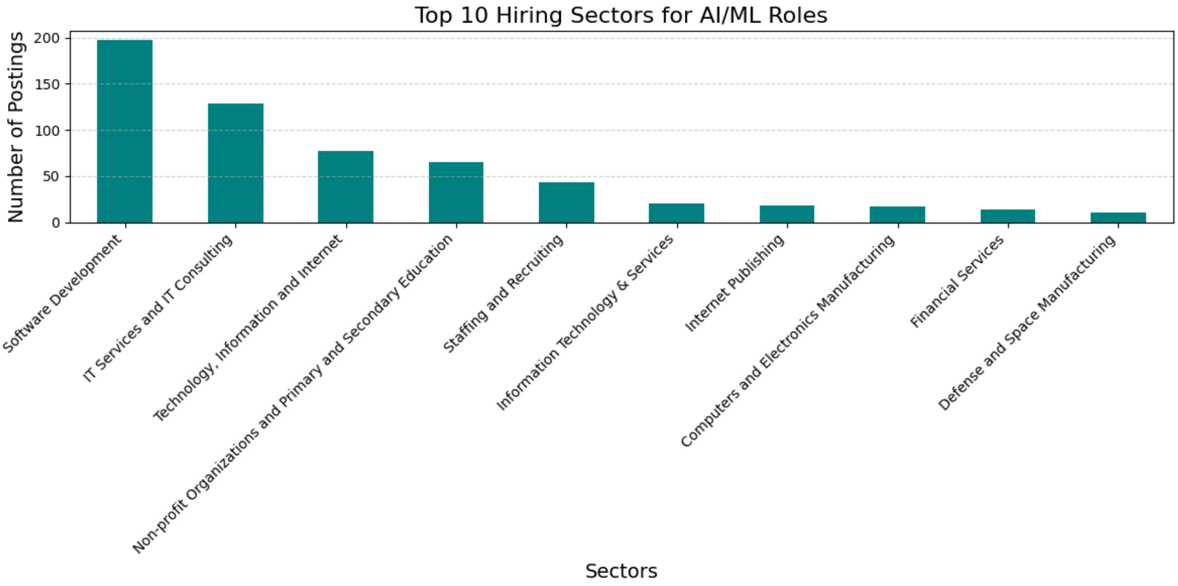

Figure 17 Top 10 Hiring Sectors for AI/ML Roles

Figure 17 illustrates the top 10 sectors hiring for AI/ML roles, based on job postings collected from March 2022 to June 2024. This sectoral breakdown reveals how AI adoption is diffusing across industry verticals, highlighting where demand for AI talent is most concentrated. The data shows that software development and IT services lead the hiring landscape, a reflection of these sectors' foundational role in AI infrastructure, platform development, and digital transformation. These companies are not only building AI tools but also offering them as services to other industries, thus driving up internal demand for AI engineers, data scientists, and ML operations specialists.

Other prominently represented sectors include finance, healthcare, telecommunications, and e-commerce, each of which is undergoing rapid transformation through AI applications. In finance, for example, AI is used in fraud detection, risk modeling, and algorithmic trading. In healthcare, demand is growing for roles related to medical imaging analysis, diagnostics, and patient data optimization. The presence of automotive and manufacturing in the top 10 further supports the research that AI is now core to industrial automation, supply chain optimization, and the development of autonomous systems.

This cross-sectoral hiring activity suggests that AI is no longer confined to "tech companies" but is becoming a horizontal enabler across nearly all sectors. It reflects a broader trend toward AI-as-infrastructure, where firms across industries are embedding intelligent systems to enhance operational efficiency, product development, and customer engagement.

For job seekers, the implications are twofold: AI career opportunities are no longer limited to Silicon Valley-style companies, and domain expertise in a specific industry, such as healthcare, finance, or manufacturing, can significantly enhance one's competitiveness. For policymakers and educators, the findings emphasize the importance of offering AI training that is sector-sensitive, enabling future professionals to apply their technical skills in context-specific ways.

3.3.2.8 Limitations

- **Primary Data**: Interviews with Avezzano-based companies are pending and will be included in future updates.
- **Geographical Scope**: The secondary analysis is limited to the United States, which may not represent global trends.
- **Time Frame**: The dataset includes postings from March 2022 to June 2024; trends may shift with future developments.

3.4 Local Perspective: Interviews with Companies in Avezzano

Following the global and national analyses of AI workforce trends, this section focuses on the local labor market dynamics in Avezzano, Italy.
Using primary qualitative data collected through interviews with five companies across various sectors, this analysis explores how AI adoption, workforce impacts, and sectoral readiness manifest at a regional level.

By comparing these localized findings with broader global and national patterns, the study aims to highlight both structural challenges and emerging opportunities specific to small- and medium-sized enterprises (SMEs) operating outside major innovation hubs.

3.4.1 Research Design

To complement the global and national analyses conducted in previous sections, this study employs a qualitative data collection strategy focusing on the local business environment of Avezzano, Italy.
The primary research aims to explore how small- and medium-sized enterprises (SMEs) are adopting artificial intelligence (AI), the challenges they face, and the workforce transformations they are experiencing.

Data were collected through semi-structured interviews with five companies operating across various sectors, including information technology, fashion, education, and import/export. Semi-structured interviews were selected to balance consistency across respondents with the flexibility needed to capture sector-specific insights and company-specific experiences with AI integration.

Participants were selected through purposive sampling, targeting firms with varying degrees of technological maturity to capture a diverse range of perspectives on AI adoption. Interviews were conducted face-to-face to facilitate in-depth discussion, minimize potential language misunderstandings, and allow for the clarification of complex technical terms where necessary.

Ethical considerations, including informed consent, confidentiality assurance, and the voluntary nature of participation, were strictly observed throughout the data collection process.
Collected data were then systematically coded and analyzed to extract both quantitative indicators (e.g., AI adoption rates, workforce impacts) and qualitative insights (e.g., perceived opportunities, anticipated challenges), allowing for a mixed-methods triangulation when compared to global and national findings.

The data collection thus serves a dual role:
(1) providing a localized perspective on AI workforce transformations, and
(2) enabling comparative analysis against broader patterns identified at the international and national levels.

3.4.2 Data Collection

Interviews with Companies in Avezzano

Data Collection Process

Objective

- **Purpose**: To capture diverse perspectives from businesses across sectors in Avezzano regarding:
    - The extent and impact of AI adoption on their operations.
    - The skills and qualifications sought for AI-related roles.
    - Challenges and opportunities faced during AI integration.
- **Participants**:
    - Five companies from different sectors, including IT, fashion (two companies), education, and import/export, were interviewed.

- Purposeful sampling ensured sectoral diversity to capture varied levels of AI adoption.

Interview Method:

Semi-structured interviews conducted in person to ensure clarity and overcome language barriers, as not all participants were fluent in English.

Sampling:

Companies actively engaged with or exploring AI technologies were prioritized for inclusion.

3.4.3 Interview Guide:

Topics covered:

- Current AI adoption and future plans.
- Workforce implications, such as new roles and skill demands.
- Challenges and opportunities arising from AI integration.

3.4.4 Ethical Considerations

- **Informed Consent**: Participants were briefed about the study's purpose and provided verbal or written consent before the interviews.
- **Confidentiality**: Company names, addresses, and identifying details were anonymized in the final report to ensure privacy.
- **Voluntary Participation**: Participants were informed of their right to withdraw at any point without repercussions.

3.4.5 Analysis Approach

3.4.5.1 Data Preparation

- **Review and Categorization**: Responses from the five companies were reviewed in detail, focusing on their perspectives about AI adoption, workforce changes, and the perceived opportunities and challenges in their respective sectors.
- **Quantitative Data Tabulation**:
    - Structured responses, such as AI adoption levels and workforce impacts, were categorized into quantifiable formats to enable statistical and visual analysis.
    - Each sector was assigned a distinct identifier to streamline data organization and facilitate comparisons.

- **Thematic Coding for Qualitative Responses**:
  - Open-ended responses on challenges, opportunities, and future outlooks were analyzed for recurring themes.
  - Themes like cost, resistance to change, and personalization opportunities were coded and quantified to reveal patterns across sectors.

3.4.5.2 Quantitative Analysis

3.4.5.2.1 AI Adoption

- **AI Adoption Levels**:
  - 2 companies (40%) have adopted AI technologies (Companies A and E).
  - 3 companies (60%) have not adopted AI technologies (Companies B, C, and D).
- **AI Adoption Areas**:
  - Companies using AI applied it in:
    - Marketing/Analytics: 2 companies
    - Operations/Automation: 1 company
    - Customer Service (e.g., chatbots): 1 company

Figure 18 A pie chart representing AI adoption levels.

