DATA BRIEF

Solving Europe’s AI talent equation: Supply, demand and missing pieces

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Tech analysis and policy ideas for Europe

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Introduction

As Europe positions itself to become **the world's first 'AI continent'**, robust evidence is needed to understand the labour market transformations driven by AI. The European Commission's 2025 AI Continent Action Plan sets out an ambitious agenda to scale up Europe's AI capabilities, calling for enhanced infrastructure, strategic sectoral uptake, and an increased AI talent base. It emphasises the dual need to retain, attract, and reskill AI talent, but also to widely stimulate AI literacy across society as part of a broader industrial strategy and innovation ecosystem.

In parallel, the Artificial Intelligence Act (2024/1689) introduced a risk-based regulatory framework that embeds **AI literacy** and human-centric design as fundamental requirements. It recognises that effective and trustworthy deployment of AI requires users and affected individuals to be equipped with basic notions of how AI systems work, including understanding their outputs, limitations, and impact. As such, AI literacy is no longer optional – it is a regulatory imperative.

Complementing these efforts, the proposed EU talent pool regulation aims to address **critical skill shortages** by matching job seekers from non-EU countries with employers in the EU. It prioritises roles in green and digital transitions and is designed to overcome barriers in international recruitment, qualifications recognition, and labour migration channels.

The Union of Skills strategy, introduced in March, provides an overarching governance framework for these AI-focused initiatives. It outlines comprehensive mechanisms to address the very skills gaps and talent shortages that this paper seeks to quantify. The Union of Skills directly supports AI talent development through targeted schemes, such as the AI Skills Academy. The Academy offers specialised training programmes on generative AI and is developing pilot AI-focused degree programmes and apprenticeships. By addressing skills development across different sectors and proficiency levels – from basic digital skills to advanced technical competencies – the Union of Skills establishes a policy context that highlights the requirement for the types of disaggregated AI skills analyses presented in this study.

Together, these four initiatives reflect a coordinated European strategy to prepare the EU labour market for the diffusion of AI technologies, across all sectors of the economy as well as across different occupations – from AI developers to AI end-users.

Despite this momentum, policymakers face a key information gap: where are AI skills most in demand, and where are they available? Aggregate statistics on ICT workers or STEM graduates are insufficient to inform specific strategies for training, migration, or workforce planning. Nor is it enough to catalogue individual AI skills in isolation: effective workforce strategies require insight into **coherent groups of skills** that reflect distinct profiles of AI expertise. Yet much of the debate around AI and jobs remains in the binary realm – AI/non-AI – without distinguishing between different types of AI expertise.

This paper addresses this gap by providing a replicable methodology and a comparative analysis of AI job vacancies and AI talent across European countries, disaggregated into **three proficiency tiers**, each one consisting of coherent bundles of AI skills:

- Tier 0 – AI literate and curious (non-technical familiarity and user-level engagement),
- Tier 1 – technical professionals in software and data roles using basic AI methods,
- Tier 2 – advanced AI engineers and researchers developing cutting-edge models or other advanced AI techniques.

Using online vacancy data from Lightcast and talent profile data from Revelio Labs, we quantify demand and supply at each proficiency level, track variation across countries, occupations and time, and explore mismatches between vacancy requirements and talent availability. The resulting evidence can help inform both skills development policies and migration strategies, as well as support regional planning and industrial policy aligned with Europe's AI ambitions.

This study contributes to the ongoing implementation of Europe's AI strategy by offering a timely, disaggregated, and policy-relevant view of the AI labour market in Europe.

The authors are deeply grateful to Ruggero Marrino Lazzaroni, whose rigorous data analysis and statistical insights strengthened the foundation of this study.

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AI proficiency levels

Why skill stratification is the right analytical approach

Our study employs a novel three-tiered classification framework to analyse both the supply and demand for AI talent in the European labour market. This approach provides a more nuanced understanding of AI workforce dynamics than simple binary (AI/no-AI) classifications while remaining more parsimonious and actionable than tracking individual skills.

A common method for gauging the demand for AI in the labour market is labelling every vacancy that mentions at least one AI skill an 'AI vacancy'. Sometimes the threshold is put at two AI skills to avoid accidentally picking up non-AI vacancies (Squicciarini & Nachtigall, 2021). Acemoglu et al. (2022) distinguish between a 'narrow' and a 'broad' definition of AI vacancies, where the narrow list of skills is more limited to strict AI, while the broader one also includes data science. We follow and expand on this approach by distinguishing between three tiers.

Individual skills, on the other hand, offer fine-grained information, but analysing them in isolation overlooks the structured way in which human capital is built and deployed. Recent research shows that skills form a **nested, hierarchical network**, where the presence and utility of advanced skills depend on the mastery of more foundational ones. In this view, skills are not independent units but aspects of a structured learning and capability system. The development of skills aligned with this nested structure command higher wage premiums, require longer education and are less likely to be automated (Hosseinioun et al., 2025).

Our three-tiered classification of AI proficiency reflects this insight: it recognises that individuals at higher tiers possess groups of complementary, advanced AI competencies as well as the foundational AI skills embedded in lower tiers, resulting in a coherent bundle of skills that makes them relevant at that proficiency level. By capturing these layered relationships, the classification provides a more accurate and policy-relevant lens on AI workforce readiness than flat skill taxonomies. It supports the design of training pathways that are better aligned with real-world skill acquisition processes and labour market demands, by distinguishing different levels of AI engagement and expertise.

Below, we first outline our three tiers of AI proficiency, then detail how we apply the classification to talent and vacancy data, and we finish by giving examples of both in each tier.

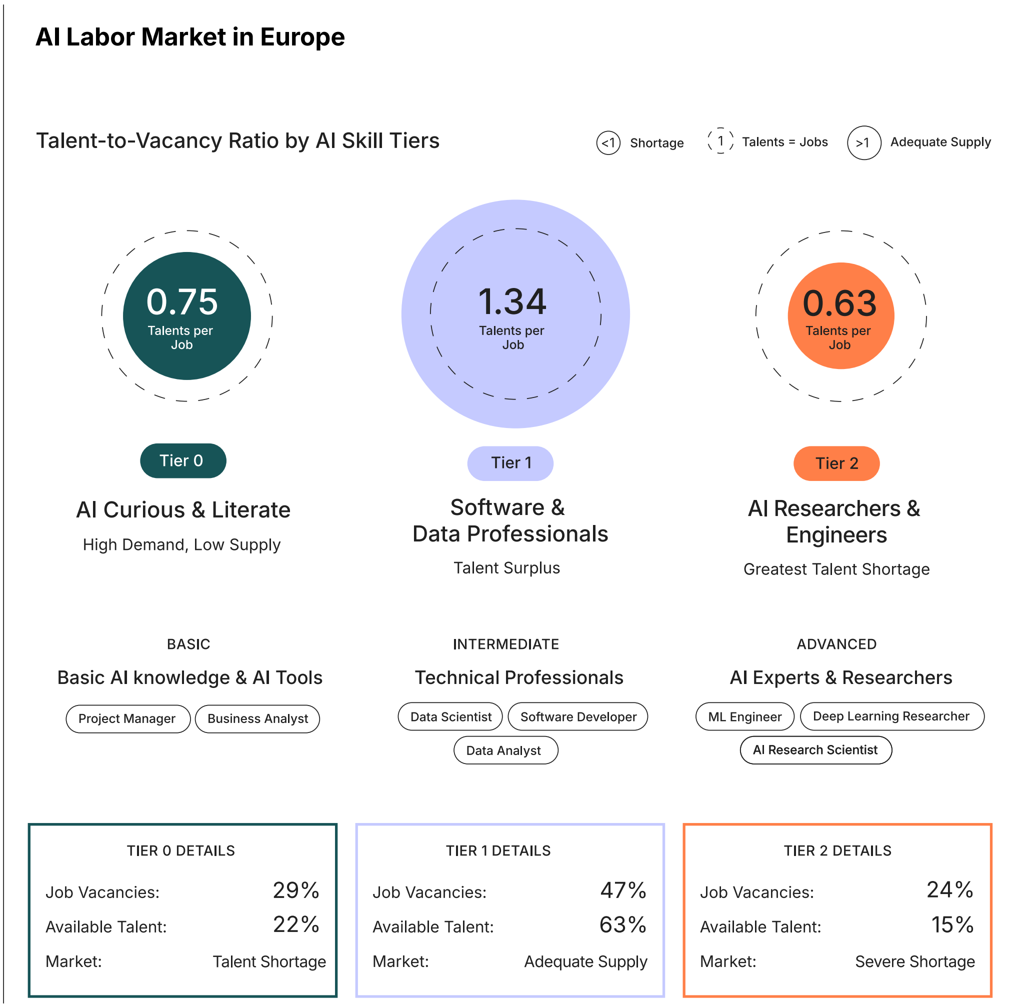
The three-tiered classification system

To systematically analyse the AI workforce ecosystem, the three-tiered classification system that we developed categorises individuals and vacancies based on their level of involvement with AI technologies, technical expertise, and professional roles.

- **Tier 0. AI curious and literate:** (individuals employed in or studying for) roles requiring familiarity with AI but not directly working with technical AI applications, and who do not fit in the other two tiers. This includes workers in non-technical roles or unrelated study fields but with basic familiarity with AI concepts and usage of AI tools as end-users.
- **Tier 1. Software & data proficiency:** (individuals employed in or studying for) technical roles or demonstrating skills involving software development or data science that may employ basic machine learning techniques. This includes data scientists who work with traditional statistical methods and fundamental machine learning algorithms but not advanced deep learning.
- **Tier 2. AI research & engineering:** (individuals employed in or studying for) roles or demonstrating skills directly involving developing, applying, or researching deep learning techniques and other advanced AI applications. This includes professionals working with complex neural network architectures and cutting-edge AI systems.

This classification system enables policy-relevant insights by distinguishing between regions concentrated in fundamental AI research versus those focused on AI implementation and application, informing targeted workforce development strategies.

Classifying talent and vacancy data



Talent data

Data source. Our talent analysis utilises comprehensive workforce data from Revelio Labs, which aggregates publicly available online professional profiles from 2024, encompassing 659 million individuals globally. From this population, we identified approximately 1.6 million individuals who constitute the global technical AI workforce. We initially restrict our analysis to all OECD nations plus India (limited to countries with more than 1000 individuals in our initial AI talent pool). For Section 5 (matching AI-skilled candidates with vacancies), we narrow the focus to countries within the EU, along with the UK, Norway and Switzerland, to match the country availability in our vacancy data.

Classification approach. To classify talent accurately across the three proficiency tiers, we employed a large language model (LLM), Llama 3.1 70B, using chain-of-thought prompting techniques. This methodology was validated against a gold-standard test dataset of 100 manually classified profiles, achieving 80% accuracy, comparable to benchmarks established in similar classification studies. For each individual profile, the model analysed educational background, technical skills, and job roles to assign the appropriate tier (0, 1, or 2), providing a detailed rationale for each classification decision. We processed a stratified random sample of 1000 profiles from each of the 30 countries mentioned above. See the full methodology in the appendix, Section A 1.1.

Vacancy data

Data source. Our vacancy analysis draws on online job advertisement data provided by Lightcast, aggregating job postings from thousands of websites across Europe. The dataset includes details such as occupation, sector, region, employer, and required skills. We restricted our analysis to vacancies posted in the 27 EU Member States, the UK, Norway, and Switzerland between May 2023 and April 2024. This includes a total of 71.6 million vacancies, out of which 0.6 million included at least one AI skill.

