AI Skills and Occupations in the European Start-up Ecosystem

Enabling Innovation, Upskilling and Competitiveness

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1. Executive summary

The rapid advancement of Artificial Intelligence (AI) is reshaping Europe's innovation landscape, with start-ups playing a central role in translating technological potential into competitive advantage. Recognising the urgent need to support this transition, the European Institute of Innovation and Technology (EIT) launched the SkillSync initiative to map AI-related workforce skills and guide targeted upskilling efforts.

This report presents a comprehensive analysis of skills within AI-focused start-ups across Europe, leveraging the ESCO taxonomy and real-world data from over 23,000 professionals in 3,600 start-ups. Through the SkillSync platform — an AI-powered tool developed by the EIT AI Community — this study identifies key skill trends, training gaps, and regional needs, supporting the strategic development of Europe's AI talent pipeline.

Key findings:

- European AI start-ups show robust expertise in core technical areas such as Python programming, machine learning, and data management. These foundational skills are broadly distributed across roles and regions, forming the backbone of AI-driven innovation.
- While core skills are common across Europe, there is significant regional variation in skill intensity, particularly in interdisciplinary areas such as project management, natural sciences, and communication. Regions with higher innovation scores tend to have stronger representation in these domains, suggesting a link between transversal skill profiles and innovation output.
- Non-university training providers excel in offering technical and industry-aligned training, while universities focus more on foundational and transferable skills. Despite this complementarity, critical gaps remain — particularly in areas like legal and regulatory skills, audiovisual technologies, and domain-specific operations — that are essential for scaling AI innovations across sectors.
- Based on a novel clustering of European regions by workforce skill profiles, the analysis identifies six regional clusters and two meta-clusters. These groupings reveal shared strengths and gaps that can guide coordinated policy responses, collaborative training initiatives, and place-based interventions.

- Regions with a greater concentration of skills in engineering, manufacturing, natural sciences, and healthcare consistently outperform others in the European Innovation Scoreboard. Conversely, overreliance on general IT skills correlates poorly with innovation, suggesting a need to move beyond baseline digital literacy toward more advanced, sector-specific capabilities.

- The study introduces a robust, standardised metric — skill intensity (SI) — to map, compare and benchmark skill distributions, enabling the continuous monitoring of workforce dynamics, fostering a data-driven approach to skills policy across Europe.

Policy implications:

- Support cross-regional collaboration through meta-cluster-based training consortia and shared resource development.

- Scale up high-impact training programmes in natural sciences, engineering, and regulatory fields — especially in lower-performing innovation regions.

- Strengthen the role of non-university providers in delivering agile, modular, and industry-relevant training.

- Encourage universities to expand offerings in specialised and emerging AI applications, including ethics, law, and sectoral domains.

- Invest in interoperable platforms like SkillSync to support continuous assessment, matchmaking, and forecasting of future skills needs.

By addressing existing skill gaps and aligning educational offerings with evolving labour market demands, Europe can build a resilient, inclusive, and future-ready AI workforce. The analysis provides not only a snapshot of current capabilities, but also a strategic framework for guiding the next phase of AI-driven growth across the continent.

2. Introduction

Artificial Intelligence (AI) is increasingly recognised as a transformative force reshaping not only economic sectors but also labour markets, education systems, and societal expectations — both across Europe and globally. As a general-purpose technology and a powerful enabler of digital innovation, AI holds the potential to boost productivity, enhance decision-making, and generate substantial societal value (OECD, 2019). However, this technological shift also introduces complex challenges, particularly in the domains of ethics, equity, and workforce preparedness. Consequently, education providers are increasingly expected to cultivate not only technical skills but also digital literacy, ethical awareness, and collaborative competencies essential for developing and deploying human-centred AI systems (HLEG AI, 2019). Addressing these issues requires coordinated policy interventions and strategic investments in skills development.

Across the European Union, AI adoption is steadily advancing. By 2023, nearly one-third of large companies had integrated some form of AI into their operations, though uptake varies considerably across sectors and Member States (Cedefop, 2025). This growing deployment of AI technologies is exposing a widening gap between the capabilities of the current workforce and the skills demanded by AI-driven economies. European reports (ARISA, 2023; 2024) have underscored the urgency of equipping employees, jobseekers, and decision-makers with technical, ethical, and transversal competences to engage meaningfully with AI systems. Labour market trends further highlight the structural shifts underway. Research by McKinsey Global Institute (2020) documents a decline in mid-skilled employment and a growing polarisation between high and low-skilled roles, a dynamic exacerbated by automation and the diffusion of AI across industries. This reconfiguration of job profiles is not limited to technology-intensive sectors; rather, it is fundamentally altering the nature of work across both technical and non-technical domains.

In this context, the European Institute of Innovation and Technology (EIT) plays a central role in advancing Europe's innovation agenda. As the EU's largest innovation network, and in close collaboration with the European Innovation Council (EIC), the EIT supports the continent's most innovative start-ups and SMEs. Its Knowledge and Innovation Communities (KICs) span a wide range of strategic sectors — including health, food, energy, climate, raw materials, manufacturing, urban mobility, and digital technologies — and have collectively supported over 5,500 start-ups[1] to date. EIT KICs are not only funding innovation through their Accelerator programmes, but are also actively engaged in intelligence-gathering efforts to better understand market dynamics and skill needs. By developing detailed organisational skill profiles and leveraging the European Skills,

[1] The EIT Ecosystem of supported start-ups: https://eit.dealroom.co/companies

Competences, Qualifications, and Occupations (ESCO)[2] taxonomy — comprising over 14,000 knowledge items — they aim to provide tailored, data-informed upskilling recommendations. Yet, identifying relevant skill gaps at the organisational level remains a methodological challenge. While top-down approaches can help identify broad deficits at the regional or sectoral level, they are often insufficient for generating actionable, individualised training guidance. A more targeted strategy involves benchmarking organisations against peers within the EIT ecosystem, based on both skill composition and geographic proximity.

Contributing to this need, this report presents findings from the *SkillSync*[3] platform — an AI-powered tool developed by the EIT AI Community to support workforce development within the European AI ecosystem. Unlike traditional survey-based assessments, SkillSync analyses actual skill data derived from the profiles of professionals working in AI start-ups. This allows for real-time identification of skill gaps (OECD, 2023a) and the delivery of personalised course recommendations for start-ups, SMEs, corporates, educational institutions, and policymakers. The report also includes a clustering analysis of European countries and regions, identifying areas with similar skill profiles among AI-driven start-ups. This comparative lens enables the detection of missing skills in specific regions by benchmarking them against more innovative or skill-intensive peers. These findings reinforce the argument that innovation depends not only on technical expertise but also on the acquisition of interdisciplinary competences, a deep understanding of application domains, and robust data governance capabilities.

Moreover, the diffusion of AI technologies is reshaping job roles beyond the technology sector. Even among workers not directly involved in AI development, there is a growing demand for digital, managerial, and socioemotional skills — particularly in occupations with high AI exposure (OECD, 2023b; 2024a). Although employers often report positive outcomes such as improved task variety and reduced physical or cognitive strain, concerns about job displacement, algorithmic surveillance, and erosion of autonomy are also gaining prominence (WEF, 2025). These labour market transformations are further intensified by concurrent macroeconomic and technological pressures. According to the World Economic Forum's Future of Jobs Report (2025), more than 20% of global jobs are expected to be impacted by 2030 due to AI, demographic change, climate imperatives, and geopolitical instability. While fears of mass automation persist, the dominant consensus points toward a reconfiguration of tasks rather than large-scale job elimination. This implies a growing need for reskilling and upskilling, particularly in sectors experiencing rapid technological disruption.

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[2] The European Skills, Competences, Qualifications, and Occupations (ESCO): https://esco.ec.europa.eu/en

[3] SkillSync platform: https://skillsync.net/ & innovation map dashboard: https://www.skillsync.eu

Despite this urgency, the current provision of training opportunities across Europe remains uneven and often poorly aligned with labour market needs (OECD, 2023c; 2024b). Addressing this misalignment places new demands on vocational education and training (VET) and higher education systems. Across the EU, these institutions are evolving to meet changing skill requirements through greater modularity, closer ties to higher education, and a stronger focus on lifelong learning and flexible learning pathways (Cedefop, 2023). However, access to AI-related opportunities is not equitably distributed. Women, older workers, and individuals without tertiary education remain underrepresented in AI-related roles, raising concerns around digital exclusion and labour market stratification (OECD, 2024b).

These developments take place within a broader geopolitical context in which the EU seeks to close the innovation gap with global competitors and ambitions to become a global leader in AI as indicated in the "AI Continent Action Plan" (European Commission, 2025)[4] with the reinforcement of AI Skills among the five domains identified. While digital adoption and research capacity have improved, the European Innovation Scoreboard continues to highlight the need for deeper and more sustained investments in research, infrastructure, and skills (European Commission, 2024). The challenge is not only to innovate, but to do so inclusively and responsibly. In sum, the emergence of AI as a general-purpose technology necessitates a fundamental rethinking of workforce strategies across Europe. Building a future-ready workforce requires more than technical upskilling — it demands interdisciplinary competences, ethical literacy, and resilience in the face of accelerating change. Addressing this multifaceted challenge calls for coordinated action among governments, industry, academia, and civil society to ensure that AI-driven transitions promote equity, social cohesion, and sustainable growth.

[4] The AI Continent Action Plan. https://digital-strategy.ec.europa.eu/en/library/ai-continent-action-plan

3. Methodology

3.1. Objectives

Upskilling has been identified as one of the four key dimensions of the European Union's *Digital Decade* policy programme, as outlined in the Horizon Europe Strategic Plan. In alignment with this objective, the EIT Knowledge and Innovation Communities (KICs) are actively supporting the European Skills Agenda and are leading and participating in several of its flagship initiatives, including the *Pact for Skills*. Within this broader commitment, the EIT AI Community — operating under the EIT Cross-KIC Strategic Synergies framework — is contributing to the development of the upskilling tool *SkillSync*. This platform, along with its accompanying database, enables an in-depth analysis of the skills of professionals working in Europe's most innovative start-ups.

The goal of this analysis is to generate tailored upskilling recommendations at both regional and national levels. The identification of skills gaps through this data-driven approach will empower EIT KICs to promote targeted training opportunities that address the specific needs of start-ups across different sectors and regions. This study contributes to the development of a forward-looking, evidence-based agenda for artificial intelligence (AI) workforce development in Europe. In doing so, the analysis aims to enhance the competitiveness and innovation capacity of European companies.

The following strategic objectives guide the scope and purpose of the analysis:

1. Provide a structured mapping of the current AI-related skill set across European start-ups, leveraging the ESCO taxonomy.

2. Identify role-specific technical and cross-cutting foundational skills that are essential for the functioning of AI-driven start-ups.

3. Evaluate the alignment between existing educational and training offerings and the actual skill needs of the AI labour market.

4. Conduct a granular analysis of workforce skill profiles across European regions and regional clusters.

5. Analyse the relationship between workforce skills and innovation performance, as captured by the European Innovation Scoreboard.

6. Detect underrepresented or missing skills across innovation tiers, enabling regions to benchmark their capabilities and prioritise targeted upskilling strategies.

7. Offer a methodological framework for tracking changes in AI skill intensity over time, supporting policy evaluation, impact assessment, and the refinement of future skills development strategies.

3.2. Data

The analysis presented in this report is based on data generated through the SkillSync platform, which integrates a comprehensive database comprising the skills of over 130,000 professionals employed in European start-ups. It also includes more than 80,000 training courses offered by a wide range of professional education providers. Within this dataset, a subset of 3,600 start-ups specialising in Artificial Intelligence has been identified, with skill profiles derived from an analysis of 23,000 professionals working in these companies.

The dataset is observational in nature and includes professionals from start-ups that have received support through EIT KICs' Accelerator programmes, as well as others operating within their strategic domains. Additionally, the dataset incorporates data from start-ups supported by the European Innovation Council (EIC). While the sample does not fully represent all European countries and regions — introducing a potential bias due to its non-random sampling approach — the breadth and depth of the data offer valuable insights. Despite these limitations, the richness of the dataset enables the extraction of meaningful conclusions, contributing to a more nuanced understanding of the skills landscape among professionals working in Europe's most innovative start-ups.

3.2.1. Organisations and start-ups

At the time of this report, the SkillSync database comprises a total of 59,225 organisations. However, only a selected subset has been included in the present analysis, based on specific criteria applied during the data extraction and normalisation process to ensure data quality and analytical relevance. For inclusion in this study, start-ups were required to meet the following conditions:

- Possess complete metadata, including a verified presence in Internet.
- Employ professionals with identifiable skills.
- Be headquartered or located within Europe.
- Be classified by EIT KICs as a start-up with a primary focus on Artificial Intelligence.

A total of 3,607 start-ups satisfied all these criteria, forming the dataset used in this analysis. It is important to note that the geographic distribution of start-ups across Europe is not uniform, resulting in an inherent bias toward countries with a larger presence of qualifying start-ups. To address this, mitigation strategies have been applied, including the normalisation of metrics and the use of relative rather than absolute values.

3.2.2. Employees

Public information about the employees of the start-ups included in this dataset was obtained from publicly available sources such as LinkedIn or directly entered into the SkillSync platform when users completed their profiles. The geographic distribution of these professionals per country in the dataset is shown in Figure 1.