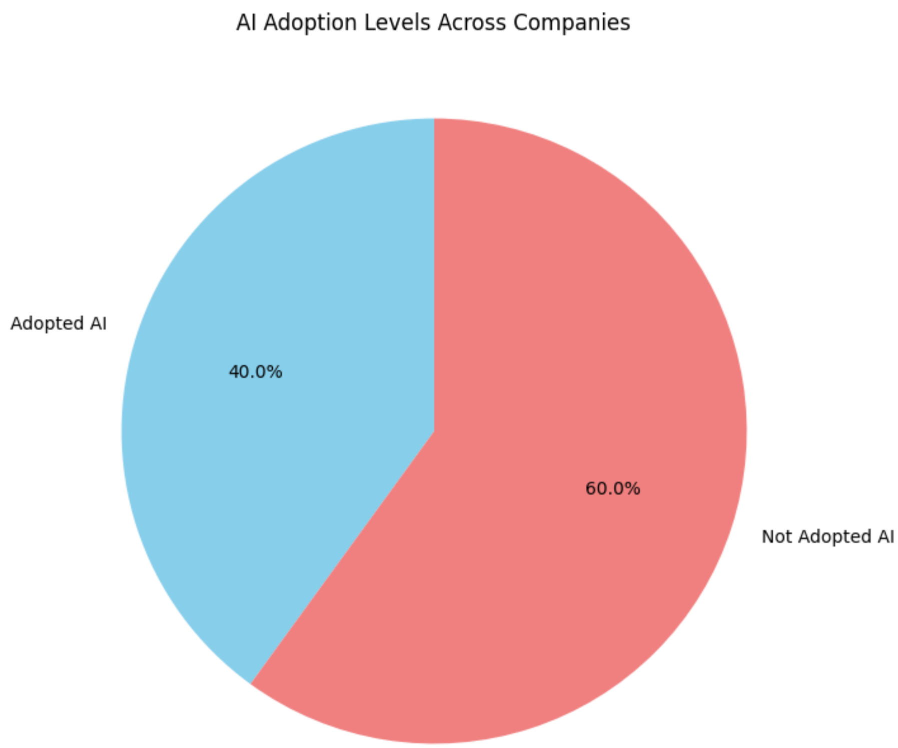

Figure 18 A pie chart representing AI adoption levels.

- Figure 18 presents a visual breakdown of the AI adoption status among the five companies interviewed in Avezzano. The pie chart reveals that 40% of these companies (2 out of 5) have already integrated AI technologies into their operations, while the remaining 60% (3 out of 5) have not yet adopted AI. This distribution reflects the relatively early stage of AI diffusion in local business contexts, particularly in SMEs operating outside major urban innovation hubs. The companies that have adopted AI (Companies A and E) primarily utilize it in marketing analytics, operations, and customer service, suggesting a focus on customer engagement and process optimization rather than core product innovation. The non-adopters, on the other hand, cited barriers such as financial constraints, lack of skilled personnel, and internal resistance to change. This disparity highlights a growing technological divide even within a limited geographical area, where digitally mature sectors such as IT and fashion are progressing faster than others like education and import/export. The chart therefore serves as a foundational indicator of sectoral digital readiness and sets the stage for deeper analysis of the organizational and workforce-level impacts explored in subsequent figures.

3.4.5.2.2 Workforce Impact

- **Impact on Workforce**:
  - Created new roles: 1 company (Company A)
  - Changed existing roles: 2 companies (Companies A and E)
  - No significant changes: 1 company (Company E)

Figure 19 A bar chart showing workforce impacts across companies.

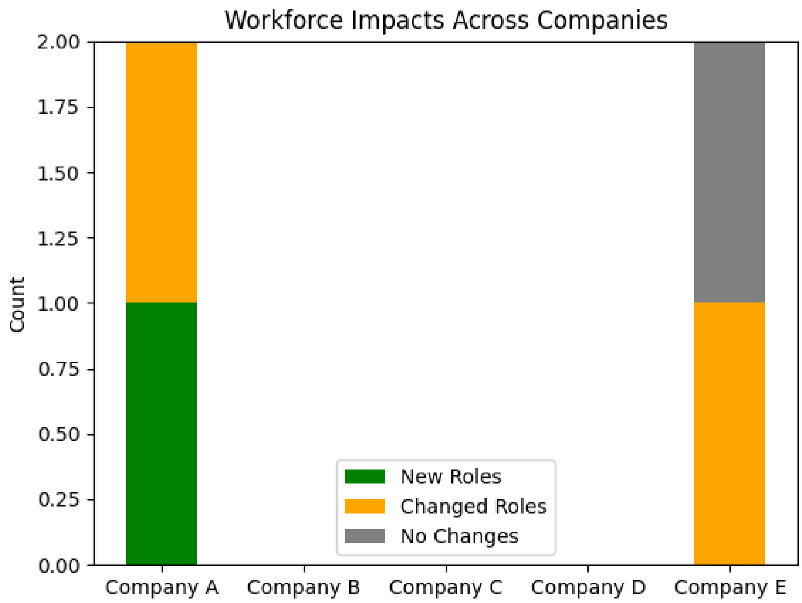

Figure 19 A bar chart showing workforce impacts across companies.

What the Chart Shows Specifically:

- **Company A:**
  - New Roles: 1 (green area).
  - Changed Roles: 1 (orange area).
  - No Changes: 0.
  - Meaning: Actively using AI, creating new positions, and significantly adjusting current ones.

- **Company B, C, D:**
  - No representation on the chart means these companies reported neither new nor significantly changed roles, likely due to limited or no AI adoption.
- **Company E:**
  - Changed Roles: 1 (orange area).
  - No Changes: 1 (grey area).
  - Meaning: Mixed impactsome roles modified by AI, while others remain unaffected.
- The figure 19 illustrates the extent to which AI adoption has influenced workforce structures within the five interviewed companies. The bar chart categorizes impacts into three main outcomes: creation of new roles, modification of existing roles, and no significant workforce changes. Company A stands out as the most proactive adopter, having both created new roles and altered existing ones in response to AI integration. Company E reported modifications to current job roles but did not introduce entirely new positions, suggesting a partial transformation where AI is used to enhance current operations without expanding the workforce structurally. In contrast, Companies B, C, and D, none of which have adopted AI technologies, reported no changes to their workforce configurations. These findings reveal that AI adoption has not only technological implications but also tangible effects on human capital strategies. The creation of new roles (e.g., data analysts, AI coordinators) and the evolution of existing ones signal a shift toward a more adaptive, digitally-oriented organizational structure in AI-engaged companies. Furthermore, the absence of change among non-adopters underscores a missed opportunity for innovation and modernization, potentially placing them at a competitive disadvantage in the long term. This figure reinforces the notion that AI acts as a catalyst for workforce evolution, with adoption status directly correlating to the degree of internal role transformation.

3.4.5.2.3 Challenges in AI Adoption

- Common challenges:
  - High implementation costs (4 companies: A, B, C, D)
  - Lack of skilled workforce (4 companies: A, B, C, D)
  - Resistance to change (3 companies: A, B, C)

Figure 20 A heatmap comparing challenges across companies

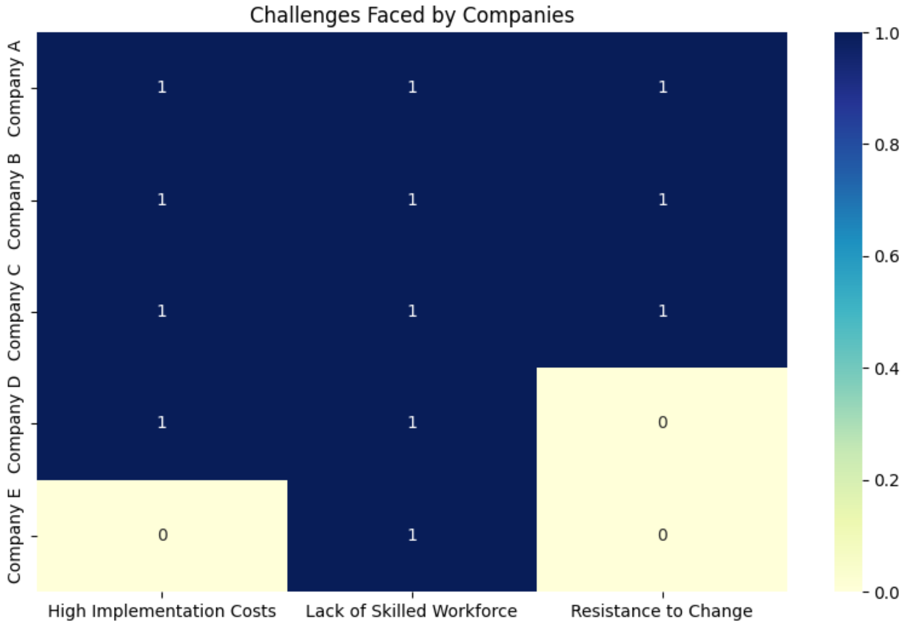

Figure 20 A heatmap comparing challenges across companies

This heatmap visualizes the main challenges faced by the five companies (Companies A–E) during AI adoption:

Numbers and their Meanings:

- The number "**1**" (dark blue squares):
  - Means the challenge was reported by the company.
- The number "**0**" (light yellow squares):
  - Means the challenge was not reported by the company.
- Figure 20 presents a heatmap illustrating the key challenges reported by each of the five companies interviewed regarding their experiences with AI adoption. The three primary obstacles identified were high implementation costs, lack of a skilled workforce, and resistance to change among employees. The heatmap uses a binary scale where "1" indicates that a company acknowledged a specific challenge, while "0" indicates it did not. The results show a clear pattern: high implementation costs and skills shortages were reported by four out of five companies (Companies A, B, C, and D), indicating that financial and human capital limitations are systemic barriers to AI integration in this regional context. Interestingly, Company E, despite being an AI adopter, did not

report high costs as a barrier, potentially due to sector-specific funding flexibility or existing infrastructure. Resistance to change was also prominent, reported by Companies A, B, and C, all of which demonstrated lower digital readiness or had only recently begun exploring AI applications. The heatmap emphasizes that these challenges are not isolated but rather widely experienced across sectors, albeit with varying intensity. This visual representation supports the argument that for AI to be more widely adopted at the local level, interventions must address both financial constraints and workforce development, while also fostering a cultural shift toward openness to technological change.

3.4.5.3 Qualitative Analysis

3.4.5.3.1 Opportunities Identified

- Recurring themes in opportunities:
    - Improved customer experience (2 mentions: Companies A, E)
    - Enhanced precision in marketing campaigns (Company A)
    - Personalized learning and training (Company B)
    - Supply chain optimization (Company D)

Figure 21 A word cloud highlighting key opportunities mentioned

Figure 21 A word cloud highlighting key opportunities mentioned

- Figure 21 presents a word cloud generated from open-ended interview responses provided by companies regarding the opportunities they associate with AI adoption. A word cloud is a text-mining visualization tool that displays words based on their frequency in the source data: the larger and bolder the word appears, the more frequently it was mentioned across all participants' responses. This method allows for the rapid identification of recurring themes and emphasizes which ideas resonate most strongly among respondents.

- In this figure, key phrases such as *"improved customer experience"*, *"enhanced precision"*, *"personalized learning"*, and *"supply chain optimization"* appear most prominently. These terms reflect the companies' perceived benefits of AI, drawn from different industry contexts. For example, companies in retail and fashion cited *enhanced precision in marketing* and *improved customer experience*, which aligns with their operational focus on consumer engagement and personalized campaigns. Their responses suggest that AI's data-driven capabilities enable better audience segmentation and interaction, ultimately leading to stronger customer loyalty and competitive advantage.
- The *personalized learning* opportunity mentioned by the education-sector company reveals interest in AI's potential to tailor content delivery and adapt educational materials to individual student needs. This is particularly relevant for sectors aiming to increase learning efficiency and student engagement. Similarly, *supply chain optimization*, identified by the import/export sector, points to AI's promise in improving logistics, inventory forecasting, and delivery accuracy, areas traditionally vulnerable to delays and inefficiencies.
- By synthesizing diverse but thematically consistent responses, the word cloud provides a visual summary of what companies hope to gain from AI adoption, reinforcing the idea that although sector-specific applications differ, the underlying goals, efficiency, personalization, and performance enhancement, are shared across industries.

3.4.5.3.2 Future Outlook

- Predicted evolution of AI:
  - Integration in customer engagement and personalization (Company E).
  - Enhanced efficiency in logistics and tracking (Company D).
  - Adaptive learning platforms in education (Company B).
  - Design innovations and supply chain improvement in fashion (Company C).

Figure 22 A radar chart comparing sector-specific AI evolution insights

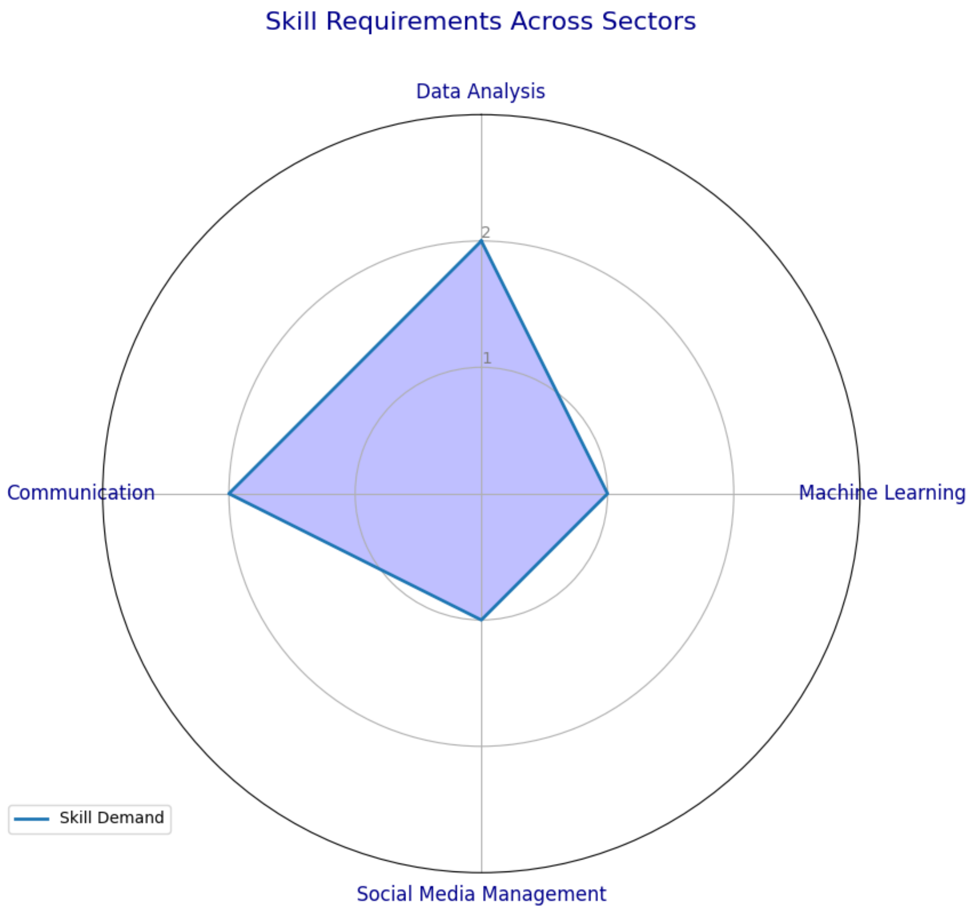

Figure 22 A radar chart comparing sector-specific AI evolution insights

- Figure 22 displays a radar chart comparing how companies from different sectors envision the evolution of artificial intelligence over the next 5 to 10 years. A radar chart is a graphical method used to visualize multivariate data across several categories, in this case, each axis represents a projected area of AI development (such as personalization, logistics, learning, or design innovation), and each company's insights are mapped onto this multidimensional space. The further a data point extends from the center, the greater the company's emphasis on that specific aspect of AI's future.
- The radar chart reveals clear sectoral patterns in AI outlooks. For example, the fashion sector (Company C) places strong emphasis on *design innovation* and *supply chain improvements*, reflecting its interest in AI's potential to accelerate trend prediction, automate design iterations, and streamline production cycles. The education sector (Company B) emphasizes *adaptive learning platforms* and *personalized student engagement*, suggesting a belief that AI will transform pedagogical approaches by

offering tailored content and real-time performance feedback, thereby enhancing learning outcomes.

- The import/export sector (Company D) highlights *logistics efficiency* and *tracking accuracy* as its top priorities. These areas are critical in global trade, and AI's integration is seen as a key tool for managing complex supply chains and improving delivery reliability. Meanwhile, Company E, operating in retail or customer-facing services, envisions future advancements centered on *customer engagement* and *personalization*, aligned with their strategic focus on consumer satisfaction and behavior-driven services.
- Overall, this chart illustrates that although AI is universally acknowledged as transformative, its anticipated evolution is shaped by sector-specific needs and goals. While all companies see potential, the areas where they expect the most impact vary depending on their operational context. This sectoral divergence underscores the importance of developing AI strategies that are not only technologically sound but also aligned with industry-specific challenges and opportunities.

3.4.5.4 Sectoral Comparisons

3.4.5.4.1 AI Adoption Across Sectors

- Companies in education (Company B), fashion (Company C) and import/export (Company D) are less likely to adopt AI compared to those in IT and retail fashion.

Figure 23 A bar chart showing AI adoption levels acrosss merged sectors.