Classification approach. We identified AI-related job postings using a skills-based approach, applying a curated Lightcast dictionary of 251 AI skills to flag job ads that mention one or more AI skills. To maintain consistency with our talent classification system, we manually extended this dictionary by assigning each AI skill to one of the three proficiency levels (0, 1, or 2), based on the same conceptual framework used in the talent classification. See the full methodology in the appendix, Section A 1.2.

Examples of classification by proficiency tier

To illustrate our classification approach, the following examples demonstrate how individuals and job vacancies are categorised at each tier.

Tier 0 – AI curious and literate

- *Talent example:* a business analyst with a basic understanding of AI applications who is familiar with AI terminology and uses pre-built AI tools for reporting
- *Vacancy example:* a marketing specialist position requiring knowledge of AI-powered analytics platforms, with basic understanding of machine learning concepts
- *Typical skills:* AI literacy, familiarity with business intelligence tools, prompt engineering

Tier 1 – Software & data professionals

- *Talent example:* a data scientist implementing basic predictive models using scikit-learn, who is proficient in Python and SQL, and performs feature engineering
- *Vacancy example:* a data analyst position requiring expertise in statistical analysis, regression modelling, and data visualisation tools
- *Typical skills:* data analytics, database management, basic machine learning algorithms, data preprocessing

Tier 2 – AI researchers & engineers

- *Talent example:* a machine learning engineer developing custom neural network architectures, optimising graphics processing unit (GPU) performance, and implementing state-of-the-art algorithms
- *Vacancy example:* a computer vision engineer position requiring experience with CNN (neural networks for image processing) architecture design, transfer learning, and GPU-accelerated computing
- *Typical skills:* deep learning frameworks, neural architecture design, MLOps (machine learning operations), reinforcement learning

AI talent in Europe

Despite widespread recognition of AI's importance, policymakers face a significant knowledge gap regarding who develops these systems, where they originate, and what drives their migration decisions. Traditional workforce statistics lack the granularity to capture the nuanced reality of the AI ecosystem, where technical skills and specialisation levels vary dramatically even within similar job titles. This information deficit comes at a particularly crucial moment for Europe, which has committed EUR 20 billion to AI development while projecting approximately 21% growth in ICT professions (CEDEFOP, 2025). The fundamental question – whether Europe will nurture local AI talent, successfully attract specialists from abroad, or watch its expertise emigrate to competing innovation hubs – has profound implications not only for economic competitiveness but also for ensuring that AI systems embody European values and priorities. This research examines talent flows, specialisation levels, and gender distribution patterns across national AI workforces in Europe, providing policymakers with actionable insights to navigate the intensifying global competition for AI expertise.

AI talent by tier across countries

Figure 1 shows the concentration of AI talent across countries, measured as the number of workers per 1000 people in each AI tier. Countries are ranked based on their proportion of tier 2 AI professionals, from highest to lowest. This visualisation helps compare how different nations are currently employing AI talent across various specialisations relative to their population size.

Figure 2 displays the distribution of AI talent based on their country of origin, defined as where they completed their bachelor's degree. Countries are again ranked by their proportion of tier 2 AI professionals, from highest to lowest. This visualisation reveals which nations are producing AI talent in different tiers and allows for comparison between where AI professionals are trained versus where they currently work.

Figure 1. Proportion of AI technical talent by country of employment

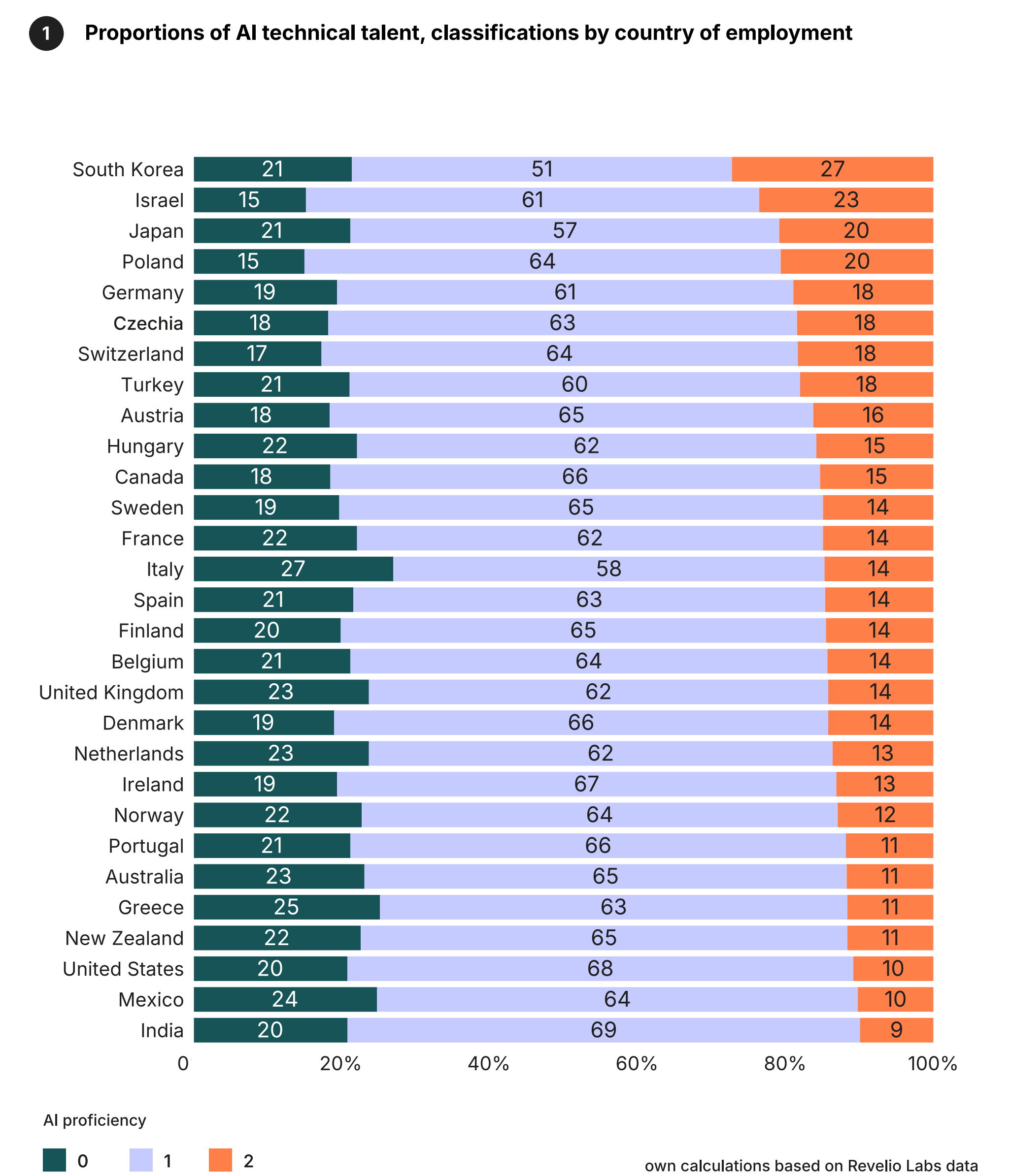
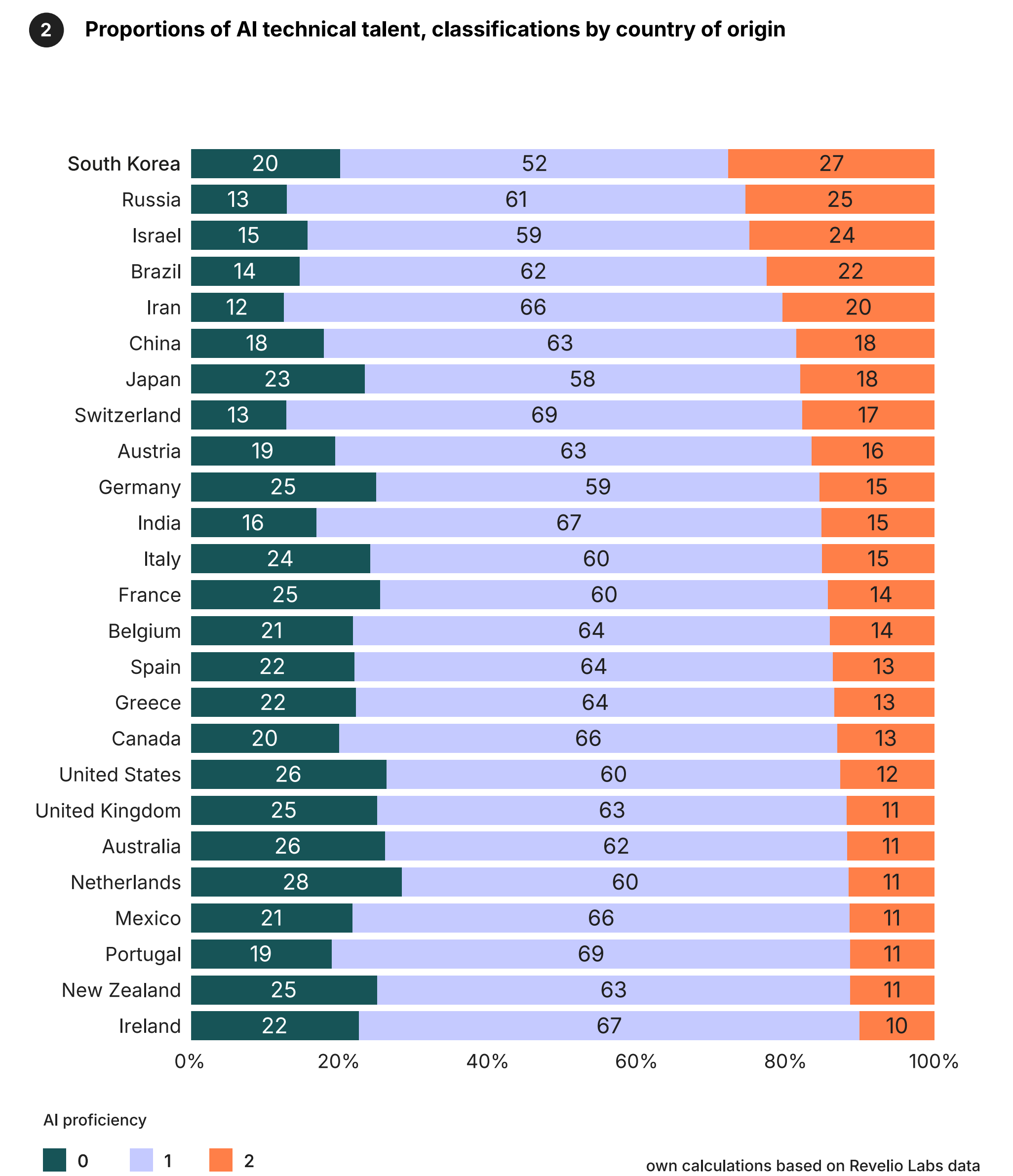


Figure 2. Proportion of AI technical talent by country of origin



Of the countries examined by this paper, Poland and Germany rank the highest among European countries in the concentration of highly skilled AI experts. Their leading roles could be attributed to strong industrial economies as well as strategic policies to attract companies and talent.