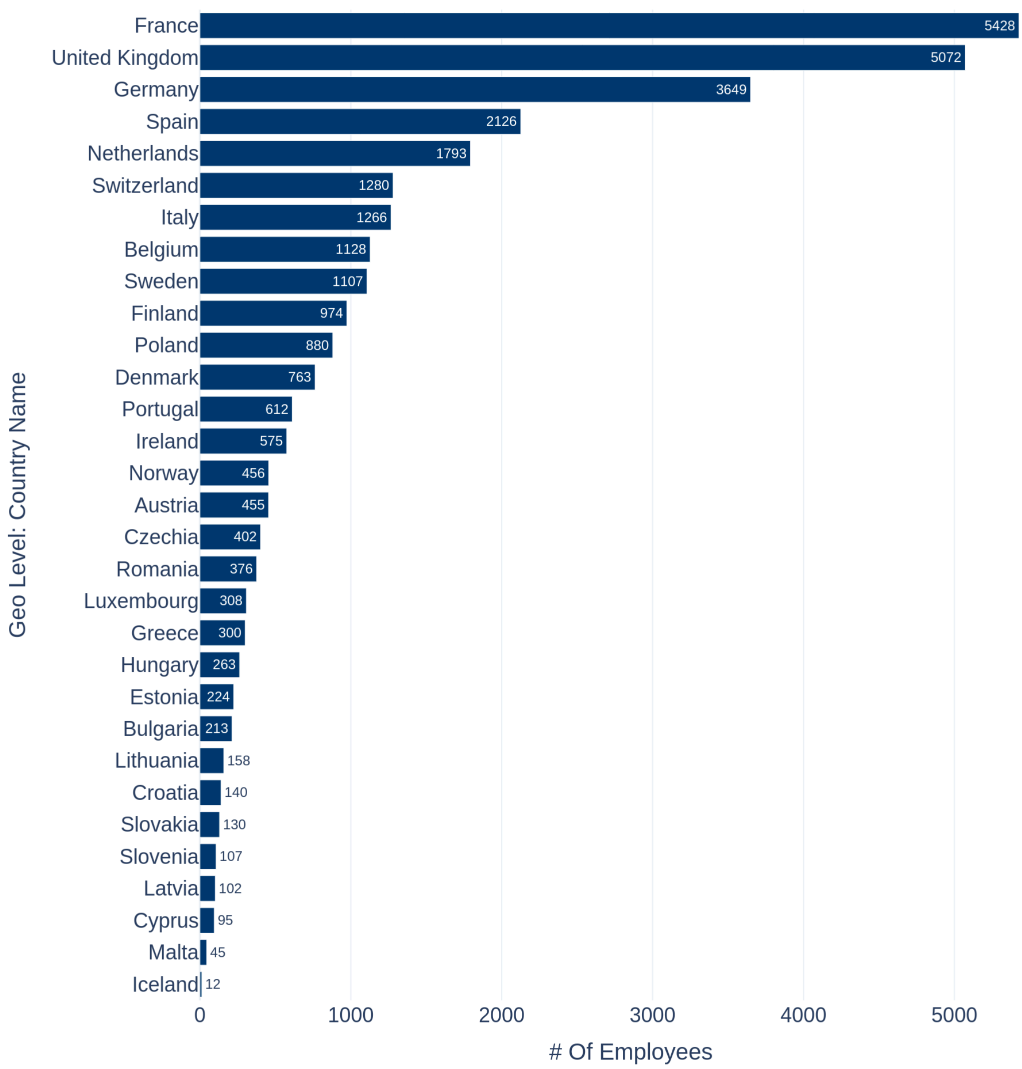

Figure 1. Number of professionals working in European start-ups focused on AI from the dataset.

The analysis of employees adopts a methodology similar to that used for start-ups, with a focus on the skills each individual contributes and their geographic association — typically inferred from the location of the start-up's headquarters. To be included in the analysis, employees must have an active LinkedIn profile containing identifiable and relevant skill information. These skills are either automatically extracted from their profiles or manually entered into the SkillSync platform via the start-up’s user interface.

From an initial pool of 139,375 professionals available in the SkillSync database, a subset of 23,190 individuals was selected for this study. This selection was based on the inclusion criteria and limited to those working in start-ups identified as being focused on Artificial Intelligence.

3.2.3. Courses

The SkillSync database includes a comprehensive catalogue of 84,712 professional training courses spanning a wide range of domains — including health, AI, languages, software, marketing, and more. These courses are sourced from a variety of educational institutions and training providers, aggregated through platforms such as *Class Central, Studyportals, and Study.eu*. This dataset offers a broad overview of available training opportunities and their associated skill sets.

To ensure analytical relevance and depth, the following filtering and categorisation processes were applied:

- **Course duration:** Only courses with a minimum duration of 10 hours were included for this analysis. This threshold was established to focus on programs that offer substantive skill development, excluding brief, introductory, or superficial offerings. After applying this filter, the dataset was reduced to 76,337 courses.

- **Provider classification:** To facilitate comparative analysis, courses were classified by provider type:
  - University courses: Representing 33,246 entries, this category includes offerings from higher education institutions, enabling analysis of the skill coverage provided by academia.
  - Non-university courses: Comprising 43,091 entries, this category covers a wide array of independent and professional training providers.

The table below summarises the filtered dataset:

Courses	Total Number of Courses	University Courses	Non-University Courses
Total	84.712	34.798	49.914
Filtered (>10h)	**76.337**	33.246	43.091

Table 1. Summary of course dataset present in the SkillSync database.

Courses in the SkillSync database are tagged with specific skills based on their descriptions and syllabi. This is done through a rigorous skill-mapping process aligned with the European Skills, Competencies, Qualifications, and Occupations taxonomy. Each course is associated with a set of relevant skills — ranging from foundational to highly specialised technical skills — depending on its content and intended outcomes. Beyond the duration filter, the categorisation of courses by provider type allows for a comparative analysis of the skill coverage offered by university and non-university training providers. This distinction highlights different educational approaches and specialisations and provides insights into the complementary roles each type of institution plays in the broader training ecosystem.

The breadth of this dataset, which includes training courses available across Europe, offers a representative snapshot of the current training landscape for AI-related skills. This information forms the foundation for identifying potential training gaps and aligning course offerings with the skills most needed by AI-focused start-ups, a topic explored in greater depth in Section 4.

3.2.4. ESCO and skills normalisation

A central challenge in the analysis of skills lies in harmonising and structuring a highly diverse and unstandardised set of skill descriptors into a unified, interpretable knowledge corpus. Within this study, skill profiling and identification for organisations were conducted by first automatically extracting skills from the LinkedIn profiles of employees. These raw inputs were then processed through a pipeline that includes automatic translation into English and the correction of spelling and typographical errors — common issues in user-generated content on online platforms. A key complication arises from the variability in how individuals report their skills. For example, one professional may list "Data Analysis", another "Data Analytics", and yet another "Statistical Analysis". While these terms are related, their differences in wording necessitate standardisation to ensure analytical coherence. To address this, we adopted the ESCO classification system, which includes approximately 14,000 standardised references for skills and competencies. In addition, we developed a custom large language model (LLM) to map user-generated skill expressions to ESCO-aligned references. This model was iteratively improved through human validation of a representative sample to ensure accuracy and semantic fidelity.

The skill normalisation pipeline leverages a suite of open-source language models, including Mixtral (developed by Mistral AI) and LLaMA (by Meta), to process raw text inputs such as skill labels and job titles. These models facilitate the mapping of diverse textual expressions to standardised ESCO concepts, enhancing both consistency and interpretability. This system is deployed on Groq's advanced computational infrastructure, which utilises Learning Processing Units (LPUs), a type of application-specific integrated circuit (ASIC) optimised for high-performance AI inference. This hardware significantly accelerates the processing speed and scalability of large language model operations, enabling efficient handling of large-scale data. Importantly, the classification model does not treat skills in isolation. Instead, it leverages the full hierarchical structure of the ESCO taxonomy, a multi-level classification system that organises skills according to various degrees of specificity. This hierarchical approach enables more precise skill categorisation and enhances the ability to draw nuanced insights from the dataset.

Input keyword	"Contract Negotiation"	"Artificial Intelligence"	"Economy"
ESCO Level 1	Skills	Knowledge	Knowledge
ESCO Level 2	Communication, collaboration and creativity	Information and communication technologies (ICT)	Social sciences, journalism and information
ESCO Level 3	Negotiating	Information and communication technologies (ICT)	Social and behavioural sciences
ESCO Level 4	-	Information and communication technologies not elsewhere classified	Economics
ESCO Level 5	-	Principles of Artificial Intelligence	Economics

Table 2. Examples of the normalisation system using the ESCO taxonomy.

Table 2 provides an illustrative example of the skill normalisation process. It demonstrates how diverse input expressions — such as *Contract Negotiation* — are mapped to their corresponding ESCO entries, always selecting the most specific level available within the ESCO hierarchy. This mapping enables access to both the fine-grained skill classification and its broader, more general parent categories. Such hierarchical structuring allows for a flexible exploration of skills data, supporting both detailed and high-level comparative analyses depending on the research or policy objectives. A variation of this methodology is also applied to extract the set of skills associated with each training course in the SkillSync database. In this case, a dedicated large language model (LLM) is employed to analyse the textual content of course descriptions and syllabi. The model generates a list of predicted skills, each associated with a confidence score indicating the degree of semantic similarity between the course content and a standardised ESCO skill.

To ensure both precision and relevance, the final set of skills linked to each course consists of only those predictions that exceed a confidence threshold of 0.7 — corresponding to an estimated 70% similarity to the matched ESCO skill reference. This filtering ensures that the skills associated with a course are meaningfully aligned with its content. The distribution of skills identified among professionals in the database, categorised by ESCO taxonomy levels, is presented in Figure 2. This visualisation offers an overview of how skills are spread across different categories, providing valuable insight into the current skills landscape within AI-focused start-ups.

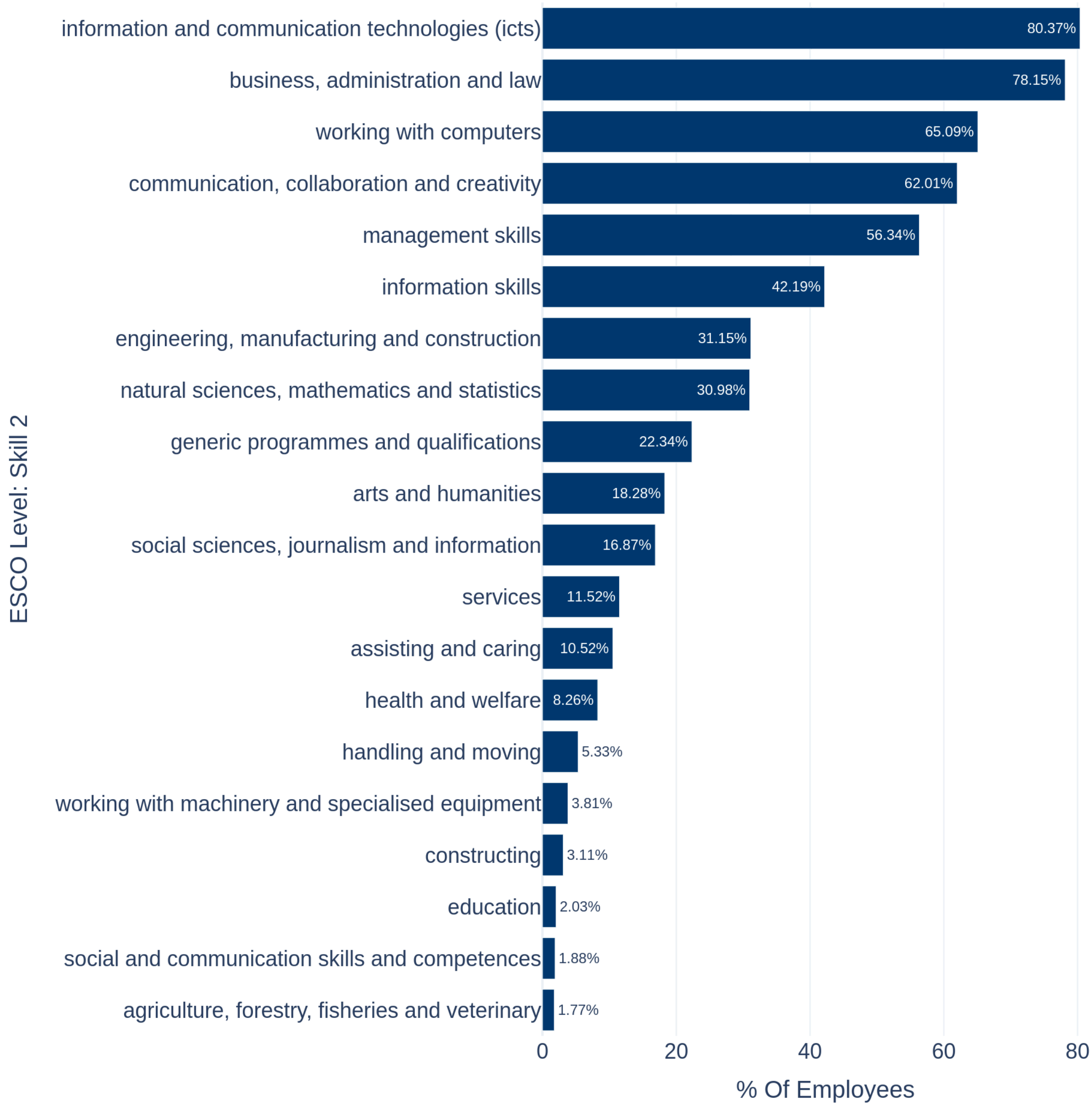

Figure 2. Set of top skills grouped per category (ESCO level 2).