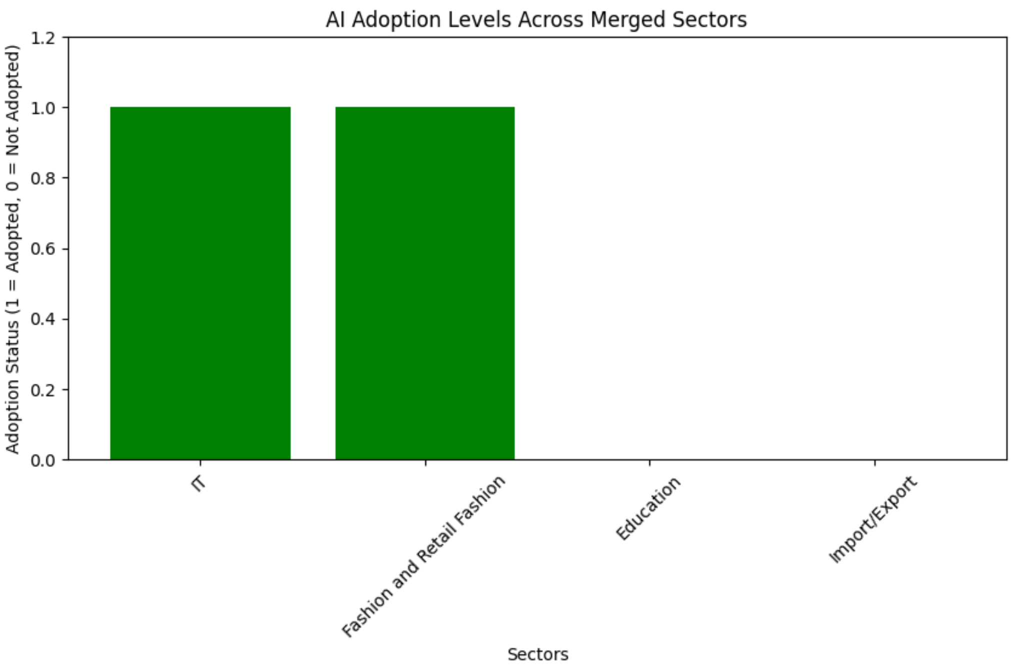

Figure 23 A bar chart showing AI adoption levels acrosss merged sectors.

- Figure 23 presents a bar chart that illustrates the level of AI adoption across four merged sectors, IT, Fashion and Retail Fashion, Education, and Import/Export, based on responses collected from the interviewed companies. Bar charts are used to compare categorical data, and in this case, each bar represents whether companies within a given sector have adopted AI (1) or not (0). This binary visualization enables a straightforward comparison of digital readiness across industries.
- The results indicate that the IT and Fashion sectors are leading in AI adoption, each showing active integration of AI technologies within their operational workflows. This is expected, as these industries tend to be more digitally mature and innovation driven. For IT, AI is a natural extension of existing systems used in data processing and automation. For Fashion, AI offers valuable tools for personalized marketing, inventory prediction, and trend forecasting, functions that are becoming essential in competitive retail landscapes.
- In contrast, the Education and Import/Export sectors show no adoption of AI at the time of data collection. This may reflect limited financial resources, lower digital infrastructure, or sectoral inertia rooted in traditional workflows. In the case of Education, there may be a hesitance to implement untested technologies in pedagogical environments. Similarly, Import/Export companies might prioritize stability and cost-efficiency over innovation, particularly in smaller regional contexts like Avezzano.
- The disparities revealed in this chart underscore a growing sectoral divide in AI adoption, where technologically agile industries accelerate ahead, while others risk falling behind. This gap highlights the need for targeted policy interventions and support programs to equip lagging sectors with both the resources and confidence to explore AI-driven solutions. Without such measures, uneven adoption may exacerbate inequality in productivity, competitiveness, and workforce development across industries.

3.4.5.4.2 Workforce Skills Demand

- Top skills required for AI-related roles:
    - Data analysis (2 mentions: Companies A, E)
    - Machine learning frameworks (Company A)
    - Social media management (Company E)
    - Communication and teamwork (2 mentions: Companies A, E)

Figure 24 A grouped bar chart comparing skill demands across sectors.

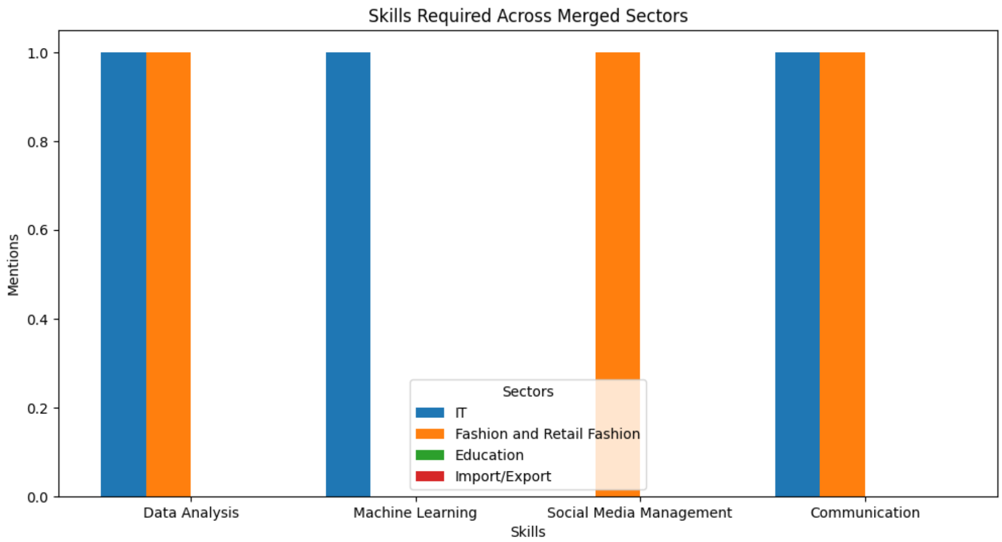

Figure 24 A grouped bar chart comparing skill demands across sectors.

- Figure 24 presents a grouped bar chart comparing the demand for specific AI-related skills across four sectors; IT, Fashion and Retail Fashion, Education, and Import/Export, based on interview data from companies in Avezzano. Grouped bar charts allow for the side-by-side comparison of multiple categories (in this case, skills) across different groups (sectors). Each skill, such as data analysis, machine learning, social media management, and communication, is represented by a cluster of bars, enabling the viewer to assess which sectors prioritize which competencies.
- The data reveals that IT and Fashion sectors are the only ones actively seeking AI-related skills, while Education and Import/Export show no immediate demand. In the IT sector, the top skills identified include *data analysis*, *machine learning frameworks*, and *communication*, underscoring the technical and collaborative nature of AI-driven work environments. This reflects the sector's foundational reliance on data and algorithmic thinking, as well as the need for teamwork in software development and systems integration.
- The Fashion and Retail Fashion sector reported demand for *data analysis*, *social media management*, and *communication*, indicating that AI in this context is largely applied toward consumer analytics and digital marketing strategies. Here, data-driven insights are used to tailor campaigns, predict customer behavior, and refine branding efforts across platforms.
- The absence of any reported AI skill demand in the Education and Import/Export sectors correlates with their low levels of AI adoption, as seen in Figure 23. This suggests a

cyclical challenge: without AI implementation, there is no immediate need for related skills, and without skilled personnel, companies may feel unprepared to adopt AI in the first place.

- This chart therefore highlights a clear mismatch between sectoral readiness and workforce capability, emphasizing the need for upskilling initiatives and educational outreach, especially in traditionally conservative sectors. Bridging this skill gap is essential for promoting equitable access to AI technologies and ensuring that all industries can harness their transformative potential.

3.4.6 Expected Outcomes

Sectoral Variations

AI adoption shows significant disparities across sectors:

- **Leading Sectors**: IT and fashion-related industries are at the forefront of AI adoption. Companies in these sectors demonstrate a readiness to integrate AI into their operations, particularly in areas like marketing, analytics, and customer service. These sectors benefit from a higher level of digital literacy and a competitive drive to enhance customer engagement.

- **Lagging Sectors**: Education and import/export sectors are slower to adopt AI, primarily due to reliance on traditional methodologies and a lack of resources or technical expertise. Resistance to change and the absence of immediate perceived benefits also contribute to this slower adoption.

Shared Challenges

Despite sectoral differences, several universal challenges to AI adoption were identified:

- **High Implementation Costs**: The financial burden of integrating AI tools and systems remains a significant barrier for companies across all sectors.

- **Workforce Skill Gaps**: A lack of employees with the required technical skills, such as proficiency in programming, machine learning frameworks, and data analysis, inhibits progress. This challenge is especially pronounced in sectors like education and import/export, where AI adoption is less established.

- **Resistance to Change**: Employee hesitation to adapt to new technologies is a shared obstacle, emphasizing the need for effective change management strategies.