Poland, which ranks first in the proportion of tier 2 talent in Europe and fourth globally, has implemented a [national strategy for AI](), focused on [AI company growth]() and innovation alongside investment in domestic capacity building. Additionally, Poland is one of the main destinations for Ukrainian refugees fleeing the war, with refugee numbers having stabilised at around one million and a 65% employment rate – the highest among countries accepting significant shares of them. Poland's high ranking as an employment destination likely stems from several factors: (i) the relocation of large numbers of Ukrainians and Ukrainian businesses following recent events; (ii) its growing reputation as an attractive place for skilled migrants from non-EU countries; and (iii) continued immigration from other Eastern European nations, including Belarus, Bulgaria, and Romania. Notably, 69% of Poland's immigrants are labour migrants, highlighting the country's appeal as a work destination. Demand for foreign talent continues to grow as Poland drafts a new digitisation strategy and oversees significant investment in new institutions to foster collaboration with the European AI ecosystem.

Germany, ranked second among European countries, boasts a large concentration of elite institutions that are some of the largest publishers of both fundamental and applied research in the global ecosystem. This creates a vibrant skills environment that may lead to its strong positioning as both an origin and destination of top global technical talent. Countries like Switzerland also rank highly and remain competitive through deliberate efforts to attract key AI talent.

While this research concentrates on European AI jobs and talent, previous research found that the EU's AI workforce has a higher proportion of technical experts in tier 2 talent and more AI experts in all tiers per capita compared with leading AI nations like the US and UK. Although many of the national AI strategies in Europe set out goals to increase the attractiveness of domestic AI industries by building up institutions and attracting top talent, there is still high migration of its AI talent pool to the US. However, many leaders in Europe see the current American political climate as an opportunity for the region to attract disillusioned top talent from the US and reverse a historic pattern of brain drain. AI engineers, entrepreneurs and researchers may see Europe as an attractive alternative location, with more freedom and commitment to human-centric development of technology, reversing this migration trend in the coming years.

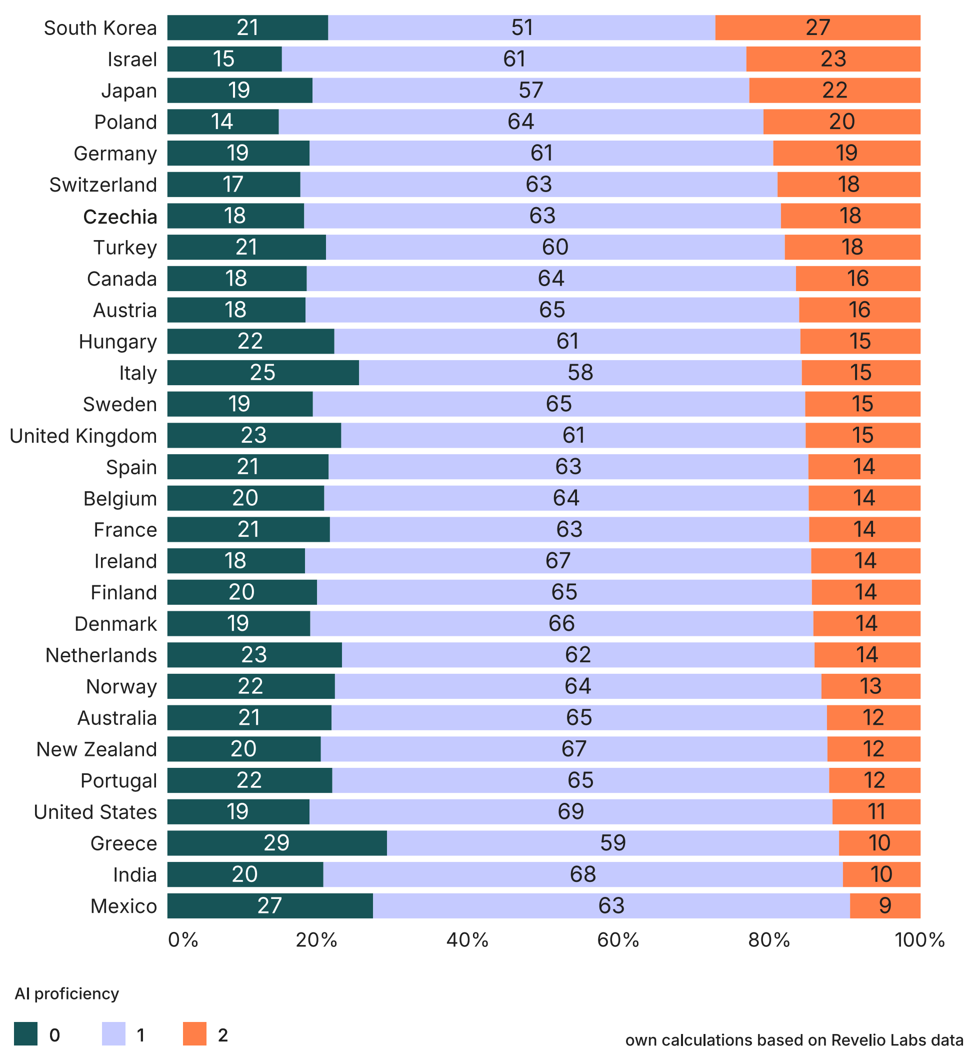
International AI talent by tier across countries

Figure 3 displays the distribution of international AI technical professionals based on their countries of origin, showing the proportion of them in each AI tier per 1000 people who have migrated from their home countries. Countries are ranked from highest to lowest based on their proportion of tier 2 talent production. For example, 32% of the Swiss talent outside Switzerland falls into tier 2.

Figure 4 shows the same metrics but classified by destination countries, revealing where international AI professionals are currently employed. For example, 27% of the non-Korean AI talent in South Korea falls into tier 2.

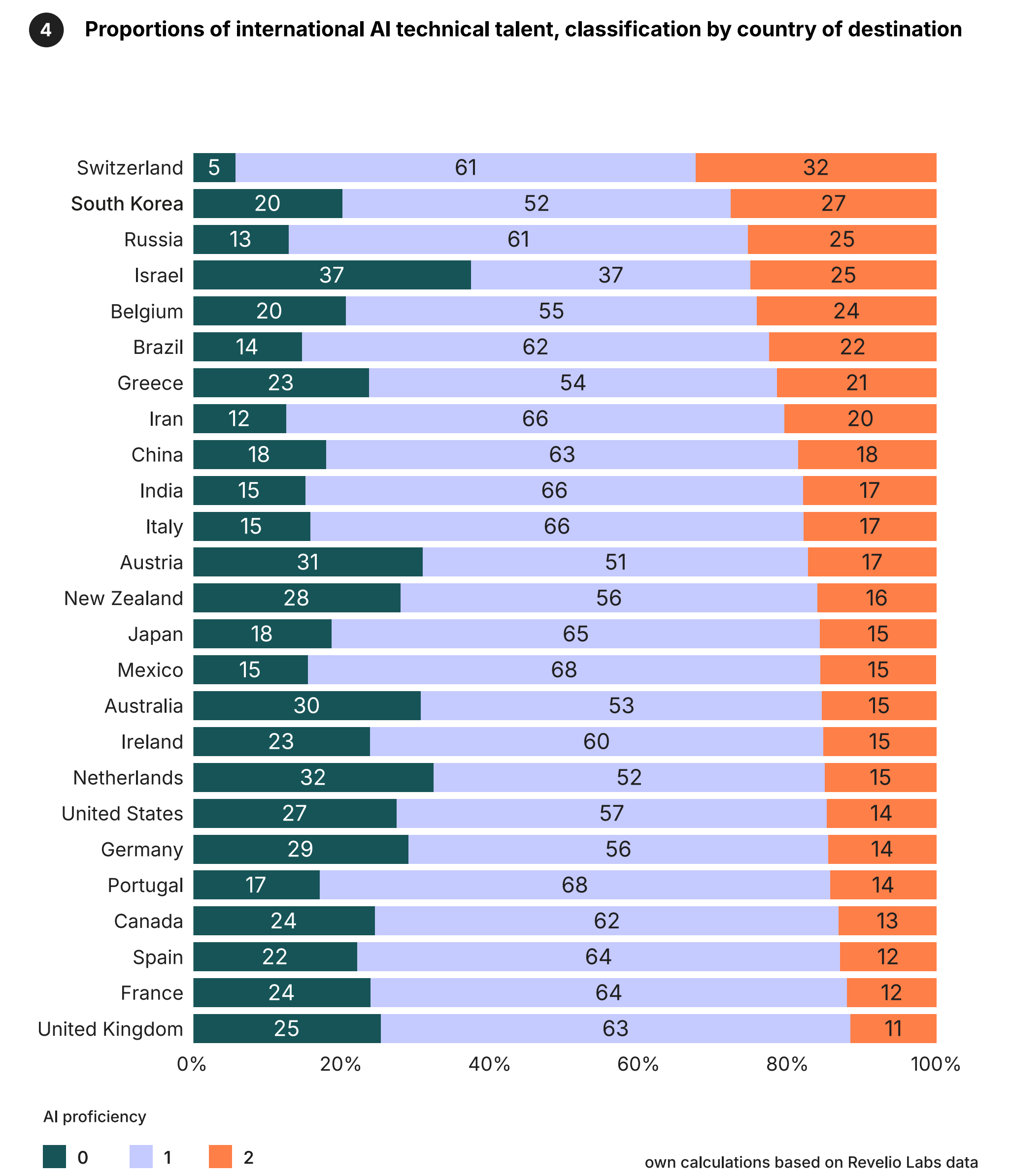
Figure 3. Proportion of international AI technical talent by country of origin

3 **Proportions of international AI technical talent, classification by country of origin**



own calculations based on Revelio Labs data

Figure 4. Proportion of international AI technical talent by country of destination



The purpose of these graphs is to better understand the relationship between domestic talent development and international recruitment, capturing nuances of which countries talent may originate from and which countries are most successful at attracting top talent. These charts highlight the complexity hidden within AI workforces globally, as countries seek to balance the flow of skilled labourers. Although typically considered a global AI leader, the **UK** has a lower proportion of tier 2 talent, even as a destination country for top talent. More stringent immigration requirements may give rise to challenges in attracting foreign professionals, especially those with non-traditional AI backgrounds. A 2024 Stack Overflow survey of 65 000 contributors found that only 66% of developers have either a bachelor's or master's degree, with fewer than half studying coding formally. Hence, formal education requirements may result in the missing out of thousands of AI professionals.