3.2.4.1. Model evaluation for extraction and normalisation

To evaluate the effectiveness of the multicategory classification model used in SkillSync for skill prediction, we calculated accuracy as the ratio between the number of correctly predicted skills and the total number of predicted skills. This was aggregated across multiple employees within each company. Following a random sampling of predicted skills and subsequent manual validation, the model achieved an overall accuracy of 0.89. This indicates that 89% of the skills predicted by the system accurately matched validated ESCO skill references. Such a high level of accuracy underscores the robustness and reliability of the skill extraction and normalisation pipeline, particularly given the complexity of the task. The model performs within a multi-class classification problem encompassing over 14,000 ESCO skill categories, a setting in which achieving high precision is notably challenging. This result reinforces the suitability of the system for large-scale, automated skill profiling across diverse organisational datasets. A similar methodology was applied to the dataset of training courses, where the set of associated skills is derived from course descriptions and syllabi. In this case, for each course iii, the accuracy was computed by determining the proportion of predicted skills that were relevant and valid for that course, and then averaging across the entire dataset.

A manual validation of a random subset of these courses yielded an average accuracy of 0.81, indicating that 81% of the predicted skills were relevant to the course content. This validation was further supported by an automated cross-check using an additional LLM, which incorporated expanded skill definitions and refined semantic matching logic. Given the same high-dimensional classification space of the ESCO framework, this result further demonstrates the effectiveness of the model in mapping complex educational content to structured skill categories. These accuracy levels validate the capability of the large language models developed within the SkillSync framework for extracting and standardising skills in alignment with the ESCO taxonomy.

Despite the strong performance, it is important to acknowledge limitations. Certain ambiguous or overly broad terms — such as *Operations* or *Design* — can vary significantly in meaning across contexts (e.g., business operations vs. surgical operations). These semantic ambiguities present a persistent challenge for standardisation and highlight the need for continued refinement of the classification models.

To address these challenges and maintain high data quality over time, we recommend regular retraining and review of the implemented models to adapt to evolving language usage in professional profiles and course descriptions. This is particularly significant given the dynamic nature of the labour market and the rapid emergence of new skills, especially in the field of AI. In addition to model-driven processes, SkillSync includes a user-editable interface that enables both companies and training providers to manually review and adjust their automatically generated skill profiles. This feature allows users to refine the set of skills associated with their organisation or educational content, ensuring greater alignment between real-world expertise or curriculum and the standardised output. By incorporating human-in-the-loop validation, this process improves the relevance and accuracy of the personalised upskilling recommendations and analytics delivered by the platform.

3.3. Metrics: Understanding Skill Intensity

The Skills Intensity metric is a relative measure that looks at how prevalent a specific skill is among professionals in a given set (e.g. a region, a country or an occupation) comparing the specific skill with the total number of the skills present in the set. Instead of just counting how many people have a skill, it compares that number with the size of the set (e.g. the local workforce in a region). The relative measure allows comparing sets of different sizes. This helps us to understand how "embedded" or widespread a skill is within a region or group — not just in absolute numbers, but in proportion to the local context.

To make comparisons fair across all regions, we also use a standardised version of this metric that shows whether a region has more or less of a skill than the European average:

- A **positive** value means the region has more professionals with that skill than most others.
- A **negative** value means the region is below average for that skill.
- A value **close to zero** means the region is roughly in line with the European average.

By using this approach, we can highlight where certain skills are especially strong or missing, and identify regional priorities for training and development.

For instance, if the skill "machine learning" has a high skill intensity (SI) in a certain region, it suggests that a larger share of professionals there are specialised in this area compared to the European average. This makes this region a stronghold for that particular expertise. On the other hand, a low value in a different region could indicate a need to strengthen local capacity in that skill through targeted training programs.

4. Results

4.1. Assessment of existing skills

AI skills play a critical role in accelerating innovation and fostering sustained competitiveness within the European start-up ecosystem. In recent years, the demand for AI expertise has significantly increased, driven by rapid advancements in machine learning, data science, and automation technologies. start-ups across Europe, particularly those supported by the EIT Knowledge and Innovation Communities (KICs), have cultivated a robust foundation of expertise across diverse sectors — from healthcare to energy and beyond. Building on this foundation, the SkillSync initiative enhances their capacity by offering tailored upskilling opportunities in AI. This empowers start-ups to address challenges across various domains while maintaining adaptability in an ever-evolving digital landscape.

4.1.1. General overview

This section examines the distribution and significance of AI skills within European start-ups. The analysis provides a comprehensive overview of the AI-related skills observed among professionals across a range of occupations, classified according to the European Skills, Competencies, Qualifications, and Occupations framework. Emphasis is placed on identifying the most prevalent and strategically relevant AI skills. Moreover, the assessment explores gaps in available training resources, highlighting specific skills that are underrepresented or missing in current educational offerings. By pinpointing these gaps, the analysis may contribute to the design of more effective and targeted upskilling strategies.

The study reveals both the strengths of existing professional expertise and the areas in need of development. These insights support the creation of refined skill profiles that better position European start-ups as leaders in AI innovation. Organising the analysis according to the ESCO classification enables a structured exploration of skill distribution across occupations. This approach facilitates the identification of both foundational and specialised skill sets essential for driving AI innovation. In particular, the analysis distinguishes between broadly applicable foundational skills and niche skills crucial to AI-specific roles. This dual perspective offers a deeper understanding of how various occupations contribute to building AI capabilities within the start-up landscape.

To ensure the robustness and validity of the findings, the scope of the analysis is limited to European countries. Furthermore, only skills possessed by at least 100 professionals are included in the dataset, ensuring a reliable basis for interpretation.

4.1.1.1. Most prevalent set of skills

Analysing the most prevalent skills in AI across European start-ups offers a comprehensive insight into the core skills driving innovation, both within specific occupations and across broader ESCO classifications. Accordingly, this section adopts a dual perspective: first, by *role* (*occupation)*, examining the distinct skill sets required for individual roles within the AI domain; and second, by *ESCO category*, classifying skills according to the structured hierarchy of the ESCO framework. This twofold approach enables the identification of both the unique skills associated with particular roles and the broader skill clusters that collectively shape the AI landscape.

An in-depth analysis of the **most prevalent skills** by occupation offers valuable insights into the specific skills that define various roles within the AI ecosystem of European start-ups. This role-based approach enables the identification of both unique and overlapping skill sets across occupations, fostering a nuanced understanding of the technical and practical expertise required in the field of artificial intelligence. To identify the most prevalent skills per occupation, the following selection criteria were applied:

- start-ups must be explicitly focused on artificial intelligence and based in Europe.
- Only occupations directly associated with AI were considered.
- The most prevalent skills are defined as the top five ESCO skills, ranked by frequency within each occupation in descending order.
- The identified skills correspond to the most granular level within the ESCO taxonomy framework.

Occupation	Top 5 skills (ESCO last level)	SI per role %
Data Warehouse Designer	web programming, Python (computer programming), ICT project management methodologies, database, Java (computer programming)	13.14
Database Designer	web programming, Python (computer programming), ICT project management methodologies, database, Java (computer programming)	12.99
Artificial Intelligence Engineer	Python (computer programming), ICT project management methodologies, Java (computer programming), JavaScript, C++	11.69
Database Developer	SQL, Python (computer programming), Java (computer programming), JavaScript, C++	11.06
Computer Vision Engineer	Python (computer programming), statistics, machine learning, use markup languages, deep learning	7.27
Data Analyst	statistics, database, use spreadsheets software, cloud technologies, research design	6.36
Business Intelligence Manager	project management, statistics, align efforts towards business development, business analysis, management consulting	6.28
Data Scientist	statistics, use spreadsheets software, research design, data science, deliver visual presentation of data	4.83
Bioinformatics Scientist	web programming, statistics, data science, computer programming, computer engineering	4.69
Chief Data Officer	database, cloud technologies, MySQL, data science, deliver visual presentation of data	4.44
Big Data Archive Librarian	statistics, database, MySQL, business intelligence, analyse big data	4.3
Database Integrator	database, MySQL, business intelligence, data extraction, transformation and loading tools, PostgreSQL	3
Data Quality Specialist	statistics, database, business processes, process data, data engineering	2.97
Data Entry Clerk	database, use spreadsheets software, use word processing software, process data, data models	2.58
ICT Business Analyst	cloud technologies, business strategy concepts, business intelligence, apply change management, innovation processes	1.95
ICT Information and Knowledge Manager	deliver visual presentation of data, business intelligence, data mining, business processes, data models	1.36
ICT Operations Manager	operations management, innovation processes, manage budgets, systems development life-cycle, hardware components	0.57
Data Protection Officer	cybersecurity, risk management, manage keys for data protection, internal auditing, write work-related reports	0.53

Table 3. Most prevalent skills per occupation based on the skill intensity metric.

Table 3 summarises the core skills associated with each role, based on the Skill Intensity metric. For instance, the role of a *computer vision engineer* is marked by technical skills such as *Python programming, statistics,* and *machine learning* — emphasising the significance of advanced programming and analytical capabilities. Similarly, data analysts frequently demonstrate expertise in *statistics, database management*, and *spreadsheet software*, illustrating the data-centric nature of their profession.

The findings from this analysis present a structured distribution of skills across AI-related occupations in European start-ups. The interplay between shared and role-specific skills provides a more refined understanding of current labour market demands. By pinpointing the most prevalent skills within each occupation, these insights can inform the design of targeted training courses and upskilling initiatives for professionals and organisations seeking to meet the evolving requirements of the AI sector.

A complementary analysis of the **most prevalent skills across ESCO categories** further elucidates the broader skill clusters shaping the AI talent landscape. This section categorises AI-related expertise at ESCO Level 2, identifying the dominant skill groups that underpin AI-focused start-up environments. At this level of analysis, we gain a deeper understanding of both core and general skill sets required in AI contexts. To identify the most prevalent skills per ESCO category, the following criteria were employed:

- The analysis aggregates skill frequencies at the second level of the ESCO taxonomy, highlighting the top five most common skills within each category.
- Only skills directly associated with the AI sector were included, with each skill represented at the most detailed level available within the ESCO framework.
- The analysis is limited to European countries, including the United Kingdom.

Table 4 outlines the leading skill clusters according to ESCO Level 2. For example, the *Management skills* category encompasses skills such as project coordination, task management, and autonomy, while the *natural sciences, mathematics,* and *statistics* category reflects the essential technical foundation required in AI-driven settings. Within these broader categories, highly relevant AI-specific skills emerge, offering a clearer picture of the expertise driving innovation and operational success in the sector.

While some ESCO Level 2 categories effectively encompass AI-related skills, they represent a smaller proportion of the dataset or contain fewer AI-specific skills within their classifications. Nonetheless, these categories often include foundational skills that are essential to the successful implementation of AI initiatives. For example, the *generic programmes and qualifications* category groups transversal skills such as *communication* and *team building* — key skills that underpin effective collaboration and project execution. These foundational skills are not only critical for AI-related projects, but are also broadly applicable across diverse professional contexts, reinforcing their relevance in interdisciplinary and innovation-driven environments.

ESCO Skill (Level 2)	Top 5 skills (ESCO last level)	SI per ESCO category %
Information and Communication Technologies (ICT)	SQL, web programming, Python (computer programming), operating systems, machine learning	35.94
Business, Administration and Law	project management, ICT project management methodologies, management and administration, entrepreneurship, business strategy concepts	18.68
Working with Computers	use Microsoft office, use markup languages, programming computer systems, use spreadsheets software, use word processing software	8.13
Communication, Collaboration and Creativity	align efforts towards business development, deliver visual presentation of data, solving problems, negotiating, implement marketing strategies	7.84
Management Skills	manage teamwork, leading and motivating, lead a team, developing objectives and strategies, plan digital marketing	7.73
Natural Sciences, Mathematics and Statistics	statistics, physics, mathematics, molecular biology, 3D modelling	4.44
Engineering, Manufacturing and Construction	industrial engineering, concepts of telecommunications, computer engineering, network engineering, electronics	4.37
Information skills	research design, analyse big data, stay up to date with social media, process data, manage data	3.6
Arts and Humanities	natural language processing, graphic design, digital image processing, digital media, Unity (digital game creation systems)	1.77
Generic Programmes and Qualifications	communication, team building, personal development, personal skills and development, assertiveness	1.66
Social Sciences, Journalism and Information	economics, search engines, social network analysis, journalism, postediting	1.41
Health and Welfare	biotechnology, medical devices, medical imaging technology, pharmaceutical industry, migration	1.37
Services	dock operations, cyber security, sports, hotel operations, military aviation	0.94

ESCO Skill (Level 2)	Top 5 skills (ESCO last level)	SI per ESCO category %
Assisting and Caring	arrange tables, providing health care or medical treatments, have emotional intelligence, guarantee customer satisfaction, manage major incidents	0.73
Handling and Moving	create model, making models, install containers, pack soap, cleaning	0.33
Working with Machinery and Specialised Equipment	operate automated process control, broadcast using Internet Protocol, analyse images, use a telecine, driving vehicles	0.27
Constructing	monitor swimming-pool infrastructure, monitor system performance, conduct performance tests, constructing, test electronic units	0.21
Education	e-learning, education science, pedagogy, action research, scientific research methodology	0.16
Agriculture, Forestry, Fisheries and Veterinary	logging, e-agriculture, conservation agriculture, agroecology, agronomy	0.12
Social and Communication Skills and Competencies	social and communication skills and competencies, collaborating in teams and networks, communicating, supporting others, leading others	0.11
Core Skills and Competencies	core skills and competencies, mastering languages, working with digital devices and applications	0.05
Languages	languages	0.05
Self-management Skills and Competencies	self-management skills and competencies, maintaining a positive attitude, working efficiently, taking a proactive approach	0.04
Life Skills and Competencies	life skills and competencies, applying general knowledge, applying entrepreneurial and financial skills and competencies, applying cultural skills and competencies	0.02
Thinking Skills and Competencies	thinking skills and competencies, dealing with problems, planning and organising, thinking creatively and innovatively	0.01
Physical and Manual Skills and Competencies	physical and manual skills and competencies, responding to physical circumstances	0.00

Table 4. Most prevalent AI related skills and their skill intensity per skill category (ESCO Level 2).