Unique Opportunities

Each sector perceives distinct opportunities for AI integration:

- **IT Sector**: AI is seen as a means to drive innovation in product development and service optimization, making processes more efficient and scalable.
- **Fashion Sector**: Personalized marketing and enhanced supply chain management are key opportunities, allowing companies to meet customer demands with greater precision.
- **Education**: While lagging in adoption, education presents potential for adaptive learning platforms and personalized student engagement strategies.
- **Import/Export**: AI can improve logistics efficiency, optimize inventory management, and enhance forecasting accuracy.

Broader Implications

The findings underscore AI's transformative potential as an enabler of growth and efficiency across diverse industries:

- **Workforce Evolution**: AI is reshaping roles by creating new opportunities while simultaneously redefining existing ones. Companies that embrace reskilling and upskilling initiatives will be better positioned to leverage AI's capabilities.
- **Dependence on Overcoming Barriers**: Widespread adoption depends on addressing cost-related challenges and bridging workforce skill gaps. This requires concerted efforts from industry stakeholders, educational institutions, and policymakers.
- **Long-term Impact**: AI's adoption trajectory suggests that industries with higher digital maturity will lead the way, influencing others through demonstrated benefits and market pressure to stay competitive.

Limitations

Sample Size and Representation

The data collection was limited to interviews with five companies in Avezzano, which may not fully capture the diversity of perspectives across industries. While efforts were made to include companies from various sectors, such as IT, fashion, education, and import/export, the findings may not generalize to regions with different economic or technological environments.

Geographical Scope

The study is geographically confined to Avezzano, Italy. This location, with its specific economic and cultural context, may not reflect the broader trends of AI adoption and workforce dynamics in other regions or countries. Regional factors, such as local labor market conditions and technological infrastructure, may have influenced the results.

Sectoral Diversity

Although a mix of sectors was included, key industries with significant AI adoption potential, such as healthcare, finance, and manufacturing, were not part of the study. This could limit the scope of the findings when drawing conclusions about sector-wide trends in AI adoption.

Language Barriers and Communication

Interviews were conducted in person to address potential language barriers, as not all participants were fluent in English. While this approach improved clarity, it may have introduced subtle biases in the interpretation of responses or omitted nuanced perspectives that participants were unable to articulate due to language constraints.

Potential Response Bias

Participants may have provided socially desirable responses, especially regarding the opportunities and challenges associated with AI adoption. This could result in an overemphasis on the positive impacts of AI or underreporting of organizational challenges such as resistance to change or skills gaps.

Time Constraints

The interviews were designed to be brief (5–10 minutes) to encourage participation. However, this time limitation may have restricted the depth of responses, particularly for open-ended questions on opportunities, challenges, and the future outlook for AI.

Technological Focus

The study prioritized companies with some engagement in AI or openness to discussing its potential. This focus may have excluded organizations with little to no interest in AI, thereby skewing the results towards those already exploring or adopting the technology.

Ethical and Cultural Factors

While ethical considerations were followed, such as anonymizing company identities and ensuring voluntary participation, cultural norms and interpersonal dynamics may have influenced how openly participants shared their views. Some responses might reflect cautious or guarded opinions due to concerns about confidentiality or judgment.

Implications for Analysis

The limitations outlined above suggest that while the findings provide valuable localized insights, caution should be exercised in generalizing the results to broader contexts. Future studies should consider expanding the sample size, geographical coverage, and sectoral diversity to build a more comprehensive understanding of AI's workforce implications.

4. Discussion

4.1 Summary of Key Findings

This study investigates the multifaceted impact of artificial intelligence (AI) on labor markets by employing a three-tiered methodology: a global comparative analysis using OECD AI skills data, a meso-level examination of AI/ML-related job postings in the United States, and a micro-level qualitative study of SMEs in Avezzano, Italy.

At the global level, the OECD data presents a nuanced view of AI skills penetration across countries, sectors, and demographic groups. Countries like the United States, India, and Canada exhibit high levels of AI literacy among LinkedIn members, particularly in sectors such as technology, finance, and professional services. In contrast, Southern European economies, including Italy, lag significantly behind, especially in public sector readiness and educational integration of AI content. Gender disparities remain persistent, with female representation in AI talent pools still considerably lower than male counterparts.

Additionally, the industry-level insights from OECD data indicate a profound asymmetry in AI readiness. Fields such as manufacturing, education, and healthcare reveal slower uptake and skills penetration, pointing to structural and institutional gaps that hinder digital transformation in these traditionally human-centric domains. The skills migration data suggests a net outflow of AI talent from less digitally mature economies, reinforcing the digital divide narrative on a global scale.

At the national level, the dataset of 862 AI/ML-related job postings from the United States was analyzed to extract trends in role types, contract types, experience levels, skill requirements, and sectoral distribution. The findings confirmed that AI-related jobs are not confined to Silicon

Valley tech giants but are increasingly dispersed across sectors like healthcare, finance, marketing, and public services. Despite this diversification, roles such as machine learning engineer, data scientist, AI consultant, and computer vision specialist dominate the job landscape.

In terms of skills, the postings strongly emphasize not only technical competencies (e.g., Python, TensorFlow, NLP, cloud platforms) but also soft skills such as adaptability, critical thinking, teamwork, and AI ethics. A significant finding is the rising demand for hybrid roles that require both domain expertise and AI literacy, a pattern aligned with the literature on complementarity effects (e.g., Bick et al., 2024; IBM, 2023).

At the local level, interviews conducted with five SMEs in Avezzano provided insights into the real-world experience of AI adoption in peripheral economic regions. While some firms demonstrated a proactive attitude toward digitalization, many admitted being at the early stages of exploration. They cited financial constraints, talent shortages, and lack of access to institutional support (training, funding, AI consultancies) as primary barriers.

Interestingly, all companies acknowledged that AI is "inevitable," but only a few had begun implementing it in targeted areas such as customer segmentation, inventory optimization, or workflow automation. The interviews revealed a fragmented perception of AI, viewed alternately as a threat to human employment and as an essential tool for remaining competitive.

Furthermore, when asked about workforce readiness, the majority of interviewees pointed to the misalignment between local education institutions and industry needs. While technical schools and universities exist in the region, their curricula have yet to catch up with the rapidly evolving AI skillset requirements. This resonates with findings from the OECD AI education readiness index and complements the skill mismatch problem discussed in multiple literature sources (Schwab, 2016; Martinelli et al., 2021).

In sum, the key findings reveal a paradox: AI is both widespread and uneven, both transformative and inaccessible, depending largely on geography, institutional capacity, and strategic vision. The cross-level integration of these findings suggests that AI's labor impact is not just a technological outcome, but a deeply socio-economic and policy-driven process.

4.2 Interpretation of Results in Light of the Literature

The findings presented across the global, national, and local levels reinforce and in some cases nuance existing literature on the labor market effects of artificial intelligence. This section critically compares empirical insights from Chapter 3 with the core debates reviewed in the literature, thereby embedding the results within established theoretical and policy frameworks.

At the global level, the observed cross-country asymmetries in AI skills penetration substantiate the arguments of Schwab (2016) and TTC/EC/CEA (2022), who describe a fragmented digital transition across economies. OECD data aligns with Frey and Osborne's (2013) suggestion that technological transformations amplify existing structural inequalities, with digitally advanced nations benefiting disproportionately. Countries like Italy exhibit low AI skill penetration and a slower diffusion rate, findings echoed in the DIPE0025 policy analysis, which warned about institutional inertia and fragmented industrial strategy.

In terms of sectoral variation, the findings confirm Cirillo et al. (2021) and Martinelli et al. (2021), who emphasize that the benefits and challenges of AI adoption are highly sector-specific. The low AI penetration in education and public administration observed in the OECD dataset supports the claim that certain sectors are systematically excluded from AI investment and innovation pipelines. Meanwhile, the high concentration of AI-literate workers in tech and finance is consistent with previous findings by IBM (2023), suggesting the reinforcement of digital monopolies and skill polarization.

The national-level analysis of U.S. job postings highlights the emergence of hybrid roles, occupations that combine domain-specific expertise with AI and data literacy. This corroborates Bick et al. (2024), who noted that generative AI adoption does not eliminate jobs but reshapes them, shifting skill requirements and work processes. The prominence of roles like "prompt engineer" and "AI ethics analyst" also adds empirical weight to Schwab's (2016) assertion that Industry 4.0 is generating novel job categories previously non-existent in the labor taxonomy.

Moreover, the coexistence of technical and soft skill requirements in job descriptions, such as adaptability, critical thinking, and ethical judgment, provides real-world confirmation of theoretical propositions by Engberg et al. (2024) and Damioli et al. (2023) about complementarity effects. These findings support the idea that AI does not merely replace tasks but augments human capacities, demanding a reconfiguration of workforce capabilities rather than a complete substitution.