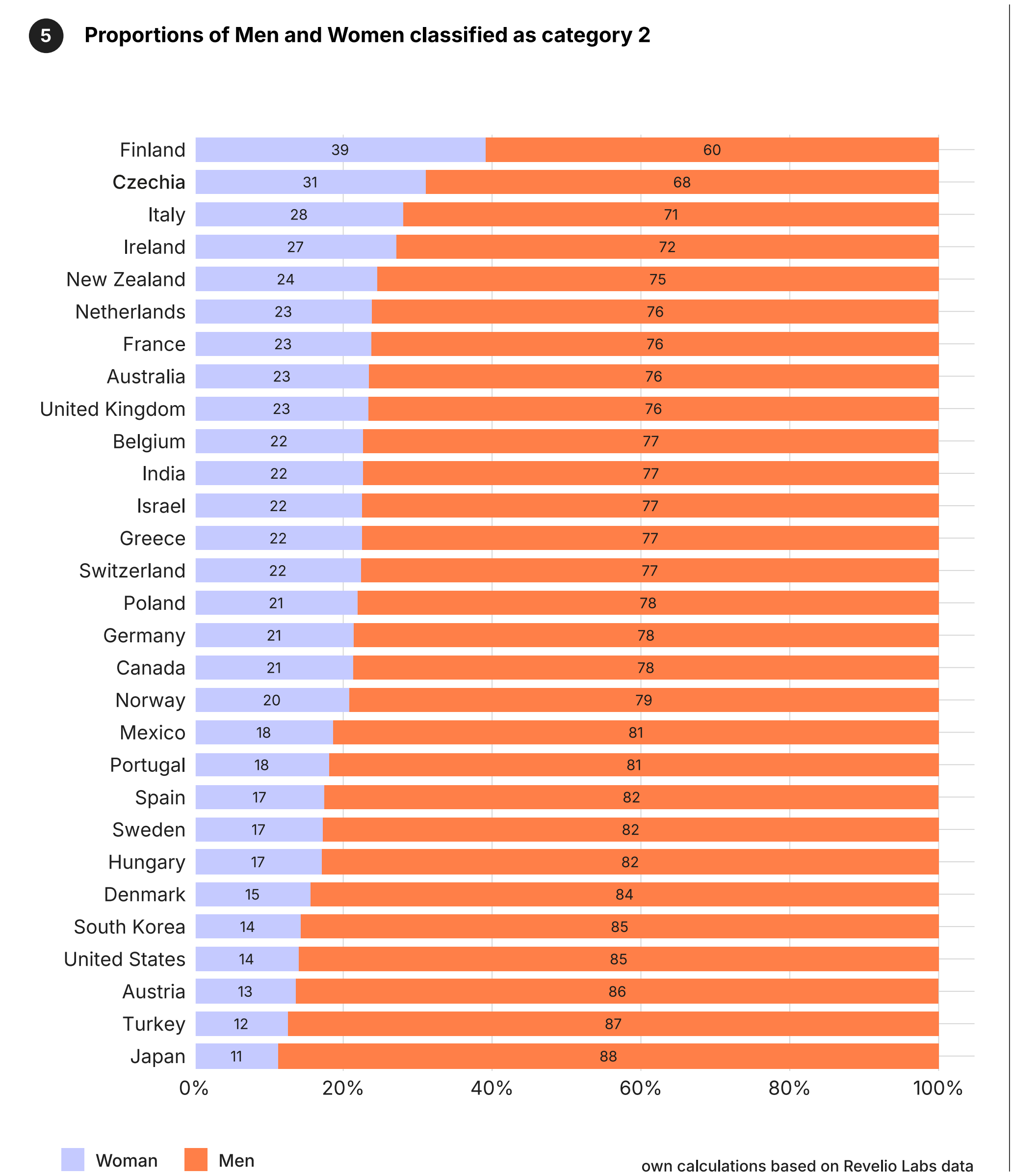
The European AI industry demonstrates domestic talent development as well as international recruitment. Countries like **Poland**, **Switzerland** and **Germany** represent both talent origin countries and destinations. Previous research indicates that the high levels of AI talent in these countries may be due to factors such as more liberal migration policies to facilitate the hiring of top talent – like Germany's Blue CardEU or Poland's new employment policies – and stronger protections. Poland has also expanded recognition of foreign credentials and qualifications for certain professions, with the acceptance of different degrees and educational pathways reducing underemployment in the country. Citing the enormous labour shortage of skilled workers, Germany digitalised and modernised consular services to enable a more streamlined and easy digital process to obtain a visa, preventing large bureaucratic obstacles from dissuading top talent from applying to work in the country.

Other factors driving the AI lead in Central and Eastern Europe include extensive investment to expand infrastructure, a better environment for venture capital, and strategic focus on the concentration of a skilled technical workforce. Lower-ranking destination countries are also aiming to attract top professionals: Italy has laid out ambitious plans to recruit international talent while boosting local capacity in AI.

These national-level approaches are now being complemented by coordinated EU-wide efforts to attract and retain talent. As Commission President Ursula von der Leyen noted in her June 2025 letter to the European Council, work is underway to roll out the Union of Skills' strand on attracting, developing and retaining talent. This includes the 'Choose Europe for Science' initiative to attract the world's best scientists and researchers to Europe. The forthcoming visa strategy will include steps to support the arrival of top students, researchers and trained professionals, while the EU Talent Pool will serve as a vital tool for international recruitment. Notably, targeted efforts are being made to align labour mobility projects with market needs. For example, with a Legal Gateway Office being piloted with India initially seeks to attract skilled researchers, professionals and students in the ICT sector.

Figure 5 shows the proportion of tier 2 professionals for each gender, divided by country. Compared with Figures 1 and 2 where we examine the shares of jobs classified from tier 0 to tier 2, this chart gives the gender breakdown of the most technical AI talent of different national workforces. Countries are ranked from the highest to lowest proportion of women among tier 2 talent.

Figure 5. Proportion of men and women classified as tier 2



Unlike the overall proportions of highly technical AI professionals, the EU leads in women's representation of technical talent, occupying 7 out of the top 10 rankings globally. **Finland**, **Czechia**, and **Italy** have the highest shares of women in AI talent globally. No European country selected for this study has been able to ensure parity in the representation of women in the AI talent pool. Although women accounted for 32.8% of [total graduates] in STEM fields in the EU in 2021, this percentage has not yet translated into higher rates of participation in the labour market, especially in more senior positions.

Finland leads overall with the highest proportion of women among AI talent in tier 2, representing 39% of the total labour force. While this could be driven by a relatively small sample size of Finnish AI labour market conditions, it could also reflect strong gender equality policies like the Act on Equality between Women and Men, requiring universities and employers to address gender gaps in things such as salaries and working conditions. The country also boasts a strong work-life balance, including a historic flexible working schedule offered by a majority of companies since 2011. Now, legislation mandates that employees in Finland must be offered flexible working hours and locations for at least half of their working hours. Employees can also bank their working hours by working longer during other periods, enabling professionals to meet personal commitments without it coming at the expense of their professional careers. This may be a contributing factor to the rates of gender parity in tier 2, but direct causality cannot be attributed.

Similarly, **Czechia**, with women representing 31% of tier 2 talent, has observed a steady increase in women applying to study AI at a tertiary level in the country and it monitors R&D for gender considerations. Czechia has strategically aimed to increase the representation of women in research, including by equalising opportunities for women and men and acknowledging the barriers to women building careers in the field due to, for instance, prejudice or the demands of parenthood.

With women making up 28% of the workforce, **Italy** similarly boasts strong parental leave policies and good work-life balance. Among OECD countries, it also has the highest percentage of AI papers published by authors that include at least one woman.

By contrast, despite advances in gender equality in Scandinavian countries, **Sweden** and **Denmark** rank low in the proportion of women in tier 2, at 17% and 15% respectively. Likewise, **Germany** and **Poland** lag behind many other countries with regard to women as tier 2 talent, despite the large proportion of tier 2 talent relative to the rest of Europe. This indicates that ensuring gender equality in AI talent pools has required concerted and continual effort, and all European countries must continue to ensure that women are able to join, remain, and ascend the career ladder.

AI job vacancies in Europe

The diffusion of AI across the economy is reflected in changing skill demands posted in job vacancies. While much attention has focused on the demand for AI skills in general, less is known about the geography, depth, and breadth of AI skill demand across occupations and countries in Europe. This section addresses that gap by examining online job vacancy data to map where AI jobs are emerging, which AI proficiency levels employers are seeking, and how demand is evolving over time. This evidence is particularly relevant for workforce planning at the EU and national levels, as it reveals the scale of AI labour demand, its distribution and changing profile.

Overall, mid-level AI proficiency accounts for the highest number of vacancies (almost half of AI vacancies), followed by low (about a third) and high levels (about a fifth), respectively. However, the absolute number of AI vacancies varies greatly by country, as do both the share of AI vacancies in the total and the proportion of proficiency levels.

AI vacancies by tier across countries

Figure 6 shows the **absolute number of AI-related job postings** across European countries, broken down by the tier of AI proficiency required. In absolute terms, the large countries dominate the market of AI vacancies. In one year (2023-2024), about 168 000 AI vacancies were posted in the **UK**, followed by 102 000 in **Germany** and 88 000 in **France**. Together, these three countries account for 57% of all AI vacancies in Europe, reflecting not only their large economies, but also their advanced AI ecosystems. Each of them announced extensive national AI strategies early on: Germany launched its national AI strategy in 2018, spending about USD 100-500 million per year and both the UK and France launched revised strategies in 2021 after their first initiatives in 2018.

The **UK, France and Germany** consistently ranked as the top three countries in Europe in terms of AI patents, AI investment and AI research on the 2024 AI World Index. In 2023, Germany produced more AI patents (300) than the UK (115) and France (97) combined. In terms of AI investment, Germany and the UK were in a neck-and-neck race in 2023 (USD 2.2 billion and USD 2.1 billion), but in 2024 the UK (USD 3 billion) overtook both Germany (USD 1.8 billion) and France (USD 1.6 billion).

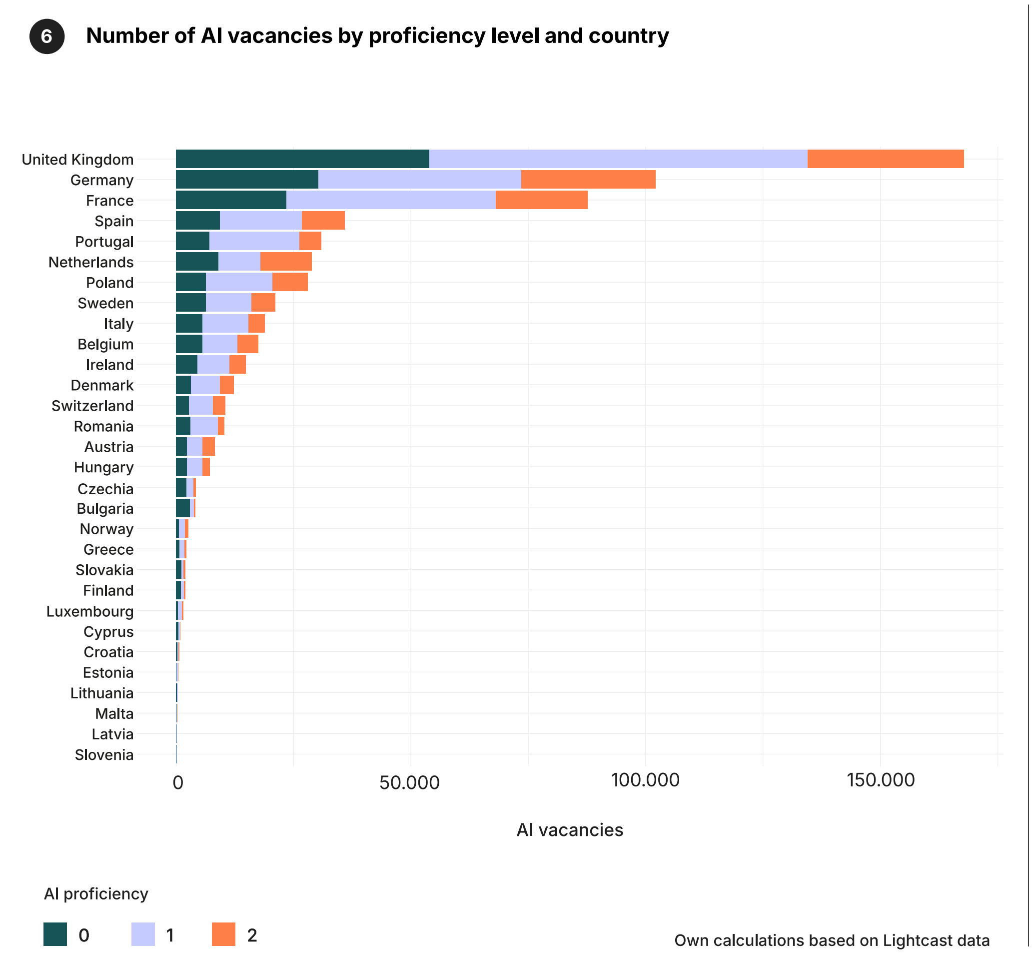
AI research publications show a similar picture: in 2023 the UK (12 700) was in a close race with Germany (12 600), and both outpaced France (8 700). AI publications seem to have slowed down in 2024, but still the UK (4 300) overtook Germany (3 500) and France (2 600) that year (2024 AI World Index). Focusing on the 100 most cited (or most impactful) AI publications, Germany and the UK are the only two European countries in the top 10 of authors' national affiliations (*AI Index 2025*

Annual Report, figure 1.1.11).