In addition, the analysis identifies several ESCO Level 2 categories that are minimally represented among the most prevalent AI skill clusters. Categories such as *thinking skills* and *competencies and languages* appear less frequently in the dataset. However, this limited representation does not necessarily imply lower relevance. Rather, it reflects the current sectoral distribution of AI start-ups, which are predominantly concentrated in specific technical domains, with fewer ventures focusing on areas such as *agriculture, forestry*, or other specialised fields. This uneven distribution underscores potential gaps — and opportunities — where AI companies might expand their reach to better align with broader European policy priorities. Initiatives such as the European Green Deal, the Pact for Skills, and the Digital Education Action Plan offer strategic directions that could be supported by more diversified applications of AI technologies, especially in underrepresented sectors.

For a more detailed perspective, the analysis could be extended to ESCO Level 3, where skill categories are broken down into more specific skills. While this would provide deeper insights into the nuances of skill requirements, it would also introduce a broader and more fragmented set of categories. This, in turn, could reduce the generalisability of conclusions and complicate the overall interpretation of the results. Therefore, to preserve analytical clarity and coherence, this report focuses on the most prevalent ESCO Level 2 categories.

The **most relevant AI-related skills** at the most granular ESCO level are presented in the following figure, ordered by their prevalence across employees — and, by extension, the companies in which they work. This visualisation offers a comprehensive view of the core technical and transversal skills driving AI development across European start-ups, while also identifying areas where targeted training initiatives could further strengthen workforce capacities. To determine the most relevant skills, the following selection criteria were applied:

- A minimum of 100 employees within AI start-ups must possess the skill, ensuring broad recognition across the sector.
- Only the top 20 skills were selected for in-depth analysis.
- The scope of the analysis is limited to companies operating within European countries.

After applying these filters, a ranked list of key skills was generated, based on the percentage of AI start-ups in which each skill is present. As illustrated in Figure 3, general skills such as *project management* and *Python* (*computer programming*) proficiency are among the most prevalent, with approximately one-third of the AI start-up workforce possessing them. This prevalence is consistent with expectations, given **SkillSync's focus on start-ups operating within the artificial intelligence domain**.

Skills such as *Python* and *statistics* are widely represented across the dataset, underscoring the foundational role of programming and analytical capabilities in AI development. Additionally, data-centric skills — such as *SQL* — feature prominently, reflecting the data-intensive nature of AI-related projects.

The inclusion of domain-specific skills such as *machine learning* further highlights the sector's reliance on specialised knowledge for the design, development, and deployment of AI models. These findings collectively emphasise the importance of both general-purpose and highly technical skills in shaping a capable AI workforce. For a broader and more generalisable overview of relevant skills within the AI sector, a complementary analysis can be conducted at a higher level of aggregation within the ESCO taxonomy.

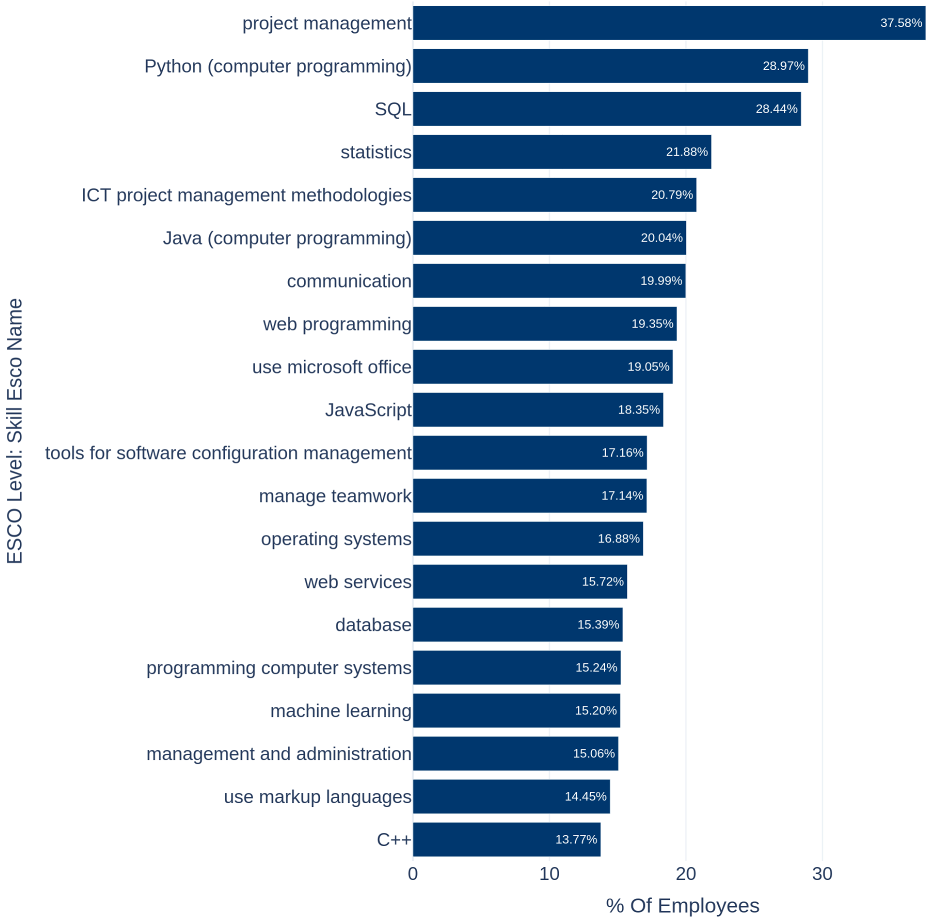

Figure 3. Most relevant skills in the dataset (at lowest ESCO level).

4.1.1.2. Most prevalent set of skills in current training offer

This section aims to analyse the most prevalent skills addressed in currently available training courses. In contrast to subsequent sections that focus on identifying skill gaps in relation to industry needs, the purpose here is to provide a snapshot of the educational landscape, capturing which skills are most frequently covered in existing offerings. As previously noted, to ensure both relevance and depth, only courses with a minimum duration of 10 hours were included in the analysis. Course content has been categorised using the ESCO taxonomy, allowing for a systematic overview of skill coverage across different levels of classification.

Furthermore, a distinction is made between courses offered by universities and those provided by non-university organisations. This differentiation enables a comparative analysis of skill coverage, highlighting the respective contributions of academic institutions and other training providers to the development of AI-related skills.

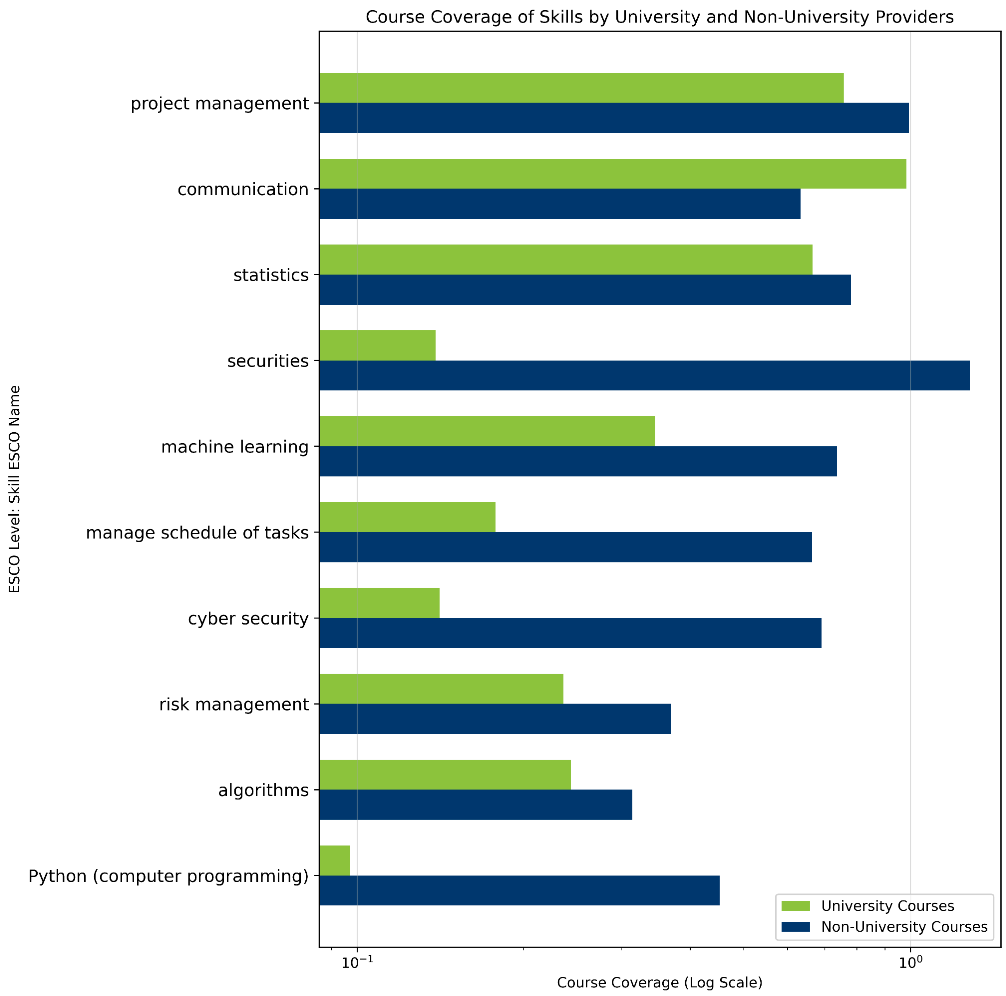

Figure 4. Logarithmic scale for top 10 course coverage of skills by university and non-university providers (ESCO Last Level)

Figure 4 presents the top 10 skills most frequently covered in training courses, as classified at the most detailed level of the ESCO taxonomy. Skills such as *project management, communication,* and *statistics* emerge as particularly prominent, with substantial coverage across both university and non-university course offerings. Notably, technical skills such as *machine learning* and *cybersecurity* are also well represented, reflecting a strong alignment between course content and the specialised skill demands of advanced AI applications.

In terms of provider distribution, university-based courses contribute significantly to the development of foundational skills, particularly *communication* and *statistics*. In contrast, non-university training providers dominate the provision of more specialised skills, including *Python* (*computer programming*) and *cybersecurity*. Actually, non-university providers surpass universities in the coverage of nearly all listed skills, except for communication. This trend highlights the prominent role of non-university institutions in delivering agile, targeted, and technically focused upskilling opportunities. The observed distribution suggests a functional division, wherein universities prioritise the development of broader, transferable skills, while non-university providers respond more directly to evolving industry demands for technical expertise.

To enhance the visibility of skills with relatively low course coverage, a logarithmic scale was applied to the x-axis of Figure 4. This allows for better interpretation of less frequent offerings, particularly in niche skill areas. At a more aggregated level of analysis (ESCO Level 2), the dominant skill categories shed light on the overarching thematic orientation of current training programs. *Information and Communication Technologies (ICT)* and *Business, Administration and Law* emerge as particularly prevalent, proposing a dual emphasis on technical proficiency and managerial acumen. Additionally, communication, collaboration, and creativity-related skills are frequently addressed, underscoring the importance of interpersonal and innovative capabilities in contemporary AI-related occupations.

As observed at a more granular level, both universities and non-university providers offer a substantial proportion of courses within broad ESCO categories such as *Information and Communication Technologies (ICT)* and *Business, Administration and Law*. However, notable distinctions emerge in their areas of emphasis. **Universities** are more prominently engaged in broad-based skill development, particularly within domains like *Natural Sciences*, which underpin data-driven disciplines central to AI. In contrast, **non-university providers** tend to concentrate on applied technical areas, including information skills and skills related to working with computers, responding more directly to immediate, market-driven demands for specialised expertise. This pattern aligns with previous findings, wherein non-university institutions surpassed universities in the coverage of most specific skills. Their capacity to offer targeted, modular, and technically focused training reinforces their role as key players in addressing evolving industry needs.