At the local level, the case of Avezzano SMEs deepens the understanding of regional digital divides in practice. While OECD and IBM reports identify infrastructure and talent as major enablers of AI diffusion, this study shows how these constraints are experienced by real businesses. The mismatch between local educational offerings and the evolving needs of companies validates concerns raised by Acemoglu et al. (2022) and Schwab (2016) regarding the lag in institutional response to AI transitions. Furthermore, the dual perception of AI, as both an opportunity and a threat, mirrors broader ambivalence in the literature about AI’s socio-economic impacts (Frey & Osborne, 2013; DIPE0025, 2023).

Finally, the hesitation among local firms to invest in AI despite acknowledging its importance parallels IBM’s (2023) findings that many organizations face strategic paralysis due to insufficient internal digital maturity. This suggests that beyond policy declarations and theoretical models, the real bottleneck may lie in micro-level institutional capacity, cultural readiness, and access to targeted support mechanisms.

4.3 Theoretical and Practical Implications

This study makes several contributions to the theoretical and practical understanding of how artificial intelligence is transforming the labor market across global, national, and local dimensions.

4.3.1 Theoretical Contributions

First, the study reinforces the emerging consensus in literature that AI's impact on labor is not monolithic, but instead structured by a complex interplay of sectoral context, geographic location, institutional preparedness, and policy frameworks (Acemoglu & Restrepo, 2021; Martinelli et al., 2021; Schwab, 2016). The combination of macro-, meso-, and micro-level data creates a methodological bridge between economic models of technological substitution and more localized, qualitative understandings of workforce adaptation.

Second, by highlighting the complementarity effect, the rise of hybrid jobs requiring both domain knowledge and AI proficiency, the study expands the literature's understanding of skill transformation in the AI era. This supports and extends prior work (Engberg et al., 2024; Bick et al., 2024) by providing fresh empirical evidence from real job markets and small business settings.

Third, the research foregrounds the role of institutional mismatch, the disconnect between education systems and evolving industry needs, as a structural barrier to inclusive AI transformation. While this theme has been touched upon in policy reports, this study integrates it into a theoretical understanding of workforce readiness, particularly in underrepresented regions like Avezzano.

Finally, the study offers a multi-level framework for studying technological change, emphasizing the need for mixed methods and triangulated data to capture the layered reality of

AI's labor impact. This addresses an important gap in the literature, where empirical studies often focus on either aggregate data or case-specific narratives, but rarely both.

4.3.2 Practical Implications

From a practical standpoint, the findings carry actionable insights for policymakers, educators, and business leaders.

For policy-makers, the results underscore the urgency of regionally targeted AI strategies. Rather than generic national plans, interventions must consider local contexts, infrastructure gaps, and sectoral specificities. In Italy, for instance, SMEs in regions like Abruzzo require access to targeted training programs, AI consultancy networks, and digital infrastructure investments, initiatives currently concentrated in the North.

For educational institutions, the study signals a need to modernize curricula at both secondary and tertiary levels. Integrating interdisciplinary modules that blend AI literacy with sectoral expertise, particularly in non-STEM domains such as business, health, and public administration, can help bridge the readiness gap. Local universities and vocational schools in Avezzano and similar regions should play a more strategic role in reskilling and upskilling efforts.

For business leaders, the study suggests that AI adoption should not be viewed as a binary "implement or not" decision, but as a gradual integration process aligned with human capital strategies. Firms that prioritize staff retraining, promote digital culture, and strategically map automation to value creation will be better positioned to adapt sustainably.

Finally, for international organizations and institutions such as OECD and the EU Commission, the findings validate the importance of data-informed and place-based policies. Cross-country benchmarking efforts like the OECD AI Skills indicators must be expanded and made more accessible to regional planners and educators.

4.4 Limitations of the Study

While this study provides a multi-level and data-rich perspective on the labor market impacts of artificial intelligence, it is not without its limitations. These constraints stem from both methodological design and the broader scope of the research topic.

4.4.1 Temporal Constraints and Data Availability

The OECD and U.S. job posting datasets used in this study reflect AI-related developments primarily up to the year 2023–2024. Given the rapidly evolving nature of AI technologies, especially the recent diffusion of generative AI tools such as ChatGPT, Copilot, and Bard, some labor market transformations may not yet be fully captured in the data. Additionally, job postings may not always reflect actual hiring outcomes or internal reskilling efforts within firms, introducing a potential discrepancy between labor demand and labor absorption.

4.4.2 Geographic and Institutional Scope

While the inclusion of a local case study (Avezzano) offers rich contextual insight, the findings from five SMEs cannot be generalized to all regional economies in Italy or Europe. Each locality possesses its own institutional infrastructure, labor market dynamics, and socio-cultural specificities. Therefore, the insights derived from Avezzano should be interpreted as indicative rather than representative.

Furthermore, the study does not include insights from public sector institutions, trade unions, or workers' organizations, which could have added depth to the qualitative component.

4.4.3 Sectoral Limitations

The focus on job postings and digital skills datasets may inherently bias the analysis toward high-skill, high-tech sectors, potentially underrepresenting the experiences of low-skill or informally employed workers who are also affected by AI. This creates a visibility gap, particularly in sectors like agriculture, hospitality, or low-tech services.

4.4.4 Methodological Constraints

Although the study combines qualitative and quantitative methods, it is primarily exploratory in nature. The qualitative interview sample is limited in number, and interviews were conducted in a semi-structured format, which may introduce interviewer interpretation bias. Additionally, the study did not employ econometric modeling or longitudinal analysis, which would be necessary to establish causal relationships or trace longer-term trends.

4.5 Suggestions for Future Research

The findings and limitations of this study point to several promising directions for future research. As AI continues to evolve, its interactions with labor markets will become increasingly complex, multidimensional, and embedded within institutional and cultural contexts. Future inquiries can build upon the foundation of this study by expanding the scope, refining methods, and deepening analysis in the following areas:

4.5.1 Longitudinal and Causal Analysis

Future research should incorporate longitudinal datasets that track the evolution of AI job postings, workforce transitions, and skill dynamics over time. This would allow scholars to examine causality, particularly whether increases in AI hiring correspond with displacement, reskilling, or sectoral shifts. Moreover, the use of econometric techniques such as panel regressions or difference-in-differences models would strengthen the analytical rigor of findings.

4.5.2 Cross-Country Comparative Studies

Given the pronounced disparities in AI adoption across countries and regions, comparative case studies could illuminate how different policy environments, education systems, and labor institutions mediate AI's impact. For instance, comparing Avezzano with a similarly sized town in Northern Europe or East Asia could yield valuable insights into best practices and structural constraints.

4.5.3 Worker-Centered Perspectives

While this study focuses on job postings and employer perspectives, future research should incorporate more worker-centered approaches. Surveys, interviews, or ethnographic studies of employees navigating AI integration could reveal hidden forms of resistance, adaptation, or emotional responses to automation, dimensions often missing in macro-level data.

4.5.4 Inclusion of Public Sector and Informal Labor

Much of the literature, and this study, focuses on formal private sector employment. Yet the public sector, as well as informal or precarious labor, plays a vital role in national economies. Examining how AI affects job quality, bureaucratic processes, and service delivery in these areas would broaden the analytical lens.

4.5.5 Educational System Transformation

Another fruitful area of research involves tracing how universities, vocational schools, and adult learning platforms respond to AI-induced skill gaps. Longitudinal studies tracking curriculum reforms, digital learning tools, and graduate outcomes could help assess the effectiveness of reskilling efforts and align education with real labor market needs.

4.6 Final Remarks

The relationship between artificial intelligence and the future of work is among the most urgent and complex questions of our time. As machines acquire capabilities once thought to be uniquely human, societies are confronted not only with technical challenges but also with profound questions about labor, dignity, inclusion, and economic justice.

This study has attempted to go beyond surface-level narratives, of either utopian optimism or dystopian fear, by empirically investigating how AI is being adopted, translated, and experienced at different levels of the global economy. By combining macro-level data, meso-level hiring patterns, and micro-level organizational insights, the study reveals that the impact of AI is neither linear nor uniform. It is shaped by historical legacies, institutional architectures, educational systems, and cultural perceptions.

What emerges is a picture of AI as both an accelerator and a magnifier: it accelerates change where infrastructure and vision are present, but it also magnifies existing inequalities where institutional gaps persist. AI is not just a technological shift; it is a social project, one that requires intentional design, inclusive governance, and ongoing critical scrutiny.

As the next wave of AI systems becomes more autonomous, generative, and embedded in decision-making processes, the role of education, ethics, and public policy will be more important than ever. If left unregulated or unevenly distributed, AI could deepen divisions across class, geography, and skill. But if approached with foresight, collaboration, and human-centered values, AI could also serve as a tool to build more resilient, equitable, and creative societies.