All of this results in the fact that the UK, Germany and France are the only European countries that produced more than 10 notable AI models1 in the 2003-2024 period (ibid., figure 1.3.3). This includes Mistral Large 2 for language generation and Mistral OCR for multimodal generation in France; Stable Diffusion for image generation and the DeepL LLM for translation in Germany; and several of UK-based Google DeepMind models, including Veo for video generation, Gemini 2.0 Pro for multimodal generation and AlphaProteo for biology (EPOCH AI). Still, these numbers are dwarfed by the US and China, which have each produced over a 100 notable AI models in the past 10 years.

However, several smaller countries including **Spain**, **Portugal**, **the Netherlands** and **Poland,** also register non-negligible volumes of AI job postings, each showing over 25 000 AI vacancies. This suggests that AI skills demand is not limited to Europe's largest labour markets. The Netherlands notably produced 79 AI patents in 2023, making it the only other EU country in the top 10 on the AI World Index.

Figure 6. Number of AI vacancies by proficiency level and country



Source: Own calculations based on Lightcast data.

To understand just how central AI roles are within national labour markets – regardless of the country's economic size – we present the **share of AI vacancies out of total job postings** by country in [Figure 7](). **Portugal** and **Cyprus** top the ranking, each with AI jobs representing more than 3% of all online vacancies, which is three times the average in Europe. **Luxembourg**, **Romania**, and **Ireland** follow closely behind, all with AI job shares exceeding 2%.

While **Portugal** does not yet feature in any global rankings of AI publications, patents or private investment – in either the AI World Index or Stanford's *AI Index Annual Report* – its government launched an [AI Portugal 2030 strategy]() in 2019 with a budget of about EUR 50-100 million per year. To compare, while Portugal's nominal GDP is only 6% of Germany's, its AI strategy budget is about 20% of

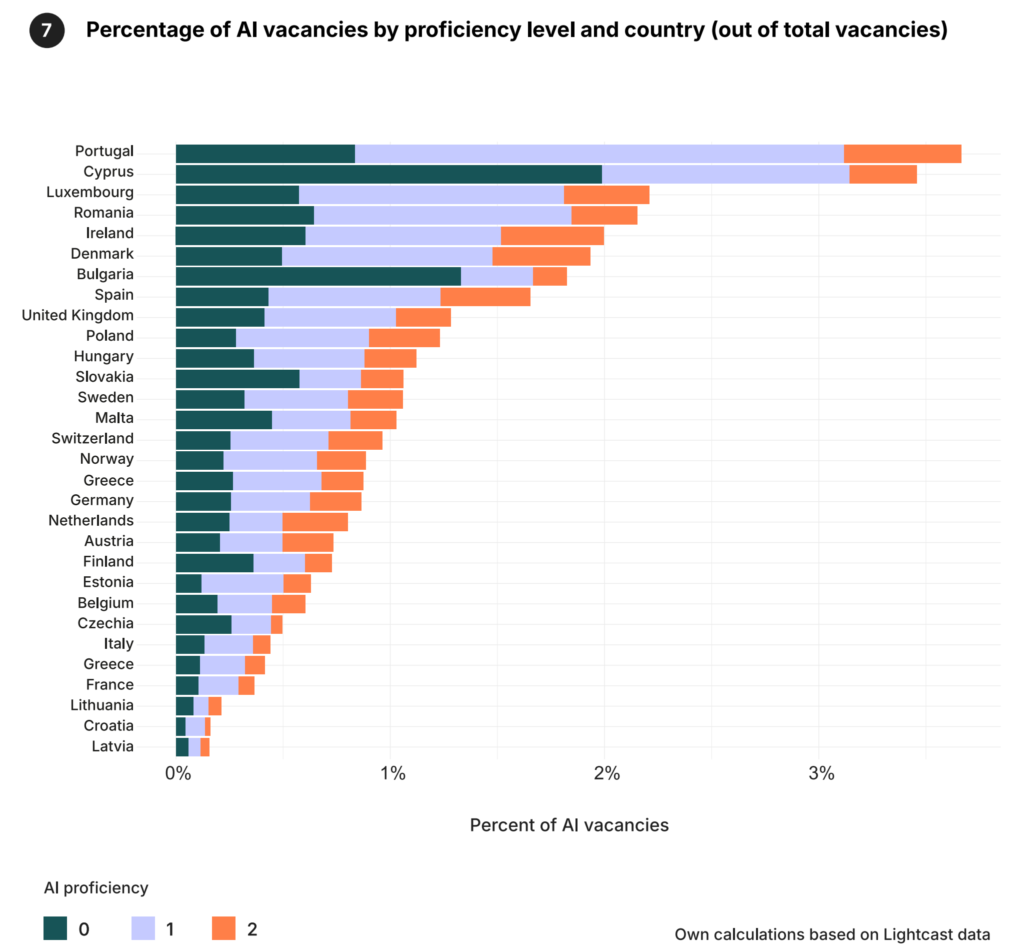
Germany's AI strategy budget (see above). The strategy aims to build up a knowledge-intensive labour market with a strong AI research, innovation and production ecosystem. The Portuguese AI strategy supports Digital Innovation Hubs, AI innovation vouchers, AI adoption in the public sector and 'co-labs' between companies and research centres, each of which could potentially explain the high share of AI vacancies in Portugal.

Luxembourg also presented its strategic vision for AI in 2019, seeking to 'make the Grand Duchy one of the most advanced digital societies in Europe and the world, create a data-driven and sustainable economy, and to support human-centric AI development'. Relative to its population size, Luxembourg does attract large private investment in AI, reaching USD 99.3 million per million inhabitants, the highest ratio by far in Europe (AI World Index). Strategically located between the two European AI giants (France and Germany), Luxembourg aims to become a cutting-edge, cross-border hub for applied AI research. Co-authorship data show that this strategy is working as Germany and France are Luxembourg's leading two collaborators on AI publications and patents (AI World Index – LU).

The strategy is also paying off, as Luxembourg and also Cyprus featured in the top 10 population-adjusted ranking of AI publications, with 154.7 and 93.3 AI publications per million inhabitants respectively in 2024 (AI World Index). Over the last 10 years (2013-2023), Luxembourg has increased its population-adjusted number of AI patents by 8.2%, which is the largest increase of all documented countries (*AI Index 2025 Annual Report*, figure 1.2.5). This made it the second highest producer of AI patents per 100 000 inhabitants in 2023 (ibid., figure 1.2.4).

The findings on Portugal and Luxembourg highlight that smaller or mid-sized countries can lead in AI hiring intensity, even if their absolute numbers remain modest. By contrast, the UK and Germany – despite their high total vacancy counts – fall into the mid-range in relative terms. This indicates that AI roles remain a smaller fraction of overall hiring in these labour markets. France even dangles at the bottom end, with less than 0.5% of all vacancies requesting AI skills.

Figure 7. Percentage of AI vacancies by proficiency level and country (out of total vacancies)



Source: Own calculations based on Lightcast data.

Finally, to compare the distribution of skill requirements across the countries, we present the **relative proportion of AI jobs by proficiency level** (out of all AI vacancies) within each country in Figure 8. It reveals striking cross-country variation in the depth of AI skill demand.

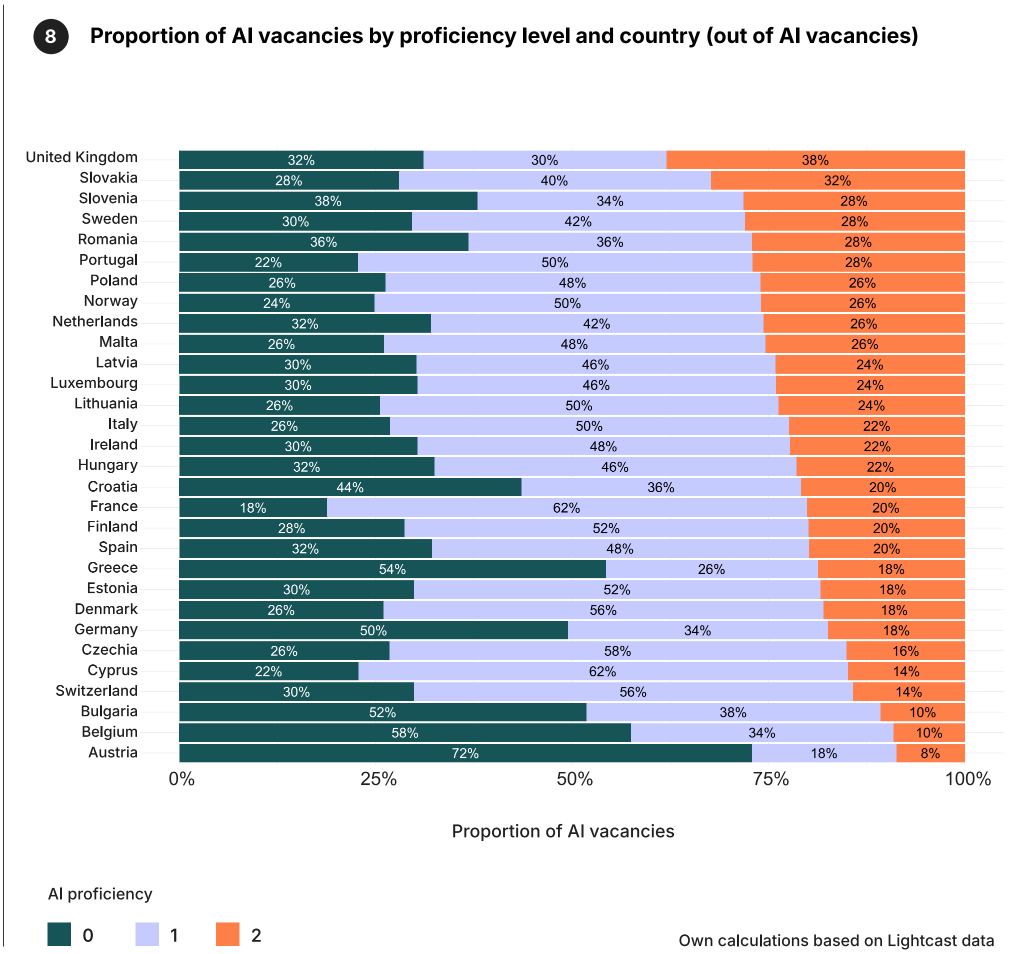
Countries such as the **Netherlands** and **Austria** show a strong tilt towards demand for high-level AI skills (tier 2), with over a third of AI postings requiring such advanced capabilities. The high level of AI proficiency requested in the **Netherlands** is reflected in the number of newly funded AI companies (24) in 2024 (*AI Index 2025 Annual Report*, figure 4.3.12). Austria also shows high levels of private AI investment (USD1.5 billion) (ibid, figure 4.3.8).

Estonia and Portugal gravitate towards mid-level AI proficiency demand with about

62% of vacancies requesting at least a tier 1 AI skill, but not a tier 2 one. By contrast, in **Bulgaria** and **Cyprus**, AI job postings are dominated by tier 0 skills, suggesting more superficial integration of AI into work tasks. Also in **Finland**, **Czechia** and **Slovakia** tier 0 vacancies represent more than half of total AI vacancies.