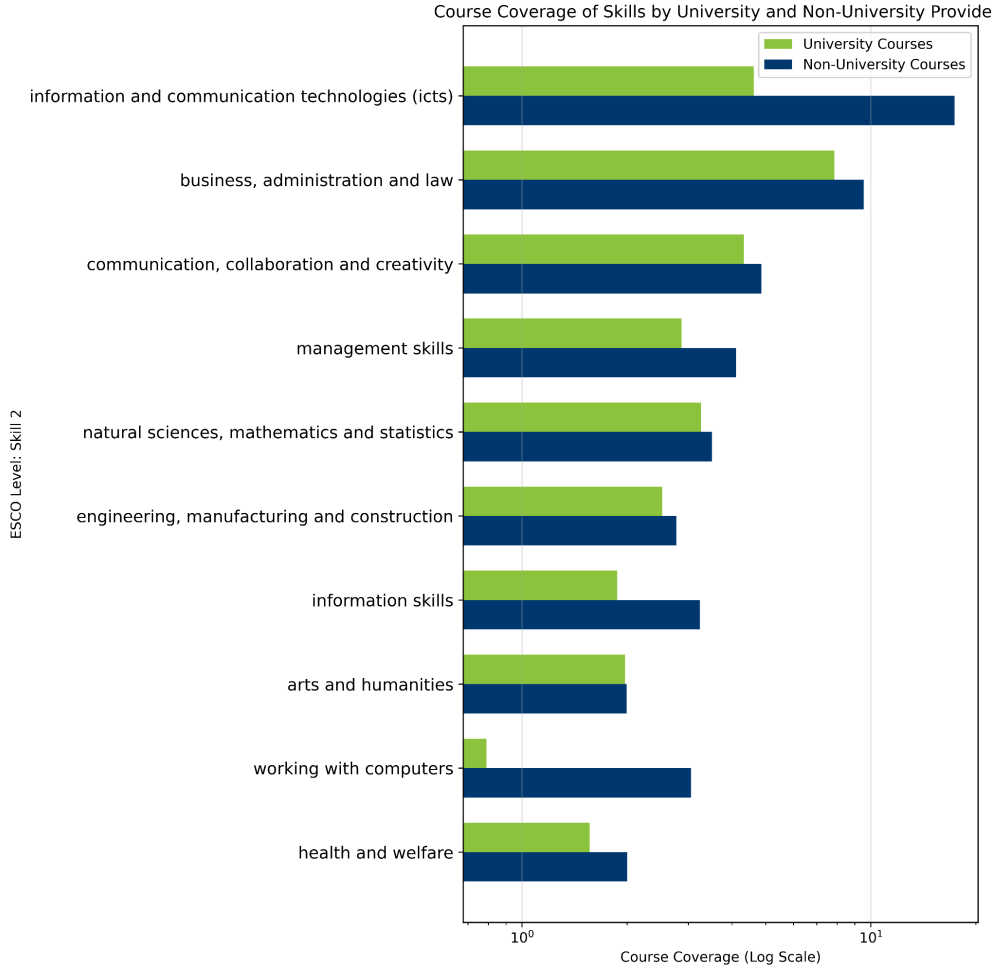

Figure 5. Top 10 course coverage of skills by university and non-university providers (ESCO Level 2). Logarithmic scale

Overall, the analysis reveals a robust training ecosystem that supports the development of both technical and transversal skills critical for professionals in the AI sector. Crucially, universities and non-university providers appear to serve complementary functions: universities contribute to foundational, transferable skill formation, while non-university providers address job-specific, practice-oriented training needs. This nuanced understanding of the current training landscape provides an essential baseline for the discussions in the subsequent sections.

4.1.2. Regional analysis

The objective of this analysis is to explore **regional similarities and differences** in workforce skills across Europe, employing NUTS levels to capture geographic granularity. In addition, the European Innovation Scoreboard is incorporated to examine the relationship between **regional skill profiles and levels of innovation**, thereby offering insight into how workforce skills align with innovation performance across the continent.

To ensure the robustness and reliability of the findings, the analysis is based on the following criteria:

- Skills must be reported by a minimum of 100 employees to be included in the dataset.
- The analysis is restricted to European countries, including the United Kingdom.

After applying these filters, the final dataset comprises 3,958 distinct skills across 31 countries at NUTS Level 0. This dataset forms the basis for a comparative analysis of regional skill compositions and their potential link to innovation outcomes across Europe.

4.1.2.1. Regional clustering of skills

European regions exhibit notable similarities in the skill sets of their professional workforces. Based on their degree of similarity, these regions can be grouped into clusters, offering valuable insights not only into the current distribution of skills but also into how regional upskilling strategies might be more effectively designed and implemented. The process of forming regional skill clusters was carried out in three main steps:

1. **Standardisation of skill sets**
   To ensure comparability across regions, skill sets were standardised. This step reduced the potential bias introduced by highly prevalent skills (e.g., *Project Management*) or by the dominance of populous countries (e.g., France and Germany). For this purpose, a specific metric — *Skill Intensity* (SI) — was developed, allowing for a more balanced representation of regional skill profiles.
2. **Development of clustering methodology**
   An unsupervised learning technique, agglomerative clustering, was applied to identify groups of regions with similar skill profiles. This method allowed for the emergence of natural clusters based solely on underlying data patterns, without the imposition of predefined categories.
3. **Results aggregation**
   Clustering results were summarised across multiple levels of skill aggregation, using the ESCO classification system. Regional groupings at the national level were defined according to the NUTS Level 0 classification. For a detailed understanding of the skills taxonomy, readers are referred to the ESCO framework.

The clustering analysis yielded six distinct country-level clusters based on similarities in AI-related skill profiles (as shown in Figures 6 and 7).

i. **Central Europe:** Germany, United Kingdom, Netherlands, France, Belgium and Switzerland
ii. **Southern Europe:** Portugal, Spain and Italy
iii. **Northern Europe:** Denmark, Norway, Sweden and Finland.
iv. **Ireland**[5]
v. **Eastern Europe & others:** Romania, Poland, Estonia, Czechia, Luxembourg, Slovakia, Cyprus, Croatia, Slovenia, Malta, Lithuania, Iceland, Latvia and Bulgaria.
vi. **Austro-Hungarian and Greek** cluster[6].

These six clusters can be grouped into two broader meta-clusters based on higher-level similarities in their workforce skill profiles:

- **Western and Northern Europe** (meta-cluster A)
  Central, Southern, Northern Europe and Ireland.

- **Expanded Eastern Europe** (meta-cluster B)
  Austria, Hungary and Greece, Eastern Europe & others.

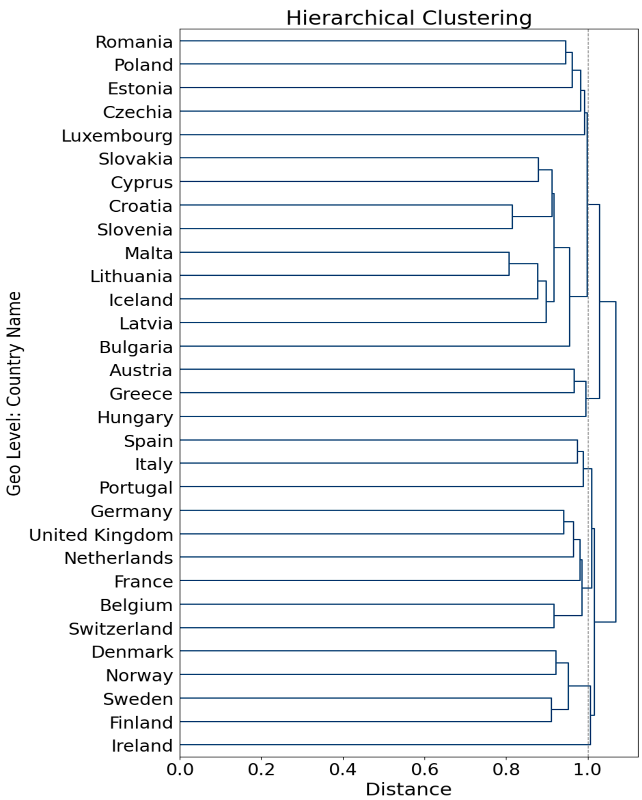

Figure 6. National pairings and groupings according to skills similarity.

[5] Ireland's skills profile is very close to the Northern Europe cluster.
[6] Austro-Hungarian and Greek cluster is very close to the Eastern Europe cluster

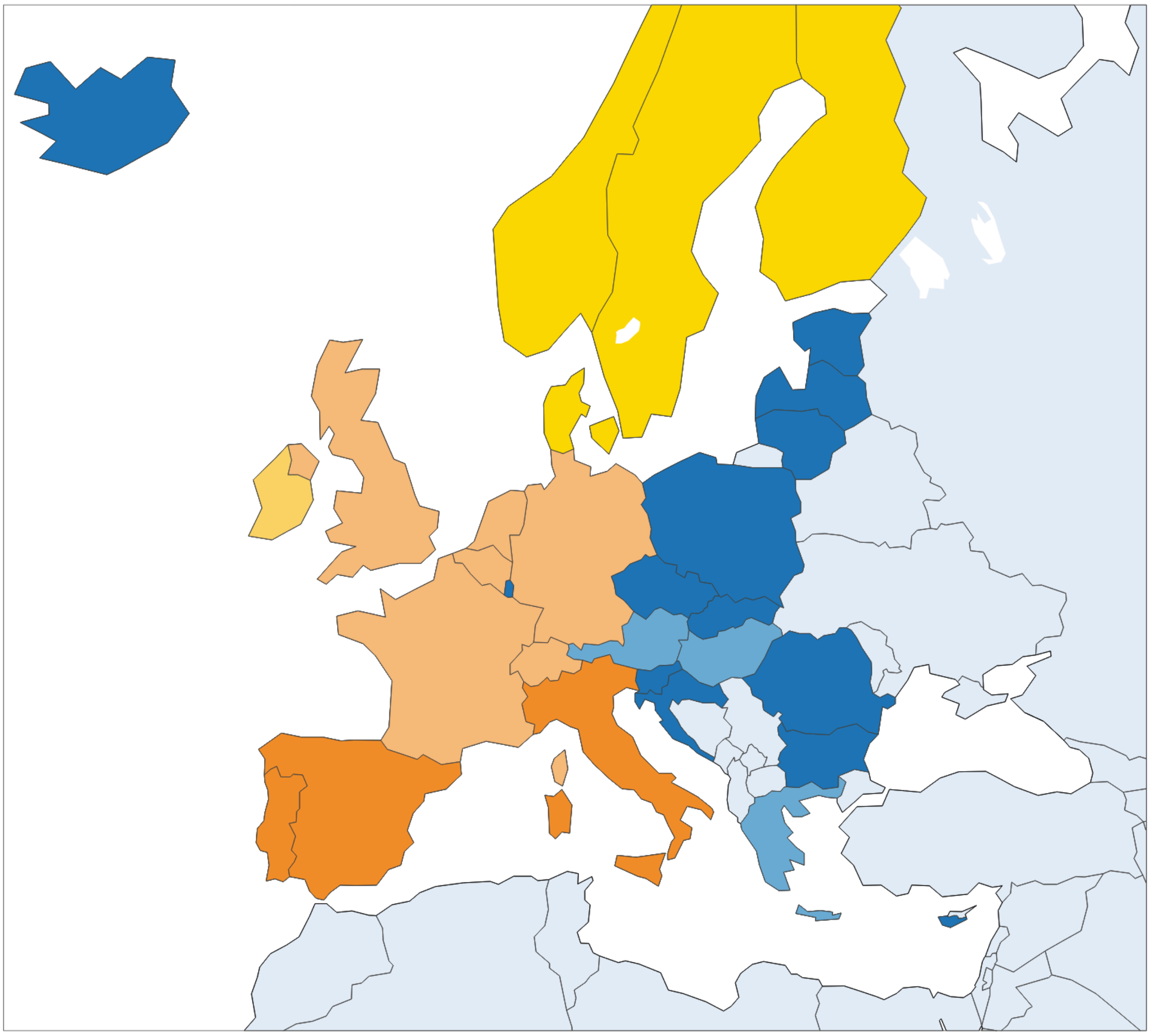

Figure 7. Geographical clusters based on similarity of skills.

The two meta-clusters reflect broader regional patterns in AI-related skills and provide a strategic framework for understanding cross-national similarities and divergences in workforce development. They can serve as a foundation for designing coordinated upskilling and reskilling initiatives at a pan-European level, considering the distinctive capabilities and needs of each regional grouping.

Building on the previous analysis, Figure 7 presents a geographical map of the regional skill clusters, offering a visual representation of how countries are grouped based on the similarity of their workforce skill profiles. By spatially displaying the data, the map not only illustrates the composition of each cluster but also highlights the geographical proximity of countries that share similar skill characteristics.

The colour scheme employed differentiates the six clusters and visually distinguishes their grouping into the two previously defined meta-clusters. This facilitates easier interpretation of regional trends and enables a more intuitive understanding of the distribution of AI-related skills across Europe. This geographic visualisation adds a critical layer of context to the analysis by supporting the identification of regional strengths, gaps, and potential areas for collaboration. It provides a strategic lens through which policymakers, educators, and industry stakeholders can assess alignment between workforce skills and broader regional development objectives.

These clusters based on the skills profiles have a strong match with those based on the Innovation performance index of the European Innovation Scoreboard (European Commission, 2024). This correlation between the innovation performance and the skills of professionals is deeply analysed in the next section.

To complement the visual insights provided in Figure 7, Table 5 presents a structured overview of the skill composition within each regional cluster. This tabular representation allows for a clearer understanding of the specific skills that define each group of countries, highlighting both areas of strength and potential skill gaps. By grouping countries based on shared workforce skill profiles, the analysis facilitates the identification of common skills as well as areas where targeted skill development may be most beneficial.

Given the extensive volume of data, Table 5 provides a summarised view by listing the five most and five least prevalent skills within each cluster. These rankings are derived from the relative frequency of specific skills among professionals in each region, offering a concise reference point for the defining characteristics of each cluster's workforce. For a more detailed account of skill distributions across clusters.

Each country is assigned to one of the six clusters based on the aggregate skill profile of its workforce. The information in Table 5 offers a high-level summary of the distinctive and recurring skill patterns observed across regions, serving as a valuable resource for identifying cluster-specific upskilling opportunities. This clustering approach supports more strategic and data-informed planning for workforce development, enabling policymakers, education providers, and industry stakeholders to align training investments with regional labour market needs.

Furthermore, this framework fosters collaboration among regions with similar skill profiles and provides a foundation for benchmarking progress in addressing skill gaps. By highlighting shared challenges and strengths, it contributes to the creation of coordinated, cross-regional strategies for building resilient and future-ready AI talent ecosystems across Europe.