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Appendix A – OECD.AI Visualizations

All visualizations in this appendix are derived from the OECD AI Observatory's "AI Jobs and Skills" database, based on LinkedIn Economic Graph data. The figures were accessed on April 25, 2025. Each visualization provides insight into AI workforce dynamics at a global level, supporting the broader-to-local analytical flow of this study.

Citation for all visualizations:
OECD.AI (2025), data from LinkedIn Economic Graph, last updated 2025-04-07, accessed on 2025-04-25,

Figure 1: Net Migration Flows of AI-Skilled Professionals (2019–2023)

Net migration of LinkedIn members with AI skills. Dark blue bars indicate talent inflows, light blue indicate outflows.

Figure 2: Cross-Country AI Skills Penetration (2016–2023)

Relative AI skills intensity by country compared to a global average.

Figures 3–7: AI Skills Penetration by Industry (2016–2024)

These figures display AI skills prevalence across five key sectors:

- **3:** Education
- **4:** Financial Services
- **5:** Manufacturing
- **6:** Professional Services
- **7:** Technology, Information & Media

Figure 8: Growth of Hiring AI-Skilled Professionals (2016–2023)

Trend showing the increase in hiring rates of AI-skilled professionals across 43 countries.

Figure 9: Gender Participation in the Global AI Workforce (2016–2024)

Share of AI-skilled professionals by gender across the globe.

Figure 10: Top 20 AI Skills Worldwide (2015–2022)

The most frequently reported AI skills among LinkedIn users.

Appendix B: Dataset Description

- **Source**: The data for this analysis was sourced from an online job posting aggregator, which compiles AI/ML job listings across the United States.
- **Scope of Data**: The dataset includes job postings from March 2022 to June 2024, providing a comprehensive view of the AI/ML job market trends during this period.
- **Data Fields Description**:
    - **Title**: The job title of the posting.
    - **Location**: The city or region where the job is located.
    - **CompanyName**: The name of the company offering the job.
    - **ContractType**: Specifies whether the job is full-time, part-time, or contract-based.
    - **ExperienceLevel**: Indicates whether the position is for entry-level, mid-level, or senior-level candidates.
    - **Description**: A text description of the job responsibilities and requirements.
    - **Sector**: The industry sector under which the job is categorized.

Addition to *Data Sources* & *Appendix B*: Dataset Licence Statement

"The AI and ML Job Listings USA dataset (Wickramasinghe, 2024) is released under the Open Data Commons Attribution (ODC-By 1.0) licence on Kaggle. Use of the data in this study complies with the licence requirement to attribute the original contributor and link back to the dataset page (https://www.kaggle.com/datasets/kanchana1990/ai-and-ml-job-listings-usa). No personal or proprietary information is included in the dataset."

Methodology

- **Data Cleaning**: The dataset was cleansed to remove any incomplete entries and normalize data entries across various fields to ensure consistency in analysis.
- **Data Analysis Techniques**:
    - **Statistical Analysis**: Used to quantify the distribution and frequency of job titles, locations, and other categorical data.
    - **Data Visualization**: Employed to illustrate the data analysis findings using Python's Matplotlib and WordCloud libraries.

- **Software and Tools**:
  - **Python**: Primary programming language used.
  - **Pandas**: Python library for data manipulation and analysis.
  - **Matplotlib**: Python library for creating static, animated, and interactive visualizations.
  - **WordCloud**: Python library for creating word cloud images.

Visualizations

- **Figure 11: Top 10 Job Titles in AI/ML Job Postings**
  - Description: This bar chart shows the most common job titles, highlighting the demand for specific roles within the industry.
- **Figure 12: Top 10 Locations for AI/ML Job Postings**
  - Description: This bar chart displays the geographic distribution of job postings, identifying hotspots for AI/ML jobs.
- **Figure 13: Top 10 Companies Hiring for AI/ML Roles**
  - Description: This bar chart lists the companies with the highest number of postings, indicating their prominence in the AI/ML sector.
- **Figure 14: Distribution of Contract Types in AI/ML Job Postings**
  - Description: This bar chart shows the variety of employment contracts offered, from full-time to part-time and contractual.
- **Figure 15: Experience Level Distribution in AI/ML Job Postings**
  - Description: This bar chart categorizes job postings by required experience level, from entry to senior level.
- **Figure 16: Word Cloud of Job Descriptions**
  - Description: A word cloud visualization that highlights the most frequently mentioned terms in job descriptions, offering insight into common qualifications and skills.
- **Figure 17: Top 10 Hiring Sectors for AI/ML Roles**

- Description: This bar chart shows the sectors most actively hiring for AI/ML roles, such as technology and healthcare.

Code Listings

- **Data Analysis Code**: The complete Python code used for data cleaning, analysis, and visualization is provided to ensure reproducibility of the results presented in this study.

```
import pandas as pd
import matplotlib.pyplot as plt
from wordcloud import WordCloud
# Load the dataset
data = pd.read_json(dataset)
# Top 10 Job Titles
job_titles = data['title'].value_counts().nlargest(10)
plt.figure(figsize=(12, 6))
job_titles.plot(kind='bar', color='dodgerblue')
plt.title('Top 10 Job Titles in AI/ML Job Postings', fontsize=16)
plt.xlabel('Job Titles', fontsize=14)
plt.ylabel('Number of Postings', fontsize=14)
plt.xticks(rotation=45, ha='right')
plt.grid(axis='y', linestyle='--', alpha=0.6)
plt.tight_layout()
plt.show()
# Top 10 Locations
locations = data['location'].value_counts().nlargest(10)
plt.figure(figsize=(12, 6))
locations.plot(kind='bar', color='forestgreen')
plt.title('Top 10 Locations for AI/ML Job Postings', fontsize=16)
plt.xlabel('Location', fontsize=14)
plt.ylabel('Number of Postings', fontsize=14)
plt.xticks(rotation=45, ha='right')
plt.grid(axis='y', linestyle='--', alpha=0.6)
plt.tight_layout()
plt.show()
# Top 10 Companies
companies = data['companyName'].value_counts().nlargest(10)
plt.figure(figsize=(12, 6))
companies.plot(kind='bar', color='salmon')
plt.title('Top 10 Companies Hiring for AI/ML Roles', fontsize=16)
plt.xlabel('Companies', fontsize=14)
plt.ylabel('Number of Postings', fontsize=14)
```

```
plt.xticks(rotation=45, ha='right')
plt.grid(axis='y', linestyle='--', alpha=0.6)
plt.tight_layout()
plt.show(
# Distribution of Contract Types
contract_types = data['contractType'].value_counts()
plt.figure(figsize=(12, 6))
contract_types.plot(kind='bar', color='purple')
plt.title('Distribution of Contract Types in AI/ML Job Postings', fontsize=16)
plt.xlabel('Contract Type', fontsize=14)
plt.ylabel('Number of Postings', fontsize=14)
plt.xticks(rotation=0)
plt.grid(axis='y', linestyle='--', alpha=0.6)
plt.tight_layout()
plt.show()
# Experience Level Distribution
experience_levels = data['experienceLevel'].value_counts()
plt.figure(figsize=(12, 6))
experience_levels.plot(kind='bar', color='orange')
plt.title('Experience Level Distribution in AI/ML Job Postings', fontsize=16)
plt.xlabel('Experience Level', fontsize=14)
plt.ylabel('Number of Postings', fontsize=14)
plt.xticks(rotation=0)
plt.grid(axis='y', linestyle='--', alpha=0.6)
plt.tight_layout()
plt.show(
# Word Cloud of Job Descriptions
description_text = " ".join(description for description in data['description'])
wordcloud = WordCloud(width=800, height=400, background_color='white').generate(description_text)
plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.title('Word Cloud of Job Descriptions', fontsize=16)
plt.show()
# Top 10 Hiring Sectors
sectors = data['sector'].value_counts().nlargest(10)
plt.figure(figsize=(12, 6))
sectors.plot(kind='bar', color='teal')
plt.title('Top 10 Hiring Sectors for AI/ML Roles', fontsize=16)
plt.xlabel('Sectors', fontsize=14)
plt.ylabel('Number of Postings', fontsize=14)
plt.xticks(rotation=45, ha='right')
```

```
plt.grid(axis='y', linestyle='--', alpha=0.6)
plt.tight_layout()
plt.show()
```

Appendix C: Survey Questions

Form Survey: AI and Workforce Dynamics

Title

The Role of Artificial Intelligence in Workforce Dynamics: Survey for Thesis Research

Introduction

Dear Participant,

Thank you for taking the time to contribute to this research. I am a master's student studying the impact of artificial intelligence (AI) on workforce dynamics for my thesis.

This survey aims to gather insights into how companies adopt AI, the skills required for AI-related roles, and the challenges and opportunities arising from AI integration.

Your responses will remain anonymous and confidential. The survey will take approximately 5-10 minutes to complete.

If you have any questions or concerns, feel free to contact me.

Thank you for your valuable input!