Finland is an interesting example of tier 0 skills demand. Already in 2018, the University of Helsinki and learning company MinnaLearn launched a massive open online course, 'Elements of AI', which contributed to raising public awareness of machine learning-based AI. Under the Finnish Presidency of the Council of the EU in 2019, the course was translated into all EU languages. By May 2023, it had enrolled over a million students from more than 100 countries. While the original 2018 module merely introduced AI to the wider public, the sequel released in late 2020 focused on building AI.

Figure 8. Proportion of AI vacancies by proficiency level and country (out of AI vacancies)



Source: Own calculations based on Lightcast data.

AI vacancies by tier across occupations and time

AI is expected to impact a wide range of occupations, beyond mere ICT professions (Eloundou et al., 2024; Felten et al., 2021). Such wide applicability across the economy would effectively make it a general-purpose technology (Agrawal et al., 2023). To investigate this for the European labour market, we split our online job vacancy data into two groups: ICT specialists and other occupations. As detailed in the appendix (Section A1.2), we use the Eurostat definition of ICT specialists, which includes ICT managers and associate professionals (ISCO numbers 133, 25 and 35) as well as other groups primarily involved in the production of ICT goods and services (ISCO numbers 2152, 2153, 2166, 2356, 2434, 3155 and 742).

The data reveal that almost two thirds of AI vacancies can be found in non-ICT occupations (388 642) while the remaining third are in ICT professions (234 448). Of course, within each group the share of AI vacancies out of all posted vacancies is much higher for ICT specialists (4.3%) than for non-ICT specialists (0.6%). What this means is that AI skills are on their way to becoming a 'core skill' for ICT professions but are simultaneously in demand across all other occupations in the economy. Even though they represent a small share of vacancies in non-ICT professions, they nonetheless signify a large demand given the scale of these other occupations.

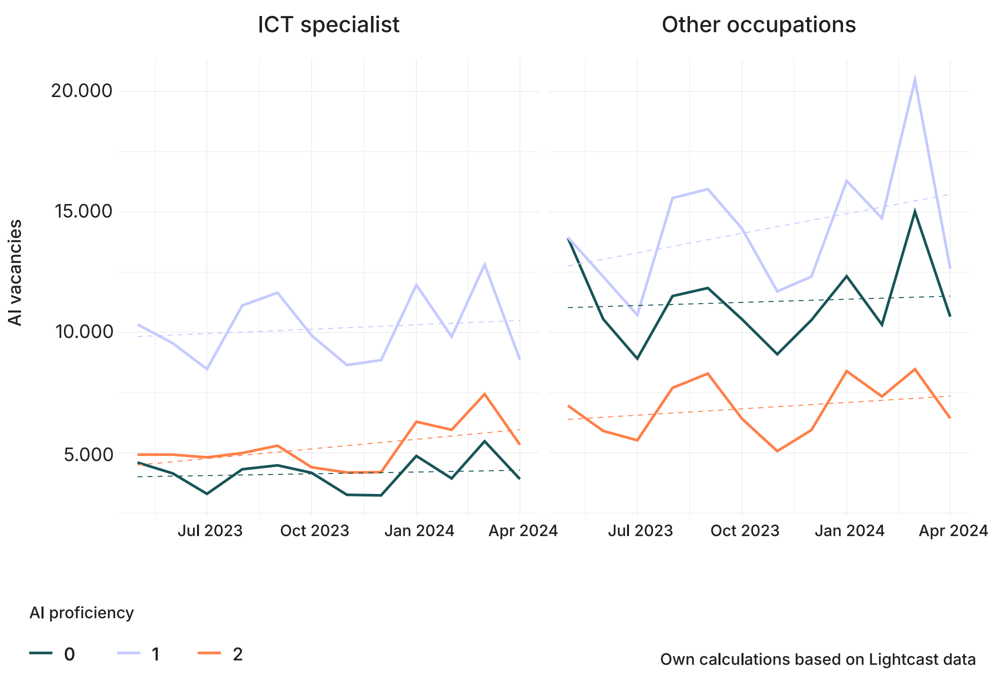
We track how this demand evolves for the two occupational groups and three proficiency levels during our observation period (May 2023 to April 2024). Figure 9 shows several additional, interesting insights.

First, mid-level AI skills still account for the largest number of posted vacancies for both ICT and non-ICT occupations. However, low- and high-level AI skills switch ranks across the groups: high-level AI skills come in second place for ICT specialists, while low-level AI skills come for other occupations.

Second, there is a slight-to-large positive trend across all the groups and all the levels. For ICT specialists, tier 2 skills demand shows the strongest increase, suggesting a need for deepening AI expertise in these professions. For other occupations, it is mostly the demand for mid-level AI proficiency that is rising markedly over time.

Figure 9. Evolution of the AI vacancy count by occupation over time (EU27+UK+NO+CH)

9 **Evolution of AI vacancy count by occupation over time (EU27+UK+NO+CH)**



Source: Own calculations based on Lightcast data.

If these trends continue, this only emphasises the above statement that a large share of AI skills demand will originate from a wide range of occupations beyond the ICT professions.

Mismatches in proficiency levels between AI vacancies and talent

The growing policy interest in strengthening Europe's AI capabilities – whether through education, reskilling, or talent attraction – requires a detailed understanding of not just aggregate supply and demand, but also their alignment across specific skill levels. While the previous sections examined data on AI vacancies and AI talent separately, this section brings the two strands together to assess **how well the skills requested by employers align with the skills available in the labour force**, consistently using our three-tier proficiency framework.

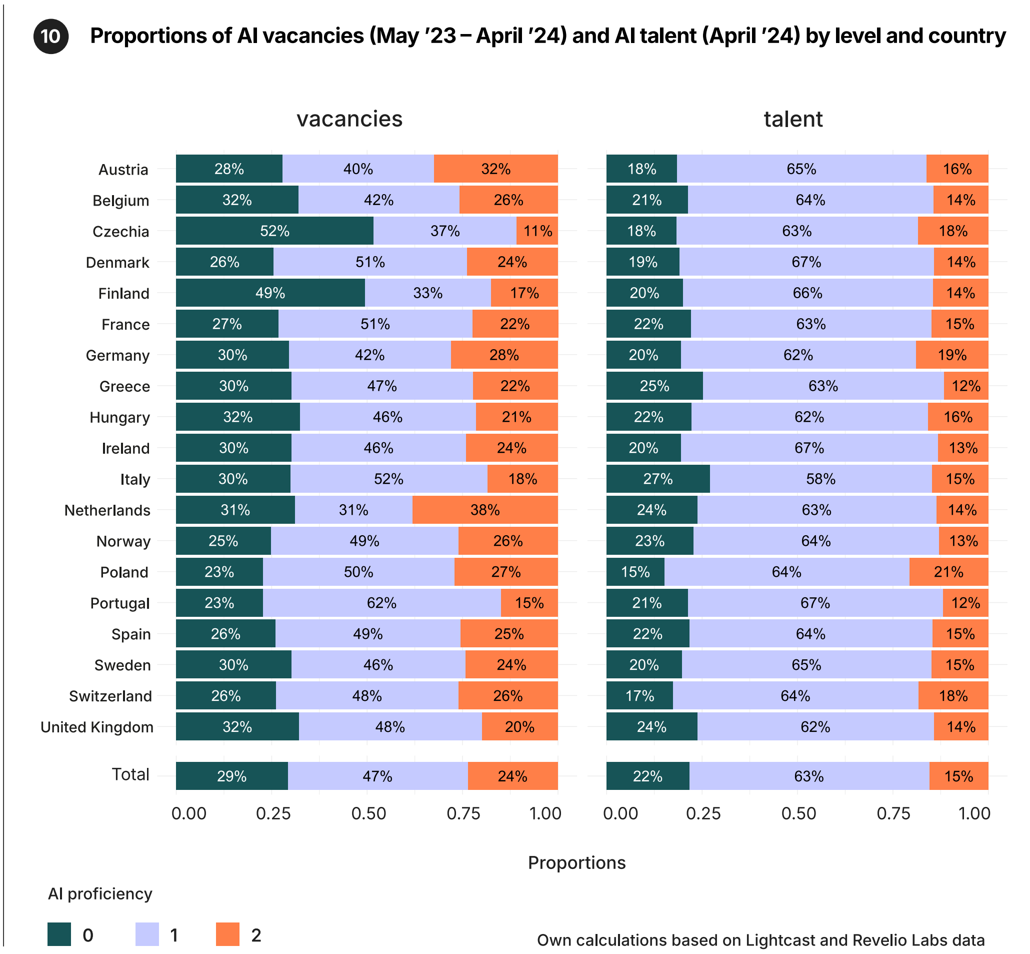
Analysing such mismatches is essential for designing targeted policy responses. For example, a shortfall in tier 2 (advanced) talent might call for more specialised academic programmes or incentives to attract experienced professionals from abroad. A gap at tier 0, by contrast, might point to the need for broader AI literacy programmes for the general workforce or public administration. Moreover, mismatches may be particularly pronounced in countries with emerging AI ecosystems, where demand is growing faster than domestic supply, or in economies heavily reliant on international recruitment.

In bringing together the two data sources, this section highlights the availability of talent per vacancy at each of the proficiency levels. Given the limitations in comparing the two data sources (see A1.3 in the appendix), we do not compare the absolute numbers, but rather show the shares of the proficiency levels in each data source (in Section 5.1) and the ratios of AI-skilled individuals per vacancy by proficiency level (in Section 5.2).

Proficiency shares in AI vacancies and talent

Figure 10 presents the distribution of AI vacancies and AI talent across 19 European countries, disaggregated by AI proficiency tier (0, 1, and 2). For each country, the chart compares the **share of job vacancies** and the **share of identified AI talent** at each proficiency level, expressed as a proportion of that country's total AI vacancies or talent, respectively. This allows for a direct comparison of the structure of demand and supply across proficiency levels.

Figure 10. Proportion of AI vacancies (May 2023–April 2024) and AI talent (April 2024) by level and country



Source: Own calculations based on Lightcast and Revelio Labs data.

Two general patterns are immediately observable.

Mid-level AI skills are currently the backbone of AI demand and supply in Europe. In most countries, tier 1 (software and data talent) accounts for the largest share of both AI vacancies and AI talent. On average, 47% of AI vacancies and 63% of AI talent belong to this mid-level tier. This suggests that mid-level AI skills currently form the core of both employer demand and workforce composition in much of Europe.

Both top-tier AI development and low-tier AI literacy skills are short in supply. Tier 0 (AI literacy and curiosity) is sought after in 29% of AI vacancies but only represents 22% of AI talent on average. Similarly, tier 2 (AI researchers and engineers) represents 24% of AI vacancies, but only 15% of AI talent. This creates a visible imbalance at both the expert and novice levels: relatively fewer AI-skilled candidates in the labour market have a low or high degree of AI proficiency than explicitly sought in job postings in the past year.

These descriptive results illuminate the diversity of AI labour market structures across European countries, as well as potential tensions between employer requirements and available skills at different levels of AI proficiency. Delving deeper into specific country patterns reveals three noticeable country clusters.

(Tier 2 leaders) Germany, Poland, and Switzerland exhibit a strong alignment between above-average demand (26%-28%) and above-average supply (18%-21%) of top-tier AI talent (Tier 2), marking them as established or consolidating hubs for advanced AI development in Europe. These three countries illustrate how either industrial legacy or targeted industrial strategies, combined with migration-friendly policies, can result in a self-reinforcing cycle of high-level AI development.