	Meta-cluster A Western and Northern Europe				Meta-cluster B Expanded Eastern Europe	
	Southern Europe	Central Europe	Northern Europe	Ireland	Eastern Europe & Others	Austro Hungarian & Greece
Most prevalent Skill categories	thinking skills and competencies	health and welfare	communication, collaboration and creativity	assisting and caring	working with computers	thinking skills and competencies
	education	core skills and competencies	business, administration and law	social and communication skills and competencies	agriculture, forestry, fisheries and veterinary	physical and manual skills and competencies
	engineering, manufacturing and construction	engineering, manufacturing and construction	education	physical and manual skills and competencies	self-management skills and competencies	information and communication technologies (ICT)
	health and welfare	services	engineering, manufacturing and construction	constructing	generic programmes and qualifications	information skills
	social and communication skills and competencies	arts and humanities	management skills	communication, collaboration and creativity	life skills and competencies	engineering, manufacturing and construction
Least prevalent Skill categories	languages	education	life skills and competencies	core skills and competencies	information skills	communication, collaboration and creativity
	information and communication technologies (ICT)	generic programmes and qualifications	self-management skills and competencies	natural sciences, mathematics and statistics	physical and manual skills and competencies	core skills and competencies
	core skills and competencies	business, administration and law	information and communication technologies (ICT)	thinking skills and competencies	education	agriculture, forestry, fisheries and veterinary
	physical and manual skills and competencies	self-management skills and competencies	working with computers	agriculture, forestry, fisheries and veterinary	health and welfare	generic programmes and qualifications
	business, administration and law	working with computers	thinking skills and competencies	social sciences, journalism and information	engineering, manufacturing and construction	management skills

Table 5. Skills prevalence per cluster - 5 most and least prevalent skill categories (ESCO Level 2).

Based on the data presented in Table 5, the following analysis explores the distinctive skill patterns of each regional cluster and their grouping into two broader meta-clusters:

Meta-cluster A (*Western and Northern Europe*) is characterised by a high prevalence of cognitive, transversal skills. These include *health and welfare, communication, collaboration and creativity,* and *engineering, manufacturing and construction*. These categories are strongly associated with higher levels of innovation and adaptability, aligning with the high innovation scores as shown in the following sections.

- **Southern Europe** shows a balanced skill composition with a strong presence of *thinking, engineering*, and *health and welfare* skills. Its high ranking in *social and communication skills* suggests a workforce profile well-aligned with service-oriented and collaborative environments. However, *ICTs* and *language skills* appear among the least prevalent, pointing to opportunities to reinforce digital and international competencies.
- **Central Europe** stands out for its emphasis on *health and welfare, core skills and competences,* and *engineering*, reflecting a technically solid and well-rounded employees. The lower presence of *education* and *generic programmes and qualifications* may initially appear as a gap; however, this is consistent with the nature of AI-focused start-ups, which tend to prioritise specialised, applied skills over broader academic or generalist training. This suggests that while formal education pathways may be less represented, there is strong reliance on practical, domain-specific expertise and on-the-job learning, characteristic of agile innovation environments.
- **Northern Europe** presents a profile heavily oriented towards *communication*, *business administration, and management* skills, indicative of a mature, innovation-driven economy. The relatively lower intensity in *ICTs*, *working with computers*, *thinking* and *life* skills further reinforces this positioning, as it reflects a workforce primarily engaged in high-level, knowledge-intensive roles rather than operational or routine tasks. This skill composition is typical of advanced innovation ecosystems, where value creation relies more on strategic thinking, leadership, and collaboration than on basic technical or manual competences.
- **Ireland** differs from other members of Meta-cluster A by exhibiting a stronger emphasis on *physical and manual skills, assisting and caring,* and *construction*. While it shares strengths in *communication and collaboration*, the relatively low presence of *mathematics and statistics* and *core skills* may indicate the need to further strengthen STEM and foundational competencies to complement its practical expertise.

Overall, Meta-cluster A includes countries with more advanced innovation systems and a diverse mix of skills that support complex, knowledge-intensive work. The diversity within the meta-cluster suggests strong potential for *specialisation and mutual reinforcement through collaborative upskilling strategies.*

Meta-cluster B (*Expanded Eastern Europe*) shows a more technical and operational skill orientation. Categories such as *physical and manual skills, ICTs, working with computers,* and *agriculture* are more prevalent, whereas transversal competencies appear consistently underrepresented depending on the cluster.

- **Eastern Europe & Others** *(Romania, Poland, Estonia, Czechia, Luxembourg, Slovakia, Cyprus, Croatia, Slovenia, Malta, Lithuania, Iceland, Latvia and Bulgaria)* show a similarly technical profile as the *Austria, Hungary & Greece* cluster, with an emphasis on *self-management, computing,* and *agricultural* skills. Gaps in *thinking skills, education,* and *communication* reflect challenges in promoting adaptability and creativity, which are critical for AI and digital transformation.

- **Austro-Hungarian and Greek cluster** displays strengths in *manual, ICT,* and *information skills*, suggesting a workforce with practical and technical proficiency. However, *management skills* or *communication collaboration*, and *creativity* are among the least prevalent, highlighting key areas where strategic investment in soft skills and leadership development could enhance regional innovation potential.

In contrast with Meta-cluster A, the regions in Meta-cluster B may benefit most from targeted development of transversal and innovation-enabling skills. Tailored training strategies should aim to enhance digital fluency, soft skills, and lifelong learning mechanisms to support future competitiveness.

In summary, this regional clustering reveals valuable insights into the distribution of skills across Europe. By identifying shared strengths and region-specific gaps, the analysis supports the design of more effective and geographically tailored upskilling policies. Furthermore, the complementarities between clusters and meta-clusters offer opportunities for interregional cooperation, knowledge transfer, and joint training initiatives.

4.1.2.2. Skills vs European Innovation Scorecard

This section examines the relationship between regional Skill Intensity (SI) and innovation performance, using the European Innovation Scoreboard (EIS) as a benchmark for assessing innovation across European regions. The EIS's core metric — the summary innovation index (SII) — ranks regions based on a composite of indicators including research activity, investment in R&D, and the availability of human resources in science and technology. By linking regional SII scores to Skill Intensity, the analysis aims to identify the specific skills that are most strongly associated with higher levels of innovation output.

This approach provides valuable insights into the skill sets that underpin regional innovation capacity and can inform the design of targeted upskilling strategies to enhance innovation potential. To perform this analysis, SII data was retrieved from Eurostat and integrated with the SkillSync database. This combined dataset enables a robust exploration of the alignment between regional skill composition and innovation performance across Europe.

4.1.2.2.1. Innovation index levels vs skills intensity: Heatmap

In this analysis, regional clusters were examined based on their innovation rankings, as defined by the European Innovation Scoreboard (EIS). By grouping regions into the EIS performance tiers — Innovation Leaders, Strong Innovators, Moderate Innovators, and Emerging Innovators — we facilitate a structured comparison of prevalent skill intensity (SI) levels across varying degrees of innovation performance. This approach enables the identification of specific skills consistently associated with top-performing regions, offering insight into the skills that may contribute to elevated innovation output.

Conversely, it helps uncover potential skill gaps in less innovative regions, revealing strategic opportunities for targeted upskilling and workforce development. Understanding these regional skill differentials is key to aligning training initiatives with innovation objectives, addressing territorial disparities, and fostering more inclusive and balanced innovation-led growth across Europe.

Key findings from this comparative analysis include:

- The **Innovation Leaders** group exhibits a high concentration of skills in areas such as *management and information skills*, *natural sciences, mathematics and statistics*, and *communication, collaboration, and creativity*. This points to a solid foundation in both technical and managerial skills, which are critical to sustaining high innovation performance.

- A distinct set of skill categories appears prominently in the Leaders group but is notably underrepresented in the **Emerging Innovators** group. These include:
    - **Management skills:** Skills in organising, planning, and leading teams or projects, essential for both strategic leadership and operational effectiveness.
    - **Health and welfare:** Skills related to healthcare provision, well-being, and social support systems, important for innovation in public health and care sectors.
    - **Natural sciences, mathematics, and statistics:** Analytical and quantitative skills fundamental to scientific research, data analysis, and evidence-based decision-making.
    - **Engineering, manufacturing, and construction:** Technical skills related to design, production, and infrastructure development, reflecting capabilities vital for industrial and technological innovation.

In contrast, the **Strong Innovators** group presents a more evenly distributed skills profile, with minimal variance in Skill Intensity across categories. This balanced distribution suggests a broad and versatile workforce skill base, potentially supporting adaptability and cross-sectoral innovation.

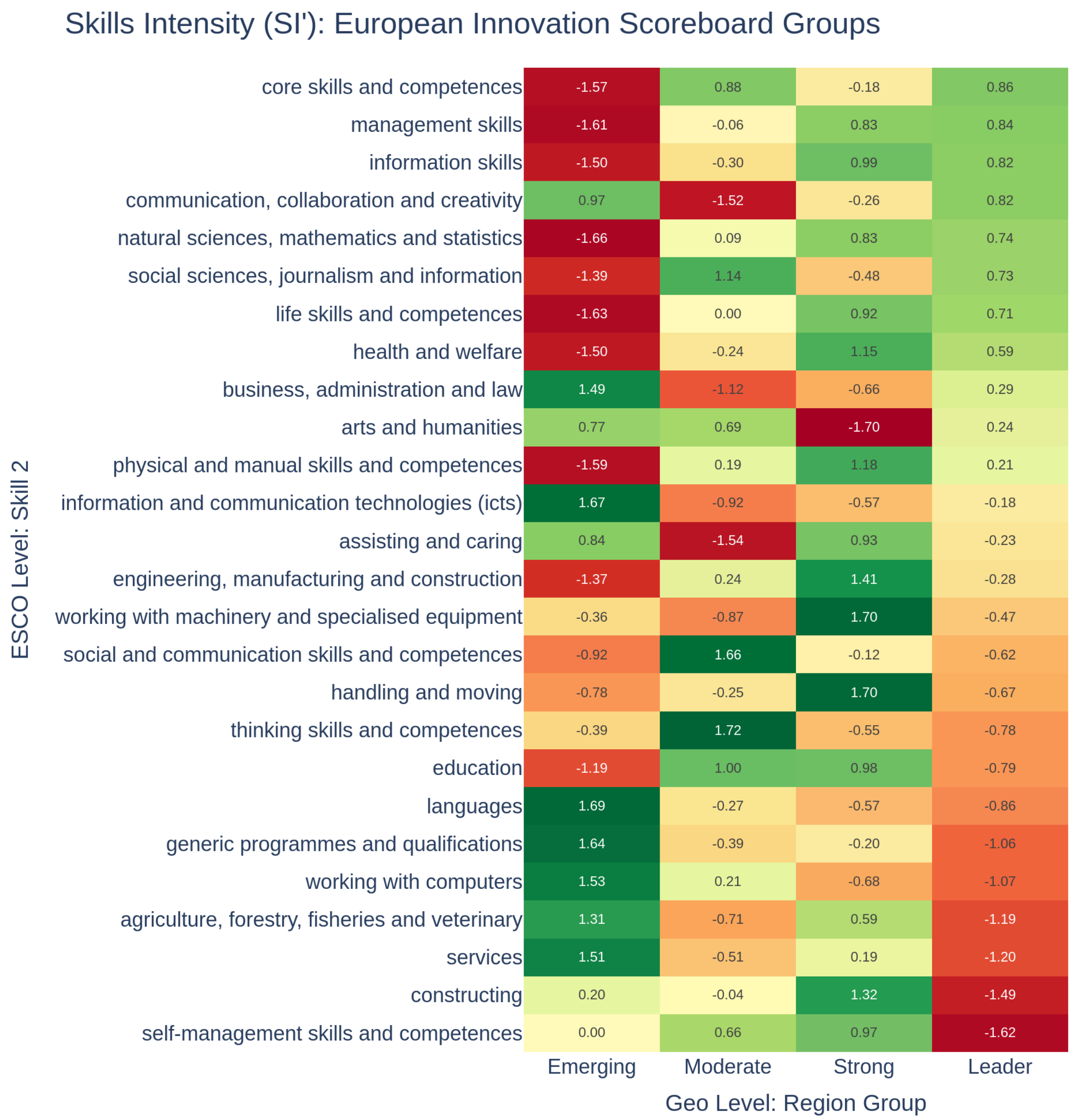

Figure 8. Correlation between skill intensity (SI') at ESCO Level 2 and group of innovation index.

4.1.2.2.2. Summary innovation index vs skills intensity: Correlation analysis

Building on the comparative analysis, a correlation analysis was conducted to examine the extent to which variations in *Skill Intensity* (SI) across European regions align with their respective European Innovation Scoreboard (EIS) scores. By statistically correlating skill intensity with regional innovation performance, as measured by the *Summary Innovation Index (SII)*, this analysis aims to pinpoint the specific skill domains most strongly associated with innovation outcomes. Key findings from the correlation analysis include:

- **Skills linked to advanced technological sectors beyond traditional IT** — such as *natural sciences*, *healthcare and welfare*, *manufacturing*, and *specialised technical fields* — demonstrate the strongest positive correlation with higher SII scores. These skills appear to be central drivers of regional innovation, supporting R&D-intensive activities, complex problem-solving, and knowledge-based economic growth.

- In contrast, **skills primarily associated with conventional IT domains** — including *basic programming*, *general office software proficiency*, and *routine digital tasks* — tend to correlate negatively or weakly with SII scores. While these skills are important for ensuring baseline digital literacy and operational efficiency, they do not appear to contribute significantly to the kind of high-value innovation measured by the index. Their functional role supports foundational infrastructure rather than frontier innovation, thus limiting their impact on overall innovation performance.