Best regards,
Utku Onat Ateş

Section 1: Background Information

1. What is the name of your company? *(Optional)*
2. What is your role within the company? *(Short answer)*
3. What is the size of your company? *(Multiple choice)*
    - Fewer than 10 employees
    - 10–50 employees
    - 51–200 employees
    - 201–500 employees
    - More than 500 employees

4. What industry does your company operate in? *(Short answer)*

5. What percentage of your company's operations currently involve AI technologies? *(Multiple choice)*
    - o None
    - o Less than 10%
    - o 10–30%
    - o 31–50%
    - o More than 50%

Section 2: AI Adoption

6. Has your company adopted AI technologies? *(Multiple choice)*
    - o Yes
    - o No
7. If yes, which areas of your business utilize AI? *(Checkboxes)*
    - o Customer service (e.g., chatbots)
    - o Operations/Automation
    - o Marketing/Analytics
    - o R&D/Innovation
    - o Other (please specify): ___________
8. What is the primary goal of adopting AI in your company? *(Multiple choice)*
    - o Increase efficiency
    - o Reduce costs
    - o Improve customer experience
    - o Gain competitive advantage
    - o Other (please specify): ___________

Section 3: Workforce Implications

9. How has AI adoption affected your workforce? *(Checkboxes)*
    - o Increased headcount
    - o Reduced headcount
    - o Created new roles
    - o Changed existing roles
    - o No significant changes
10. What are the top three skills required for AI-related roles in your company? *(Checkboxes)*
    - o Programming (e.g., Python, R)
    - o Machine learning frameworks (e.g., TensorFlow, PyTorch)
    - o Data analysis
    - o Cloud computing
    - o AI ethics and compliance
    - o Communication and teamwork
    - o Other (please specify): ____________
11. Have you experienced challenges in recruiting for AI-related roles? *(Multiple choice)*
    - o Yes
    - o No

Section 4: Challenges and Opportunities

12. What are the main challenges your company faces in adopting AI? *(Checkboxes)*
    - o High implementation costs
    - o Lack of skilled workforce
    - o Resistance to change among employees
    - o Regulatory compliance issues

- Other (please specify): ___________

13. What opportunities do you see AI providing for your business? *(Paragraph)*

Section 5: Future Outlook

14. How do you see AI evolving in your industry in the next 5–10 years? *(Paragraph)*

Conclusion

15. Is there anything else you would like to share about AI's impact on your company? *(Paragraph)*

Appendix B: Survey Data Analysis Visuals

Figure 18: AI Adoption Levels Across Merged Sectors

Description: This bar chart shows the adoption status of AI across four sectors (IT, Fashion and Retail Fashion, Education, Import/Export). Companies in IT and Fashion and Retail Fashion are more likely to adopt AI, with Education and Import/Export lagging behind.

Code:

```
import matplotlib.pyplot as plt
# Data for AI adoption across merged sectors
sectors = ['IT', 'Fashion and Retail Fashion', 'Education', 'Import/Export']
adoption_levels = [1, 1, 0, 0]  # 1 = Adopted AI, 0 = Not Adopted AI
plt.figure(figsize=(10, 6))
plt.bar(sectors, adoption_levels, color=['green' if x == 1 else 'red' for x in adoption_levels])
plt.title('AI Adoption Levels Across Merged Sectors')
plt.xlabel('Sectors')
plt.ylabel('Adoption Status (1 = Adopted, 0 = Not Adopted)')
plt.xticks(rotation=45)
plt.ylim(0, 1.2)
plt.show()
```

Figure 19: Workforce Impacts Across Companies

Description: A stacked bar chart illustrates how AI adoption has impacted workforce dynamics. Changes include the creation of new roles and transformation of existing roles.

Code:

```
# Data for workforce impacts
companies = ['Company A', 'Company B', 'Company C', 'Company D', 'Company E']
new_roles = [1, 0, 0, 0, 0]
changed_roles = [1, 0, 0, 0, 1]
no_changes = [0, 0, 0, 0, 1]
# Create a stacked bar chart
import numpy as np
x = np.arange(len(companies))
width = 0.5
plt.bar(x, new_roles, width, label='New Roles', color='green')
plt.bar(x, changed_roles, width, bottom=new_roles, label='Changed Roles', color='orange')
plt.bar(x, no_changes, width, bottom=np.array(new_roles) + np.array(changed_roles), label='No Changes',
color='gray')
plt.xticks(x, companies)
plt.title('Workforce Impacts Across Companies')
plt.ylabel('Count')
plt.legend()
plt.show()
```

Figure 20: Challenges Faced by Companies in AI Adoption

Description: This heatmap visualizes the distribution of challenges like high costs, lack of skilled workforce, and resistance to change across the five companies.

Code:

```
import seaborn as sns
import pandas as pd
# Data for challenges
data = pd.DataFrame({
  'Company': ['Company A', 'Company B', 'Company C', 'Company D', 'Company E'],
  'High Implementation Costs': [1, 1, 1, 1, 0],
  'Lack of Skilled Workforce': [1, 1, 1, 1, 1],
  'Resistance to Change': [1, 1, 1, 0, 0]
})
```

```
# Create a heatmap
plt.figure(figsize=(10, 6))
sns.heatmap(data.iloc[:, 1:], annot=True, cmap='YlGnBu', xticklabels=data.columns[1:],
yticklabels=data['Company'])
plt.title('Challenges Faced by Companies')
plt.show()
```

Figure 21: Opportunities Highlighted by Companies

Description: A word cloud emphasizing frequently mentioned opportunities, including improved customer experience, precision in operations, and personalized learning.

Code:

```
from wordcloud import WordCloud
# Combine all open-ended responses related to opportunities
opportunities_text = "Improved customer experience Enhanced precision Personalized learning Supply chain
optimization"
# Create a word cloud
wordcloud = WordCloud(width=800, height=400, background_color='white').generate(opportunities_text)
plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.title('Opportunities Highlighted by Companies')
plt.show()
```

Figure 22: Skills Required Across Merged Sectors

Description: A grouped bar chart comparing the demand for key AI-related skills across IT and Fashion and Retail Fashion.

Code:

```
import numpy as np
# Data for workforce skills after merging sectors
skills = ['Data Analysis', 'Machine Learning', 'Social Media Management', 'Communication']
skill_counts = {
    'IT': [1, 1, 0, 1],
```

```
    'Fashion and Retail Fashion': [1, 0, 1, 1],
    'Education': [0, 0, 0, 0],
    'Import/Export': [0, 0, 0, 0]
}
x = np.arange(len(skills))
width = 0.2
plt.figure(figsize=(12, 6))
# Plotting bars for each sector
for i, (sector, values) in enumerate(skill_counts.items()):
    plt.bar(x + i * width, values, width, label=sector)
plt.title('Skills Required Across Merged Sectors')
plt.xlabel('Skills')
plt.ylabel('Mentions')
plt.xticks(x + width * 1.5, skills)
plt.legend(title='Sectors')
plt.show()
```

Figure 23: Sectoral Comparisons of AI Adoption Levels

Description: A bar chart comparing AI adoption levels across merged sectors (IT, Fashion and Retail Fashion, Education, Import/Export), indicating higher adoption in IT and Fashion and Retail Fashion.

Code:

```
import matplotlib.pyplot as plt
# Data for AI adoption across merged sectors
sectors = ['IT', 'Fashion and Retail Fashion', 'Education', 'Import/Export']
adoption_levels = [1, 1, 0, 0]  # 1 = Adopted AI, 0 = Not Adopted AI
plt.figure(figsize=(10, 6))
plt.bar(sectors, adoption_levels, color=['green' if x == 1 else 'red' for x in adoption_levels])
plt.title('Sectoral Comparisons of AI Adoption Levels')
plt.xlabel('Sectors')
plt.ylabel('Adoption Status (1 = Adopted, 0 = Not Adopted)')
plt.xticks(rotation=45)
```

```
plt.ylim(0, 1.2)
plt.show()
```

Figure 24: Sectoral Skills Demand Visualization

Description: A radar chart displaying the demand for skills such as data analysis, machine learning, social media management, and communication across merged sectors, highlighting sector-specific skill requirements.

Code:

```
from math import pi
# Data for skill requirements
categories = ['Data Analysis', 'Machine Learning', 'Social Media Management', 'Communication']
values = [2, 1, 1, 2]  # Example data
values += values[:1]  # Close the radar chart
angles = [n / float(len(categories)) * 2 * pi for n in range(len(categories))]
angles += angles[:1]
plt.figure(figsize=(8, 8))
ax = plt.subplot(111, polar=True)
plt.xticks(angles[:-1], categories, color='grey', size=12)
ax.plot(angles, values, linewidth=2, linestyle='solid')
ax.fill(angles, values, alpha=0.4)
plt.title('Skill Requirements Across Sectors')
plt.show()
```