(Tier 2 aspirants) Austria and the Netherlands show above-average proportions of Tier 2 AI vacancies (32%-38%) with a below-average share of Tier 2 talent (14%-16%), suggesting a movement towards advanced AI capabilities. This may indicate that these two countries are entering a phase of rapid ecosystem expansion, with growing demand for high-end AI skills outpacing the local talent pipeline. It could also mark a transition from AI adopters to AI developers, raising the demanded level of AI skills. Either local training pipelines will need to scale up rapidly, or steps must be taken to attract and retain specialised AI professionals from abroad. In both cases, government strategies and incentive structures seem geared towards attracting international talent to fill emerging gaps.

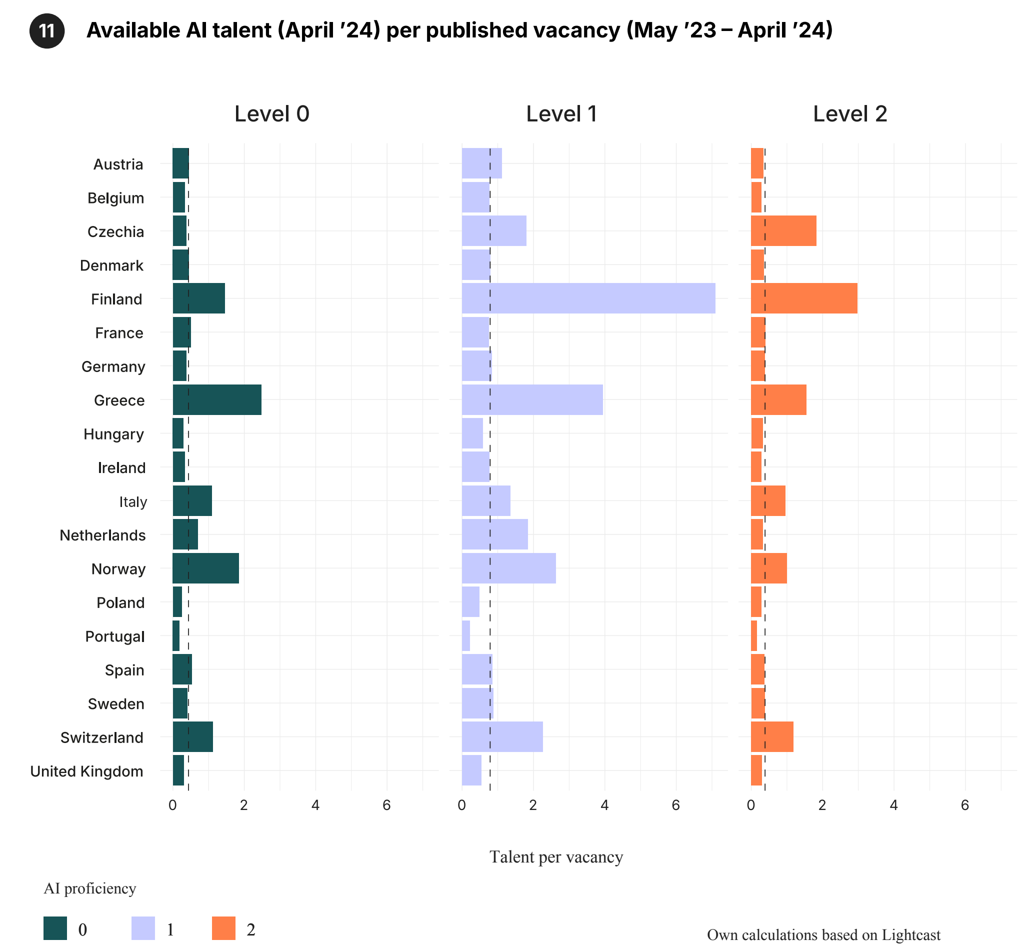
(Tier 0 aspirants) Finland and Czechia stand out for their exceptionally high shares of Tier 0 AI vacancies (49%-52%), but below-average shares of Tier 0 talent (18%-20%), indicating a gap between employer expectations and available workforce capacity at the foundational level. In both countries, the limited availability of entry-level AI talent may act as a barrier to inclusive AI diffusion across workplaces. Addressing it could unlock broader workforce participation and support the integration of AI tools beyond specialised technical domains.

Number of AI talent per vacancy at each proficiency level

Figure 11 compares the available supply of AI talent, measured through webscraped online CVs in April 2024, with the demand for AI skills, captured by online job vacancies posted between May 2023 and April 2024. The ratio presented reflects the number of available AI talent per job posting at each AI proficiency level (0, 1, or 2), across EU Member States.

This indicator provides a rough first approximation of potential AI skill mismatches by level and geography. A higher ratio suggests greater supply relative to demand, with a relatively larger proportion of AI talent competing for a more limited number of AI vacancies. A lower ratio may point to tighter labour markets and greater recruitment difficulty, with high demand and low availability of AI-skilled candidates. The ratio cannot, however, be interpreted as a shortage indicator, as not all available talent is searching for a position, nor is every posted vacancy open throughout the entire observation period (see the limitations expressed in A1.3 in the appendix).

Figure 11. Available AI talent (April 2024) per published vacancy (May 2023–April 2024)



The figure reveals a small number of AI talent per vacancy on average, signalling a potential short supply of AI skills, though this varies across proficiency levels and countries.

On average, **across proficiency levels,** the ratio of talent per vacancy is highest for the mid-level tier, with low-level and high-level AI roles showing tighter labour markets with a limited supply of appropriate talent fit. In many countries, there is approximately one qualified candidate for every tier 1 vacancy, indicating a better balance between supply and demand. By contrast, there are fewer than half as many candidates with the appropriate skills for tier 0 and 2 vacancies, reflecting a limited supply of talent and competing demand for those individuals.

The figure also reveals significant **cross-country differences** in the balance between AI talent supply and demand. First of all, some countries consistently show a larger supply of talent proportional to the number of vacancies across all the proficiency levels. These countries are Finland, Greece, Italy, Norway and Switzerland. Finland especially shows an exceptionally high relative supply of tier 1 talent, with a ratio of about seven AI-skilled candidates per vacancy at this mid-level proficiency. Some of these countries dominate the European AI landscape and have been proactive in attracting diverse talent pools across each skill tier, like Germany and Switzerland. Other countries, like Greece, have national strategies that seek to ensure reliable funding for AI research and academic institutions, as well as plans for diffusing AI knowledge across diverse groups of people. This ratio may also be shaped by the size of each national AI talent pool, which may offer fewer professional opportunities and lead to brain drains as top talent emigrates to other AI hubs with relatively more professional opportunities.

Second, some countries have a high relative supply at specific proficiency levels but not at every level, such as Czechia for tiers 1 and 2 or the Netherlands for tiers 0 and 1. This could reflect successful efforts to attract specialised talent to the country, or specific educational measures that have led to the proliferation of a specific high-skill tier. Czechia may have a larger supply of technically skilled AI talent because its national AI strategy has focused on things like the 'opening of new master's and doctoral study programmes and fields in AI' as short-term objectives. Meanwhile, medium- and long-term objectives include updating the curriculum for children and strengthening lifelong learning support for workers, which would increase the pool of talent with tier 0 skills. Even so, these countries may face difficulties in the future if AI skills are not diffused across industries and roles and they may require more investment in the upskilling and reskilling of the general workforce to adopt AI technologies.

These findings underline the importance of differentiating AI workforce planning by skill level. There appears to be a relatively larger supply of tier 1 AI talent, with shortages more likely at both the high-proficiency (specialised AI engineering) and low-proficiency levels (AI-literate knowledge workers). The broader adoption of and adaptation to AI technologies will require countries to increase the number of individuals within each tiered skillset in order to meet the demand for talent across the board.

Conclusion

This paper provides a comparative mapping of AI job vacancies and AI talent across Europe, using a novel three-tiered classification to capture variation in AI proficiency across both job requirements and workforce capabilities. By distinguishing between AI literacy (Tier 0), software and data proficiency (Tier 1), and advanced AI research and engineering (Tier 2), we offer a more structured and interpretable view of AI labour market dynamics than simple binary or extensive skill-by-skill approaches. As recent research shows, skills are not independent units but form nested hierarchies where advanced capabilities build on more fundamental ones. A tiered framework reflects this reality and enables more policy-relevant insights than granular skill-level monitoring alone.

Our results show that **mid-level AI skills (Tier 1)** are the **backbone of the European AI labour market**, accounting for most of both AI demand and supply. By contrast, both **entry-level AI literacy (Tier 0)** and **high-end AI engineering (Tier 2)** remain relatively **undersupplied**. The shortage of deep AI expertise (Tier 2) limits the development and deployment of advanced AI applications, particularly in sectors aiming to push the technological frontier. Meanwhile, the limited availability of AI-literate talent (Tier 0) constrains the broader diffusion of AI tools across non-technical roles and everyday work environments. These patterns vary substantially across countries, revealing distinct labour market profiles that reflect differences in industrial structure, talent policies, and educational capacity.

The findings reveal two core takeaways. First, AI skills strategies must be **geographically differentiated**: not all countries or sectors require the same type of AI expertise. Second, it is essential to track both demand and supply by **proficiency level**, not just skill tags or occupational proxies. A level-based approach clarifies what is meant by 'upskilling' in the AI era. Progression from Tier 0 to Tier 2 may span multiple years of education and cannot be the default expectation for every worker. Instead, upskilling efforts can more realistically focus on *horizontal layering* of AI capabilities within each tier – for example, equipping (non-AI) business analysts, statisticians, or project managers with AI-relevant tools and knowledge within their domain. In this way, AI talent can flow in across all three tiers, not just move up the levels vertically.

This structured understanding of AI proficiency can help make the EU's broader AI policy and Union of Skills goals more actionable. It supports more targeted implementation of the AI Act's literacy requirements, the EU Talent Pool's matching mechanisms, and the AI Continent Action Plan's objective to expand Europe's AI capabilities across sectors and skill levels. By embedding the idea of skill hierarchies into workforce policy, Europe can build not only more AI jobs, but also better pathways into them.

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Appendix

Methodology – AI talent

Data source. This study utilises comprehensive workforce data provided by Revelio Labs, a workforce intelligence company that aggregates and structures publicly available professional profiles, job postings, and related sources. The dataset from 2024 encompasses 659 million individuals in the global workforce. From this extensive population, we identified approximately 1.6 million individuals who constitute the global technical AI workforce based on our classification framework. The Revelio dataset includes gender estimates derived from census data on first-name gender distributions, enabling gender-based analyses of AI talent. Our analytical approach employs both absolute figures by country and per capita statistics, utilising World Bank population data for national and metropolitan area comparisons.

Identifying and classifying AI talent. To systematically analyse the AI workforce, we developed a three-tiered classification system that categorises individuals based on their level of involvement with AI technologies, technical expertise, and professional roles. Each tier represents a distinct level of technical engagement with AI development and implementation.

Our previous data briefs on AI talent flows and distribution highlighted the limitations of existing talent classification frameworks. Through feedback and ongoing conversations with relevant stakeholders – including policymakers, industry representatives, and academic partners – we recognised a pressing need for a more nuanced understanding of the AI talent pool, particularly for policy development purposes. Traditional binary classifications of AI talent have become increasingly outdated as the field has matured and diversified. These simplistic frameworks fail to capture the spectrum of AI-related roles that have emerged, from specialised deep learning researchers to applied data scientists and adjacent technical professionals who interact with AI systems. This limitation becomes particularly problematic when regions and nations attempt to assess their AI ecosystems, identify skills gaps, and develop targeted workforce strategies.