This distinction underscores the importance of fostering advanced, interdisciplinary, and sector-specific skills to enhance regional innovation capacity, particularly in areas aligned with Europe's strategic innovation and industrial priorities.

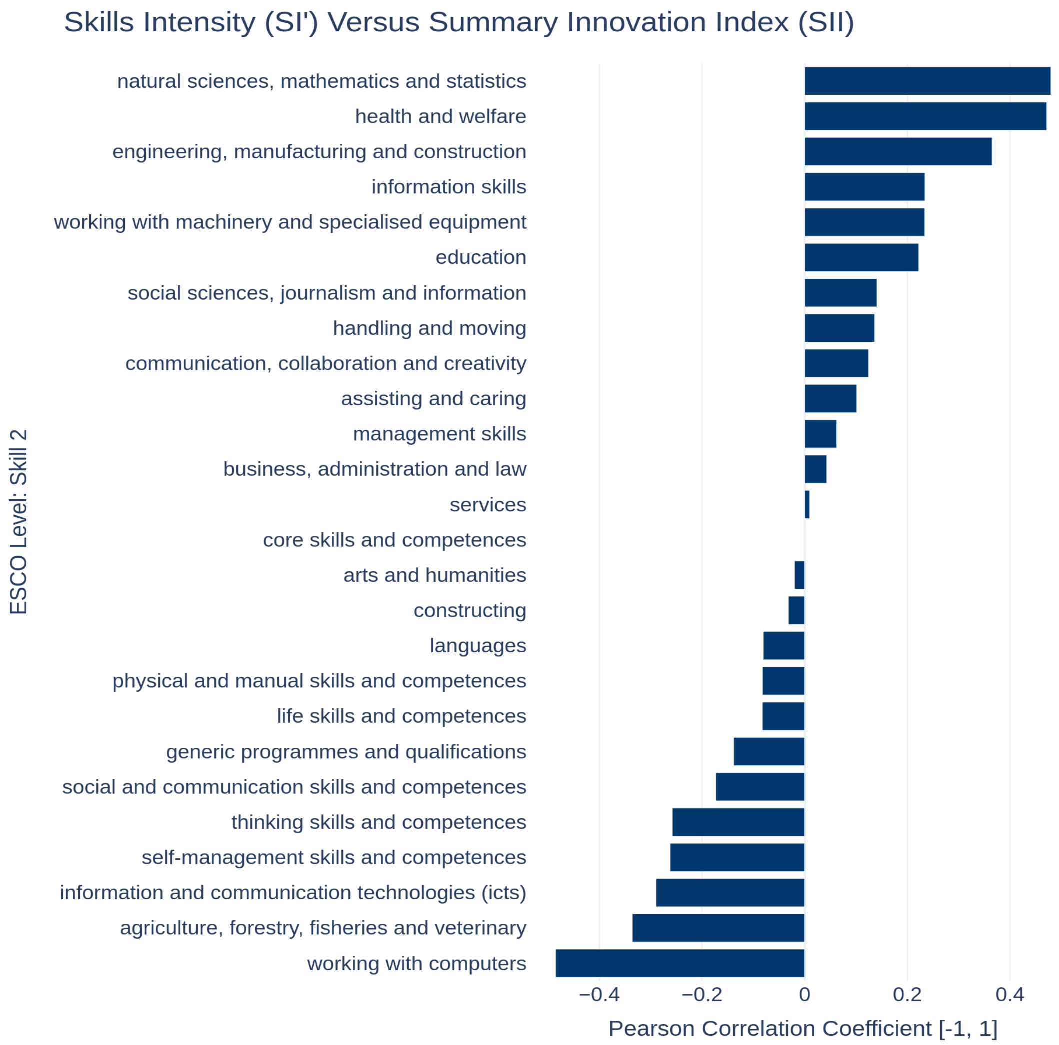

Figure 9. Correlation between SII and ESCO Level 2 SI'.

4.2. How to make Europe more innovative

To reinforce Europe's position as a global leader in Artificial Intelligence, it is essential to address existing skill gaps within the workforce and implement targeted upskilling initiatives. A highly skilled and adaptable workforce is a fundamental enabler of innovation, equipping start-ups to effectively respond to technological advancements, shifting market demands, and strategic priorities such as digital transformation and sustainability.

This section aims to identify specific areas of expertise that are currently underrepresented in European AI-focused start-ups and that may be constraining innovation and competitiveness. By analysing both skill deficits and the landscape of available upskilling opportunities, we can develop informed strategies to enhance the AI capabilities of professionals across diverse sectors and strengthen the development and adoption of AI-driven solutions.

The analysis is structured into two key components:

- **Identification of missing skills:** This subsection highlights skills that are underrepresented or absent in the current skill sets of AI professionals in Europe. Identifying these gaps is critical for anticipating future demands and ensuring that start-ups are equipped to innovate, scale, and remain competitive in a fast-evolving technological landscape.
- **Upskilling recommendations:** Building on the identified gaps, this subsection presents strategic guidance for addressing skill shortages through targeted training interventions. Recommendations are grounded in a comparative analysis of existing course offerings — spanning both university and non-university providers — as well as regional skill needs as identified in previous sections.

Through this approach, we aim to provide actionable insights to support European start-ups in building a resilient and future-ready talent base. Ultimately, this will contribute to consolidating Europe's leadership in AI innovation and ensuring that its workforce remains aligned with the demands of a rapidly evolving global AI ecosystem.

4.2.1. Missing skills

To enhance Europe's competitive position in Artificial Intelligence, it is critical to identify and address skill gaps at the **regional level**. Understanding which skills are underrepresented in specific regions — and how these gaps may be limiting innovation capacity — can support the development of targeted upskilling strategies. By addressing these deficiencies, regions can better align their workforce capabilities with those of higher-performing peers, ultimately fostering more balanced and inclusive innovation across Europe.

This analysis focuses on identifying key missing skills in each region, based on its **Summary Innovation Index score** and its **proximity** — defined in terms of skill similarity — to other regions with stronger innovation performance. The methodology is structured in three main steps:

- **Skill similarity grouping by region:** To ensure a detailed and context-sensitive analysis, regions are assessed at the most granular NUTS level. Each region is paired with the most similar region in terms of skill profile that also possesses a higher Innovation Index. This approach enables the identification of realistic and relevant skill development targets by comparing regions that share workforce characteristics but differ in innovation outcomes.

- **Identification of skills to improve:** For each region, we determine the top 10 skills that are more prevalent in the reference region (i.e. the region with a higher innovation score) but less prevalent in the target region. These skills represent actionable development priorities-skills that, if strengthened, may significantly contribute to increasing the target region's innovation potential.

- **Consolidation of missing skills by innovation tier:** After identifying the skill gaps for each region, the data are aggregated by Innovation Index tier (Emerging, Moderate, Strong, Leader). This step yields a consolidated overview of the most frequently missing skills associated with each innovation category, offering strategic insight into common regional challenges and shared opportunities for targeted intervention.

The analysis produced a comprehensive inventory of **missing skills** for each region, organised by their Innovation Index classification. Below, we present the most frequently missing skills at ESCO Level 4 within each innovation tier, with a particular emphasis on skills that are *uniquely absent* in specific innovation categories.

The patterns observed in skill deficiencies across innovation levels broadly reflect the foundational needs of AI-driven regional ecosystems. For instance, core skills in fields such as *law*, *medicine*, and *financial or economic data analysis* appear consistently across regions. These skill areas form a critical base for sustainable innovation and growth, particularly in sectors where regulatory knowledge, health systems, and financial literacy intersect with AI applications. This finding reinforces earlier insights (see Figure 9) indicating the importance of a strong foundation in finance and legal literacy as enablers of technological advancement.

	Top 10 missing skills (ESCO Level 4) per Summary Innovation Index (SII)			
	Emerging	Moderate	Strong	Leader
1.	creating artistic designs or performances	analysing financial and economic data	operating lifting or moving equipment	operating lifting or moving equipment
2.	operating audio-visual equipment	database and network design and administration	operating machinery for the manufacture and treatment of textiles, fur and leather products	planning events and programmes
3.	analysing financial and economic data	biology	planning events and programmes	philosophy and ethics
4.	medicine	operating audio-visual equipment	architecture and town planning	analysing financial and economic data
5.	selling products or services	using digital tools to control machinery	operating audio-visual equipment	developing objectives and strategies
6.	using digital tools for collaboration and productivity	operating lifting or moving equipment	philosophy and ethics	recording legal information
7.	working in teams	operating machinery for the manufacture and treatment of textiles, fur and leather products	analysing financial and economic data	operating machinery for the manufacture and treatment of textiles, fur and leather products
8.	work skills	medicine	allocating and controlling resources	mining and extraction
9.	management skills	designing systems and products	medicine	developing policies and legislation
10.	environmental protection technology	architecture and town planning	law	training on operational procedures

Table 6. Top 10 missing ESCO skills categories per Summary Innovation Index (SII) regions.

However, while certain skill gaps are shared, it is crucial to **consider the order of priority** in which regions require these missing skills. The urgency and relevance of each skill differ based on a region's specific stage in AI development and its broader innovation trajectory. This nuance is essential for designing tailored upskilling strategies that are not only aligned with regional capacities and goals, but also capable of delivering efficient and impactful outcomes.

Moreover, distinct variations in skill gaps emerge across regions, highlighting unique needs and opportunities for targeted interventions. These differences reflect the heterogeneous nature of Europe's innovation landscape and the need for place-based policy approaches that respond to local strengths and limitations. The following breakdown provides a region-by-region summary of the most salient missing skills, supporting the formulation of customised pathways toward AI-enabled innovation.

- **Emerging Regions**
  These regions display foundational skill gaps, particularly in areas related to *management* (e.g. using digital tools for collaboration and productivity, working in teams, and basic management skills) and *marketing* (e.g. selling products or services, creating artistic designs or performances). These skills are essential for attracting and sustaining AI-related projects, as they support both internal operational efficiency and external market engagement.
- **Moderate Regions**
  Skill gaps in moderate regions indicate a transition toward more advanced skills. Missing skills include *system and product design*, *database and network design and administration*, and *biological sciences*. This reflects the growing need for technical and domain-specific knowledge as these regions progress toward higher levels of innovation in technology and natural sciences.
- **Strong Regions**
  These regions exhibit skill gaps that are partially aligned with those of both Moderate and Leader regions. A notable distinction, however, is the absence of skills related to *allocating and controlling resources*, underscoring an emerging need for *strategic and operational management* skills within highly technical environments. This suggests that strengthening managerial skills could enhance coordination and scalability in innovation processes.
- **Leader Regions**
  Despite their high innovation performance, Leader regions demonstrate gaps in *legal and regulatory skills* (e.g. recording legal information, developing policies and legislation). This highlights the increasing importance of legal expertise in managing complex AI systems and innovation ecosystems. Addressing these gaps can improve *contract management*, *regulatory compliance*, and *ethical governance*, all of which are critical for sustaining responsible innovation in high-performing regions.

The analysis of skill gaps across Europe's regions reveals that, while certain skills are universally important, each region exhibits distinct priorities for targeted upskilling aligned with its current innovation status. Emerging regions require foundational business and digital skills — particularly in management and marketing — to build the capacity to attract and sustain AI-related initiatives. Moderate regions must strengthen their technical and scientific capabilities, with particular emphasis on system design, database administration, and biological sciences, to move toward more innovation-intensive activities. Strong regions should prioritise advanced management skills, particularly in resource allocation within technical domains, to support the coordination and scaling of innovation. Finally, Leader regions — despite their high levels of performance — face gaps in legal and regulatory expertise, highlighting the need to enhance capabilities in policy development, legislative processes, and ethical compliance to manage the complexities of AI deployment.

Adopting a targeted, region-specific approach to upskilling, grounded in each region's unique innovation trajectory, will enable Europe to build progressively on existing strengths while addressing strategic weaknesses. By investing in tailored skills development, the European AI ecosystem can foster inclusive and sustainable innovation, ensuring that all regions contribute to and benefit from Europe's continued leadership in Artificial Intelligence.

4.2.2. Upskilling recommendations

To effectively address the skill gaps identified across European regions and strengthen their AI capabilities, this section examines the availability and relevance of targeted training programmes aligned with the specific upskilling needs of regions at each level of the Summary Innovation Index: *Emerging*, *Moderate*, *Strong*, and *Leader*. By assessing the extent to which key AI-related skills — identified as missing in previous analyses — are covered by current training offerings, we aim to evaluate whether the existing educational landscape supports regional efforts to enhance innovation capacity.

Drawing on the SkillSync filtered course dataset (see Section 3.2.2), which includes a diverse array of relevant training programmes mapped to skills in the ESCO taxonomy, we calculate the percentage of courses that address each of the missing skills identified in Section 4.2.1. This approach enables a detailed examination of how well current training provision — distinguished by university and non-university providers — aligns with regional skill needs. In doing so, the analysis identifies whether existing educational resources are sufficient or whether additional policy and investment efforts are required to expand training opportunities in specific domains or geographies.

Given that many of the missing skills are shared across innovation tiers, we present a consolidated visualisation rather than disaggregated charts for each group. This aggregated perspective, illustrated in Figure 10, allows for a comprehensive assessment of overall coverage across all innovation levels, highlighting the respective contributions of university and non-university institutions in addressing skill gaps. Furthermore, it helps to identify skill categories that remain consistently underserved, regardless of a region's innovation standing — thereby flagging priority areas for targeted upskilling investment.

To improve the interpretability of skills with limited course coverage, a logarithmic scale has been applied to the x-axis in Figure 10. This adjustment enhances the visibility of low-frequency skill categories that may otherwise be obscured.

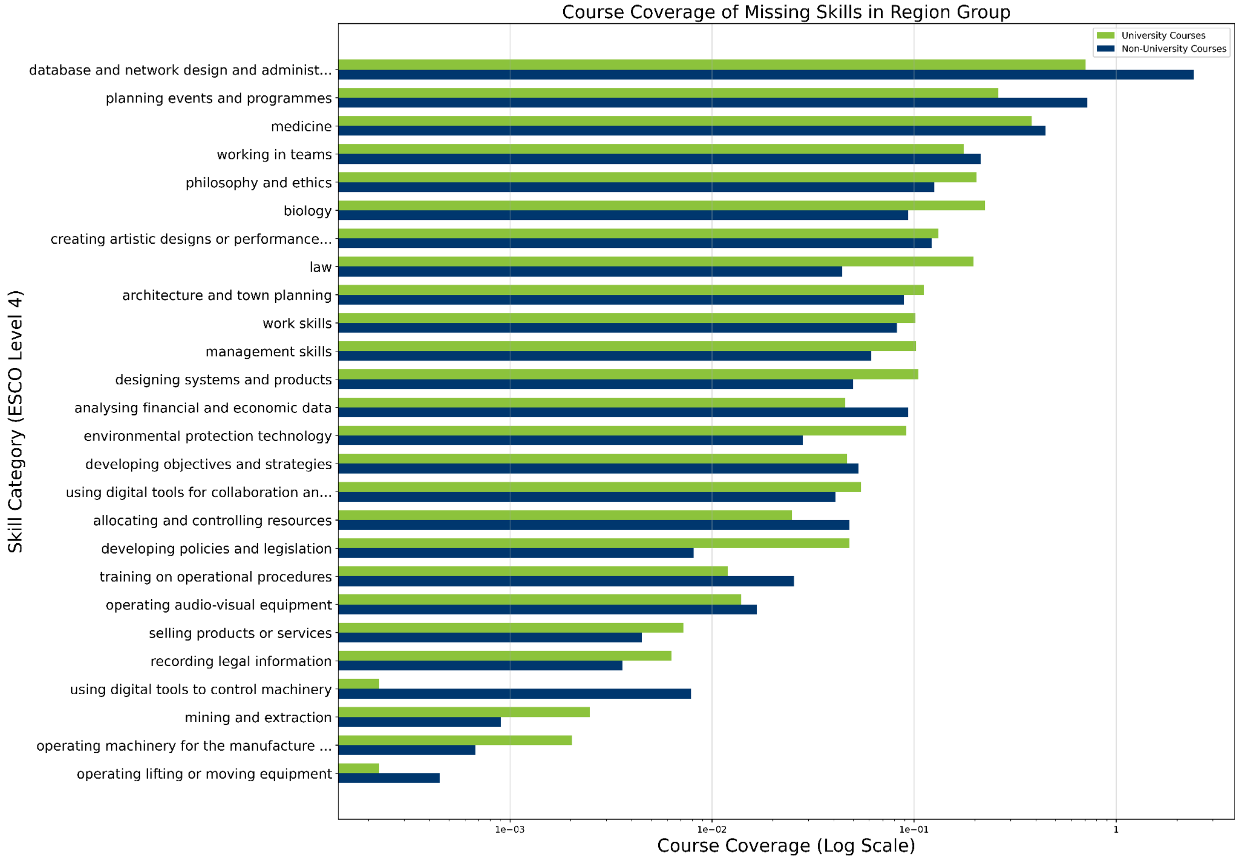

Figure 10. Course coverage for missing skills of all innovation index groups (axis x in logarithmic scale).

The proportion of university and non-university training courses covering each identified skill gap is shown in Figure 10, using a logarithmic scale to enhance the visibility of categories with limited course offerings. This visualisation provides a comparative perspective on the availability of educational resources designed to address region-specific skill needs, as identified by their respective "Skill Intensity" classification.

By analysing course coverage by both skill category and provider type, the analysis offers relevant insights into the alignment between current training provision and the skill demands of regions at different innovation levels. Contributions from both university and non-university providers vary across skill domains, revealing the following patterns:

- **High coverage:** Skills in areas such as *Law*, *Medicine*, and *Philosophy and Ethics* show relatively high coverage from both university and non-university providers. This is encouraging, given that these skills are recognised as foundational across all innovation tiers. The breadth of offerings in these areas supports broad accessibility and facilitates rapid upskilling.

- **Balanced coverage:** Skill sets such as *Using digital tools for collaboration and productivity* and *allocating and controlling resources* are also well-supported by both types of providers. These skills are especially relevant to innovation-driven environments, where digital coordination and efficient resource management are critical enablers of performance.

- **Low coverage:** Certain skill domains — such as *Operating lifting or moving equipment* — are covered far less frequently in existing course offerings. Despite being less directly associated with high-tech AI roles, gaps in these areas could affect specific sectors or regions where such operational skills are essential to supporting broader innovation goals. Left unaddressed, these shortfalls could hinder regional competitiveness.

Given the variation in course coverage, each region should prioritise upskilling in skill categories most closely aligned with its immediate and long-term development needs. While many regions share foundational skill requirements, the prioritisation and urgency of these needs vary, reinforcing the importance of customised and context-specific training strategies.

In conclusion, although non-university providers are making significant contributions to meeting current skill demands, there remains a critical need for universities to expand their targeted offerings, particularly in areas with limited coverage. A balanced and complementary approach — leveraging both academic institutions and agile non-university providers — will be essential for building a robust, future-ready workforce. Such coordination will support a more coherent and inclusive European skills agenda, enabling all regions to progress along their respective innovation pathways.

5. Conclusions

This report offers a comprehensive analysis of AI-related skill dynamics within European start-ups, identifying the specific expertise required to enhance AI capabilities across diverse regional contexts. Employing the ESCO taxonomy, regional clustering, and the Skill Intensity (SI) metric, the study has enabled a detailed mapping of both prevalent and underrepresented skills, offering actionable insights into workforce strengths and gaps. The main key conclusions emerging from the findings include:

1. **Strong foundation in technical and analytical skills:** European AI start-ups demonstrate a robust foundation in core technical skills such as Python programming, machine learning, statistics, and data management (e.g., SQL and database design). These skills are particularly concentrated in roles such as Data Scientists, AI Engineers, and Computer Vision Specialists. The dominance of these skills reflects the data-centric and algorithm-driven nature of contemporary AI development.

2. **Divergence between general and specialised roles:** The ESCO-based classification illuminates a dual structure in skill distribution: foundational skills (e.g., project management, spreadsheet use) are widely shared across roles, while specialised skills (e.g., deep learning, computer vision, or bioinformatics) are concentrated in specific occupational niches. This indicates the coexistence of horizontal and vertical skill pathways within the AI workforce.

3. **Core AI skills across regions:** Foundational AI-related skills — such as software development, data management, and project management — are consistently prevalent across all regions, regardless of innovation maturity. These core skills form the technical and administrative backbone of AI-driven innovation and are essential for supporting sustainable growth across sectors. Their ubiquity underscores the importance of maintaining a robust base of generalisable, high-impact skills.

4. **Regional skill gaps and priorities:** Despite shared core skills, each region demonstrates distinct skill gaps and upskilling priorities aligned with their respective positions on the innovation spectrum. *Emerging regions* tend to lack foundational skills in data and interdisciplinary skills, while *Leader regions* increasingly require specialised expertise in advanced systems, automation, and legal frameworks. These differences call for tailored, region-specific upskilling strategies that support local innovation trajectories.

5. **Training ecosystem mirrors sectoral demands but reveals gaps:** Current training offers — particularly from non-university providers — are well-aligned with immediate technical

demands, offering significant coverage in areas like Python, machine learning, and cybersecurity. However, gaps remain in the provision of interdisciplinary and sector-specific training, particularly in niche domains or emerging AI applications. Universities tend to focus on foundational skills, suggesting a complementary but potentially under-leveraged role in meeting fast-evolving skill needs.

6. **Training ecosystem must evolve to address strategic skill gaps:** While many high-priority skills are addressed through current training offerings, others — such as those related to logistics, audiovisual operations, and domain-specific legal or regulatory knowledge — remain underserved. A more proactive alignment between training provision and regional innovation objectives is necessary to foster inclusive AI-driven growth.

7. **Regional clustering of skill profiles:** Through a data-driven clustering methodology, the study identifies six broad regional skill clusters, each representing common strengths and shared areas for development. These groupings provide a valuable framework for collaborative upskilling initiatives, enabling regions with similar profiles to share resources, co-develop training programmes, and coordinate policy responses tailored to their specific workforce needs.

8. **Correlation with the European Innovation Scorecard:** The analysis reveals a positive correlation between innovation output and the presence of skills in advanced domains, including engineering, healthcare, manufacturing, and natural sciences. Regions that demonstrate higher concentrations of these skills tend to perform better on the innovation index, suggesting that investment in high-impact skill domains can enhance regional competitiveness and AI leadership.

9. **Skill intensity correlates with innovation performance:** The regional analysis indicates that higher innovation scores are associated with stronger representation of management, communication, and natural science-related skills. This suggests that high innovation performance requires a broader skill mix that goes beyond technical proficiency to include strategic, organisational, and scientific capabilities.

10. **Regional clustering reveals shared strengths and gaps:** The six regional clusters and two meta-clusters identified in the analysis reflect distinct patterns in workforce skill composition. Meta-cluster A (Western and Northern Europe) is more closely associated with skills linked to innovation leadership, whereas Meta-cluster B (Expanded Eastern Europe) demonstrates foundational gaps in digital and managerial skills. These distinctions underline the need for tailored, regionally sensitive upskilling strategies.

11. **Strategic upskilling recommendations:** To close the identified skill gaps, the report recommends a balanced and coordinated upskilling strategy that combines the strengths of both university and non-university providers. Targeted course development — especially in underrepresented foundational and interdisciplinary skills — is essential for elevating regional innovation capacity. Crucially, these efforts must be customised to the unique skill profiles and innovation ambitions of each region.

This report provides a strategic framework for aligning AI skill development with regional innovation goals, offering actionable insights to support evidence-based workforce and education policy.

By fostering a balanced mix of foundational and specialised skills, and by mobilising a diverse ecosystem of training providers, Europe can develop a resilient and future-ready AI talent pipeline. Such a coordinated approach is essential for maintaining Europe's global leadership in AI, driving inclusive growth, and enabling innovation across all regions.

6. References

ARISA, *'Core Curricula for AI-related roles, D4.2 Core Curricula'*. 2024
https://aiskills.eu/wp-content/uploads/2024/10/D4.2_Core-Curricula.pdf

ARISA, "*AI Skills Needs Analysis - An insight into the AI roles and skills needed for Europe*", 2023.
https://aiskills.eu/wp-content/uploads/2023/06/ARISA_AI-Skills-Needs-Analysis_V1.pdf

High-Level Expert Group on Artificial Intelligence (HLEG AI), *'Ethics Guidelines for Trustworthy AI'* 2019.
https://digital-strategy.ec.europa.eu/en/library/ethics-guidelines-trustworthy-ai

European Centre for the Development of Vocational Training (Cedefop), *'The future of vocational education and training in Europe: synthesis report'* 2023.
https://www.cedefop.europa.eu/files/3094_en.pdf

European Centre for the Development of Vocational Training (Cedefop), "*Skills empower workers in the AI revolution - First findings from Cedefop's AI skills survey*", Policy Brief, 2025.
https://www.cedefop.europa.eu/en/publications/9201

European Commission (EC); Directorate-General for Research and Innovation, "*European Innovation Scoreboard 2024*", Publications Office of the European Union, 2024.
https://data.europa.eu/doi/10.2777/779689

European Commission (EC); "*AI Continent Action Plan*". COM(2025) 165; 2025.
https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=COM:2025:165:FIN

McKinsey Global Institute, *'The future of work in Europe: Automation, workforce transitions, and the shifting geography of work'*, 2020.
https://www.mckinsey.com/~/media/mckinsey/featured%20insights/future%20of%20organizations/the%20future%20of%20work%20in%20europe/mgi-the-future-of-work-in-europe-discussion-paper.pdf

OECD, *'Artificial Intelligence in Society'*, OECD Publishing, Paris, 2019.
https://www.oecd-ilibrary.org/science-and-technology/artificial-intelligence-in-society_eedfee77-en

OECD, "*Artificial intelligence and the changing demand for skills in the labour market*", OECD, Paris, 2024a.
https://www.oecd.org/en/publications/artificial-intelligence-and-the-changing-demand-for-skills-in-the-labour-market_88684e36-en.html

OECD, "*Who will be the workers most affected by AI? A closer look at the impact of AI on women, low-skilled workers and other groups*". OECD Publishing, Paris, 2024b.
https://www.oecd.org/en/publications/who-will-be-the-workers-most-affected-by-ai_14dc6f89-en.html

OECD, "*Emerging trends in AI skill demand across 14 OECD countries*", OECD Publishing, Paris, 2023a.
https://www.oecd.org/en/publications/emerging-trends-in-ai-skill-demand-across-14-oecd-countries_7c691b9a-en.html

OECD, "*The human capital behind AI - Jobs and skills demand from online job postings*", OECD Publishing, Paris, 2023b. https://www.oecd.org/en/publications/the-human-capital-behind-ai_2e278150-en.html

OECD, "*OECD Employment Outlook 2023 - Artificial Intelligence and the Labour Market*", OECD Publishing, Paris, 2023c. https://www.oecd.org/en/publications/2023/07/oecd-employment-outlook-2023_904bcef3.html

World Economic Forum, *"Future of Jobs Report 2025: The jobs of the future – and the skills you need to get them"*, 2025. https://www.weforum.org/publications/the-future-of-jobs-report-2025

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