Our refined classification system offers direct insights into regional AI development trajectories and educational priorities. By distinguishing between regions where talent concentrates in fundamental AI research (tier 2) versus AI implementation and application (tier 1), policymakers can gain a valuable perspective for economic development planning, immigration policies, and educational investment. This ecosystem understanding can also reveal opportunities for targeted upskilling initiatives. When demand for tier 2 AI talent increases, organisations can efficiently upskill tier 1 professionals to address labour market gaps quickly. Similarly, targeted programmes can help women transition from tiers 0 and 1 to tier 2, addressing gender disparities in AI talent.

- **Tier 0.** AI curious and literate individuals: workers who are not covered by the other two classes, such as those in non-technical roles or studying for degrees in unrelated fields. This class includes individuals who have an interest in deep learning, data science, and machine learning but do not currently work in a position or study in a field that directly involves these areas.
- **Tier 1.** Software & data professionals: individuals working in technical roles or studying for degrees involving software development or data science, who may employ basic machine learning techniques in their work, such as linear regression. This class includes data scientists who do not work with advanced deep learning methods.
- **Tier 2.** AI researchers & engineers: individuals currently employed in roles that directly involve developing, applying, or researching areas of AI deep learning techniques, such as computer vision, generative models, or other advanced machine learning applications. This class includes those who work with neural network architectures like self-attention transformers, RNNs, CNNs, LSTMs, etc.

More information about these classifications can be found in interface's last paper on the technical tiers in the AI talent pool.

Approach. To address the challenges in distinguishing between our three AI talent tiers, we employed a large language model (LLM) classification approach. This methodology utilises natural language understanding capabilities to analyse professional profiles, educational backgrounds, and technical skills, offering an alternative to traditional rule-based classification systems. We selected a stratified random sample of 1000 profiles from all OECD nations plus India, limited to countries with more than 1000 individuals in our initial AI talent pool. This was further narrowed to encompass EU Member States, Switzerland, the UK and Norway. This selection builds upon previous research which identified significant patterns in global AI talent distribution, including:

- significant migration of European AI talent to the United States,
- India's emergence as a primary source of AI talent globally,
- a pronounced divide between Northern/Western Europe (with higher proportions of international talent) and Southern/Eastern Europe.

For a comprehensive background on previous AI talent research methodologies and findings, we refer readers to *AI's Missing Link: The Gender Gap in the Talent Pool*.

We selected Llama 3.1 70B as our classification model based on three criteria:

- alignment with our research transparency values through an open-source solution,
- superior performance in preliminary benchmarking against proprietary alternatives,
- enhanced data sovereignty, eliminating dependence on third-party APIs.

Each individual profile was processed independently through the model using a specialised classification prompt optimised for our three-tiered taxonomy.

We approached this task through the lens of a natural language processing (NLP) classification methodology for scientific study. Our classification prompt was developed through systematic optimisation using DSpy, a framework developed by the Stanford NLP group that enables rigorous, experimental approaches to prompt engineering.

To validate our optimised prompt, we established a gold-standard test dataset comprising 100 manually classified profiles. Our final prompt achieved 80% accuracy on this test set, which falls well within the acceptable range for complex multi-class classification tasks using LLMs. This level of accuracy is comparable to or exceeds benchmarks established in similar classification studies, where accuracies for policy topic classification using LLMs ranged from 58% to 83%. Additionally, even studies implementing consensus mechanisms for similar complex classification tasks achieved only moderately higher accuracies of around 92%. It is worth noting that our classification task involves distinguishing between professional profiles that contain overlapping skills and ambiguous descriptions, making them inherently challenging to categorise even for human experts. Given these considerations, our 80% accuracy provides sufficient reliability for our large-scale classification task while acknowledging the inherent limitations of automated classification for nuanced professional categories.

Our classification methodology implements chain-of-thought prompting – a state-of-the-art technique well established in recent LLM research. This approach requires the model to articulate its reasoning process before providing a classification decision, which has been demonstrated to improve output quality and reliability. For each profile, the LLM provided both a detailed rationale outlining the specific factors considered (skills, education, and job titles) and final classification label (0, 1, or 2) corresponding to our predefined tiers.

This approach not only improved classification accuracy but also provided valuable qualitative insights into the distinguishing characteristics of each talent tier, enhancing both the reliability and interpretability of our classification results. The transparency of the reasoning chain further allows for systematic error analysis and potential refinement of classification criteria in future research.

Limitations

Sample sizes. While we were able to obtain consistent samples of 1000 workers for each country in our primary analysis, sample sizes varied significantly when classifying talent by country of bachelor's degree origin. Countries with stronger data protection policies typically had fewer publicly available profiles, potentially resulting in less representative findings for these nations. Similarly, countries with smaller overall populations of technical workers contributed fewer samples to our dataset. For transparency and to assist readers in evaluating the reliability of country-specific findings, a complete breakdown of sample sizes by country is provided in this report.

Using undergraduate degrees as origin proxies. The country of an individual's undergraduate degree serves as a proxy for their origin, based on the assumption that most people pursue their early education in their country of origin. This method is generally reliable, as seen in these OECD data cases. Nonetheless, we acknowledge that outliers do exist and recommend the OECD report *Education at a Glance 2020* for detailed statistics. We believe that these effects do not substantially alter the primary insights regarding key source countries for AI talent.

Gender prediction limitation. While the data do not feature ground truth gender information, Revelio Labs estimates users' gender using census data information: each user's first name is checked against national census registries to estimate the gender shares of people with that name. This method can present issues with names that are not common: for those, the gender assignment is essentially random; nonetheless, they are by distribution a small minority of the population. A significant limitation in our dataset is the binary representation of gender (men and women), which fails to capture the diverse spectrum of gender identities present in the workforce. Given the scope and scale of our study, and the limitations of available global data sources, this binary representation is unavoidable for achieving consistent analysis across different regions and demographics. However, we recognise the importance of more inclusive gender representations and advocate for future improvements in data collection methods that can better capture the full spectrum of gender identities in the workforce.

Self-reporting. The Revelio Labs dataset partially addresses the lack of self-reporting by including predicted skills. They also account for geographical differences in profile creation by applying sampling weights to adjust for roles and locations underrepresented in the sample (as described before). This approach helps approximate the true estimate of the underlying population as closely as possible.

This limitation is further mitigated in this paper's context, as we are mainly examining a more technologically advanced segment of the global workforce. These individuals typically possess the digital literacy and necessary equipment to create and maintain profiles on professional career websites. They often enjoy the benefits of self-reporting their skills.

Skill taxonomy limitations. The current skill taxonomy used by Revelio may not encompass all the necessary skills for specific AI domains, such as AI chip development. This gap means that professionals with specialised skills in areas like hardware or AI chip design might not be sufficiently recognised or included in the dataset. The absence of these specialised skills in the taxonomy can skew the understanding of the full spectrum of AI talent and hinder the comprehensive identification of expertise across all AI-related fields.

Methodology – AI vacancies

Data source. Our analysis draws on online job advertisement data provided by Lightcast, a labour market analytics company that aggregates and processes job postings from thousands of websites across Europe. Lightcast uses a combination of NLP and proprietary data engineering methods to extract structured information from unstructured vacancy descriptions. The resulting dataset includes details such as occupation, sector, region, employer and required skills, along with metadata on posting and closing dates. For this study, we restrict the analysis to vacancies posted in the 27 EU Member States, between May 2023 and April 2024. We also add the UK, Norway and Switzerland, because these countries are present in the talent data as well (see Section 3).

Identifying and classifying AI vacancies. We identify AI-related job postings using a skills-based approach. Specifically, we apply a curated dictionary of AI skills (provided by Lightcast) to the vacancy dataset, flagging job ads as AI jobs if they mention one or more AI skills. The dictionary includes skills across multiple AI-related domains, such as machine learning, NLP, and computer vision. Our dataset contains 71 609 680 vacancies across 30 countries and 12 months. Among these, 99.1% are vacancies that do not contain a single AI skill. The remaining 0.9% request at least one AI skill and we label them 'AI vacancies' as such.

We further enrich the skills dictionary by adding levels of AI proficiency to each skill, as explained in Section 2. We classify an AI job as tier 0, 1, or 2 if it mentions at least one tier 0, 1, or 2 AI skill respectively. About a third of our AI vacancies only request low-level AI skills (tier 0), almost half request mid-level AI skills (tier 1) and the remaining fifth request high-level AI skills (tier 2).

Data aggregation. The unit of analysis in the raw data is the job posting. We aggregate this data by month, AI proficiency tier (0, 1, 2 or non-AI) and an indicator for whether the occupation is considered an ICT specialist or not. We use the definition of ICT specialists provided by Eurostat, which includes both ICT managers and (associate) professionals as well as other professions that primarily involve the production of ICT goods and services2. By also tracking the non-AI vacancies, we can analyse the relative frequency of AI-related postings by computing the share of such postings in total vacancies within a given region and month.

Limitations. It is worth noting that while the Lightcast dataset is large, timely, rich and granular, it may not capture all job vacancies posted in each country. Some selection bias may exist due to the differential coverage of platforms across countries and sectors (Vermeulen & Amaros, 2024). Online job advertisement data also overrepresent high-skill occupations, such as managerial and professional roles, and tend to capture formalised and standardised skills better than informal ones (Cammeraat & Squicciarini, 2021; Fernández-Macías & Sostero, 2024). Nevertheless, its consistency over time and comprehensive skill tagging make it well suited for trend and comparative analysis of AI demand in the labour market.

Methodology – vacancy and talent comparison

To match the vacancy data to the talent data we take three steps. First, we select the countries that are present in both datasets, which are the following 19 countries: Austria, Belgium, Switzerland, Czechia, Germany, Denmark, Greece, Spain, Finland, France, Hungary, Ireland, Italy, Netherlands, Norway, Poland, Portugal, Sweden and the UK.

Second, we aggregate both datasets to the same level of analysis, which is the combination of country and AI proficiency level. This means that we drop all other disaggregates that are present in one dataset but not the other, such as gender and country of origin in the talent data, or occupation and month in the vacancy data.

Third, to calculate the ratio of AI talent per vacancy, we divide total AI-skilled professionals by total vacancies per proficiency level. Since AI talent by proficiency level is calculated as proportions out of a sample of 1000 random profiles in each country, we scale up the proportions of each tier by the total size of the AI workforce present in that country – as detected by the same data source (Revelio Labs).

Box A1. Note on comparing vacancies with CVs

The vacancy data used in this paper are a sum of posted vacancies over 12 months up to and including April 2024. The talent data are the stock of online profiles present on April 2024. We are thus comparing a flow with a stock.

On the vacancy side, this does not mean that all reported vacancies were still open in April 2024. With an average posting duration of 2 months, we can assume that about a sixth of the reported vacancies are open at any given time. However, this does not mean either that each vacancy gets filled after the posting duration period is over. Some unfilled vacancies might be reposted later in the year.

On the talent side, not all people with an online profile in April 2024 were necessarily looking for a job at that time. With an average tenure of 3 years, we can assume that about a third of online profiles would be open to new job opportunities. Also, not all AI-skilled individuals necessarily have up-to-date online profiles, although this would likely be a smaller bias given the tech-savviness of this target group.

Furthermore, as we are comparing two different data sources, data collection efforts may differ across the sources and geographies. Given these limitations, as well as those described in the methodological sections above, we decided to solely compare proportions and ratios of talent and vacancies, and not their absolute numbers.

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